FINAL REPORT
for the
MANNRRSS II PROGRAM MANAGEMENT
of
NEVADA'S NATURAL RESOURCES
with
REMOTE SENSING SYSTEMS,
BEATTY, NV
prepared for the
Department of Energy

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PREFACE

This document provides the Final Report on The Management of Nevada's Natural Resources with Remote Sensing Systems (MANNRRSS) II program. This is a Department of Energy (DOE)-funded project tasked with utilizing hyperspectral and ancillary electro-optical instrumentation data to create an environmental characterization of an area directly adjacent to the Nevada Test Site (NTS).

The program is a follow on to an effort undertaken in the MANNRRSS I program. The experience gained through the detailed study of the baselined area will allow for larger and longer term programs of natural resource management through remote sensing to be performed in a cost-effective and efficient manner.

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TABLE OF CONTENTS

<u>Section/Title</u>	<u>Page</u>
PREFACE.....	i
1.0 INTRODUCTION.....	1-1
1.1 PROJECT OVERVIEW	1-1
1.2 DOCUMENT OVERVIEW	1-1
1.3 REVIEW OF THE MANNRRSS I PROGRAM	1-1
1.4 GENERAL STUDY AREA BACKGROUND.....	1-2
1.5 GENERAL REMOTE SENSING BACKGROUND	1-4
1.6 RESEARCH QUESTIONS AND OBJECTIVES.....	1-6
1.6.1 Mineral Mapping	1-6
1.6.2 Discrimination of Vegetation at the Species Level.....	1-6
1.6.3 Change Detection and Vegetation Stress.....	1-6
1.6.4 Linear Feature Mapping.....	1-6
1.6.5 Slope Stability	1-6
1.6.6 Multi-Resolution Comparisons	1-7
1.6.7 Automated Analysis.....	1-7
1.7 BACKGROUND OF REMOTE SENSING DATA USED IN THIS STUDY	1-7
1.7.1 Hyperspectral Data.....	1-7
1.7.2 Ancillary Remote Sensing Data.....	1-7
1.8 ACQUISITION, CALIBRATION AND DELIVERY	1-9
1.8.1 SpecTIR Data Collection	1-9
1.8.2 Terra Data Collection.....	1-10
1.9 COMPARISON AND EVALUATION OF SPECTIR AND TERRA SPRING DATA.....	1-14
2.0 GEOLOGIC ANALYSIS.....	2-1
2.1 STRUCTURAL SETTING.....	2-1
2.2 REGIONAL GEOLOGY	2-5
2.3 LOCAL GEOLOGY	2-5
2.4 GEOLOGICAL REMOTE SENSING	2-6
2.5 ANCILLARY INSTRUMENTATION	2-7
2.5.1 ASTER.....	2-7
2.5.2 ASD FieldSpec.....	2-7
2.6 METHODS	2-8
2.6.1 Introduction.....	2-8
2.6.2 Masking.....	2-8
2.6.3 Minimum Noise Fraction (MNF).....	2-9
2.6.4 Pixel Purity Index (PPI).....	2-10
2.6.5 Spectral Angle Mapper	2-10
2.6.6 Mixture-Tuned Matched Filter	2-10
2.7 DATA ANALYSIS	2-10
2.7.1 Mineral Mapping	2-10
2.7.2 Minerals	2-13
2.7.3 Classification Results.....	2-15
2.7.4 Multispectral Mapping.....	2-25

2.7.5	Remote Sensing Mineral Map vs. USGS Geology Map.....	2-31
2.8	MULTI-RESOLUTION STUDIES	2-32
2.8.1	Spatial Resolution	2-32
2.8.2	Spectral Resolution	2-34
2.8.3	Comparison of Analyses Created by Different Analysts.....	2-37
2.8.4	Change Detection of Illite.....	2-39
2.8.5	Hillshade Images.....	2-41
2.8.6	Fault/Linear Feature Map	2-42
2.8.7	LiDAR-derived Map Versus USGS-mapped Faults.....	2-44
2.8.8	Detection of Manmade Disturbances.....	2-45
2.8.9	Slope Stability Map.....	2-47
2.8.10	Modeling Hazards with Combined Slope and Mineral Maps.....	2-50
2.9	DISCUSSION	2-51
2.9.1	What the Mapping Results Mean in the Context of Known Regional Geology....	2-51
2.9.2	Comparison of USGS Field Maps and Remotely Sensed Mineral Maps	2-51
2.9.3	Areas of Concern: Slope Stability.....	2-52
2.9.4	What Can Hyperspectral Do?	2-52
2.9.5	What Can the Fusion with Lidar Provide?.....	2-52
2.9.6	What Can the Fusion with High-resolution Aerial Imagery Provide?.....	2-53
2.10	GEOLOGICAL ANALYSIS CONCLUSIONS	2-53
3.0	VEGETATION ANALYSIS	3-1
3.1	BOTANICAL AND FLORISTIC STUDY AREA BACKGROUND	3-1
3.2	REMOTE SENSING MEASUREMENTS OF VEGETATION	3-1
3.3	METHODS	3-2
3.3.1	Field Data.....	3-2
3.3.2	Pre-processing.....	3-3
3.4	SPECIES DISCRIMINATION	3-4
3.4.1	Masking with NDVI	3-4
3.4.2	Reduce Data Dimensionality	3-5
3.4.3	Using the Data to Spectrally Characterize Vegetation Species	3-6
3.4.4	Field Validation	3-17
3.5	SEASONAL CHANGE DETECTION.....	3-18
3.5.1	Stacking and Co-registration.....	3-18
3.5.2	NDVI and Calculating Percent Change	3-19
3.6	RESOLUTION DEGRADATION.....	3-19
3.7	ANALYSIS OF PLANT VIGOR WITH RESPECT TO SLOPE AND ASPECT.....	3-20
3.8	ANALYSIS AND RESULTS.....	3-21
3.8.1	Species Discrimination	3-21
3.8.2	Trees.....	3-22
3.8.3	Non-tree Riparian Vegetation.....	3-24
3.8.4	Shrubs	3-25
3.9	CHANGE DETECTION.....	3-29
3.9.1	Change Detection Increases.....	3-29
3.9.2	Change Detection Decreases.....	3-33
3.10	SPATIAL RESOLUTION DEGRADATION	3-34

3.11	VEGETATION STRESS WITH RESPECT TO SLOPE AND ASPECT	3-35
3.12	VEGETATION ANALYSIS CONCLUSIONS	3-36
4.0	AUTOMATED HYPERSPECTRAL ANALYSIS: DESCRIPTION AND PERFORMANCE EVALUATION.....	4-1
4.1	MOTIVATION.....	4-1
4.2	SCENE LEVEL PRODUCTS	4-2
4.2.1	Example Scene Summary	4-3
4.2.2	Scene Level Performance	4-11
4.3	DATASET LEVEL PRODUCTS	4-17
4.3.1	Targeted Mapping	4-17
4.3.2	Spectral Library Generation.....	4-27
4.4	REPEATABILITY	4-38
4.4.1	Targeted Mapping Repeatability.....	4-38
4.4.2	Library Generation Repeatability	4-38
4.5	CHANGE DETECTION.....	4-40
4.6	ALGORITHM PORTABILITY	4-43
4.7	AUTOMATED HYPERSPECTRAL ANALYSIS CONCLUSIONS.....	4-47
5.0	CONCLUSION	5-1
5.1	HYPERSPECTRAL SPATIAL RESOLUTION	5-1
5.2	HYPERSPECTRAL SPECTRAL RESOLUTION	5-1
5.3	REFLECTANCE CORRECTION OF HYPERSPECTRAL DATA	5-1
5.4	GEOREGISTRATION	5-2
5.5	ANCILLARY DATA: LIDAR	5-2
5.5.1	Ancillary Data: High Precision Orthophotography	5-2
5.6	AUTOMATION	5-2
5.7	OUTLOOK.....	5-3
6.0	ACKNOWLEDGMENTS.....	5-1
APPENDIX A	VEGETATION TRANSECT DATA.....	A-1
A.1	LOCATION OF VEGETATION TRANSECT DATA.....	A-1
APPENDIX B	AUTOMATED ANALYSIS ALGORITHMS	B-1
B.1	ALGORITHM DEVELOPMENT	B-1
B.2	ALGORITHM FEATURES.....	B-1
B.3	AUTOMATED CLASSIFICATION.....	B-2
B.3.1	Whitening.....	B-2
B.3.2	Endmember Extraction	B-12
B.3.3	Classification.....	B-16
B.3.4	Anomaly Identification	B-19
B.4	MAPPING.....	B-21
B.5	LIBRARY GENERATION	B-23
B.6	DIFFERENCE DETECTION.....	B-23
B.7	SPEED	B-25
B.8	MAGIC NUMBERS.....	B-26

B.9	AUTOMATED ANALYSIS CONCLUSION	B-27
APPENDIX C VENDOR SUPPLIED DOCUMENTS.....		C-1
C.1	TERRA REMOTE SENSING, SPRING 2007 COLLECTION FINAL REPORT	C-1
C.2	TERRA REMOTE SENSING, FALL 2007 COLLECTION FINAL REPORT	C-2
C.3	SPECTIR CORPORATION, SPRING 2007 COLLECTION REPORT	C-3
C.4	SPECTIR CORPORATION, SPRING 2007 COLLECTION QUALITY ASSURANCE REPORT .	C-4
APPENDIX D LIST OF DATA PRODUCTS.....		D-1
D.1	PRIMARY DATA PRODUCTS.....	D-1
D.2	SECONDARY DATA PRODUCTS	D-1
APPENDIX E LIST OF REFERENCES.....		E-1
E.1	GEOLOGICAL REFERENCES	E-1
E.2	VEGETATION ANALYSIS REFERENCES	E-2
E.3	AUTOMATED ANALYSIS REFERENCES.....	E-3
APPENDIX F LIST OF ACRONYMS AND ABBREVIATIONS.....		F-1

LIST OF FIGURES

<u>Figure/Title</u>	<u>Page</u>
FIGURE 1-1. OASIS VALLEY IMAGERY	1-3
FIGURE 1-2. BEATTY/OASIS VALLEY STUDY AREA.....	1-4
FIGURE 1-3. ELECTROMAGNETIC (EM) RADIATION	1-5
FIGURE 1-4. (A) LiDAR-DERIVED DEM DATA; (B) USGS 10-METER DEM DATA.....	1-8
FIGURE 1-5. ILLUSTRATION OF THE MUCH GREATER DETAIL INHERENT WITH THE LiDAR-DERIVED DEM	1-9
FIGURE 1-6. ASD FIELD SPECTRA COMPARISON: CALIBRATED REFLECTANCE AND FIELD REFLECTANCE	1-10
FIGURE 1-7. (A) SYNTHETIC CALIBRATION TARGETS; (B) TERRA COLOR-INFRARED CALIBRATION TARGETS	1-11
FIGURE 1-8. PREPARATION OF REFLECTANCE TARGETS	1-12
FIGURE 1-9. CONFIGURATION OF BRIGHT, MEDIUM AND DARK AGGREGATE REFLECTANCE.....	1-13
FIGURE 1-10. COMPARISON OF AVERAGED CALIBRATION TARGET SPECTRA.....	1-13
FIGURE 1-11. COMPARISON OF ANALYTICAL SPECTRAL DEVICES (ASD) CALIBRATION TARGET SPECTRA	1-14
FIGURE 1-12. CALIBRATION SITES, SPRING AND FALL HYPERSPECTRAL ACQUISITIONS	1-15
FIGURE 2-1. WALKER LANE REGION OF WESTERN NEVADA.....	2-1
FIGURE 2-2. WALKER LANE INTERSECT: SIERRA NEVADA MOUNTAINS AND GREAT BASIN AND RANGE.....	2-2
FIGURE 2-3. GREAT BASIN GEOGRAPHY	2-3
FIGURE 2-4. GEO-MECHANICAL BASIS BEHIND CRUSTAL EXTENSION, UPLIFTING AND DOWN-DROPPING	2-4
FIGURE 2-5. STRUCTURAL RELATIONAL TOPOGRAPHY WITHIN WALKER LANE.....	2-4
FIGURE 2-6. USGS MAP OF LOCAL GEOLOGY OF STUDY AREA.....	2-6
FIGURE 2-7. HYPERSPECTRAL CLASSIFICATIONS OF MINERAL ENDMEMBERS.....	2-11
FIGURE 2-8. HYPERSPECTRAL CLASSIFICATION MAP OF ILLITE	2-12
FIGURE 2-9. ILLITE MAPPED USING A MATCHED FILTERING ALGORITHM	2-13
FIGURE 2-10. SUB-AREA 1: ACID SULFATE CENTER	2-16
FIGURE 2-11. SUB-AREA 2: AGGREGATE DUMP.....	2-17
FIGURE 2-12. SUB-AREA 3: VOLCANIC EXTRUSIONS	2-18
FIGURE 2-13. SUB-AREA 4: OXIDIZED CLAY.....	2-19
FIGURE 2-14. SUB-AREA 5: TUFF COOLING UNIT.....	2-20
FIGURE 2-15. SUB-AREA 6: CHLORITE DUMPS.....	2-21
FIGURE 2-16. SUB-AREA 7: OPEN PIT MINE.....	2-22
FIGURE 2-17. SUB-AREA 8: BARE MOUNTAIN.....	2-23
FIGURE 2-18. SUB-AREA 9: SULFO-SALT PRECIPITATION.....	2-24
FIGURE 2-19. BAND RATIO INDEX: R: 4/7, G: 4/6, B: 4/10	2-25
FIGURE 2-20. CLOSER VIEW OF BAND RATIO INDEX: R: 4/7, G: 4/6, B: 4/10	2-26
FIGURE 2-21. BAND RATIO INDEX: R: 7/6, G: 6/5, B: 6/4	2-27
FIGURE 2-22. CLOSER VIEW OF BAND RATIO INDEX: R: 7/6, G: 6/5, B: 6/4	2-27
FIGURE 2-23. BAND-RATIO 4/5; USED TO CLASSIFY ALUNITE.....	2-28
FIGURE 2-24. BAND-RATIO 7/6; USED TO MAP KAOLINITE	2-29
FIGURE 2-25. BAND-RATIO SIDE-BY-SIDE WITH THE HYPERSPECTRAL DATA CLASSIFICATION	2-30
FIGURE 2-26. COMPARISON OF FALSE-COLOR IMAGES	2-30
FIGURE 2-27. USGS MAP DESIGNATIONS	2-31
FIGURE 2-28. SPATIAL RESAMPLING OF HYPERSPECTRAL IMAGE DATA	2-32
FIGURE 2-29. SPATIAL RESAMPLING OF HYPERSPECTRAL IMAGE DATA, DIFFERENT RESOLUTIONS.....	2-34
FIGURE 2-30. PLOT OF KAOLINITE RESAMPLED TO MAJOR SENSOR SPECTRAL RESOLUTIONS.....	2-35
FIGURE 2-31. CLOSE-UP VIEW OF THE KAOLINITE PLOT	2-36
FIGURE 2-32. MAPPING INDIVIDUAL CLASSIFICATIONS FOR 5, 10 AND 17 NANOMETER RESOLUTION DATA	2-37
FIGURE 2-33. VARIATION IN SPATIAL DISTRIBUTION OF THE PARTICULAR MINERALS	2-38
FIGURE 2-34. TODD MORKEN'S MAPPING OF MINERALS IN THE SAME SCENE	2-39
FIGURE 2-35. SPECTIR IMAGERY (SPRING 2007) AND TERRA REMOTE SENSING DATA (FALL 2007)	2-40
FIGURE 2-36. SPECTIR IMAGERY (SPRING) AND TERRA REMOTE SENSING (FALL) COMPARISON.....	2-41
FIGURE 2-37. GEOMETRY OF THE SUN ORIENTATION AND ANGLE WITH RESPECT TO TARGET	2-41
FIGURE 2-38. LiDAR GENERATED MAP.....	2-42
FIGURE 2-39. LiDAR HILLSHADE IMAGES	2-43
FIGURE 2-40. LiDAR HILLSHADE IMAGE SHOW TUFF UNITS THAT CLOSELY FOLLOW CONTOUR.....	2-44
FIGURE 2-41. LiDAR-DERIVED MAP VERSUS USGS-MAPPED FAULTS.....	2-45

FIGURE 2-42. USE OF HILLSHADE IMAGES TO DETECT DISTURBANCES ON THE SURFACE OF THE EARTH	2-46
FIGURE 2-43. HILLSHADE IMAGE EXAMPLE SHOWING IDENTIFICATION OF ANOMALIES	2-47
FIGURE 2-44. SLOPE INTENSITY MAP GENERATED FROM THE LIDAR DIGITAL ELEVATION	2-48
FIGURE 2-45. SLOPE INTENSITY OF OPEN PIT MINE IN SUB-AREA 1	2-49
FIGURE 2-46. CONTRAST VISUALIZATION OF PIT MINE SLOPE	2-49
FIGURE 2-47. SLOPE AND MINERAL CLASSIFICATION DATASETS USED TO IDENTIFY POTENTIAL HAZARD	2-50
FIGURE 2-48. SLOPE IMAGERY SHOWING SEVERE VERTICAL FEATURES	2-51
FIGURE 3-1. LABORATORY REFERENCE SPECTRA FOR SELECTED VEGETATION SPECIES	3-1
FIGURE 3-2. LOCATIONS OF VEGETATION FIELD TRANSECTS	3-3
FIGURE 3-3. COMPARISON OF (A) TERRA COLOR-INFRARED IMAGE WITH (B) FALSE-COLOR COMPOSITE	3-5
FIGURE 3-4. COTTONWOOD (A AND B) AND WILLOW (C AND D) TRAINING AREAS	3-7
FIGURE 3-5. RUSSIAN OLIVE (A AND B) AND TAMARISK (C AND D) TRAINING AREAS	3-8
FIGURE 3-6. SENESCED REPARIAN (A AND B) AND SENESCED (C AND D) TRAINING AREAS	3-9
FIGURE 3-7. CREOSOTEBUSH (A AND B) AND BITTERBRUSH (C AND D) TRAINING AREAS	3-10
FIGURE 3-8. RABBITBRUSH (A AND B) AND SALTBUSH (C AND D) TRAINING AREAS	3-11
FIGURE 3-9. SALTBUSH TRAINING AREA	3-12
FIGURE 3-10. FIELD PHOTOS OF TRAINING AREAS	3-13
FIGURE 3-11. ADDITIONAL FIELD PHOTOS OF TRAINING AREAS	3-14
FIGURE 3-12. LOCATIONS OF TRAINING AREAS CORRESPONDING TO SECTION 3 FIGURE NUMBERS	3-15
FIGURE 3-13. TRAINING SPECTRA USED IN A MATCHED-FILTER (MF) ALGORITHM	3-16
FIGURE 3-14. (A) COTTONWOOD MF RESULT BEFORE CUT-OFF THRESHOLD WAS APPLIED	3-18
FIGURE 3-15. COTTONWOOD CANOPIES SHOWING EDGE EFFECTS CAUSED BY MISREGISTRATION	3-19
FIGURE 3-16. ANALYSIS RESULTS, (A) LIDAR, (B) NDVI FOR TERRA, (C) ASPECT, (D) SLOPE	3-21
FIGURE 3-17. OVERVIEW OF SPECIES MAPPED WITH TERRA SPRING HYPERSPECTRAL DATA	3-22
FIGURE 3-18. EXAMPLE OF COTTONWOOD MAPPING WITH HYPERSPECTRAL DATA	3-23
FIGURE 3-19. VISUAL COMPARISON: (A) COTTONWOOD AND WILLOW (B) COTTONWOOD AND RUSSIAN OLIVE....	3-23
FIGURE 3-20. EXAMPLE OF TAMARISK MAPPING WITH HYPERSPECTRAL DATA	3-24
FIGURE 3-21. EXAMPLE OF SENESCED AND GREEN VEGETATION MAPPING WITH HYPERSPECTRAL DATA	3-25
FIGURE 3-22. FIELD PHOTOS OF SHRUBS (A) CREOSOTEBUSH (B) SALTBUSH (C) RABBITBRUSH (D) BITTERBRUSH..	3-26
FIGURE 3-23. DIGITAL ORTHOPHOTOGRAPHY OF SALTBUSH WITH CORRESPONDING FIELD PHOTOS	3-27
FIGURE 3-24. BITTERBRUSH MAPPING	3-28
FIGURE 3-25. CREOSOTEBUSH MAPPING	3-29
FIGURE 3-26. OVERVIEW OF THE VEGETATIVE CHANGES IN OASIS VALLEY	3-30
FIGURE 3-27. CHANGE DETECTION RESULTS IN GREENNESS WITH CATTAILS AND BULLRUSH	3-31
FIGURE 3-28. CHANGE DETECTION RESULTS IN GREENNESS WITH SALT GRASS	3-32
FIGURE 3-29. PLANT SPECIES: 1.- BULL RUSH 2.- NUT SEDGE 3.-SALT GRASS 4.- SPOROBOLUS	3-33
FIGURE 3-30. CHANGE DETECTION FOR COTTONWOOD	3-34
FIGURE 3-31. IKONOS RESOLUTION AND SPOT RESOLUTION	3-35
FIGURE 4-1. SCENE FROM TERRA DATASET	4-3
FIGURE 4-2. SCENE SUMMARY OUTPUT BY AUTOMATED ANALYSIS	4-4
FIGURE 4-3. CLASSIFICATIONS FOR EXAMPLE SCENE	4-5
FIGURE 4-4. RADIANCE SPECTRA OF THE SCENE DOMINANT CONSTITUENTS	4-6
FIGURE 4-5. PURITY (LEFT) AND FIT DISTANCES (RIGHT) OF THE PIXELS IN THE EXAMPLE SCENE	4-7
FIGURE 4-6. THE FIT DISTANCE DISTRIBUTION FOR THE EXAMPLE SCENE	4-8
FIGURE 4-7. ONE OF THE TWO ANOMALOUS REGIONS OF THE EXAMPLE SCENE	4-8
FIGURE 4-8. SECOND EXAMPLE OF AN ANOMALY	4-9
FIGURE 4-9. THE ABUNDANCE OF THE NINTH CONSTITUENT OF THE SCENE	4-10
FIGURE 4-10. ALL OF THE CONSTITUENT ABUNDANCE MAPS FROM THE EXAMPLE SCENE	4-11
FIGURE 4-11. FIDELITY FIGURES OF MERIT FOR THE FULL SPRING TERRA DATASET	4-12
FIGURE 4-12. GEOGRAPHIC DISTRIBUTION OF SCENE FIDELITY	4-13
FIGURE 4-13. EXAMPLE OF SPECTRAL CONFUSION	4-15
FIGURE 4-14. ROAD LINED WITH BUSHES DEMONSTRATING A FORM OF ANOMALIES	4-16
FIGURE 4-15. RGB VIEW OF JOSHUA TREE SCENE	4-18
FIGURE 4-16. SUMMARY OUTPUTS FROM THE JOSHUA TREE TARGET SOURCE	4-19
FIGURE 4-17. TARGET SPECTRUM ABUNDANCE OVER THE ENTIRE DATASET	4-20
FIGURE 4-18. MAPPING OF JOSHUA TREE (RED), CREOSOTE (GREEN), AND BITTERBRUSH (BLUE)	4-21

FIGURE 4-19. AUTOMATED JOSHUA TREE MAPS	4-22
FIGURE 4-20. TARGET MAPS OF THREE GEOLOGICAL CONSTITUENTS, N-S LINE OF TERRA SPRING DATASET.....	4-23
FIGURE 4-21. VEGETATION MAPS OF THREE SPECIES ALONG THE E-W LINE, TERRA SPRING DATASET	4-24
FIGURE 4-22. FIFTY-SIX SPECTRA OF THE N-S LINE BY AUTOMATED EXTRACTION PROCESS.....	4-27
FIGURE 4-23. SPECTRA AND ORTHOPHOTOGRAPHY, AUTOMATED SUMMARY, SPRING TERRA DATASET N-S LINE	4-28
FIGURE 4-24. SPECTRA OF TEN SELECTED GEOLOGICAL CONSTITUENTS, N-S LINE LIBRARY	4-29
FIGURE 4-25. MAPPED DISTRIBUTION OF TEN SELECTED GEOLOGICAL CONSTITUENTS, N-S SPRING LIBRARY	4-30
FIGURE 4-26. CLOSEUP OF THE MIDDLE OF THE N-S LINE, SUB-AREA 1	4-31
FIGURE 4-27. ILLUSTRATION OF OVERLAP OF THE MANUAL AND LIBRARY MAPS FOR ILLITE	4-32
FIGURE 4-28. SPECTRA OF SEVEN SELECTED VEGETATION CONSTITUENTS FROM THE N-S LINE LIBRARY	4-33
FIGURE 4-29. MAPPED DISTRIBUTION OF SEVEN SELECTED VEGETATION CONSTITUENTS, N-S LINE LIBRARY	4-34
FIGURE 4-30. SIDE BY SIDE COMPARISON OF A PORTION OF THE RIPARIAN CORRIDOR	4-35
FIGURE 4-31. THE SPECTRA OF EIGHT SELECTED ROOF CONSTITUENTS FROM THE N-S LINE LIBRARY	4-36
FIGURE 4-32. MAPPED DISTRIBUTION OF EIGHT SELECTED VEGETATION CONSTITUENTS, N-S SPRING LIBRARY ..	4-37
FIGURE 4-33. SELECTED GEOLOGICAL CONSTITUENTS AUTOMATICALLY EXTRACTED; FALL DATASET	4-39
FIGURE 4-34. EXAMPLE OF THE SHORT TERM CHANGE DETECTION FOR THE TERRA SPRING E-W DATASET	4-41
FIGURE 4-35. SEASONAL CHANGE MAP, A PORTION OF THE N-S FLIGHT LINE DIFFERENCE.....	4-42
FIGURE 4-36. EXAMPLE SCENE: CUPRITE NV VISIBLE COLORS VS AUTOMATED SCENE	4-43
FIGURE 4-37. RADIANCE SPECTRA EXTRACTED BY THE AUTOMATED SCENE ANALYSIS	4-43
FIGURE 4-38. PIXEL FIT DISTANCES FOR THE CUPRITE SCENE	4-44
FIGURE 4-39. SELECTED CONSTITUENT FROM THE AVIRIS CUPRITE SCENE	4-44
FIGURE 4-40. ABUNDANCE OF ALL SIXTEEN CONSTITUENTS FOUND IN THE CUPRITE SCENE.....	4-45
FIGURE 4-41. SIDE BY SIDE COMPARISON SHOWING EXCELLENT AGREEMENT FOR COMPARED MINERALS	4-46
FIGURE 4-42. COMPARISON CLASSIFICATION USING THE AUTOMATICALLY EXTRACTED ABUNDANCES.....	4-46
FIGURE A-1. SIX UNIQUE PLANT COMMUNITIES WITHIN STUDY AREA	A-1
FIGURE A-2. SPATIAL DISTRIBUTION OF PLANT CANOPIES IN TRANSECT 1, MENODORA/LARREA.....	A-5
FIGURE A-3. SPATIAL DISTRIBUTION OF PLANT CANOPIES IN TRANSECT 2, SALAZARIA/CHRYSOTHAMNUS	A-6
FIGURE A-4. SPATIAL DISTRIBUTION OF PLANT COVER IN TRANSECT 3, NATIVE MARSH	A-7
FIGURE A-5. SPATIAL DISTRIBUTION OF PLANT COVER IN TRANSECT 4, SAALTGRASS GREASWOOD	A-7
FIGURE A-6. SPATIAL DISTRIBUTION OF PLANT COVER IN TRANSECT 5, SALTGRASS/NUTSEDGE.....	A-8
FIGURE B-1. SCATTER PLOTS OF PIXEL FIT DISTANCE VERSUS PIXEL RADIANCE FOR THREE SIGNAL SCALINGS.....	B-4
FIGURE B-2. ILLUSTRATION OF THE SHIFT DIFFERENCE TECHNIQUE.....	B-4
FIGURE B-3. ILLUSTRATION OF THE MODIFIED SHIFT DIFFERENCE ESTIMATE OF THE WHITENING MATRIX.....	B-6
FIGURE B-4. ILLUSTRATION OF DEFINING THE SENSOR MASK	B-7
FIGURE B-5. INTERPOLATION ACROSS A ROW OF SIX BAD ELEMENTS.....	B-8
FIGURE B-6. SPECTRUM OF EIGENVALUES RECOVERED FROM A WHITE NOISE SOURCE	B-9
FIGURE B-7. PROCESS TO ESTIMATE THE TRUE NOISE EIGENVALUES	B-10
FIGURE B-8. RADIANCE SPECTRUM BEFORE AND AFTER THE WHITENING TRANSFORMATION.	B-11
FIGURE B-9. SEPARATION OF TWO PIXELS FOLLOW A WELL DEFINED DISTRIBUTION ("CHI" DISTRIBUTION)	B-11
FIGURE B-10. FIT DISTANCES RESULTING FROM UNMIXING MAY NOT FOLLOW CHI DISTRIBUTION EXACTLY	B-15
FIGURE B-11. A HISTOGRAM OF THE EFFECTIVE NUMBER OF BANDS ACROSS THE TERRA SPRING DATASET.	B-16
FIGURE B-12. ENDMEMBERS EXTRACTED FOR AN EXAMPLE SCENE	B-17
FIGURE B-13. EXAMPLE SCENE ENDMEMBERS AND CLASSIFICATION.....	B-17
FIGURE B-14. IN THE DISTANCE WHITENED SPACE, THE TYPICAL SIGNAL IS APPROXIMATELY 43 UNITS LONG....	B-18
FIGURE B-15. FIT DISTANCES OF THE EXAMPLE SCENE	B-20
FIGURE B-16. FIT DISTANCE VERSUS BRIGHTNESS.....	B-20
FIGURE B-17. EXAMPLE OF A FOUND ANOMALY.....	B-21
FIGURE B-18. DIFFERENCE DETECTION EXAMPLE	B-25

LIST OF TABLES

<u>Table/Title</u>	<u>Page</u>
TABLE 3-1. SPATIAL AND SPECTRAL RESOLUTION FOR THE IKONOS AND SPOT MULTISPECTRAL SATELLITES ...	3-20
TABLE 3-2. AVERAGE NDVI VALUES ACCORDING TO SLOPE AND ASPECT FOR SPRING AND FALL DATASETS	3-36
TABLE 4-1. ANALYSIS OF ALUNITE CONTENT	4-24
TABLE 4-2. OVERLAP OF ILLITE MAPS	4-25
TABLE 4-3. OVERLAP OF ALUNITE MAPS	4-25
TABLE 4-4. OVERLAP OF BITTERBRUSH MAPS	4-26
TABLE 4-5. OVERLAP OF CREOSOTE BUSH MAPS.....	4-26
TABLE 4-6. OVERLAP OF SALT BUSH MAPS.....	4-26
TABLE 4-7. RESULTS OF THE OVERLAP OF THE MANUAL AND LIBRARY MAPS FOR ILLITE	4-31
TABLE 4-8. AREAS AND OVERLAPS OF ALUNITE AND ILLITE TARGET MAPS, FALL AND SPRING DATASETS.....	4-38
TABLE A-1. PLANT COMMUNITIES CHARACTERIZED IN THE STUDY AREA.....	A-2
TABLE A-2. PERENNIAL PLANT SPECIES FOUND IN VEGETATION TRANSECTS	A-3
TABLE A-3. PLANT SPECIES COVER WITHIN SIX SAMPLED COMMUNITIES	A-4
TABLE D-1. LIST OF PRIMARY DATA PRODUCTS	D-1
TABLE D-2. LIST OF SECONDARY DATA PRODUCTS	D-2

1.0 INTRODUCTION

1.1 Project Overview

The Management of Nevada's Natural Resources with Remote Sensing Systems (MANNRRSS) II program is a Department of Energy (DOE)-funded project tasked with utilizing hyperspectral and ancillary electro-optical instrumentation data to create an environmental characterization of an area directly adjacent to the Nevada Test Site (NTS). The program is a follow on to an effort undertaken in the MANNRRSS I program. The experience gained through the detailed study of the baselined area will allow for larger and longer term programs of natural resource management through remote sensing to be performed in a cost-effective and efficient manner.

As highlighted in Sierra Nevada Corporation (SNC) proposal 01-02804 Rev 01, the logistical difficulties in conducting MANNRRSS I research within the boundaries of NTS proved difficult. The area immediately west of NTS, Oasis Valley, was chosen as a terrain and ecological analog for the NTS (Figure 1-1). The baseline geospatial products created in this program will be made accessible to decision-makers in the future for remote sensing-based land management/study issues.

A collaborative agreement between the University of Nevada-Reno (UNR), the Desert Research Institute (DRI) and SNC was implemented in order to enhance the respective capabilities of each entity by utilizing remote sensing datasets. UNR's research focuses on mineral mapping, and geological hazard identification. DRI will explore the potential to map individual species of vegetation or groups of species, in addition to identifying temporal changes in vegetation. SNC will be the primary point of contact for the data vendor and will coordinate the efforts of DRI and UNR. Furthermore, SNC will investigate methods of automating aspects of analysis as they pertain to the goal of increasing cost-effectiveness of remote sensing programs.

1.2 Document Overview

The body of this document is divided into three main sections, corresponding to the geological, botanical, and automation portions of the program studies. Each chapter is relatively self-contained. After the main body and conclusion section there are five appendices containing details of vegetation transect data (Appendix A), a description of the automated analysis algorithms developed for the program (Appendix B), vendor supplied information on their data product deliveries (Appendix C), a list of data products available through this program (Appendix D), a list of References (Appendix E), and a list of Acronyms and Abbreviations (Appendix F).

1.3 Review of the MANNRRSS I Program

The original MANNRRSS program sought to utilize hyperspectral image data to create an environmental baseline characterization of an area of importance to DOE on or in proximity to the NTS. The project included hyperspectral mapping and characterization of minerals and vegetation at select locations within NTS during July and October of 2005.

Visible, near-infrared and shortwave infrared (VNIR/SWIR) hyperspectral data was collected over NTS by the SpecTIR Corporation of Sparks, Nevada during July of 2005 using the HyperSpecTIR-3 sensor. A series of sensor calibration and image registration errors by the vendor resulted in delay of the program objectives. A collection of new imagery was proposed by SpecTIR in order to satisfy contractual obligation. Subsequent image data analysis by

graduate students from UNR's Arthur Brant Laboratory for Exploration Geophysics (ABLE) resulted in the creation of basic mineral and vegetation distribution maps of the Nonproliferation Test and Evaluation Complex (NPTEC) facility and area in proximity (NPTEC, 2005), located on the NTS (Figure 1-3). In addition, a secondary investigation into the relationship of ground sample distance (GSD) or pixel size and resulting spectral signatures was conducted (Figure 1-4). Overall ground support to corroborate image data results were severely impacted by security precautions on the NTS, which was a large part of the rationale in moving subsequent research projects off of the site.

1.4 General Study Area Background

Beatty, Nevada is situated in the Oasis Valley at the headwaters of the Armagosa River approximately 100 miles to the northwest of Las Vegas and along U. S. Route 95. Yucca Mountain, Nevada Test Site, and the Nevada Test and Training Range lie about 15 miles to the east of Beatty (Figures 1-1 and 1-2). The study area is also near the transition zone that divides the southern Great Basin and the northern Mojave deserts with an annual average precipitation of 6.2 inches (157 mm). The three month winter average maximum and minimum temperatures are 58 and 31 F° (15 and -1 C°), while the three month summer averages maximum and minimum are 94 and 58 F° (34 and 15 C°). Plant community structure in the study area is a function of elevation, soil moisture availability and salinity and past and current land use practices. Evergreen and deciduous shrubs are the dominant plant growth-forms at high elevations, perennial grasses and deciduous trees are dominant in riparian areas, but trees tend to be replaced by shrubs as salinity of riparian areas increases with the exception of salt-tolerant invasive tamarisk trees. Plant cover is positively correlated with soil moisture and elevation, while species diversity is positively correlated with elevation and negatively correlated with land disturbance and soil salinity. Geologic units include volcanic rhyolites, metamorphic quartzites and sedimentary limestones, resulting in mixed mineralogies on alluvial fans and in valley bottoms. Elevations range from approximately 1,460 ft (445 m) on valley bottoms to a maximum of 4,760 ft (1,450 m), with slopes varying from less than 1 percent to greater than 60 percent.

Figure 1-1 shows a near-infrared color combination (R: near-infrared, G: red, B: green) of ASTER imagery is shown above. Vegetation is represented in red, clays and volcanoclastic materials are shown as bright scene features, carbonates are visible in bluish colors and volcanic features are dark-toned. Area outlined in yellow shows the study area, more detail is provided in Figure 1-2.

Figure 1-1. Oasis Valley Imagery

Figure 1-2 shows the location of Beatty/Oasis Valley study area due west of the Nevada Test Site (NTS) and the Nevada Test and Training Range (NTTR), along the Highway 95 corridor. Yellow boxes show the approximate area imaged by the hyperspectral sensors. The north-south box is centered on Oasis Valley. The east-west box covers a portion of the Bull Frog hills to the west and northern slopes of the Bare Mountains in the east. The smaller “X” boxes in the lower left of the figure were flown by SpecTIR only and cover the ghost town of Rhyolite and adjacent pit mines. The town of Beatty and Nevada Highway 95 are shown for reference, map coordinates are UTM zone 11, NAD 83.

Figure 1-2. Beatty/Oasis Valley Study Area

1.5 General Remote Sensing Background

For over 30 years remote sensing measurements have been made to classify different land cover types, perform geologic and mineral mapping, estimate vegetation vigor, and detect vegetation landscape change (Goetz et al., 1985). A synoptic approach to this work can significantly save time and effort in the field. Optical remote sensing takes advantage of reflected solar energy in the 4.0 – 2.5 μm wavelength region shown in Figure 1-3. The various spectral resolutions used to make measurements in this wavelength region combined with an instruments spatial resolution are what set different instruments and datasets apart. Spatial resolution corresponds to one pixel in an image. As an example, 1 m spatial resolution corresponds to an image pixel with associated reflected radiance values for a particular 1 meter by 1 meter footprint on the ground. Government operated multispectral satellites such as Landsat and ASTER continue to provide information about the earth's surface that is commonly referenced in scientific literature. However, spatial and spectral resolution of these instruments limits the research that scientists can perform using these data. During the past decade commercial satellites such as IKONOS and Quickbird have offered multispectral data products that achieve 4 meter or better spatial resolution. While the spatial resolution of these instruments is adequate for accomplishing many fine scale vegetation-related remote sensing tasks, multispectral resolution is not sufficient for the challenging job of species discrimination. Furthermore, these satellites do not cover the

short-wave infrared portion of the spectrum where many diagnostic spectral features for geologic materials occur. Continued advancements in instrument technology have improved instrument capabilities with regard to both spectral and spatial resolution. Thus, there is now a greater level of detail for both mineral mapping and vegetation remote sensing measurements using airborne hyperspectral instruments.

Figure 1-3 shows the Electromagnetic (EM) radiation reflected by materials on the surface of the Earth are measured in discrete wavelengths in order to compare differences in percent reflectance, indicative of photon energy absorption. The portion of the EM spectrum measured in optical remote sensing generally ranges from 400 to 2500 nanometers. This encompasses the visible (VIS), near-infrared (NIR) and shortwave-infrared (SWIR). The amount of energy per wavelength reflected to the sensor is related to phenomena at the molecular level of a particular surface.

Figure 1-3. Electromagnetic (EM) Radiation

1.6 Research Questions and Objectives

1.6.1 Mineral Mapping

The primary goal is to create a comprehensive map of surficial mineralogy using hyperspectral image data. This will include, but not be limited to minerals in the iron oxide, phyllosilicate and carbonate groups. Classification maps will be created using various analytic methodologies in order to emphasize different aspects of map information (Boardman, 1994). This includes mapping of the strongest mineral signatures in the area of study, in addition to creating a density slice distribution map for each mineral, resulting in a way to determine not only the strong presence of a mineral, but also the distribution of intensity of spectral features.

1.6.2 Discrimination of Vegetation at the Species Level

Most spaceborne remote sensing studies of vegetation attempt to group similar vegetation types or plant communities because they lack the spectral resolution that is necessary for detailed mapping. More recently, airborne hyperspectral surveys have been tested in a variety of environments in an attempt to discriminate individual vegetation species (e.g., Miao et al, 2007; Lawrence et al., 2006; Clark et al., 2005; Mundt et al., 2005; Schmidt and Skidmore 2003). The creation of such species maps with hyperspectral remote sensing data has the potential to provide a more automated approach for creating botanical inventories on federal lands. We explore the use of mapping with hyperspectral data for selected vegetation species.

1.6.3 Change Detection and Vegetation Stress

Analysis and comparison of co-registered temporally different datasets enables observations of changes in vegetation vigor. Such change detection amongst vegetation may be related to human caused stress, such as pollutants, fire damage, irrigation patterns and seasonal differences related to phenology. Our goal was to determine what types of vegetation change was detectable with hyperspectral data. We also wanted to determine what effects slope and aspect have on vegetation vigor.

1.6.4 Linear Feature Mapping

The high-resolution ability of LiDAR to detect minute topographical relief allows an analyst to create detailed Digital Elevation Models (DEM). Various secondary products can in turn be produced from the DEM, including contour maps, slope aspects and hillshade images. Hillshade images were investigated from various sun angles and directions to create optimal representations of linear features which are possibly indicative of fault traces. Faults can be expressed surficially as large vertical and/or horizontal offsets, or they can be older or ill-exposed, in which eroded soil has covered a great deal of their severe features. Faults can also be concealed at the surface but inferred by certain processes such as geothermal activity or mineral alteration. Hillshade products were used to create a map of linear features expressed on the surface of the study area. Comparison to United States Geological Survey (USGS) fault maps will be conducted. We will then be able to comment on the comparative ability of LiDAR to replicate ground-based observations, and perhaps introduce areas previously unrecognized as displaying faulting.

1.6.5 Slope Stability

High-resolution slope maps created with a LiDAR-derived DEM will identify the steepest areas within the study area. We will investigate these data as they relate to surficial mineral

classifications in an attempt to observe if any apparent relationships are present. Any correlations could provide information pertinent to geological hazards identification. However, in the arid desert environment of the study area, we do not see the high likelihood of landslides, mudslides, etc. associated with similar image data investigations of previous research. Although there may be exceptions such as open pit mines of which the walls are composed of varying clay minerals. Integrity of the walls may be able to be modeled based upon slope and mineral information.

1.6.6 Multi-Resolution Comparisons

The effect of resolution constraints upon resultant mineral and vegetation maps will be explored so that resolution thresholds for various levels of mapping detail may be determined. To do this, the airborne hyperspectral data acquired for this study will be resampled to different resolutions of common industry-standard sensors such as AISA, AVIRIS, HyMap, IKONOS and SPOT. The results of mapping at various spatial and spectral resolutions may then be compared and serve to guide the selection of the most cost effective dataset for future mapping objectives.

1.6.7 Automated Analysis

Analysis of remote sensing data has traditionally been a relatively labor intensive and expensive endeavor, due to the size and complexity of the datasets involved. As part of the cost effectiveness goals of the program, we identified methods for labor reduction and automation of many aspects of the data analysis needed to achieve the goals outlined above. We implemented algorithms to perform most hyperspectral analysis tasks automatically or with greatly reduced labor costs, and evaluated the algorithm performance.

1.7 Background of Remote Sensing Data Used in this Study

1.7.1 Hyperspectral Data

Several hyperspectral datasets were taken of the target area. The target area consisted of two long strips, a North-South strip centered on the Oasis valley, and an East-West strip following a local mountain chain (Figure 1-2). These two areas overlap in order to allow a common area for field work related to quality control of the datasets. All hyperspectral datasets were requested to have one meter spatial resolution, 10 nm spectral resolution, have a reflectance correction applied, and to be georeferenced to an accuracy of one meter.

The SpecTIR Corp. and Terra Remote Sensing Inc. were each contracted to acquire airborne hyperspectral data for the study area in the April of 2007. The purpose for duplicating the data coverage was to increase the probability of obtaining high quality data and to compare the capabilities of separate vendors. Both SpecTIR and Terra used the AISA dual sensor (Appendix C) that covers the 0.4 – 2.5 μm wavelength region and acquired 1 m data. Figure 1-2 shows the approximate locations of the areas imaged. Both vendors were given the same specifications for the hyperspectral data to be provided.

The North-South line was again imaged in September 2007 by Terra remote sensing to allow study of seasonal change detection in the Oasis valley area.

1.7.2 Ancillary Remote Sensing Data

Several ancillary datasets were acquired to complement the hyperspectral data. In order to evaluate the value added by these data, they were used where possible in the study goals outlined above. Future remote sensing efforts can use these results to evaluate the cost effectiveness of collecting these additional datasets.

In addition to the hyperspectral data Terra simultaneously acquired Light Detection and Ranging (LiDAR) and digital orthophotography data during spring 2007. LiDAR employs an active airborne sensor system that emits a narrow beam of light at the ground at a frequency of approximately 5000 times per second. The time it takes for the light to return is recorded and later corrected for aircraft motion. Post-processing is commonly handled by the data vendor with deliverables in the form of a Digital Elevation Model (DEM) with sub-meter horizontal accuracy and centimeter accuracy in the vertical direction. Geo-registered DEMs are compatible with other spatial data in a Geographic Information System (GIS) and enable analyses related to slope, aspect, and elevation. Ten-meter DEMs are presently available for the entire United States from the United State Geological Survey, however,

Figure 1-4 shows (a) LiDAR-derived shaded relief image illustrates the level of detail inherent in the LiDAR-derived DEM data (b) shaded relief generated from a USGS 10-meter DEM is shown for comparison. The red line is Highway 95 along the floor of Oasis Valley for reference.

Figure 1-4. (a) LiDAR-derived DEM Data; (b) USGS 10-meter DEM Data

Figure 1-5 illustrates the much greater detail inherent with the LiDAR-derived DEM. The digital orthophotography was acquired with a 14 megapixel camera. Subsequent data processing removed distortion to provide geo-registered true-color image data with 15 cm spatial resolution. (a) shows 15 cm Spatial Resolution (digital orthophotography) (b) shows 1 meter Spatial Resolution (Terra color infrared composite).

Figure 1-5. Illustration of the Much Greater Detail Inherent with the LiDAR-derived DEM

1.8 Acquisition, Calibration and Delivery

1.8.1 *SpectTIR Data Collection*

SpectTIR data was acquired on April 2-3, 2007 while visibility was greater than 100 miles. ATCOR atmospheric modeling software was used to convert radiance data into calibrated reflectance. This process incorporated the use of a LIDAR-derived DEM provided by Terra.

In addition to the modeled reflectance data an empirical line calibration (Conel et al., 1987) was used as a secondary correction to reflectance. The reflectance spectra of bright and dark targets measuring 5 m by 5 m (Figure 1-6) provided by SpecTIR and deployed by DRI, UNR and SNC personnel were recorded with a field spectrometer during the time of acquisition. Fifty spectral measurements were acquired at two second intervals and averaged to representative spectra for each target; field spectral measurements of bare soil and a water body were also recorded and averaged. Global positioning systems (GPS) measurements of all calibration surface footprints were made to within 0.5 m accuracy and supplied to the vendor. The best empirical line calibration results were achieved with the water and bare soil spectra as dark and bright targets, respectively.

The positional accuracy of the data was 0.46 m and covered more than 60 km². Over 29 GB of reflectance data was delivered to DRI on August 07, 2007.

1.8.2 Terra Data Collection

1.8.2.1 Spring Acquisition

Terra data was collected acquired on April 9, 2007 between 10:56 – 14:13 PDT while visibility was greater than 100 miles. Calibration targets were deployed by DRI in the same location used for the SpecTIR acquisition. The same method of field measurements was conducted and the averaged bright/dark target spectra were supplied to Terra along with the earthen spectra collected during the SpecTIR acquisition. Terra was not satisfied with their first attempt at atmospheric correction using ATCOR software. Their best calibrated reflectance results were achieved with an empirical line calibration method that used the bright target, soil, and water. Figure 1-6 shows ASD field spectra for calibration surfaces compared with corresponding pixels of the Terra calibrated reflectance data for the spring acquisition.

Figure 1-6. ASD Field Spectra Comparison: Calibrated Reflectance and Field Reflectance

Positional accuracy is within 1 m in the along track direction and 1-4 meters in the across track direction. Over 300 GB of calibrated reflectance data covering more than 77 km² was delivered to DRI on July 17, 2007.

Figure 1-7 (a) shows synthetic calibration targets deployed in the field for the Fall acquisition. (b) Terra color-infrared composite showing the calibration targets (image center), each pixel is 1 m by 1 m, red pixels are shrubs. Figure 1-12 shows location of calibration site within the study area.

Figure 1-7. (a) Synthetic Calibration Targets; (b) Terra Color-Infrared Calibration Targets

1.8.2.2 Fall Acquisition

Terra data was acquired on Sept. 25, 2007 between 11:00 – 13:53 PST while visibility was greater than 100 miles. To improve the calibration to reflectance, DRI sub-contracted a local quarry operator to prepare a configuration of bright, medium and dark aggregate reflectance targets (Figures 1-8 and 1-9). The motivation for different sized targets was to compare single-pixel image spectra extracted from the smaller targets with the averaged spectra of 36 pixels from the corresponding 8 m by 8 m target. For the smaller targets we assumed a 1 m or better positional accuracy would yield at least one pure pixel within a 3 m by 3 m target. If space, materials or money were in short supply the single pixel target spectra would be acceptable for calibration (Figure 1-10). However, the noise-level was reduced when more pixels were averaged, resulting in fewer artifacts in the calibrated reflectance data. The synthetic calibration targets used in the spring collect were also deployed in the fall acquisition but none of these spectra were used in the final calibration. After ATCOR was applied to the radiance data fifty field spectral measurements for each of the large targets were averaged and used in a secondary empirical line correction. Figure 1-11 shows a comparison of Analytical Spectral Devices (ASD) calibration target spectra with the corresponding Terra calibrated reflectance spectra.

Figure 1-8 shows (a) Schematic showing configuration of aggregate calibration targets used in the fall acquisition (b) collecting spectral measurements on the on the 3x3 meter white target. Figure 1-12 shows the location of calibration site within the study area.

Figure 1-8. Preparation of Reflectance Targets

Figure 1-9 shows (a) color-infrared composite from Terra fall data showing the field calibration site. Corners of the targets were recorded in the field with a precision (>3 cm horizontal accuracy) global positioning system, corner coordinates are displayed on the image with yellow dots (b) field photo showing calibration targets used in fall data acquisition (view to west). Figure 12 shows location of the calibration site within the study area.

Figure 1-9. Configuration of Bright, Medium and Dark Aggregate Reflectance

Figure 1-10 shows comparisons of averaged spectra from pixels in 8x8 m targets with single pixel spectra from the 3x3 m targets.

Figure 1-10. Comparison of Averaged Calibration Target Spectra

Figure 1-11 shows averaged field spectra for the white, gold, and dark aggregate targets compared with ATCOR-derived reflectance spectra and empirical-line derived spectra. Spectra of synthetic calibration targets is not shown.

Figure 1-11. Comparison of Analytical Spectral Devices (ASD) Calibration Target Spectra

1.9 Comparison and Evaluation of SpecTIR and Terra Spring Data

Field spectral measurements were compared with the corresponding image spectra for both Terra and SpecTIR datasets. Expert knowledge was also used to explore the spectral quality of the datasets. After applying the secondary reflectance correction both datasets modeled the field spectra well. However, the Terra data covered approximately 28 km² more terrain at the north end of the North-South flight box. Although it was specified in the contract, this same area was not covered by SpecTIR. Therefore, we chose the most complete dataset for further processing.

Figure 1-12 below shows the location of calibration sites for the spring and fall hyperspectral acquisitions within the study area.

Figure 1-12. Calibration Sites, Spring and Fall Hyperspectral Acquisitions

2.0 GEOLOGIC ANALYSIS

2.1 Structural Setting

The area of study lies within the southwestern region of the Great Basin and the southern end of the Walker Lane belt. Beatty falls within the southern portion of the Goldfield block, one of nine crustal blocks that comprise Walker Lane (Cornwall, 1972). The area is also located within the Southwestern Nevada Volcanic field. Tectonic extension in the area began in the mid to late Miocene and resulted in substantial block tilting. During the final states of these processes, volcanism surged and resulted in structurally controlled and distributed mineralization. Sawyer, et al. studied the feasibility of Caldera-related vs. detachment faulting mineralization events. The research, based upon regional geologic studies of NTS, concluded that the cause of mineralization of mineral deposits in and around NTS was due to detachment faulting.

Walker Lane is a linear north/northwest-trending depression which ranges approximately 500 miles from the Las Vegas area to south-central Oregon; see Figure 2-1. It is an area, to include Owens Lake and Death Valley, of major tectonic activity that comprises the Walker Lane Fault Zone. Walker Lane consists of a distinct structural style within the Sierra Nevada and Basin and Range provinces; the region is subject to extensional force resulting in normal fault movement (Figure 2-2).

This region, found within western Nevada and eastern California, has been subjected to significant tectonic activity within the recent geological history of the area. This has major repercussions for resultant geological activity, including earthquakes, intrusive and extrusive igneous emplacements and mineralization of host rock. A bulk of historic and present mining within the State of Nevada occurs in the Walker Lane due to this phenomenon.

Figure 2-1. Walker Lane Region of Western Nevada

Walker Lane intersects two major types of regional geology – the Sierra-Nevada Mountains, uplifted granite batholiths which mark the western perimeter of the Great Basin and the Basin and Range, a region noted for alternating uplifted ranges and down-dropped basins. Walker Lane has been subjected to both compressional and extensional forces resulting in structurally complex rock units; see Figure 2-2.

Figure 2-2. Walker Lane Intersect: Sierra Nevada Mountains and Great Basin and Range

The Great Basin is a geological province spanning a large part of the western United States, and encompasses the study area; see Figure 2-3. Basin and range topography refers to the extensional force applied to the crust of the earth, effectively stretching and thinning the crust. The topographic features stemming from this are alternating mountain ranges and basins (Figure 2-4). Uplifted areas appear as mountains, which bound the down-dropped basin areas. Its boundaries are formed by the Sierra Nevada Mountain range to the west, the Wasatch Mountains and high plateaus to the east, basalt-capped ridges of the Snake River Plains to the north and an indistinct southern perimeter partially marked by the Colorado River. The thinning of the crust has increased heating of the subsurface (Figure 2-5). Meteoric waters infiltrate permeable alluvium and rock and are sometimes heated at depth and then rise toward the surface along deeply penetrating faults and manifesting as hot springs. Beatty displays direct evidence of this in the form of active hot springs, which are located near the center of Oasis Valley, and also coincident to the boundaries of the study area.

As Figure 2-3 shows, the Great Basin is a geographic region within the western United States which possesses waterways having no outlet to the Pacific Ocean. Largely bordered by mountains, large plateaus, etc., hydrographic repercussions of these topographical barriers result in large-scale evaporation of incoming precipitation. Basin and range topography has formed due to crustal extension of the area. This is manifested via alternating mountain ranges, which are uplifted, and basins which form in the down-dropped crustal blocks.

Figure 2-3. Great Basin Geography

Figure 2-4 describes the geo-mechanical basis behind crustal extension, uplifting and down-dropping in the western United States and subsequent formation of range and basin topography.

Figure 2-4. Geo-mechanical Basis behind Crustal Extension, Uplifting and Down-dropping

Figure 2-5 shows a simplified relationship between crustal extension, basin and range topography and heating and subsequent mineralization of thin areas of the crust is shown above. This structural depiction is generally applied to the majority of the area found within the Walker Lane.

Figure 2-5. Structural Relational Topography within Walker Lane

2.2 Regional Geology

The regional geology features units ranging from Precambrian to Quaternary (Maldonado, 1990). Older Precambrian endmembers include gneissic granite, quartz monzonite and quartz-biotite schist. Younger Precambrian rocks include quartzite, siltstone, micaceous shale or schist, and marble, dolomite and limestone. The Paleozoic unit is comprised of limestone and dolomite. The Mesozoic unit features granodiorite and quartz monzonite intrusions and megabreccias. Tertiary time includes volcanic and tuffaceous clastics, including welded tuffs. Tertiary and Quaternary units both feature alluvial fans. Lastly, recent Quaternary basalt flows and cinder cones are prevalent throughout the area.

2.3 Local Geology

The bulk of local bedrock geology is comprised of middle-to-late Miocene ash-flow tuff which emanated from the adjacent calderas of the southwest Nevada volcanic field (Stuckless, 2007), (Figure 2-6). Four major tuff or ash-flow units intersect the boundaries of the study area. The Timber Mountain and Paintbrush (Pliocene) and Crater Flat (Miocene) ash-flow tuffs and rhyolitic ash-flow dominate the area's geology. Older welded tuff, basalt, sedimentary breccia and conglomerate and hydrothermally altered rhyolites form a minority of the area (Fridrich, 2007). The northern tip of Bare Mountain, a Paleozoic carbonate unit, intersects the southern boundary of the East/West flight box. The area has been exploited for mineralization for a variety of precious and commodity metals (Eng, 1995).

The top view of Figure 2-6 shows a United States Geological Survey (USGS) map of the local geology within the area of study to denote distinct geological units, based upon ground surveys. The area of study polygon is draped upon the geology map in order to reference the available variety of units within each particular flight box. At center, an ASTER true-color image shows the variety of volcanoclastic and dolomitic rocks dominating the East/West box, while alluvium, evaporites and altered volcanic tuffs comprise the bulk geology of the North/South flight box. At bottom, a merged geology and ASTER map emphasizes each dataset's unique characteristics.

Figure 2-6. USGS Map of Local Geology of Study Area

2.4 Geological Remote Sensing

The Landsat series of sensors, whose advent resulted in spaceborne measurements of large masses of land, allowed geologists to study the correlation between spectral reflectance of image data and observed land features. Advances in laboratory measurement of spectra resulted in a deep understanding of the diagnostic features of many common, and increasingly uncommon minerals found in various geological environments on and within the Earth. Today a large body of knowledge is available for geologists and image scientists based upon the accrual of research experience. The modern-day testing ground for mineral mapping using spectral sensors is

undoubtedly Cuprite, Nevada. Cuprite is one of the most mapped, tested and ground-truthed areas in the world, due to its distinct alteration mineralogy that is so well-suited to the advantages of reflectance imaging spectroscopy (Kruse, 1993). The discovery of an unknown, at the time, mineral was due to being mapped as an anomaly in the area. Buddingtonite is an ammonium feldspar which develops (rarely) in an acid sulfate environment. This discovery led to a wide-spreading interest in utilizing airborne hyperspectral image data in an exploration fashion. Since the early 1990's hyperspectral has continued to be used to study known and unknown geological environments in order to understand their surficial mineralogy.

2.5 Ancillary Instrumentation

2.5.1 ASTER

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) is a 14 band imaging spectrometer which is operated by the National Aeronautics and Space Administration (NASA). The geological mapping aspect of the data is based upon multispectral spectral resolution capability. This results in being able to map broad mineralogical groups such as phyllosilicates, carbonates and iron oxides, however the spectral resolution is not detailed enough to delineate individual minerals within the group, e.g., kaolinite, dickite, illite, etc. in the phyllosilicate group. The spatial resolution capabilities of the sensor are similar to other spaceborne platforms, in that the resolution is low to moderate in the reflective portion of the EMS (15 m in the visible and near-infrared, 30 m in the shortwave-infrared) and low in the emissive bands (90 m). The technology utilized in the ASTER sensor resulted in a few improvements over Landsat TM capabilities. First, the total number of spectral bands in the VS and TIR are higher, resulting in the increased ability to spectrally delineate objects on the ground. Next, the SNR of ASTER is superior to Landsat TM, which also results in an enhanced ability to map endmembers. In total, ASTER spectral data is well suited for moderate (district) scale geological mapping. The image data is best applied when using low spatial and spectral resolution to map targets of interest over a large spatial extent.

2.5.2 ASD FieldSpec

An Analytical Spectral Devices, Inc. (ASD) FieldSpec Pro portable spectroradiometer was used throughout the study in order to make measurements of bulk and crushed rock samples both in the field and in the laboratory. The range of measurement available with the instrument is from 350 to 2500 nm, which spans a larger segment of spectrum than that available with the aerial hyperspectral data. The FieldSpec Pro uses three individual photon array detectors which are optimized for respective ranges of the electromagnetic spectrum due to the chemical properties of the detector. An 8 degree foreoptic was used in all measurements, which provided a moderate sized field of view appropriate for measuring bulk and crushed samples in laboratory as well as outcrops and patches of earth in the range of 1 to 10 square meters. In general, crushed samples yielded a higher reflectance spectrum and enhanced spectral clarity versus bulk samples, and these were retained for comparison to image data. A 99% reflectance Spectralon panel was used to calibrate the instrument in order to make measurements in reflectance. Calibrations were made liberally in response to either detectable changes in the weather, cloud movement, or the range from foreoptic to target.

2.6 Methods

2.6.1 Introduction

The methodology used to process hyperspectral data is lengthy, somewhat complex and requires user input at nearly each stage of data processing. The total size of the data is a unique challenge which compounds the need for a well-developed, comprehensive and logical plan to produce an analytical product. The structure of our plan to analyze the data revolves around the traditional ENVI hourglass method, with minor modifications at certain points in the order of the plan (ITTVis, 2008). The data used to begin the process was the Terra RS hyperspectral data calibrated to apparent reflectance using an empirical line correction with ATCOR atmospheric removal. The data was delivered in georectified form, which slightly increases the time to perform specific algorithms.

Two different strategies were utilized to analyze the data. The first was to process the imagery in large segments, divided into the north/south, east/west and second-day east/west data. Each segment was processed as one whole file. The second was to process each file individually and then add each classification product to a comprehensive GIS. Comparison of results from each method were compared for a single area and found to be similar, in terms of the distribution of the present minerals. The former strategy was employed for the remainder of the data processing.

Hyperspectral data collected by two data providers, Terra Remote Sensing and SpecTIR, were examined to determine the utilization of respective data for the goals of this project.

Both datasets were approximately similar in spatial resolution. The TerraRS dataset was collected at 5 nm spectral resolution, while the SpecTIR dataset was collected at 10 nm dataset. This resulted in a sizeable difference in total size of the datasets; this has ramifications for computer processing time, because additional bands per flightline increase the amount of data. In addition, the TerraRS data covered a larger spatial extent than the SpecTIR dataset. This was attributed to airspace restrictions which the latter data provider encountered at the northern and eastern margins of the planned flight bounding box. The result was that the TerraRS dataset was larger in total size, but more comprehensive in spatial extent. The final but most important metric used to determine which dataset would be utilized to concentrate upon comprehensive mapping of surficial mineralogy was the quality of the correction to apparent reflectance. The Terra RS image data appeared to match library spectra better than the SpecTIR data.

2.6.2 Masking

One of the most important steps in the processing of hyperspectral data processing is the identification of what you do not want to map. This information is powerful and can result in less processing time and more time used for interpretation of spectra. The specific targets identified for removal in spectral processing were 1) manmade objects, such as buildings, paved highways and roads, automobiles and other metallic objects; 2) pixels comprised predominantly of vegetation; 3) abnormal pixels (data artifacts). The methods used to define and identify pixels that fall within these three categories varied. For the manmade objects, manual identification was deemed the most time efficient way to detect these. The observation of linear features and relatively bright structures was the best way to determine presence. Although not all manmade objects were mapped this way, the majority of these objects were found. A region of interest layer consisting of vector polygons was constructed to mark groups of pixels which displayed houses, roads, automobiles, etc. For the mapping of vegetation, a simple Normalized Difference Vegetation Index (NDVI) band ratio was used. The NDVI function is based upon the

identification of spectral features unique to vegetative scene components. Specifically a chlorophyll trough and reflectance peak in the near infrared are identified and then divided by each other. The resulting image identifies the presence of vegetation as a function of the difference between the low reflectance value of chlorophyll and the high reflectance value of the near IR. Band 61 was used for the chlorophyll trough and 85 was used as the near-IR reflectance band. A histogram stretch was then employed to narrow the vegetation matches according to the inspection of the corresponding spectral image data. For the E/W box, a 0.272 threshold was sufficient; for the N/S box, a 0.135 threshold was optimal. In each instance the histogram threshold utilized was liberal, in order to remove as much vegetation as possible from further processing. Abnormal pixels are defined here as those which display spectra which deviate greatly from expected ground measurement. This includes spiking, not-a-number (NaN), and other aberrations. For the most part these were identified by specifying within ENVI processes that zero values, NaN values should not be considered in the processing. Spikes and such were found using simple statistical methods to separate outliers. Visual inspection of such pixels was undertaken, and these were then marked using an Region of Interest (ROI). The cumulative mask was created by adding each of these identified pixels to be summed into one mask file. This mask file was then used for the subsequent processing.

2.6.3 Minimum Noise Fraction (MNF)

The Minimum Noise Fraction (MNF) process is a data cloud transformation which is used to separate two distinct components: noise and coherent data (Green, 1988). The algorithm is essentially a double-cascaded principal components transform. The data is first transformed orthogonally by variance and the noise is separated from the data. The next transform performs principal components analysis upon the noise-whitened data (Green, et al.). By identifying this threshold the noisy data can be separated and removed from further processing. This results in a couple advantages: first, the overall size of the dataset can be reduced significantly, which has repercussions for processing time; next, the dimensionality can be determined, which is an important metric for determining the spectral uniqueness of pixels within a spatial extent, in addition to characterizing the relative, qualitative signal to noise of the spectral data. The cumulative mask discussed previously was used to note pixels not to consider in the MNF process. In addition, bands 177 through 195 and 160 through 163 were removed from the processing due to abnormal behavior in the respective water band segments and the tail end of the shortwave infrared measurement. Specifically, the abnormal behavior was manifested as extremely low and commonly negative values in the water band, and as negative values in the longest wavelengths. A specific number of MNF bands, 30, were selected to be produced instead of choosing an arbitrary eigenvalue cutoff band. This method was employed due to past experience with the dimensionality of the specific sensor data utilized in this project, as well as prior experimentation with dimensionality in numerous subsets of the image data. A visual inspection of each MNF band was used to determine spatial coherence of the band. If the band appeared to have coherence, it was retained for further processing. Note: this determination is entirely qualitative, although a quantitative metric is possible, by inspection of eigenvalue. An eigenvalue determination of noise/coherence can be set, however this quantitative measure is largely arbitrary, and the visual method produced better results when implemented in small sample datasets.

2.6.4 Pixel Purity Index (PPI)

The pure pixel index (PPI) is the next step performed in the ENVI hourglass process. The identified “good” MNF bands are input into the PPI algorithm, which is a statistical treatment used to identify spectral unique endmembers within the data cloud. These endmembers are characterized as the most spectrally extreme which also ideally represent spectrally pure substances on the ground. In the framework of n-dimensionality, an n-dimensional scatterplot is computed in a random vector. The most extreme data points are recorded. This process repeats for each pixel in the image and a tally is created which informs us which pixels have been recorded as extreme most often, which correlates to the most spectrally unique endmembers. Default ENVI settings were implemented for this process. A manual step was next used to threshold the number of pure pixels utilized for the next step in the process. The PPI image was opened and inspected for a general sense of the distribution of the pixels. Next, the spectral data was opened and linked to the PPI image. The histogram plot was then opened for the PPI image and was used to set a threshold which seemed to reduce redundant pure pixels while still retaining unique pixels. This was determined by viewing the spectral signatures of the corresponding pure pixels via the spectral data z-profile. Once a satisfactory compromise was found between retaining pure endmembers and reducing redundancy, the histogram stretch values were recorded and then a threshold to ROI function was used to output an ROI file for both the spectral and PPI image. The ROI file was saved and retained for further usage in the next processing step.

2.6.5 Spectral Angle Mapper

Spectral Angle Mapper (SAM) is an unsupervised algorithm commonly used to identify materials versus a reference spectrum, from either a library or in-scene region of interest.

The reference and tested spectrum are both treated as vectors and the angle between them is then found. An important attribute of the algorithm is that it tends to mitigate the effects of shadows and topography because it does not discriminate a positive identification based on these factors. Specifically only vector direction is utilized for identification, not vector length. Lastly, it tends to produce results fairly quickly, and thus serves as a quick classification method for testing purposes. An automatic classification and “rule” image are generated as the results. The rule image is of most use in analysis, as a histogram stretch can be used to set identification thresholds.

2.6.6 Mixture-Tuned Matched Filter

The mixture-tuned match filter algorithm was used utilized to test the portability of classification results versus SAM. The algorithm uses input spectra from library or from an in-scene reference to compute likeness in terms of sigma. In addition, an infeasibility image is generated to aid in identification of probable false positive pixels. A high match filter score in concert with a low infeasibility score results in an acceptable match.

2.7 Data Analysis

2.7.1 Mineral Mapping

A comprehensive map of surficial mineralogy of the study area was created using VNIR/SWIR reflectance hyperspectral image data classifications (Figure 2-7). The bulk detectable mineralogy of the area included iron oxide, sulfates, clays, volcanic minerals and carbonates, which were found in locations consistent within the geological context of their respective areas. The mapping

strategies employed for this task were split into two types: abundant presence and intensity. Abundant presence mapping is an important remotely-sensed map product primarily to field studies and situations where the best exposed and purest mineral examples need to be found at first glance. In this situation, judicious use of classification image thresholding is utilized in order to reduce the total number of pixels classified in the scene for a given mineral. The resulting classification is less cluttering and highlights only the areas where the analyst has very high confidence that the mineral will be found upon ground inspection. In turn, field geologists can take this map, then make field observations and subsequently extrapolate the presence of particular minerals for large areas, often coincidentally with rock units on geology maps.

Figure 2-7 shows the hyperspectral classifications of mineral endmembers which are draped upon high-resolution panchromatic imagery. Ten unique endmembers were identified and mapped within the area of study. These minerals largely follow the geological context of the area, with classes such as: volcanoclastic, evaporite, carbonate, oxidized and alteration products/clays. Specific areas of interest are identified above within individual polygons which correspond to a particular number. The algorithms used to map the minerals included spectral angle mapper and matched filtering. The map was constructed to emphasize the best examples of each mineral, in contrast to showing the absolute cover per pixel.

Figure 2-7. Hyperspectral Classifications of Mineral Endmembers

In the second instance, intensity maps indicate the presence of a mineral without the use of severe classification thresholding (Figure 2-8). This map result can be applied to geomorphology studies of the area, and is particularly useful in monitoring erosion, transportation and depositional behavior of observed areas. A close-up view of the sub-area 1 classification is shown in Figure 1-9. Although geomorphological processes were not specifically addressed in this report, individual mineral intensity maps were created for future studies of the area.

A hyperspectral classification map of illite is shown in Figure 2-8 below. This map emphasizes the simple presence of the mineral in relative terms. Black indicates no presence while red indicates the strongest presence. Information about geological processes, in addition to the presence of a mineral, can be indicated on this type of map, due to identification of weathering of rock.

Figure 2-8. Hyperspectral Classification Map of Illite

The pit mine area identified in Figure 2-8 is shown in greater detail in Figure 2-9. The mineral illite was mapped using a matched filtering algorithm. Warm colors here indicate the strongest presence of the mineral, as measured by the intensity of the 2200 nanometer absorption feature.

The use of both manual inspection of the image data and pure pixel indices resulted in the identification of 10 distinct mineral endmembers within the area of study. The minerals include types of sulfates, clays, carbonates, an evaporite, an iron oxide a zeolite and volcanic glass. Each

mineral mapped was found in an area of expected geological context. The various geological environments we see in the area of study are of hydrothermal alteration, evaporative crust, volcanic extrusion and carbonate sedimentary beds.

Figure 2-9. Illite Mapped Using a Matched Filtering Algorithm

2.7.2 Minerals

Alunite, $\text{KAl}_3(\text{SO}_4)_2(\text{OH})_6$, is a potassium aluminum sulfate hydroxide formed by the alteration of potassium-rich feldspars by sulfuric acid. These sulfuric acids are present in hydrothermal solutions, which can also carry valuable metals important to the mining industry. Alunite visibly appears massive, displays high albedo and can be oxidized. At first glance, an outcrop of alunite can appear no different than limestone or a clay. The importance of the identification of this mineral in relation to limestones obviously has potential economic implications.

The observation of alunite laboratory spectra indicates that there are many unique characteristics of this mineral. In the visible segment of the EM spectrum we see no unique diagnostic features – it is overall indicative of a highly reflective sample, and there are no substantial electronic or other absorptions present. In the infrared portion of the spectrum, we see a typical sulfate absorption at 1.75 and the diagnostic double OH-related vibrational absorptions at 2.15 and 2.32.

Mirabilite, $\text{Na}_2\text{SO}_4(10\text{H}_2\text{O})$, is a hydrous sodium sulfate, and it forms in an evaporative environment. It generally forms as a sulfosalt crust around saline springs and playas. This class of sulfate evaporites has general features which are easily perturbed by their hydration states. This phenomena of hydration flux makes absolute identification of specific sulfate evaporite minerals more difficult. Observation of mirabilite spectra reveals the 1.0, 1.22 and 1.75 diagnostic features indicative of many sulfates of this class. The lack of absorptions and the prominence of a relative peak at 2.28 is diagnostic of this particular mineral.

Kaolinite, $\text{Al}_2\text{Si}_2\text{O}_5(\text{OH})_4$, is a clay mineral derived from the alteration of feldspar minerals by acidic geothermal activity. It is another mineral that is related to mineralization, and can be of economic importance. The spectra of kaolinite indicates a high albedo in the visible spectrum and the diagnostic doublet OH absorption at 2.2 is highly unique to this mineral.

Illite, $(\text{K}, \text{H}_3\text{O})(\text{Al}, \text{Mg}, \text{Fe})_2(\text{Si}, \text{Al})_4\text{O}_{10}[(\text{OH})_2, (\text{H}_2\text{O})]$, is a micaceous clay that occurs due to hydrothermal alteration of mica and/or feldspar. It has numerous ion substitutions and is noted for its non-expansive nature. Illite spectra can exhibit either unique or non-unique features in the visible range. It can have a greenish tint, as seen in the reflectance peak at .58, and resulting from absorptions at blue and red wavelengths. Otherwise illite is largely spectrally bland in the visible and near-infrared, and appears bright. OH absorptions at 2.2 and 2.34 are highly diagnostic, however the 2.2 can result in confusion with other clay minerals without sufficient spectral resolution. The 2.34 absorption helps to eliminate miss-identification.

Calcite, CaCO_3 , is a calcium carbonate that can form under many different conditions. In the context of our study area, the calcite we observe comes from different environments. The first example was dissolved by acidic water and subsequently precipitated post-transportation. The second was gravel/aggregate, obviously not naturally occurring. This mineral can be identified on the ground by the use of hydrochloric acid, which induces effervescence due to the release of CO_2 . In the visible spectrum it appears bright, but otherwise featureless. In the infrared calcite has a large diagnostic absorption at 2.33.

Dolomite, $\text{CaMg}(\text{CO}_3)_2$, is a sedimentary carbonate mineral which forms so-called dolostone. In many aspects it is similar at first inspection to calcite – visibly bright and usually massive in form. When hydrochloric acid is applied to it, it does not fizz unless in powdered form – a test which can be employed in the field. The spectra appears quite similar to calcite as well, with a few minor differences. The diagnostic feature in the infrared is shifted down relative to calcite to 2.31.

Chlorite, $(\text{Mg}, \text{Fe})_3(\text{Si}, \text{Al})_4\text{O}_{10}(\text{OH})_2(\text{Mg}, \text{Fe})_3(\text{OH})_6$, is a phyllosilicate mineral which has many ion substitutions. It is found in low and medium temperature metamorphic rocks, in addition to the igneous and hydrothermal settings. It appears visibly green, which is reflected in its peak in the visible spectra at .58. In the infrared an OH absorption is found at 2.32.

Opal/Volcanic Glass (Obsidian), $\text{SiO}_2(\text{H}_2\text{O})$, is hydrated silica which is technically not a mineral due to lack of crystalline structure. Instead it is referred to as a mineraloid. For practical purposes we treat it as a mineral. It is deposited within fissures of rocks such as basalt at low temperatures. Water content is variable and generally falls within 3 and 10 percent. *Volcanic glass*, SiO_2 , is formed when lava is immediately cooled upon being expelled. The spectra for opal/chalcedony and volcanic glass are nearly identical and will be combined for classification purposes as volcanic glass until laboratory measurements prove otherwise. Generally opaque in the visible and near infrared regions of the spectrum, the diagnostic feature for these mineral is found at 2.25 is very broad relative to other common mineral absorptions.

Zeolites, $(\text{Na}, \text{Mg})_2\text{Al}_2\text{Si}_3\text{O}_{10}(\text{2H}_2\text{O})$, are hydrated aluminosilicate minerals with many different cations. They form at the intersection of volcanic rock, ash and circulated brine. Zeolites are commonly employed for industrial purposes such as being a component of concrete, in addition to chemical filtering properties. The spectral features of specific zeolite minerals are quite similar - spectrally featureless in the visible and near-infrared, while the shortwave-infrared features a small unique 2.13 absorption upon a large reflectance peak ranging from nearly 2.0 to 2.45.

2.7.3 Classification Results

2.7.3.1 Sub-area 1: Acid Sulfate Center

Sub-area 1 is centrally located in the North/South flight box. Geothermal activity in the local area has resulted in the creation of acid sulfate minerals, in the form of alunite and kaolinite. The hyperspectral data was able to identify and measure the distribution of five distinct minerals: kaolinite, alunite, illite, silica and zeolite (Figure 2-10). The spectra of these minerals are each largely dissimilar owing to diagnostic absorption features. The mapped minerals did not seem to indicate a proper contact existing between them. Ground-based investigation of the area did reveal areas of oxidation and non-oxidation which may have a relationship to a particular mineral. The inexact definition of mineral boundaries may be due to the significant amount of mixing between the parent outcrops and the detrital weathering product. The minerals alunite, illite and kaolinite were able to be mapped with a high degree of confidence due to their unique absorption features. The minerals zeolite and silica were not as easy to distinguish due to their lack of any prominent absorption feature.

Figure 2-10 below shows Sub-area 1 which is centrally located in the North/South flight box. Geothermal activity has resulted in the creation of acid sulfate minerals, in the form of alunite and kaolinite. The classification figure above demonstrates the measured distribution of five minerals: kaolinite, alunite, illite, silica and zeolite. The corresponding spectra of these minerals are shown in a comprehensive plot, to the right. Diagnostic absorption features are demarcated by arrows. Ground-based photographs demonstrate the field view vs. measured presence of a particular mineral. This approach to mapping can be very powerful when distinct contacts between minerals or mineral assemblages is desired.

Figure 2-10. Sub-area 1: Acid Sulfate Center

2.7.3.2 Sub-area 2: Aggregate Dump

Sub-area 2 features five unique endmembers, two of which seem to appear anomalously (Figure 2-11). Chlorite and calcite are not mapped anywhere else in the North/South flight box, which makes their detection an intriguing prospect in terms of geothermal potential importance. Both calcite and chlorite might be expected in a geothermal setting, owing to dissolution in acidic water and later precipitation. This rationale led us to believe that a current or, at minimum, younger spring might be present. Upon ground inspection, the area was found to be a gravel/aggregate dump. A single pile consisting half of chloritic and half carbonate rock was found, thus resolving the presence of the anomaly. The spectra of chlorite and calcite are both distinctive, however there exists slight overlap in both minerals' absorption features (near 2300 nanometers) in the SWIR. The reflectance peak at approximately 580 nanometers is a unique characteristic of chlorite. Spectral separation can be easily accomplished by taking advantage of this difference between the two, yielding a high confidence mineral distribution map.

Figure 2-11 below shows Sub-area 2 which features five unique endmembers, two of which seem to appear anomalously. Chlorite and calcite are not mapped anywhere else in the

North/South flight box, which makes their detection a potentially important finding. Both calcite and chlorite might be expected in a geothermal setting. This rationale led us to believe that a current or, at minimum, younger spring might be present.

Figure 2-11. Sub-area 2: Aggregate Dump

2.7.3.3 Sub-area 3: Volcanic Extrusions

Sub-area 3 displays three minerals – silica (volcanic glass), zeolite and illite (Figure 2-12). The area is largely covered with volcanoclastic materials. Tuffs of different composition are commonplace, indicative of volcanic activity. In close proximity to the study area, multiple calderas are found which distributed the observed blankets of tuff. The ground photo above shows a distinct contact between the silica-rich rock and the zeolite. These features are visible throughout the local area and common to ridgelines, peaks, etc. These are possible cooling units, with obsidian or volcanic glass at the bottom and grading up towards unwelded tuff. The presence of illite may suggest the flow of water through permeable rock, thereby facilitating the alteration of feldspars to clay. The spectral features of each endmember are very distinct. Silica has a prominent wide absorption feature centered at 2250 nanometers. Zeolite is unique in that it displays a large reflectance peak in the SWIR, and no absorption feature. Illite has a common OH absorption feature at 2200 nanometers.

Figure 2-12 of sub-area 3 displays three minerals – silica (volcanic glass), zeolite and illite. The area is largely covered with volcanoclastic materials. Tuffs of different composition are commonplace, indicative of volcanic activity. In close proximity to the study area, multiple calderas are found which distributed the observed blankets of tuff. The ground photo above shows a distinct contact between the silica-rich rock and the zeolite. These features are visible throughout the local area and common to ridgelines, peaks, etc. The presence of illite may suggest the flow of water through permeable rock, thereby facilitating the alteration of feldspars to clay. The spectral features of each endmember are very distinct. Silica has prominent absorption feature centered 2250 nanometers. Zeolite is unique in that it displays a large reflectance peak in the SWIR, and no absorption feature. Illite has a common OH absorption feature at 2200 nanometers.

Figure 2-12. Sub-area 3: Volcanic Extrusions

2.7.3.4 Sub-area 4: Oxidized Clay

Sub-area 4 is comprised of large outcrops of oxidized kaolinite (Figure 2-13) of which are the largest in vertical profile in the entire area of study. Weathering of the outcrops is not extensive due to the arid environment found in the study area. The spectral signature of the feature allowed separation into both oxidized and unoxidized clay units. The complete identification of a particular clay rock sample can be split into the two categories because the absorption features (OH) resulting in the diagnostic doublet of kaolinite is governed by a different physical process (vibrational) than that of the absorptions which cause the reflectance peak indicative of goethite (electronic). The unoxidized faces of the outcrop most likely indicates areas where the wind and water have helped to erode the weathering outer layer of rock away, yielding a fresh face.

Figure 2-13 below shows Sub-area 4 which is comprised of large outcrops of oxidized kaolinite. Weathering of the outcrops is not extensive due to the arid environment found in the study area. The complete identification of a particular clay rock sample can be split into two categories, such

as the outcrops found here. This is because the absorption features (OH) resulting in the diagnostic doublet of kaolinite is governed by a different physical process (vibrational) than that of the absorptions which cause the reflectance peak indicative of goethite (electronic).

Figure 2-13. Sub-area 4: Oxidized Clay

2.7.3.5 Sub-area 5: Tuff Cooling Unit

Sub-area 5 displays silica and illite in an area of high topographical relief (Figure 2-14). The silica classification follows contour, suggesting a relationship between the mineral and the structure of the geology, such as the presence of a caldera perimeter. USGS maps do not specifically indicate a caldera structure here, however the area is included in a local caldera field. Ground-based observation revealed the silica ring to be the lower portion of a tuff cooling unit, which yields obsidian/volcanic glass. This is indicative of a viscous volcanic extrusion, such as rhyolite. The upper portion of the package will possibly yield a gradient of welded to lightly or non-welded tuff.

Figure 2-14 below shows Sub-area 5 which displays silica and illite in an area of topographical relief. The silica classification follows contour, suggesting a relationship between the mineral and the structure of the geology. The classification may be indicative of the perimeter of a caldera. USGS maps do not specifically indicate a caldera structure here, however the area is included in a local caldera field. Ground-based observation reveals the class as a tuff.

Figure 2-14. Sub-area 5: Tuff Cooling Unit

2.7.3.6 Sub-area 6: Chlorite Dumps

Sub-area 6 is located in proximity to an open-pit mine, which likely exploited gold. Adits, shafts and exploration pits are found throughout the area and gangue material is found near their respective openings (Figure 2-15). The gold traditionally exploited in the Bullfrog Hills was hosted in a chloritic rock as shown in the figure. Illite, an alteration product is also associated with mineralization in this instance. Both minerals are able to be mapped with high confidence due to absorption features that are prominent yet found in different portions of the SWIR spectrum. Disturbed surfaces can be identified with image-specific contextual information and the mapped presence of oxidized rock material. In this instance, oxidized rocks appear in loose halos of waste rock near the mouths of mine exploration tunnels.

Figure 2-15 shows Sub-area 6 located in proximity to a gold open-pit mine. Adits and exploration pits are found throughout the area and gangue material is found near the respective openings. The gold traditionally exploited in the Bullfrog Hills was hosted in a chloritic rock as shown above. Illite, an alteration product is also associated with mineralization in this instance. Disturbed surfaces can be identified with image-specific contextual information and the mapped presence of oxidized rock material.

Figure 2-15. Sub-area 6: Chlorite Dumps

2.7.3.7 Sub-area 7: Open Pit Mine

Sub-area 7 focuses on an inactive open-pit mine located in the eastern portion of the East/West flight box (Figure 2-16). The mine exploited gold in a hydrothermally-altered host rock. The clay minerals kaolinite and illite are the major components of the pit walls, while trace amounts of chlorite and carbonate are found within the lower portion of the pit. Oxidation of the clays has occurred and is highlighted at the steps, rim and road leading from the pit. Ground-based investigation yielded significant weathering and degradation of certain portions of the pit walls, particularly at the interface of kaolinite and illite. The clay walls have become largely unstable in a near vertical orientation. The proximity to Bare Mountain suggests that the convergence of carbonate rock and the host rock spurred mineralization along a fault located planar to the location of the pit. The spectral absorption features of illite and kaolinite are found at similar areas of the SWIR spectrum, approximately 2200 nm. The distinctive doublet feature of kaolinite, and the sharp single absorption of illite result in the ability to effectively separate the two minerals in a map product.

Figure 2-16 shows the Sub-area 7 focus on an inactive open-pit mine located in the eastern portion of the East/West flight box. The clay minerals kaolinite and illite are components of the pit walls. Trace amounts of chlorite and carbonate are found within the pit. Oxidation of the

clays has occurred and is highlighted at the steps, rim and road leading from the pit. The proximity to Bare Mountain suggests that the convergence of carbonate and the host rock spurred mineralization along a fault located planar to the location of the pit.

Figure 2-16. Sub-area 7: Open Pit Mine

2.7.3.8 Sub-area 8: Bare Mountain

The northeastern tip of Bare Mountain is found within a limited portion of the area of study and is distinctive, both visually on the ground and spectrally, as measured by the hyperspectral image data (Figure 2-17). A large amount of mining activity has occurred in the dolostone, as evidenced by illite and goethite dumps upon the dolomite classification. This may be because specific sorts of mineralization occur at the interface of carbonate host rocks and later metamorphism, commonly caused by intrusion of magma nearby. These types of mineralization are referred to as skarns; and although no instance of this occurrence was found in the literature, perhaps this was the earlier miner's rationale for searching for precious metals here. The spectral features of dolomite are very distinctive, as a large absorption feature is found at 2320 nanometers. Calcite appears to be very similar in spectral signature to dolomite, however the absorption feature is found at a slightly higher wavelength.

As Figure 2-17 shows, Sub-area 8 is located at the northern-most reach of the Bare Mountains, a system of largely carbonate rocks. Dolomite representing dolostone is shown above. Alteration minerals kaolinite and illite are seen at the contact between the mountain and basin fill. The contact between carbonates and other rocks are areas likely to have mineralization. Metamorphism of these areas can result in skarns; evidence of this process in the area is not seen, however an open pit mine which intersects a northernmost finger of Bare Mountain and a USGS-plotted fault. Numerous adits and exploration pits can be found in the area.

Figure 2-17. Sub-area 8: Bare Mountain

2.7.3.9 Sub-area 9: Sulfo-salt Precipitation

Sub-area 9 is located in the center portion of the north/south flight box (Figure 2-18). The transient flow of water at the surface of Oasis Valley results in the precipitation of sulfate

minerals. During the period of study the observed cover of precipitates, although not measured, visibly varied from being barely seen to forming thick crusts. The mineral mirabilite was measured with the image data. The distinctive reflectance peak near 2300 nanometers and the typical sulfate absorption at 1750 nanometers help to identify it with a high level of confidence. The particular hydration state of the sulfo-salt crust will affect the technical mineral present. This makes comparisons between ground and image data samples difficult – the amount of time that elapses between measurements will likely result in a change of hydration state.

As Figure 2-18 shows, Sub-area 9 is located in the center portion of the north/south flight box. The transient flow of water at the surface of Oasis Valley results in the precipitation of sulfate minerals. During the period of study the observed cover of precipitates, although not measured, visibly varied from being barely seen to forming thick crusts. Here the mineral mirabilite is measured with the image data. The distinctive reflectance peak near 2300 nanometers and the typical sulfate absorption at 1750 nanometers help to identify it with a high level of confidence.

Figure 2-18. Sub-area 9: Sulfo-salt Precipitation

2.7.4 Multispectral Mapping

2.7.4.1 Multispectral Mapping (ASTER) vs. High Resolution Hyperspectral Map

Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data was used to generate a regional map of common mineral groups. The map products were then compared to the high-resolution hyperspectral data to infer macro-scale mineralogical units inside and outside of the original area of study. Because the spatial and spectral resolution of ASTER is very limited in relation to aerial hyperspectral data, we focused on creating band ratio indices for major mineral classes, thereby allowing a general inference of regional mineralogy based upon the original hyperspectral classifications.

In the first band-ratio index, we used a 4/7 red band-ratio, a 4/6 green band-ratio and a 4/10 blue band-ratio (Figure 2-19). This produced an ASTER scene which pronounced the presence of carbonates in magenta, vegetation in yellow, clay alteration units in white, volcanic units in black. The varying colors of magenta near Bare Mountain help to convey the different types of carbonate units throughout the area. Although we have very limited overlap between the hyperspectral and multispectral data coverage, we can make statements about the total area comprised of carbonate rocks, in addition to being able to generally infer parent rock from weathering products (Figure 2-20).

Figure 2-19 shows an ASTER false-color combination (R: 4/7, G: 4/6, B: 4/10) which is employed to spectrally separate major scene mineral components into distinct color groups. Vegetation is yellowish, clay/altered units are bright white, alluvium is bluish and carbonates are magenta/orangish.

Figure 2-19. Band Ratio Index: R: 4/7, G: 4/6, B: 4/10

In Figure 2-20 below, a closer view of the ASTER color-combination image shown in Figure 2-19 above results in a better delineation of carbonates at Bare Mountain to the southeastern corner.

Figure 2-20. Closer View of Band Ratio Index: R: 4/7, G: 4/6, B: 4/10

The next band ratio index used 7/6 band-ratio for red, 6/5 band-ratio for green and 6/4 band-ratio for blue in order to produce a map with better clay mineral separation utility (Figure 2-21). The clay minerals were able to be split better than the previous index – yellow matches kaolinite well, while orange matches alunite (Figure 2-22). The volcanic glass class matches well with the maroon colors. Together the two indices compliment each other well, and seem to indicate that regional mineral units can be extrapolated with the use of higher spatial and spectral resolution image data. This has important implications for regional-level and district-level mineral surveys in areas where field mapping has not yet been conducted. Instead of necessitating full coverage of a limited area of study, it may be possible to fulfill the objectives of a research mission while using hyperspectral imagery to sample discrete areas across an entire ASTER, without necessarily providing adjacent flightline coverage. Because extrapolation is limited in the scope of spectral subtlety, the parameters of such missions must be well-understood in the context of the desired analytical information recovered.

Figure 2-21 shows an ASTER false-color combination (R: 7/6, G: 6/5, B: 6/4) which is employed to spectrally separate major scene mineral components into distinct color groups. Vegetation is greenish, kaolinite appears orangish, alunite appears yellow. Silica appears maroon and tuff appears greenish.

Figure 2-22 provides a closer view of the ASTER imagery which reveals an enhanced delineation of alteration minerals in the area, in addition to the large areas of exposed silica.

Figure 2-21. Band Ratio Index: R: 7/6, G: 6/5, B: 6/4

Figure 2-22. Closer View of Band Ratio Index: R: 7/6, G: 6/5, B: 6/4

Single-band band-ratio images were investigated using histogram thresholding in order to best match classification observations made with the hyperspectral imagery. Band-ratio 4/5 was used to classify alunite (Figure 2-23). The resulting image seemed to better represent mixed alunite and kaolinite mixes than a separated alunite component. Band-ratio 7/6 was used to map kaolinite (Figure 2-24). The resulting classification seemed to best match our observed extent of the mineral using hyperspectral data. An examination of this band-ratio side-by-side with the hyperspectral data classification resulted in seemingly good replication (Figure 2-25). There was mixing of both kaolinite and alunite as in the last band-ratio, but overall the delineation of the minerals boundaries seemed acceptable. A comparison of false-color images representing carbonate in magenta and zeolite in blue appeared to match the hyperspectral classification very well, and added an enhanced ability to identify weathering processes (Figure 2-26).

Figure 2-23 below shows a simple ASTER band ratio used to separate alunite from other clay minerals. The mapped extent of alunite seems to contradict that mapped hyperspectrally.

Figure 2-23. Band-ratio 4/5; Used to Classify Alunite

Figure 2-24 below, showing a simple ASTER band-ratio used to separate kaolinite from alunite, seems to replicate the mapped extent provided by the hyperspectral imagery.

Figure 2-24. Band-ratio 7/6; Used to Map Kaolinite

Figure 2-25 shows a comparison of hyperspectral and ASTER band-ratio classification images for kaolinite. The ASTER imagery provided an approximately similar result to that provided by the hyperspectral image data thus the examination of this band-ratio side-by-side with the hyperspectral data classification resulted in seemingly good replication. The separation of alunite and kaolinite was not successful.

Figure 2-25. Band-ratio Side-by-Side with the Hyperspectral Data Classification

Figure 2-26 examines a comparison of false-color images representing carbonate in magenta and zeolite in blue appeared to match the hyperspectral classification very well, and added an enhanced ability to identify weathering processes. An ASTER false-color image reasonably replicates the image classification of zeolite derived from the hyperspectral image data. The silica was not able to be mapped distinctly using a number of different methods, such as with false-color images, band-ratios or direct spectral mapping.

Figure 2-26. Comparison of False-color Images

2.7.5 Remote Sensing Mineral Map vs. USGS Geology Map

A United States Geological Survey (USGS) geology map was compared to the produced mineral maps to determine if field maps correlate well with measured mineral presence. Geology maps are created by extrapolating geologic units from a finite number of observed outcrops. Maps created via remotely-sensed data will be able to better display the dynamic properties of an area of study due to observing weathering processes, etc., however many nuances of a specific unit's rock properties cannot be remotely measured. In the instance shown in Figure 2-27, the USGS map represents the area as comprised of tuffs, gravels, breccias and alluvium. The area has been subjected to significant hydrothermal alteration, resulting in the formation of alunite and kaolinite. In this particular case, the hyperspectral data provides information that was not conveyed through the ground map description. Geology maps can be created to focus on specific aspects of the local geology – mineral type, alteration zones, structure, etc. The mere fact that a geology map exists which covers a desired location does not mean that its content provides the expected or needed information. They are thematic.

Figure 2-27 details hyperspectral mineral classifications which are draped on a USGS geology map. The area features large-scale hydrothermally altered rocks, however the geology map does not have a unit specifically for this designation. QTa represents young Holocene alluvial deposits, Tgo represents older lower Pliocene and Miocene gravels, Tmr represents Rainier Mesa Tuff, while TMA represents Ammonia Tanks Tuff, both of the Miocene Timber Mountain Group. Finally TGYZ represents younger Miocene landslide breccias. Comparison of both map and classification designations results in a better understanding of the geology of the area.

Figure 2-27. USGS Map Designations

2.8 Multi-resolution Studies

2.8.1 Spatial Resolution

Spatial resolution of remotely-sensed data, technically referred to as instantaneous field-of-view (IFOV), dictates the size of the area on the ground represented by a single pixel's spectral measurement. This size is a function of altitude (above ground level), which carries repercussions on detected energy, due to the shortening or lengthening of the path of transmission. This phenomena in turn can increase the noise with has direct repercussions upon the ability to discriminate spectra of different minerals. We investigated spatially resampled data at different pixel sizes (1, 5, 10, 15 meters) to determine the effect upon classification accuracy. The amount of area covered by an imaging spectrometer increases as the spatial resolution becomes lower, and vice versa; see Figure 2-28.

Figure 2-28. Spatial Resampling of Hyperspectral Image Data

As shown in Figure 2-28, the spatial resampling of hyperspectral image data was performed in order to analyze the classification results of modeling an increase in distance between the aircraft-mounted sensor and the ground. Four different ground sample distances (GSD) were

used in the study. One meter data was originally acquired and this data was down-sampled to 5, 10 and 15 meter pixel resolution. Figure 2-28 above shows the spatial extent covered by a lower spatial resolution. This presents advantages for both high and low resolution imagery. High resolution imagery provides high detail of an area, but an analyst may miss large-scale features that are easier to identify with coarser resolution data. Low resolution data provides a major advantage in terms of the amount imagery acquired in a low amount of time versus high-resolution data. This means that a survey may be completed in less time, and thus cost less in terms of financial and time resources.

The resampling of 1 meter data to 5, 10 and 15 meter spatial resolutions was performed for the acid sulfate centers scene. The reason for this was that the scene minerals are numerous (4 bulk and 1 minor), they are well segmented, and the diagnostic features are very unique, resulting in little analytical ambiguity, as to the identification of a single pixel's major mineral constituent. The general trends observed in reducing the spatial resolution of the image data and classifying the spectral data were a definite loss of definition of micro-scale features, such as mineral classes following drainages, etc (Figure 2-29). Very narrow classifications, such as illite on the road leading north become increasingly inaccurate, to the point that a road, well defined at 1 meter, becomes barely recognizable as a road at 15 meters. Although a subjective observation, the best pixel resolution for measuring minerals appeared to be the 5 meter data. It resulted in sufficient resolution of minerals with accompanying topographical relief information, in addition to providing a much larger area of coverage compared to the 1 meter data. The road composed of illite was still well-characterized.

The image of Figure 2-29 below shows the same scene at different resolutions. The top left scene is 1 m, the top right is 5 m, the bottom left is 10 m and the bottom right is 15 m. The same four minerals were mapped using signatures derived from the respective dataset. The results seem to indicate that the classification results are linear, however the loss in total number of pixels means that the ability to resolve spatial features decreases. In particular, illite seems to be reduced in overall presence in the 10 and 15 m images, while the other three minerals are represented in a reasonably similar fashion.

Figure 2-29. Spatial Resampling of Hyperspectral Image Data, Different Resolutions

2.8.2 Spectral Resolution

The effects of spectral resolution upon the classification accuracy of minerals can be significant. Classification results derived from 5 nanometer data will be compared to that of 10 nm and 17 nm image data, thus replicating the spectral resolution of major hyperspectral data available (AVIRIS & HyMap). A plot of kaolinite resampled to major sensor spectral resolutions was made (Figure 2-30). The overall effect of reducing the number of bands results in a smoothing of spectra, and loss of definition for very sharp spectral diagnostic features. A close-up view of the kaolinite doublet is shown, which helps to convey the loss of information encountered by spectral resampling (Figure 2-31). The difference between 5 nm and 17 nm data can have a significant effect upon spectral identification, especially in the presence of other minerals which share similar diagnostic features – in this case the minerals halloysite and dickite, which are both important to distinguish from kaolinite in mineral exploration applications. This type of modeling can be performed and spectra compared to make a determination of whether the increased size of data & high spectral resolution are necessary, or whether a smaller dataset and lower spectral resolution are optimal.

Figure 2-30 below shows a plot of kaolinite spectra at different spectral resolutions. USGS laboratory spectra is at top, AISA 5 nanometer resolution is second from top (labeled as

Prospectir in the legends), AVIRIS spectra is at center, AISA 10 nanometer resolution is second from bottom and HyMap spectra is at bottom. The graph shows the relative small segment of spectra in gray which is used to identify this mineral.

Figure 2-30. Plot of Kaolinite Resampled to Major Sensor Spectral Resolutions

Figure 2-31 is a close-up view of the kaolinite plot shown above. A segment from 2205 to 2225 nanometers centers on the diagnostic doublet feature of the mineral. The difference in spectral resolution from high-resolution laboratory to relatively low-resolution HyMap is seen to be quite minimal. However, the modeled differences in spectral resolution do not always equate to similar differences when imaged by the referenced sensors, due to differences in image detector technologies and raw data processing methodologies. In addition the context of the mineral mapped with neighboring minerals will play a vital role. Minerals with similar spectra to kaolinite, such as halloysite and dickite require sensors with resolution sufficient to delineate these as independent minerals.

Figure 2-31. Close-up View of the Kaolinite Plot

The acid sulfate centers 1 meter resolution scene was used to map the same suite of minerals as the spatial resampling exercise, this time to map image datasets with different spectral resolutions. The results of mapping individual classifications for 5, 10 and 17 nanometer resolution data show little difference in comparison to the best resolution (Figure 2-32). This is an important metric to demonstrate, because the difference in size of image datasets can vary significantly. If a lower spectral resolution is used then a smaller sized dataset can be processed, which results in quicker production of mineral maps.

Figure 2-32 shows the 1 m image dataset resampled to the spectral resolution of AVIRIS, 10 nm AISA and HyMap sensors. The 5 nm AISA data is at top left, at top right is AVIRIS, at bottom left is AISA 10 nm and at bottom right is HyMap. The result of processing each dataset independently using the same spectral endmembers seems to have produced reasonably similar

results. The differences between any two images, and more importantly between the AISA 5 nm and HyMap (being the farthest is spectral resolution), seem to be quite similar.

Figure 2-32. Mapping Individual Classifications for 5, 10 and 17 Nanometer Resolution Data

2.8.3 Comparison of Analyses Created by Different Analysts

The comparison of classification results from different analysts was made in order to determine the general differences in style of analysis and applied thresholding. The acid sulfate centers scene was used for comparison purposes. Zan Aslett created a classification image that included 4 bulk minerals. Greg Vaughan's analysis focused on 3 minerals. The spatial distribution of the particular minerals varies quite a bit (Figure 2-33). The overall amount of pixels classified as kaolinite and alunite was significantly higher for Aslett than Vaughan. Illite seemed to map in a generally similar fashion, with Vaughan mapping an additional area to the southeast portion of the scene. A novice analyst, Todd Morken, mapped the minerals in the same scene (Figure 2-34). The distribution of alunite and kaolinite seemed to follow closer to Aslett's analysis product than Vaughan's. The primary difference in mapping style involved the use liberal or conservative nature of classification thresholding. The time spent in the field increased confidence in the mapping results.

Figure 2-33 shows a comparison of classification results from different analysts. At left is Zan Aslett's classification image. At right is Greg Vaughan's classification image. Orange represents kaolinite, red is alunite, yellow is illite and blue is silica. The immediate difference in the two results is the total amount of mapped pixels. Vaughan's classification pixels are used more sparingly, while Aslett applies pixels more liberally. Aslett mapped the presence of an additional class, silica, while Vaughan did not. The results of this comparison are somewhat the norm, as different analysts have different methods that they employ to derive endmembers, in addition to personal philosophy and how to set classification thresholds. In addition, analyst Aslett was able to visit the area of study numerous times, while Vaughan did not visit once.

Figure 2-33. Variation in Spatial Distribution of the Particular Minerals

Figure 2-34 is provided by a third analyst, Todd Morken, a first-year graduate student who has limited experience in hyperspectral image data processing. He created a classification map for the same area as the other analysts. His results were largely similar, although the class in blue was misidentified. By comparing results of experienced and new analysts, new perspective on an area may be gleaned. This is in large part to the complexity and number of manual inputs required to produce a hyperspectral classification map with reasonable confidence.

Figure 2-34. Todd Morken's Mapping of Minerals in the Same Scene

2.8.4 Change Detection of Illite

The mineral illite was mapped as a major constituent of roads in the center of the north/south box. The distinct mineral maps generated from the hyperspectral data followed the roads extremely well, making a very unique classification compared to other scene endmembers. Our investigation included the study of changes in mineral distribution over time. We used SpecTIR imagery collected in Spring of 2007 and Terra Remote Sensing data acquired during the Fall of 2007 (Figure 2-35). A subset of the each dataset around the acid sulfate centers scene was gathered and processed in order to map and compare classifications of illite. The area is subject to moderate traffic, by way of hauling trucks and highway traffic. This results in a likely change of the mineral distribution over time.

Figure 2-35 shows two distinct hyperspectral image datasets that were acquired in 2007. SpecTIR collected imagery in Spring of 2007, while Terra Remote Sensing acquired their dataset in Fall of 2007. A subset of the each dataset was gathered and processed in order to map and compare classifications of illite. This area and the mineral were chosen due to the particular spatial character of the distribution of the mineral in addition to the fact that the area encounters moderate traffic, by way of hauling trucks and highway traffic. This results in a likely change of the mineral distribution over time.

Figure 2-35. SpectTIR Imagery (Spring 2007) and Terra Remote Sensing Data (Fall 2007)

The analysis of difference in the mapped distribution of illite from Spring to Fall 2007 revealed a distinct change in areas trafficked (Figure 2-36). The amount of area displaying illite in the Spring is much less than the Fall, with exception of the shoulders of the highway and the hills to the west of the highway. This may be due to local hauling trucks or excavation vehicles conducting work. The Spring data revealed much more activity around the southeastern and northern portions of the scene. This may be due to the increased stock of illite-bearing aggregate during the span of time from Spring to Fall.

The change detection analysis results provide important information on the potential difference in traffic and industry between the time of the first and second data acquisition.

Figure 2-36 shows the results of the illite classification for the Spring and Fall datasets which are alternately draped upon each other to create a sense of the unique differences between the two. At left, the Spring classification is plotted on top of the Fall classification. At right, the Fall classification is plotted on top of the Spring classification. The area due west of the center of the highway resulted in illite being detected during the Spring but not the Fall. Additional illite seems to be distributed near the private roads east of the highway during the Fall. This is probably due to an increased amount of traffic, or the continual accumulation of clay and dust, much of which may be consolidated and minimized after rainfall occurs through the next season.

Figure 2-36. SpectTIR Imagery (Spring) and Terra Remote Sensing (Fall) Comparison

2.8.5 Hillshade Images

Hillshade images were generated for photo-interpretation of digital elevation model images of LiDAR data. These images are based upon the simulation of artificial sunlight to pronounce topographic features of interest. Based upon simple geometry of the sun orientation and angle with respect to a single pixel target, various imagery products can be made to emphasize desired features (Figure 2-37). Four hillshade images were created derived from the LiDAR data, which were all based upon severe sun angles in order to pronounce slight topographical changes, similar to methods that geologists employ using stereo view of low sun angle aerial photography. The directions used were 0, 90, 180 and 270 degrees.

Figure 2-37 provides a schematic of the geometric principles involved in generating a synthetic hillshade image.

A = azimuth angle, measured clockwise from North (0-360°, discontinuous)

F = facing angle of direction similarity (0-180°, continuous)

H = horizontal angle, measured from vertical (0-90°, continuous)

Figure 2-37. Geometry of the Sun Orientation and Angle with Respect to Target

2.8.6 Fault/Linear Feature Map

Faults are usually expressed as near-linear features cutting the surrounding natural geological context. Faults were first attempted to be mapped using these observed traits. Major linear features in the scene consisted of roads, houses, etc., and were taken into account by removing them from fault analysis. The bulk of hypothesized faults were along range fronts, and many also coincided with the boundaries of washes or creeks. Both classes are referred to as linear features, as few cross-cutting relationships could be established. A map of linear features was created which incorporated a shapefile indicative of basin fill – established by finding a common contour in which alluvium was found (Figure 2-38). The ground-based investigation of certain areas within the study area revealed large washes that did not display observable fault offsets (Figure 2-39). Rather, the high shoulders of the wash indicated flood activity in the past. The presence of a fault is possible, however without establishing a trench excavation, it is very difficult to determine. Errors in fault identification were made in areas of topographic relief. Often the delineation of tuff units were misidentified as fault scarps (Figure 2-40). A modification to modeling methodology could be made to incorporate elevation information to preclude areas above a certain altitude, however this assumption could prove not to identify faults as well.

Figure 2-38 is the LiDAR-generated map showing the lowest points in Oasis Valley and surrounding areas that represent basin fill. Mapped linear features are added for reference. Specific areas investigated on the ground are identified.

Figure 2-38. LiDAR Generated Map

Figure 2-39 shows Sub-area A which depicts a series of linear features easily delineated with LiDAR hillshade images. Upon ground-based inspection of the area, many washes were found that displayed large adjacent banks, with differing levels of slumping. The high number of washes and streams of various ages made it very difficult to assess whether these features were simply the result of large amounts of water following preferential flow paths, or the faults. The prudent declaration to make is that these features appear not to be faults, but that LiDAR data can be used to point a trained neotectonic expert to this area to establish an exploratory trench. Geophysical data, such as a gravity survey, can be used for this purpose as well.

Figure 2-39. LiDAR Hillshade Images

Figure 2-40 below shows the results of linear features derived from this portion of the LiDAR hillshade image result in tuff units that closely follow contour. In some areas the tuff has terminated at washes or streams which accentuates the linearity of the feature when viewed at nadir. This introduced a number of linear features of which were found to be unrelated to faulting.

Figure 2-40. LiDAR Hillshade Image Show Tuff Units that Closely Follow Contour

2.8.7 LiDAR-derived Map Versus USGS-mapped Faults

Fault data from digitized USGS geology maps were added to the GIS for comparison to LiDAR-generated linear features data (Figure 2-41). The general trend between the two classifications was that the LiDAR could identify small-scale linear features and the USGS map indicated large fault structures. When LiDAR linear features were generally added and compared to USGS faults, then the results were similar. Otherwise, the difference in scale of mapped features meant that the fault/linear feature products are meant for different purposes. The LiDAR-generated classification would be very appropriate for a ground-based investigation of faults, while the USGS classification is suitable for more regional application and integration of fault data.

Figure 2-41 shows the distribution of faults identified by the USGS plotted on the map as cyan. The linear features found to be possible faults using LiDAR imagery are plotted in red. The low-resolution source of imagery used by the USGS resulted in large, regional faults being plotted. In contrast, many linear features identified by LiDAR analysis were small-scale and in many instances could not be delineated from overlying soil beds that were found adjacent to ancient washes and streams. The macro-scale view of both classifications results in a few similarities. At the top of the north/south flight box, many smaller linear features correspond to a single USGS fault feature. In addition many LiDAR-derived linear features form around the base of

mountains. Significant time in the field by quaternary/neo-tectonic experts must be utilized to resolve the ambiguity surrounding whether a feature is a fault, possible fault, or simply a linear feature.

Figure 2-41. LiDAR-derived Map versus USGS-mapped Faults

2.8.8 Detection of Manmade Disturbances

The LiDAR data was used initially for topographic analysis in conjunction with the mineral classification data. An ancillary use that was investigated involved the creation of LiDAR hillshade images to detect trenches, pits, holes and other moderate- to small-sized manmade disturbances on the surface of the earth (Figure 2-42). The intended purpose of the LiDAR data was to create a DEM; thus, individual values had been interpolated to remove anomalies in the data (and also potentially removing data representative of small holes). However, the creation of hillshade images from varying azimuth perspectives was found to be sufficient in delineating disturbances measuring less than .5 meters in area. The integration of mineral maps with the manmade disturbance maps increased our confidence in identifying mining disturbances – primarily with use of goethite identification, where oxidation of pyritic gangue material has occurred over a number of years.

In Figure 2-42 at left, a single hillshade image was used to detect numerous anomalies, many of which are false positives. At right, multiple hillshade images were used in tandem to produce the

detection of targets as highlighted in orange. Ground-based investigation yielded the presence of numerous manmade trench and adits, sizes of which were as small as .3 of a meter in length and 0.5 meter in width.

Figure 2-42. Use of Hillshade Images to Detect Disturbances on the Surface of the Earth

The use of a single hillshade image resulted in the identification of 188 anomalies. These anomalies were defined as having alternating high relief values across a very limited spatial extent, in addition to not being within 10 pixels of other anomalies. False positives were immediately identified through cross-checking the results with high-resolution panchromatic imagery of the area. Instead of finding only holes and related disturbances, the hillshades were also identifying outcrops of severe character, but limited size, ranging from .5 to 3 m² (Figure 2-43). This required modification of our definition of anomalies to those which trend from having low to high relief values at their edges.

In Figure 2-43 at the top, the LiDAR hillshade image shows small outcrops that appear in proximity to manmade disturbances. False-detections usually consisted of these features. The bottom of the figure shows an outcrop of volcanic rocks which were grouped as manmade disturbances with the hillshade imagery. The rock highlighted in red was difficult to remove from the results. Refinement of the GIS model to identify the disturbances should include the elevation information to identify only objects that possess down-grading slope.

Figure 2-43. Hillshade Image Example Showing Identification of Anomalies

Upon visiting field sites where we identified anomalies in the map product, almost all were successful in identifying mine-affiliated surficial alteration. For each 15 sites successfully marked, a false positive was included in the classification – always a very small outcrop that essentially acted as an inverse hole. Incorporating a DEM's *z* (elevation) information into a model to remove up-sloping features from consideration would likely eliminate a great deal of error. The use of the LiDAR data which was tailored for use as a bare-surface DEM was highly successful in this experiment. By obtaining the unfiltered DEM data and utilizing the data cloud a bit differently we are confident that a model could be refined and the results could be better.

2.8.9 Slope Stability Map

A slope map was created using LiDAR image data to make initial identification of areas of possible slope instability (Figure 2-44). The integration of surface mineral information and slope data was analyzed to derive a rudimentary analysis of areas of high slope stability and clay

minerals, which correspond to highly unstable rock. The best example in the study area was an open pit mine of which the walls stand at nearly 90 degrees and are composed of varying clay minerals (Figure 2-45). Ground investigation of the area revealed that the unstable nature of the exposed clay and the nearly vertical slope of the pit walls resulted in massive erosion of the implemented structure. The high degree of accuracy of the slope map generated allows different color tables to be applied, which correspond to differing levels of slope in the study area. Slope and contour data produce data representing the same fundamental product, however they are implemented in different visual fashions (Figure 2-46).

Figure 2-44 is a slope intensity map of the study area generated from the LiDAR digital elevation data. The absolute level of slope in terms of percent is plotted using a color table. Hot colors indicate a larger percent slope and cold colors indicate a relatively flat area. Two areas were chosen to investigate due to anomalously high slope scores.

Figure 2-44. Slope Intensity Map Generated from the LiDAR Digital Elevation

Figure 2-45 below shows Sub-area 1 which is located in the eastern portion of the east/west flight box and includes an open pit mine. The pit displays excellent resolution of the steep, nearly perfectly vertical nature of the pit walls. After masking out buildings and other manmade structures, the open pit mine was the only geological feature which displayed such high slope.

Figure 2-45. Slope Intensity of Open Pit Mine in Sub-area 1

In the left image of Figure 2-46 below, the pit mine slope classification is draped upon the high-resolution imagery background to increase contrast of the feature. At right, 5 meter contour lines generated from the digital elevation data is draped on the imagery. The two products can be implemented for similar purposes, but both have specific utilities in scientific visualization that are mutually beneficial.

Figure 2-46. Contrast Visualization of Pit Mine Slope

2.8.10 Modeling Hazards with Combined Slope and Mineral Maps

The slope and mineral classification datasets were used in conjunction to identify areas of potential hazard. The acid sulfate centers area possessed an outcrop of high slope and which consisted of kaolinite (Figure 2-47). Ground investigation of the area revealed that although located near highway 95, the outcrop was far enough from traffic as to inhibit any falling rocks from relocating into the path of vehicles. No other areas possessing both high slope and clay material were found within the study area. Further research based upon these datasets and focused upon the open pit mine could have repercussions for remotely sensed stability projects. Volcanic rocks located throughout the study area possessed high slope (Figure 2-48). The mineral identification of these outcrops was not possible due to likely being composed of silicate.

In Figure 2-47, the image at left shows the slope classification and the image at right shows the mineral classification. Sub-area 2 is the area of hydrothermal alteration in the north/south box which straddles highway 95. The tip of an outcrop near the highway possesses high slope; in the context of this altered rock mixed with unaltered silica, the host clay is more easily eroded and could result in falling debris. Upon ground inspection, the rock-fall area adjacent to the rock face is not close enough to the highway to warrant any action

Figure 2-47. Slope and Mineral Classification Datasets Used to Identify Potential Hazard

48. Outcrops with severe vertical features can be delineated using slope imagery, which could be preferable to manual identification using a hillshade image.

Figure 2-48. Slope Imagery Showing Severe Vertical Features

2.9 Discussion

2.9.1 What the Mapping Results Mean in the Context of Known Regional Geology

The bulk mineralogy of the area of study was able to be studied using airborne imaging spectroscopy, with success due to high spectral and spatial resolution. These classes included clays, sulfates, an evaporite, carbonates, iron oxide and volcanic minerals. The region is marked by volcanic rocks of different types, such as ash-flow tuff, basalt, volcanic cones, calderas, etc. The hydrothermal alteration of certain areas within the region has been well-established by past geological surveys. This is the specific niche that VNIR/SWIR hyperspectral image data is most suited for – clay and sulfate alteration mapping. This is primarily owed to OH-based vibrational absorption features resulting in diagnostic spectral characteristics in the SWIR, in addition to the rocks being brighter, and hence displaying higher reflectance. In order to fully understand the mineralogical outlay of the region in total, it would be necessary to also utilize thermal-infrared hyperspectral data. TIR data is well-suited towards identifying silicate minerals of many different classes, which comprise the majority of igneous rocks. When at the outset of mapping an area using hyperspectral remotely-sensed data, it is of utmost importance that the analyst understands what capabilities each type of data are in order to achieve the desired results.

2.9.2 Comparison of USGS Field Maps and Remotely Sensed Mineral Maps

The direct comparison of spectral classification maps and geology maps resulted in close matches of types – carbonates and altered tuff units, and inexact matches or lack of any unique mineralogy in many units. The reason for these outcomes can be complicated, but at the heart of the matter is the way in which each type of map is created. A geology map is the amalgamation of many discrete observations made at ground-level over a great amount of distance. A mineral classification map derived from remotely-sensed data is the absolute measurement of reflectance

at each pixel in the image. In the former the goal is to take the finite amount of observations and extrapolate the boundary of a particular unit based upon different rock classification categories. A unit can be broken up into sub-units based upon the grain size of a particular visible mineral, the presence or absence of weathering, etc. These observations are traditionally tethered using the interpretation of air photographs. The latter reduces the need for extrapolation of a given mineral – rather the analyst’s primary task is to apply classification algorithm thresholds judiciously in order to determine the distribution of the mineral – which can be double-checked post-classification by inspecting the spectra. As commented on previously, the USGS geology map of the region was all-inclusive and included units comprised of minerals which were not detectable by VNIR/SWIR image data, i.e., igneous mineral classes – to include feldspars, pyroxenes, garnets and other silicates.

The use of both types of maps in concert will allow a geologist to best observe the nature of the studied area in order to derive knowledge and apply it towards a specifically identified problem.

2.9.3 Areas of Concern: Slope Stability

The use of geospatial data to determine sites of potential hazard (or to observe post-hazard) is currently a topic of much discussion. Digital elevation models have been utilized to solve this class of problem, to varying degrees of success. The combination of DEM and surface mineralogy datasets has been very limited in the research literature. The study area is not particularly well-suited for this application, with the exception of the open pit mine located in the eastern portion of the East/West flight box. This is due to the arid environment which does not see rapid erosion of surfaces. In addition, landslides or rock-fall activity is very limited because the local rocks do not form dangerous boulders, etc. However the novel use of both DEM and mineral information in a single study area warrants consideration for research purposes. In particular, the use of LiDAR, and potentially hyperspectral data to identify man-made disturbances was found to be successful, and could seemingly be implemented to identify dangerous shafts, holes and adits which could prove to be dangerous.

2.9.4 What Can Hyperspectral Do?

Hyperspectral image data is well-suited to providing maps indicating the presence of certain minerals of interest to different scientists. A certain amount of knowledge must be had before initiating a similar research project in the future. The results gained by the image data are variable due to many distinct manual steps in the image processing chain which can be independently modified to create a final product. Different analysts will likely have different results, however these results should be approximately similar. As a standard procedure, it may be suggested that multiple analysts do conduct analysis independently in order to evaluate end-products and discuss strategies that were particularly relevant and successful. Although this overlapping of labor may seem to be redundant, the complexity of the identification aspect of the analysis seems to suggest that it would be time well spent – especially if margin for error is low.

2.9.5 What Can the Fusion with Lidar Provide?

The highly accurate DEM image data that we received was of particular help in analyzing the geomorphology of the area, if only undertaken as a minor role in this study. However, the advanced capability of the data to create ancillary datasets, such as hillshades, contour maps and to identify manmade features was excellent. If faced with the choice of whether to include LiDAR as an additional product to order concurrently with hyperspectral image data, we would be inclined to say ‘yes’. The ability to identify sub-pixel targets within the scope of spectral

identification processes is a very easy way to speed the endmember selection aspect of analysis, in addition to providing error-protection in the case of identification of false-positives.

2.9.6 What Can the Fusion with High-resolution Aerial Imagery Provide?

The incorporation of high-resolution aerial imagery with the hyperspectral image data was extremely important to a few particular steps in the analysis chain. First, being able to see what is visibly occurring within a scene and compare that spectrally is a great benefit. Next, the identification of targets below the pixel threshold of the hyperspectral image data is extremely important as described above. Lastly, for the aesthetic aspect of the map product, being able to overlay classification pixels on high-resolution imagery enhances the visual contrast of the map. This has some analytical utility – the increase in contrast between classified units cannot be understated; it may be worth the extra simply because the customer may be impressed by this enhancement and it's visual appeal.

2.10 Geological Analysis Conclusions

The MANNRRSS II project focused on the analysis of remote sensing datasets in order provide environmental characterization and information for land managers. The use of hyperspectral data to characterize the surficial mineralogy of the area was successful in mapping a range of unique endmembers. The resulting maps of the local mineralogy will be of assistance to the environmental knowledgebase, due to the lack of this particular sort of information in publicly available geology reports. The importance of hyperspectral classification of minerals, in regard to change detection, was demonstrated with a small investigation of the distribution of illite between Spring and Fall 2007. The digital elevation models of the study area proved useful in both traditional and novel, yet practical ways. In addition, resolution studies helped to provide a framework for optimizing the spatial and spectral parameters of future remote sensing surveys. The ground-up method of project planning and implementation proved to result in a comprehensive survey based upon remote sensing technology.

3.0 VEGETATION ANALYSIS

3.1 Botanical and Floristic Study Area Background

Plant community structure in the study area is a function of elevation, soil moisture availability and salinity and past and current land use practices. Evergreen and deciduous shrubs are the dominant plant growth-forms at high elevations, perennial grasses and deciduous trees are dominant in riparian areas, but trees tend to be replaced by shrubs as salinity of riparian areas increases with the exception of salt-tolerant invasive tamarisk trees. Plant cover is positively correlated with soil moisture and elevation, while species diversity is positively correlated with elevation and negatively correlated with land disturbance and soil salinity.

3.2 Remote Sensing Measurements of Vegetation

Figure 3-1 illustrates the nomenclature for regions of the electromagnetic spectrum that commonly display diagnostic absorption features for vegetation, in addition to other terrestrial materials such as rocks. Vegetation exhibits several prominent absorption features that distinguish it from other terrestrial materials (Figure 3-1) [Clark et al. (2003)}. Most notably is absorption near $0.68\mu\text{m}$ caused by electronic transitions in the chlorophyll molecule centered around the magnesium component of the photoactive site (Goetz et al., 1983). This feature is juxtaposed with high reflectance in the Near-infrared (NIR) plateau around $1.0\mu\text{m}$. The continuum between these wavelengths is referred to as the “red edge”. Several vegetation indices use ratio formulas to take advantage of this reflectance contrast and the red edge feature. Lesser absorptions, also due to chlorophyll, occur in the visible (VIS) portion of the spectrum and can further help differentiate between vegetation species. Other absorption features in the short-wave infrared (SWIR) part of the spectrum are related to foliar water content and the associated vibrations of water molecules.

Figure 3-1. Laboratory Reference Spectra for Selected Vegetation Species

As compared with multispectral spaceborne instruments airborne hyperspectral datasets optimize discrimination of single plant species and plant communities (Everitt et al., 1996; Ge et al., 2007;

Ge et al., 2006; Schmidtlein, S., 2005). Such high fidelity datasets are especially advantageous over multispectral instruments when working in arid environments, where plant canopy widths tend to be small (< 1 m) and often do not overlap with neighboring plants (McGwire et al., 2000). The tradeoff for increased spectral resolution with high spatial resolution, however, comes at a cost that is approximately 20 times greater than multispectral spaceborne data that covers the same unit area (this approximation is based on a cost comparison between QuickBird multispectral data acquired for an area close to the Beatty study site and the airborne hyperspectral data collected for this project). This increased cost can of course be reduced by flying the aircraft platform higher and thus degrading the spatial resolution, but then the ability to discriminate individual plants and/or communities may be compromised.

In this study we attempt to create vegetation maps at the species level using hyperspectral data. We also co-registered hyperspectral data from the spring and fall of 2007 to detect vegetation change in riparian areas and with respect to slope and aspect. Finally, we explore the effects of resampling the change detection results to the resolution of multispectral spaceborne instruments.

3.3 Methods

3.3.1 Field Data

Coincident with spring 2007 spectral data collection, six unique plant communities that occurred in the study area (flight boxes) were characterized (Table A1 in Appendix A). All perennial plant species in six transects varying from 30 to 50 m in length by 2 to 5 m in width were identified at the species level (Hickman, 1993). Canopy heights and widths of all shrubs and trees were measured and rectangular coordinates for each plant within the transects were recorded (Figure A1-A6 in Appendix A). A plot of canopy cover for transect 6 was not made because the canopy consisted of three overlapping layers of tree, shrubs and grasses. Furthermore, only total cover and heights by perennial grasses were measured in transects 3-6 because individual grass canopies tended to be contiguous with each other, and were often less than 0.0025 m^2 . Diversity indices were also calculated for each transect based on species relative cover (Townsend et al., 2003). Additional ground-truthing surveys for species-specific training areas were conducted in fall 2007 and spring 2008 because below average precipitation in spring 2007 resulted in minimal net primary productivity. Conversely, significant late summer monsoonal precipitation resulted in significant increases in net primary productivity for some species and average winter precipitation in 2008 also resulted in significantly greater plant growth in spring 2008 compared to spring 2007. The general location of vegetation transects are shown in Figure 3-2.

Figure 3-2. Locations of Vegetation Field Transects

3.3.2 Pre-processing

As mentioned earlier in the Introduction we chose the Terra spring data for the data processing that is discussed in this sections that follow. There were over 100 individual files approximately 2 GB in size for the north-south and east-west flightlines. Processing these files individually was impractical due to the time it would take to apply necessary processing steps to all the files. Instead, the files were mosaicked into two files corresponding to the east-west and north-south flightlines. The processing steps that are discussed in the paragraphs that follow were applied to both mosaicked files.

3.4 Species Discrimination

3.4.1 Masking with NDVI

To focus solely on the analysis of vegetation, all other surface cover types were masked out. Vegetation spectra commonly display strong absorption of red light near 0.68 μm , due to chlorophyll pigment (Elvidge and Chen, 1995). High reflectance from green leaves is expressed in the near-infrared. There are at least ten different spectral vegetation indices that use some type of channel ratio to take advantage of these features, the Normalized Difference Vegetation Index (NDVI) is arguably the most common. NDVI is a ratio of near infrared and red reflectance that provides a convenient, rapid estimate of the amount and some indication of health of vegetation in an image (Tucker, 1979). The ratio is written as follows:

$$(\text{NIR}-\text{Red})/(\text{NIR}+\text{Red})$$

Where NIR = Terra channel 77 (0.750 μm); Red = Terra channel 59 (0.664 μm)

The NDVI image and a three-band color-infrared (CIR) Terra reflectance image were dynamically linked on the computer display and visually inspected. Pixels that are visibly red in the CIR are related to a significant vegetation component and were used to qualitatively determine a threshold that would be applied to the NDVI. All pixels above the threshold were regarded as vegetation and included shrubs with canopies ~ 0.5 m or greater in diameter, or contiguous groups of plants such as grasses. As a result, a masking image was created and then applied to the reflectance data so that only areas of vegetation were considered for further analysis (Figure 3-3).

Figure 3-3 shows (a) Terra color-infrared image compared with (b) false-color composite to illustrate vegetation masking effect shown in, all green area is behind the mask, purple represents areas of vegetation that were not affected by masking

Figure 3-3. Comparison of (a) Terra Color-infrared Image with (b) False-color Composite

3.4.2 Reduce Data Dimensionality

Expert systems were used to reduce the data volume to channels with the most spectral information. Each pixel in the Terra data can be represented as a vector in n -dimensional space; n corresponds to the number of channels (363) that are inherently highly correlated. The Minimum-Noise-Fraction (MNF) algorithm uses two principal component transforms (Green et al., 1988). The first transform decorrelates and rescales the noise in the data, where the noise estimate comes from the data itself by looking at variations among neighboring pixels. The transformed data has noise with unit variance and no band-to-band correlations. A second transform is then applied to separate the noise from the signal in the data by identifying the

principal components. Useful spectral information in the data cube is reduced to an intrinsic dimensionality of generally less than twelve coherent channels. We chose to work with fifteen MNF channels to insure that no useful information was excluded.

3.4.3 Using the Data to Spectrally Characterize Vegetation Species

Vegetation species of interest were spectrally characterized before applying mapping algorithms that would operate on the entire dataset. First, field notes and GPS coordinates were used to locate various shrub species in the geo-registered imagery. Second, some vegetation species were identifiable with the digital orthophotography; their coordinates were used to locate the corresponding pixels in the hyperspectral data. Training areas were created for vegetation among tree and shrub species and within riparian grasses and sedges. Vegetation training areas were comprised of cottonwood, tamarisk, willow, Russian olive, senesced riparian, green riparian, creosotebush, rabbitbrush, saltbush, and bitterbrush. These species/groups were selected because individual plants/patches could provide relatively high-purity spectra at the pixel level. This would result in the best spectral characterization of these species by minimizing the spectral contribution from shadows, soil and other ground surface elements, thus, optimizing the level of accuracy of the maps produced from each training area. Examples of training areas from the image data are shown in Figures 3-4 through 3-9, with corresponding field photos shown in Figures 3-10 through 3-11. Figure 3-12 shows the location of training areas within the study area.

The mean MNF spectra were calculated for each training area. This group of spectra was used to train a classification algorithm described in the next section. Training spectra are shown in Figure 3-13.

Figure 3-4 shows examples of training areas outlined in yellow (a) cottonwood training area on Terra imagery compared with same training area shown on digital orthophotography for comparison in (b). Same comparison is made for willow training areas shown in (c) and (d). Pixels in Terra data are 1 m, for scale.

Figure 3-4. Cottonwood (a and b) and Willow (c and d) Training Areas

Figure 3-5 shows examples of training areas outlined in yellow. (a) Russian olive training area on Terra color-infrared composite compared with same training area shown on digital orthophotography for comparison in (b). Same comparison is made for tamarisk training areas shown in (c) and (d). Pixels in Terra data are 1 m, for scale.

Figure 3-5. Russian Olive (a and b) and Tamarisk (c and d) Training Areas

Figure 3-6 shows examples of training areas outlined in yellow. (a) senesced riparian training area on Terra color-infrared composite compared with same training area shown on digital orthophotography for comparison in (b). Same comparison is made for senesced training areas shown in (c) and (d). Pixels in Terra data are 1 m, for scale.

Figure 3-6. Senesced Riparian (a and b) and Senesced (c and d) Training Areas

Figure 3-7 shows examples of training areas outlined in yellow. (a) creosotebush training area on Terra color-infrared composite compared with same training area shown on digital orthophotography for comparison in (b). Same comparison is made for bitterbrush training areas shown in (c) and (d). Pixels in Terra data are 1 m, for scale.

Figure 3-7. Creosotebush (a and b) and Bitterbrush (c and d) Training Areas

Figure 3-8 shows examples of training areas outlined in yellow. (a) rabbitbrush training area on Terra color-infrared composite compared with same training area shown on digital orthophotography for comparison in (b). Same comparison is made for saltbush training areas shown in (c) and (d). Pixels in Terra data are 1 m, for scale.

Figure 3-8. Rabbitbrush (a and b) and Saltbush (c and d) Training Areas

Figure 3-9 shows examples of training areas outlined in yellow. (a) saltbush training area on Terra color-infrared composite compared with same training area shown on digital orthophotography for comparison in (b). Pixels in Terra data are 1 m, for scale.

Figure 3-9. Saltbush Training Area

Figure 3-10 shows field photos corresponding to training areas shown in Figures 3-4 through 3-9: (a) cottonwood (b) willow (c) Russian olive (d) tamarisk (e) senesced riparian (f) green riparian.

Figure 3-10. Field Photos of Training Areas

Figure 3-11 show additional Field photos corresponding to training areas shown in Figures 3-4 through 3-9 (a) creosotebush (b) rabbitbrush (c) bitterbrush (d) saltbush (e) saltbush

Figure 3-11. Additional Field Photos of Training Areas

Figure 3-12 shows the location of training areas presented in Figures 3-4 through Figures 3-11 and also Figures 3-17, 3-19, 3-21, 3-22, 3-24, 3-25, 3-26, 3-28, 3-29, 3-30, 3-31, and 3-32.

Note: All figure caption numbering shown in Figure 3-12 corresponds to Section 3 of this document, figure numbers have been prefixed by “3-”.

Figure 3-12. Locations of Training Areas Corresponding to Section 3 Figure Numbers

Figure 3-13 shows the training spectra used in a Matched-Filter (MF) algorithm that outputs a grayscale image for each input spectra (Boardman et al., 1995). The grayscale images are an estimate of the relative degree of match to the input, where 1.0 is a perfect match. The training areas were used to adjust thresholds for each image, above which all pixels were then classified as a particular species (Figure 3-14).

Figure 3-13. Training Spectra used in a Matched-Filter (MF) Algorithm

3.4.4 Field Validation

Two field visits were made in the fall of 2007 to validate the vegetation maps and adjust/expand training areas where necessary. This was accomplished by visiting predetermined locations where we recorded vegetation-type and the coordinates of individual plants or homogenous plant communities. These efforts were not intended to be a quantitative accuracy assessment but instead a qualitative assessment of the mapping results to-date. The new field data was used in a second round of image processing to improve the vegetation maps. Results are discussed in section 5.1.

3.5 Seasonal Change Detection

Spring and fall datasets enabled the detection of changes in plant vigor from one season to the next. Change in the positive direction (green-up) may be related to the following: abundant and persistent availability of surface and /or shallow groundwater; irrigated crops; species that green-up in the fall. Vegetation that senesces or drops their leaves in the fall primarily due to increasing day length is more typical of phenologic change but can also be related to fallow fields, lack of sufficient ground and surface water, and anthropogenic stress such as pollution.

3.5.1 Stacking and Co-registration

The spring and fall datasets were first “stacked” into a composite file so that differences in NDVI values between the spring and fall data could be calculated pixel-by-pixel. The co-registration accuracy was typically within one pixel but could vary by as many as four pixels.

Figure 3-14 shows (a) cottonwood MF result before cut-off threshold was applied to produce the cottonwood map shown with green polygons (b) Terra color-infrared image shown for reference. Location of figures within study area is shown in Figure 3-12.

Figure 3-14. (a) Cottonwood MF Result Before Cut-off Threshold Was Applied

3.5.2 NDVI and Calculating Percent Change

NDVI calculations were made for both the spring and fall data and masks were applied to each as discussed in section 3.5.1. The purpose of the masking was again to restrict further analysis to only pixels with a significant vegetation component. Percent change was calculated with the following equation:

$$((\text{spring_NDVI} - \text{fall_NDVI}) / (\text{fall_NDVI})) * 100$$

The results were analyzed within GIS framework to better visualize and compare with other spatial data where the most significant change had taken place. We calculated vegetation change for the N-S flightlines. Due to the error in co-registration we excluded the analysis of shrubs – a one or two pixel shift could easily produce erroneous results because the individual shrub canopies typically dominate only 2-6 contiguous pixels. In contrast, most vegetation in the riparian zone occupies larger areas of contiguous pixels and any misregistration may be apparent around the edges of canopies or patches but any change will still be captured in the greater mass of pixels (Figure 3-15). Therefore, we limited our analysis of vegetation change to the riparian areas.

Figure 3-15 shows (a) Cottonwood canopies showing edge effects caused by slight misregistration. Red pixels indicate where there is the greatest amount of senescence between the spring and fall data. However, the red rim suggests that a slight spatial shift to the southwest in the fall data compared NDVI values from pixels along the canopy perimeter in the spring data with fall NDVI values for soil that are just outside the canopy perimeter. Conversely, pixels on the northeast edges of the canopies show significant green-up (greenest pixels) and are likely a result of spring NDVI values for soil being compared with fall NDVI values near the canopy edge. (b) digital orthophotography shown for reference, a vehicle in the top center of the image is used for scale.

Figure 3-15. Cottonwood Canopies Showing Edge Effects Caused by Misregistration

3.6 Resolution Degradation

Spatial resolution and to a lesser degree spectral resolution are the major cost drivers of remotely sensed data. For this reason we were interested in determining what information would be lost with coarser resolution data. To test this we resampled the stacked data to the spatial and

spectral resolutions of the IKONOS and SPOT satellites (Jensen, 2007), these instruments specifications are presented in Table 3-1. After resampling NDVI and percent change data were calculated.

Table 3-1. Spatial and Spectral Resolution for the IKONOS and SPOT Multispectral Satellites

IKONOS			SPOT		
Band	Range	Spatial Resolution	Band	Range	Spatial Resolution
1	0.445-0.516 μm	4 m	1	0.500-0.590 μm	10 m
2	0.506-0.595 μm	4 m	2	0.610-0.680 μm	10 m
3	0.632-0.698 μm	4 m	3	0.780-0.890 μm	10 m
4	0.757-0.853 μm	4 m	4	0.780-0.890 μm	10 m

3.7 Analysis of Plant Vigor with Respect to Slope and Aspect

To determine how plant vigor differed with respect to slope and aspect we integrated with the LIDAR-derived DEM with both the spring and fall hyperspectral data. This type of analysis takes advantage of the broad area covered with a remote sensing data to look for patterns in landscape change that are associated with vegetation as it relates to changes in topography. NDVI values were generated from the spring and fall Terra data. Slope and aspect images were created from the LIDAR-derived DEM and then used to extract average NDVI values from the eight cardinal compass directions and for slopes between 10 and 45 degrees. Figure 3-16 illustrates the datasets used in these calculations.

Figure 3-16 shows data used in analysis discussed in Section 3.5, (a) LIDAR-derived shaded relief shown for reference (b) NDVI image generated from the Terra data. (c) aspect image and (d) slope images derived from LIDAR data and used to extract values from (b). Results are presented in Table 3-2.

Figure 3-16. Analysis Results, (a) LIDAR, (b) NDVI for Terra, (c) Aspect, (d) Slope

3.8 Analysis and Results

3.8.1 Species Discrimination

The Terra spring data was used in an attempt to map individual species of vegetation. Thresholds applied to NDVI calculations helped to focus image processing methods solely on most plants with a contiguous surface cover greater than 1 m². Although the calibrated reflectance data showed close agreement with ground measurements, discriminating individual species of vegetation proved to be challenging, similar to the experience of other authors (e.g., Okin et al., 2001). Figure 3-17 is presented as an overview map of our attempt to map individual species or groups of species that were mapped with Terra spring hyperspectral data. At smaller map scales it is revealed the creosotebush is not as densely distributed as the inset figure suggests.

Figure 3-17. Overview of Species Mapped with Terra Spring Hyperspectral Data

All of the tree species that we attempted to map commonly display canopies that are large enough to occupy tens of contiguous pixels with limited spectral contributions of soil and shadow; although, the same can not be said for most shrubs and smaller native vegetation. With the exception of Joshua trees, other tree species in the study area are found along riparian corridors or near to irrigation sources. Due to the greater availability of water and deep root systems trees in the riparian zone generally show well above average vigor (greater NDVI values) when compared with most shrubs. The effects of greater water availability are apparent in the spectra and help to separate the spectral means of the different species of trees (Figure 3-17). However, results were confounded by irrigated lawns and some riparian grasses and rushes that also display steep red edges and well defined chlorophyll adsorption troughs, similar to tree canopy spectra during the spring.

3.8.2 Trees

Figure 3-18 is shown as an example of cottonwood mapping with the hyperspectral data shown in green with digital orthophotography in the background. Although the trees are visibly different in color (Figure 3-19a), maps for cottonwood and willow could not be achieved without low accuracy due to omission or commission errors for one species or the other. Similarly, Russian olive and cottonwood are also visibly different in color but were also difficult to separate spectrally (Figure 3-19b). Typically tamarisk is more shrubby than tree-like, but given their large and contiguous canopy areas we included this species in the discussion of trees. Among the different tree species mapping results for tamarisk were the most successful and is

likely attributed to significant differences between the phenology of tamarisk as compared to most other trees in the study area (Figure 3-20).

Figure 3-18. Example of Cottonwood Mapping with Hyperspectral Data

Figure 3-19. Visual Comparison: (a) Cottonwood and Willow (b) Cottonwood and Russian Olive

Figure 3-20 provides an example of Tamarisk Mapping with Hyperspectral Data Shown in Green with Digital Orthophotography in the Background

Figure 3-20. Example of Tamarisk Mapping with Hyperspectral Data

3.8.3 Non-tree Riparian Vegetation

Composite images of various MNF channels suggested good spectral separability of some riparian vegetation, excluding trees. Although it was not possible to distinguish individual species of grasses, rushes and sedges, visual inspection of these areas coupled with the digital orthophotography yielded training classes for green riparian and senesced riparian vegetation. Even though the mapping results were not totally exclusive of one species they did show close agreement in the field as they are described (Figure 3-21). There were limited false-positives for both maps but errors of omission for the green riparian map were more common.

Figure 3-21 shows an example of senesced and green vegetation mapping with hyperspectral data shown in yellow and green respectively, with digital orthophotography in background

Figure 3-21. Example of Senesced and Green Vegetation Mapping with Hyperspectral Data

3.8.4 Shrubs

Leaf Area Index (LAI) is defined as the total upper leaf surface area divided by the total surface area on which the vegetation grows. In general, shrubs display lower LAIs than most trees and patches of riparian cover. As a result, there is an associated increase in the spectral contribution from shadow, soil, and woody material (Figure 3-22). The shrubs that we attempted to map were represented by similar spectral means and overlapping variances. Thus, a high degree of inaccuracy among the mapped shrubs was common with some exceptions.

Tailings piles at the eastern end of the E-W mosaic were planted with saltbush in a mining reclamation effort. This location provided good opportunity for a spectral characterization of saltbush and yielded saltbush map with fewer false-positives as compared to other shrub species, while at the same time including most of the saltbush (Figure 3-23). The main exception to false-positives is in the town of Beatty where some irrigated and riparian vegetation was included in the saltbush map. These false-positives displayed a strong chlorophyll absorption trough and red-edge similar to saltbush (Figure 3-9). These spectral characteristics are less pronounced for the other shrub species, which helps explain why a higher degree of accuracy can be achieved when mapping saltbush, especially during the spring months with hyperspectral data.

Figure 3-22 shows field photos of shrubs (hat shown for scale) (a) creosotebush (b) saltbush (c) rabbitbrush (d) bitterbrush. Digital orthophotography showing these shrubs in the same order from left to right.

Figure 3-22. Field Photos of Shrubs (a) creosotebush (b) saltbush (c) rabbitbrush (d) bitterbrush

Figure 3-23 below shows (a) Green shows saltbush map on digital orthophotography with corresponding field photo shown in (b). At the expense of reducing commission errors of non-saltbush vegetation, commission errors for saltbush became apparent in other areas such as the mine tailings pile shown in (c) where most of the saltbush was not successfully mapped.

Figure 3-23. Digital Orthophotography of Saltbush with Corresponding Field Photos

Evergreen bitterbrush canopies display a high LAI compared to most other shrub species and they are generally darker green in color. These two characteristics helped differentiate bitterbrush from neighboring creosotebush, also an evergreen shrub with similar canopy dimensions. As with the other species maps most false-positives were associated with irrigated and riparian vegetation in the town of Beatty. Creosotebush was sometimes mistaken for bitterbrush, however, bitterbrush was often found in narrow washes, typically at higher elevations than creosotebush (Figure 3-24).

Figure 3-24 shows (a) digital orthophotography showing detailed area of bitterbrush mapping outlined in green and (b) Terra color-infrared image with bitterbrush mapping shown for comparison. Shrubs in the upper half of the images are creosotebush.

Figure 3-24. Bitterbrush Mapping

Creosotebush generally displayed lower LAIs than the other shrubs that we attempted to map. Therefore, creosotebush spectra were expected to have greater contributions for shadow and soil background. To account for this we selected training pixels from a wide variety of soil backgrounds. The result was better characterization of creosotebush spectra but an associated increase in variance. This meant increased mapping errors in irrigated and riparian areas, as well as shadowed areas. There were also commission errors due to the inclusion of non-creosotebush. We made intentional omission errors in areas with light soil backgrounds, this helped reduce commission errors in areas with dark soils or in shadows. Despite these challenges, a visual estimation with the digital orthophotography suggests that the majority of creosotebush in the study area was accurately mapped (Figure 3-25).

Rabbitbrush was difficult to identify in the digital orthophotography and resulted in a limited number of training pixels. This shrub species also displayed greater phenological variability than other species of interest. The mapping results were dubious and we determined that better training areas were required to improve the mapping results.

Figure 3-25 shows (a) Terra color-infrared image showing creosotebush mapping in green (b) close-up of creosote mapping shown on digital orthophotography image and same area for comparison shown in (c) with Terra color-infrared image

Figure 3-25. Creosotebush Mapping

3.9 Change Detection

3.9.1 Change Detection Increases

The months prior to the spring data acquisition were unseasonably dry. In contrast, there were several unusually large monsoonal precipitation events prior to the fall data acquisition. This resulted in change detection results that were counterintuitive. Under a more normal precipitation regime the strongest “green-up” would be expected in the spring when there is normally more

abundant precipitation; almost the opposite happened during the course of this study. Therefore, the most water-abundant riparian areas were delineated by an overall increase in greenness. These results may be an indication of where the Armagosa River disappears and then re-emerges at the surface, or where surface and shallow groundwater are most likely available during the driest months. Figure 3-26 is an overview of the vegetative changes in Oasis Valley between spring and fall 2007.

Figure 3-26. Overview of the Vegetative Changes in Oasis Valley

The strongest and most consistent increases in greenness were associated with cattails (*Typha*, Figure 3-27) and bullrush (*Scirpis*, Figure 3-29). Field validation revealed that saltgrass was a common species in the riparian zone and was typically associated with fall green-up greater than

10% (Figure 3-23). Alkali sacaton (*Sporobolus*) was also common in riparian areas and was consistently associated with strong green-up (Figure 3-29).

Figure 3-27 shows (a) NDVI percent change results on digital orthophotography and (b) digital orthophotography from spring data shown for reference (c) terra color-infrared of fall data agrees with results of percent change calculations when visually compared to (d) terra color-infrared of spring data.

Figure 3-27. Change Detection Results in Greenness with Cattails and Bullrush

Figure 3-28 shows (a) percent change in greenness is shown on digital orthophotography data (b) field photo of greened-up saltgrass with view to south and corresponding to the open end of the magenta viewshed shown in the upper right of (a).

Figure 3-28. Change Detection Results in Greenness with Salt Grass

Figure 3-29 shows (a) percent change data shown on digital orthophotography (b) digital orthophotography shown for reference and corresponding field photo in (c), magenta viewshed is shown in (a) and (b). Plant species are: 1.- bullrush 2.- nutsedge 3.-saltgrass 4.- sporobolus.

Figure 3-29. Plant Species: 1.- bull rush 2.- nut sedge 3.-salt grass 4.- sporobolus

3.9.2 Change Detection Decreases

Senescence among cottonwood trees was visibly apparent during the fall field visit, and these changes were also apparent in the image data. Most cottonwood trees showed less than 10 percent negative change. Some of the highest negative changes were thought to possibly be associated with day-length dependent leaf senescence (Figure 3-30a). However, field checking revealed that in several cases presumed cottonwoods were actually Siberian elms. (Figure 30b-c). Similar to saltgrass, nutsedge was also widely distributed in the riparian zone and showed both strong green-up and senescence (Figure 3-29). It is possible this unpredictability associated with nutsedge was greatly influenced by irrigation run-off and a stronger response to decreasing day length than for saltgrass.

Figure 3-30 shows (a) Orthophotography shown with typical change detection result for cottonwood only. Increasing greenness in color indicates increasing green-up from spring to fall

data. (b-c) trees mapped as cottonwood that suggested anomalous senescence in the fall – field validation revealed that these trees were actually Siberian elm.

Figure 3-30. Change Detection for Cottonwood

3.10 Spatial Resolution Degradation

The change detection study was repeated after resampling the hyperspectral data at a lower spatial resolution. The same changes described above were observed at lower spatial resolution, with some subtle differences. Less detail for riparian areas that had greened-up or senesced was apparent but the broader patterns of change persisted. Detection of anomalous cottonwood senescence suffered the most from a degraded resolution; particularly when the canopy diameter of individual trees approached less than half of the coarsened spatial resolution. Figure 3-31 is

presented as an example of how details of vegetation change are lost at coarser resolutions. The area in Figure 3-31 also corresponds to the same location shown in Figure 3-27.

Figure 3-31 shows percent change calculated from Terra data convolved to (a) IKONOS resolution and (b) SPOT resolution; red pixels in (a) and (b) are false-positives associated with water, percent change data is overlain on digital orthophotography corresponding to the same area shown in Figure 3-34; (c) and (d) are Terra color-infrared images corresponding to the same area in (a) and (b) and shown at IKONOS and SPOT resolutions, respectively.

Figure 3-31. IKONOS Resolution and SPOT Resolution

3.11 Vegetation Stress with Respect to Slope and Aspect

For both the spring and fall, average NDVI values were highest on south and southeast facing aspects and on slopes less than 10 degrees (Table 3-2). Higher NDVI values in the fall 2007 data were observed for south and southeast facing after several significant precipitation events. This unexpected fall NDVI result was probably due to low morning temperatures limiting photosynthetic rates during full sunlight on north facing slopes compared to optimal temperatures and recently available precipitation for photosynthesis during full sunlight in the

middle to late part of the day on south facing slopes. The same combination of factors may have contributed to the same NDVI pattern in the spring data (i.e., highest average NDVI on south and southeast facing aspects with slopes less than 10 degrees), but with residual soil moisture from winter precipitation events providing the water. Had there been normal or above normal precipitation in the late winter/early spring months leading up to the spring data collects, in all likelihood the spring average NDVI values would have been greater than the Fall values. As for the observed slope angle results, less drainage of surface and subsurface moisture occurs on gentle slopes, therefore providing more available moisture to vegetation and thus increasing the health and vigor of plants. Variations in species composition with varying NDVI values is slope and aspect dependent which could also make the average NDVI response more variable than expected.

Table 3-2. Average NDVI Values According to Slope and Aspect for Spring and Fall Datasets

Spring		Fall	
Aspect	Average NDVI	Aspect	Average NDVI
North	0.056	North	0.174
Northeast	0.0623	Northeast	0.182
East	0.0686	East	0.194
Southeast	0.0759	Southeast	0.2
South	0.0718	South	0.193
Southwest	0.071	Southwest	0.19
West	0.065	West	0.189
Northwest	0.056	Northwest	0.177
Slope Angle		Slope Angle	
<5		<5	
5 to 10	0.15	5 to 10	0.212
10 to 20	0.127	10 to 20	0.168
20-30	0.117	20-30	0.154
30-40	0.115	30-40	0.151
>40	0.129	>40	0.166

3.12 Vegetation Analysis Conclusions

At 1 m spatial resolution we were able to produce a detailed GIS-compatible map of vegetation that displayed 0.5 m², or better, of contiguous cover. Therefore, quantifying spatially accurate estimates of shrub density, tree canopy size, or riparian area were possible with these data and something that may be useful in other types of botanical studies. Discrimination of individual species was met with moderate to low success; best results were achieved for cottonwood, tamarisk, bitterbrush and saltbush. Successful separation of tamarisk, cottonwood and Siberian elm were most likely related to differences in phenological state. These results are promising with respect to potential discrimination and class separation of invasive species such as tamarisk, as accurate mapping of invasive species is a high priority for federal, state and local land management agencies. Discrimination of willow and cottonwood was not possible without significant errors of omission and commission, likewise for the discrimination of rabbitbrush from other shrub species. Separation of green riparian and senesced riparian vegetation generally agreed with field observations.

High-accuracy (< 1 m on average) geo-registered data enabled a good comparison of spring and fall NDVI values. Therefore, it was possible to examine where changes in vegetation vigor had

taken place in the riparian zone and among irrigated trees. Due to atypical fall monsoonal events, there was an overall green-up that was most widely manifested by saltgrass and sedges. However, changes in irrigation patterns between the spring and fall data prevented consistent observations and sometimes wide areas of senescence were observed. Bullrushes and cattails were consistently associated with a strong green-up in the fall. Cottonwood trees were visibly senescing when observed in the field during the fall; this observation was consistent with resulting low to moderate negative changes in NDVI between seasons observed in the data for the same cottonwoods.

The overall patterns of change between the spring and fall data using the 1 m hyperspectral data were generally apparent at lower resampled spatial and spectral resolutions. We ascertained that the changes discussed above could be captured with 4-5 m data but not reliably with 10 m data. Therefore, the costs associated with airborne hyperspectral data could be significantly reduced by using a spaceborne instrument with sufficient spectral resolution, while at the same time compromising little in terms of spatial accuracy and mapping capabilities.

The integration of the LiDAR-derived DEM with the hyperspectral data made it possible to recognize uncharacteristic changes in phenology according to differing slope and aspects. These anomalous observations were driven by abnormal regional climate conditions that affected temperature and soil moisture on a local scale, but were detectable using the integrated datasets.

High spectral and spatial resolution image datasets still have limitations when attempting to discriminate vegetation species in arid environments. Improvements in separability of vegetation species spectra may be with the application of new end member mapping algorithms, but similar spectral signatures between arid plants and a strong soil background signature will always present challenges to species mapping. With very good orthorectification of seasonal datasets, however, changes in vegetation health and vigor can be accurately mapped at local scales, and possibly, even regional scales, given the above described resolution degradation results.

The fusion of LIDAR and hyperspectral image datasets provides a spatial data product that shows promise for the assessment of local and regional trends in vegetation response to rapid changes in climate variables such as temperature and precipitation. These data integration methods could help improve current methods of invasive species mapping and establishing baseline cover data for proposed and/or recommended land withdrawals or other changes in land management practices.

4.0 AUTOMATED HYPERSPECTRAL ANALYSIS: DESCRIPTION AND PERFORMANCE EVALUATION

4.1 Motivation

An important goal of the MANNRRSS program is the study of cost effective strategies for analysis of remote sensing data. The quantities of data produced by the current generation of instruments are large and require expert manpower for analysis and exploitation. The data products presented in this report for the Beatty area represent, for example, several thousand man hours of labor. For larger scale efforts, automation of some of the steps of analysis could represent enormous savings in overall cost.

Another byproduct of automation of analysis tasks is standardization. The state of the art of remote sensing analysis is strongly driven by the analyst, resulting in unrepeatable methodologies. The lack of standardization results in difficulty in comparing analysis results across analysts and datasets. It also causes most analyses to give results that are generally qualitative rather than quantitative.

In order to address some of these issues, an effort was made to evaluate current analysis methods and to try to automate these methods for the MANNRRSS hyperspectral datasets. We developed a suite of tools which produced synoptic summary outputs of the hyperspectral data at both the scene and dataset level. All the tools were custom written in MATLAB as part of this study, using algorithms developed as part of the MANNRRSS program. The algorithm is described in Appendix B to this document.

The goals were:

- Reduce the manpower needed for analysis.
- Reduce the effort needed for data preparation.
- Remove from analysis any use of “magic numbers”. Magic numbers are numerical inputs to an algorithm which influence the outcome but cannot be derived from first principles. These are commonly in the form of heuristics or inputs based on trial and error.
- Provide an algorithm that is data agnostic: capable of being ported to other instruments and geographies with no modification.

These primary goals led to a set of more specific goals for the effort:

- Create an automated analysis capability using gain corrected radiance datasets as input. No reflectance or other atmospheric correction should be used.
- Create an automated method for extracting the spectral signatures of the principal constituents of the hyperspectral data. Create scene level summaries of spatial distribution and abundance of principal constituents, their spectra, and samples of high resolution orthophotography of the constituents.
- Evaluate the data for anomalies which do not fit the constituent model. These anomalies will consist of spectra that are statistically very different from any of the identified constituents or their possible combinations, but were not abundant enough to be considered a scene constituent. Provide high resolution orthophotography of the anomalous areas.
- Create an automated method for mapping a constituent across the entire dataset. The operator need only identify what constituent to map, by selecting a scene-level constituent.

- Create a data-set level constituent model from the scene level constituents. This is an automated data-set level mapping of the most abundant/significant constituents.
- Analyze multiple datasets for differences, creating a map of the statistical significance of changes seen in hyperspectral datasets. Summarize the statistically significant differences using orthophotography.
- Have as little operator (analyst) inputs to the process as possible. Analyst judgment is to consist only of command choices of what constituents are interesting and evaluating the quality of the outputs.

Achieving the above goals will:

- Remove much of the analyst effort spent in data management (segmentation into computationally tractable inputs for manual analysis) and interacting with the interfaces to manual analysis tools.
- Remove the need for much of the ground work: specifically that needed in support of reflectance calibration.
- Remove the need for reflectance correction of the hyperspectral data, including trial and error iteration and evaluation of the reflectance corrections.
- Remove the effort to manually define “training” areas for the mapping of constituents. Similarly, it will remove the effort needed to manually extract the “purest” pixels of a constituent to gain the best mapping.
- Remove the effort needed to convert the continuous outputs, “rule images,” of the common manual mapping methods into a thresholded map.
- Allow repeatable, stable and quantitatively meaningful outputs.

Automation will not remove the need for an expert evaluation of the fidelity of the results. The automated analysis can greatly ease this evaluation by providing meaningful numerical results (statistical significances, numerical purities, goodness of fit). The automated analysis can also easily extract high resolution imagery of locations to allow analyst confirmation and identification.

We limited the scope of the investigation to analysis of only the hyperspectral datasets. We excluded any analysis of the spatial relationships of the data, and any analysis using the ancillary data of the digital elevation model. These ancillary data provide valuable capabilities to refine the mapping capability, as demonstrated by the manual analysis results presented elsewhere in this report. Extending this automated analysis study to include these ancillary data should be considered a future goal of MANNRRSS.

We created an automated system which achieves most of the above goals. The details of the analysis algorithms are presented in Appendix B to this report; here we will only describe the data products of the automated analysis and report on the results and performance here.

The analysis inputs are the entire radiance dataset, the entire high precision orthophotography, and the geographical inputs to allow referenced mapping of the hyperspectral pixels and the orthophotography pixels.

4.2 Scene Level Products

The primary output of the automated analysis is the scene level summaries. The algorithm to perform the summaries segments the hyperspectral data into the largest feasible scene sizes that

can fit into memory, typically around a quarter million pixels, or approximately a quarter square kilometer at 1-m pixel resolution.

Each of the segments is considered a scene and is analyzed separately. There are around 500 scenes in the spring dataset and 240 scenes in the fall dataset.

A scene summary is produced for each scene as output. A scene summary will present to the analyst up to 16 constituents (referred to as “endmembers” in the output imagery included here) which are the primary components of the scene based on spectral properties. The purest example of each endmember, based on the constituent abundance map, is shown in an orthophotography sample. In addition, orthophotography of anomalous scene regions are presented to the analyst for rapid evaluation.

The scene summaries are themselves not intended to be the final output of an analysis of the dataset, but merely an easily evaluated synoptic overview of the dataset at the scene level. The scene level results can then be used by an analyst to choose what constituents or anomalies to pursue at the dataset level through a mapping capability.

4.2.1 Example Scene Summary

Figure 4-1 shows an example scene from the spring Terra dataset. The scene includes a section of road and greenery associated with a spring to the east of the road, flowing towards the southwest. Note the two vehicles on the road. The inset shows the location of the scene (in red) relative to the dataset area.

Figure 4-1. Scene from Terra Dataset

The automated analysis produced results synthesizing the scene, including showing the dominant constituent spectra, the geographical abundance of the constituents, the spectral purity of the scene (if one constituent dominates a pixel, that is a relatively “pure” pixel), orthophotography of the spectrally purest region of the scene for each constituent, and any spectrally anomalous regions of the scene. These outputs can be seen in several ways, including in pdf and ENVI formats (Figure 4-2). Figure 4-2 shows scene summary as output by the automated analysis. Shown here is a set of pdf pages containing the summary, although the outputs are also available in several other forms.

Figure 4-2. Scene Summary Output by Automated Analysis

The automated scene analysis begins a summary with 12 endmembers for this scene. The classifications for the example scene are shown in Figure 4-3 below.

Shown in Figure 4-3 on the left: The scene in visible colors, as seen by the hyperspectral instrument. Shown on the right: The scene summary classification. This scene consists of 12 dominant endmembers. There are three major geological endmembers (red, cyan, and yellow). Most of the scene complexity is in the area dominated by the vegetation around the spring.

Figure 4-3. Classifications for Example Scene

The analyst is also presented with the radiance spectra of the scene constituents, as shown in Figure 4-4. A close-up of the SWIR (2000-2500 nm) portion of the spectra, not shown here, is also presented to clarify absorption features related to geological constituents. In spite of the spectra not being reflectance corrected, it is possible for an experienced analyst to identify many spectral features such as a “red edge” associated with photosynthesis and absorption features of geological constituents.

Figure 4-4. Radiance Spectra of the Scene Dominant Constituents

Along with the classification map, a map representing the pixel “fit distance” and “purity” are presented.

The fit distance is how well each pixel can be described by a mixture of the constituent spectra. The spectrum of a pixel is assumed to originate from radiance from a linear combination (weighted sum) of the scene constituents. The fit distance measures how far the observed spectrum lies from the closest possible combination of constituents. If the pixel spectrum can be precisely represented as a sum of constituents the fit distance is low. If the spectrum is not very consistent with the linear combination hypothesis, the fit distance will be abnormally large. The fit distance can be then considered to be a measure of how anomalous to the scene a pixel is: a marker of pixels that are not composed of the scene’s major constituents.

The purity is a measure of how dominant a single scene constituent is in the pixel. Highly mixed pixels, those having spectral contributions from many constituents, will have a low purity. Those having spectral contribution from only one constituent are considered highly pure. Purity ranges from 0 to 1. These two maps are shown in Figure 4-5. Orthophotography and spectra of the locations of interest are shown later in the summary: pixels with a fit distance large enough to indicate that they are statistically inconsistent with the constituents will be presented later in the summary, and the purest pixel of each constituent. These outputs will allow the analyst to rapidly evaluate what the constituents and anomalies are.

Figure 4-5 below shows the purity (left) and fit distances (right) of the pixels in the example scene. The purest pixels for each constituent will be used to present the analyst with photographic descriptions of the scene constituents. The largest fit distances are clearly the two

cars on the road. Cars are too small to be considered for constituents in a scene of this complexity.

Figure 4-5. Purity (left) and Fit Distances (right) of the Pixels in the Example Scene

The fit distance is not just useful for determining anomalous areas of the scene. It also is one of the more direct ways for the analyst to be sure of the quality of the scene decomposition. The fit distance represents a statistical quantity whose expected distribution is known. The analyst is therefore presented with a comparison of the expected and observed fit distance distribution. Scenes which failed to decompose properly are easily seen to have poor fit distance distributions, meaning that the scene information was inadequately captured in the constituents found. The statistical model of the expected distribution allows the computation of explicit likelihoods for the worst fitting pixels to determine if they could be statistical fluctuations or anomalies.

The fit distance distribution for the example scene distribution is shown in Figure 4-6 below and is an example of a successful decomposition. The red curve shows the distances of the pixels in the scene, and the blue curve shows the prediction for a statistically consistent model. The red curve has several outlying pixels beyond the value of 25 which are statistically anomalous. These pixels coincide with the two automobiles in the scene. However, the overall scene converged

very well, consistent with a statistical model with 240 independent spectral bands. The analyst would conclude that the constituent summary of this scene is reasonable.

Figure 4-6. The Fit Distance Distribution for the Example Scene

The anomalies that have fit distances incompatible with statistical fluctuation are ranked and presented to the analyst. The spectrum and a 30x30 meter region of the orthophotography centered on the anomaly is presented. The example scene has two truly anomalous regions in the image, both of which are cars. One of the two anomalies is shown in Figure 4-7. Unfortunately the anomalies in the example scene are mobile, and are not captured by the precision orthophotography. In Figure 4-7 in the left view, the spectrum of the car is very different than any of the constituents, and shows up as an extremely poor fit to being a mixture of the constituents. The closest matching constituent spectrum is shown to the analyst for comparison, which in this case is a senesced grass. In the right view, in addition to the spectrum of the anomaly, a 30x30 meter context of the orthophotography is given to the analyst. Unfortunately, in this case, the car has already left the scene of the crime when the orthophotography was taken!

Figure 4-7. One of the Two Anomalous Regions of the Example Scene

Figure 4-8 shows a second example of a stationary anomaly (from a mainly desert scene in the far north of the north-south spring dataset). In this case, a plastic bag (with an area smaller than the hyperspectral pixel size) is shown as a strong spectral anomaly to the analyst. The anomaly is interesting in that the physical scale of the anomaly is smaller than the hyperspectral pixel, making it a “sub-pixel” anomaly.

Figure 4-8. Second Example of an Anomaly

The final component of the scene level summary are the constituent descriptions. The constituents are ordered by relative scene abundance. For each of the constituents, the spectrum of the constituent, a map of the abundance, and a 30x30m orthophotography context of the purest pixel are shown. This allows the analyst to get a clear idea of how the scene is spectrally constituted. In the example scene, the 12 constituents span various geological and vegetative types. The outputs for a single constituent, one of two tree constituents, is shown in Figure 4-9.

Figure 4-9 shows the orthophotography close-up clearly identifies the constituent as a cottonwood. This is confirmed by the spectrum showing a “red edge” associated with vegetation, and by the distribution of the constituent in the image showing tree canopies.

Figure 4-9. The Abundance of the Ninth Constituent of the Scene

Figure 4-10 shows all of the constituent abundance maps for the example scene. The largest coverage ones are of geological constituents. The remainder is vegetation species, including senesced and green rushes and grasses. One constituent appears to be specifically the asphalt of the road, while another follows the creek bed towards the bottom of the scene.

Figure 4-10. All of the Constituent Abundance Maps from the Example Scene

4.2.2 Scene Level Performance

The scene summaries never failed to converge on a set of endmembers which described the scenes. This is by design, as the algorithm will try to divide the scene using coarser and coarser training (“seed”) areas until the smaller or less abundant endmembers will no longer be considered as primary scene constituents. For the majority of scenes, the algorithm converged immediately with the smallest seed areas of three pixels (three square meters) providing an adequate set of endmember spectra for scene decomposition. Two scenes of 526 in the spring Terra dataset required more than 50 square meters per endmember seed.

We evaluated the fidelity of the scene summaries by manual inspection as well as by creating Figure of Merit (FOM) quantities for scene fidelity. The figure of merit quantities are all based on the distribution of fit distance values across the scene. The larger the scatter in fit distances, the worse the scene is described by the endmembers in the fit. Similarly, the number of anomalous pixels, defined as not fitting the endmembers, is a useful indication of fit quality. We expect these quantities to vary with coarseness of the endmembers, and with each other, if they truly represent scene fidelity. The coarseness of the endmembers is represented by the number of seed pixels used in defining the endmembers; the larger training samples providing a more generic set of endmembers with more potential for mixture among constituents. We also expect a geographical distribution of these quantities to correlate with the spectral complexity of the scenes.

Figure 4-11 shows the fidelity figures of merit for the full spring Terra dataset. As expected, the fidelity metrics are correlated with the number of pixels in the training area (referred to as “seed” size in the figures). The more complex scenes, and therefore the larger size training areas, are found to be in areas of man-made development (downtown Beatty and along the Amargosa corridor). In Figure 4-11 the two fidelity metrics, the spread in fit distance and the number of anomalous pixels, for each of the scenes in the spring Terra dataset are shown. The symbol size is representative of the number of pixels used to define endmembers in the scene, which is a good indicator of spectral complexity in the scene.

Figure 4-11. Fidelity Figures of Merit for the Full Spring Terra Dataset

Figure 4-12 illustrates the scene seed size versus location. The great majority of scenes show no problems converging on an accurate scene summary. Figure 4-12 shows the geographic distribution of the scene fidelity, the number of anomalous pixels per scene represented by the size of the symbol, and the location of the symbol is at the scene location relative to the entire dataset.

Figure 4-12. Geographic Distribution of Scene Fidelity

The manual inspection of the scene summary reports showed that the results are generally excellent, and represented an accurate summary of scene contents. The exact result of the algorithm is, however, highly scene dependent. Two roughly similar portions of the desert may not find the same endmembers: one may find enough statistical accuracy to distinguish two closely related species, or may find enough density of coverage of a normally subpixel-sized endmember to create a training spectrum. An example of this is distinction of the desert vegetation Joshua trees, which alternated between being classified as belonging to the same endmember as another species (bitterbrush), as a scene anomaly, or as a separate endmember. Which position the Joshua tree occupied in the scene summary is a function of the abundance of Joshua trees in the scene, the size of the Joshua trees, the variation in the soils surrounding the trees, and other scene-to-scene variables.

The scene summaries were observed to differentiate among many species of vegetation, including tamarisk, Russian olive, and cottonwood among others. One notable exception is that no individual scene differentiated willow from cottonwood; these species apparently have very similar radiance spectra. Having a scene level constituent allows analyst to map the constituent

over the dataset, so having scenes that distinguish species is important to prove the feasibility of data-set level species mapping.

It is probably inaccurate to call the conflation of two species as lack of fidelity in the scene summary, as the confusion is clearly a matter of degree of separation versus scene complexity. There were occasional conflation of two clearly different types of object into one endmember. Those cases are primarily due to the existence of unnaturally bright and dark, uncolored man-made objects in the scene. These objects tended to have very generic spectra without features which made distinction difficult by placing an endmember in the spectral “middle ground” of the scene. The example shown in Figure 4-13 is typical. These confusions were not observed in the absence of man made objects. In this case a black truck seeded an endmember (endmember 4, in green in the classification map) which was then matched to a large fraction of the pixels in the scene. The generic desert varnish is apparently spectrally close enough to the black paint of the truck to confuse the scene summary algorithm.

Figure 4-13 below shows an example of spectral confusion in a scene causing conflation of two clearly differing classes of object into one scene endmember. Upper Left: The scene in visual colors. Upper Right: The scene as classified by the automated analysis. Lower Left: Orthophotography of the purest pixel of the constituent labeled “endmember 4”, in green in the classification map. Lower Right: The spectrum of endmember 4.

Figure 4-13. Example of Spectral Confusion

The anomaly detection performance was also observed to be very good at detecting man made objects in a natural background and rare or unique naturally occurring objects. There were two broad classes of errors observed in the anomaly detection.

The first anomaly detection error was a tendency for peculiar mixtures of endmembers in the scene to be found as anomalies. This occurred when the typical spatial scale of the endmember was small, e.g., a shrub, causing the spectral training pixels to be contaminated by some unrelated background spectrum, e.g., the soil surrounding the shrub. This lack of purity in the

training pixels then caused instances of the endmember in other background contexts to be classified as an anomaly. This was generally observed with shrubbery at the edges of roads, where the endmember spectra were derived from shrubs with undisturbed desert backgrounds. Figure 4-14 illustrates an example of this failure. In general the fit distances for this form of anomalies were small, and can be readily ignored.

Figure 4-14 shows a road lined with bushes in a primarily desert scene. The orthophotography has red marks to show what pixels are close to anomalous (red) and those that are flagged (yellow). There are several bushes along the road edge that are close to anomalous (two bushes are actually flagged as anomalous). The grey scale image shows the fit distance for the pixels in the area (brightness is proportional to the fit distance), showing the tendency for bushes along the road to have worse matches to the constituent model. The worsened matches along the road are due to a different background soil interfering with the matching of the bush endmember spectrum. Other anomalous pixels seen in the area are generally due to man-made debris (litter).

Figure 4-14. Road Lined with Bushes Demonstrating a Form of Anomalies

The second form of anomaly detection error was an inefficiency to find some man made objects that are white. If the scene contained some significantly bright and featureless natural spectrum, these become spectrally difficult to distinguish. This failure is directly analogous to the failure in scene constituent classification noted above and illustrated in Figure 4-13. The only difference is that the scene summary orthophotography picks the dominant natural spectrum as the representative example of the constituent, and the man made object is classed as the dominant natural endmember.

Finally it should be noted that more complex scenes tended to produce more anomalies, to the point where the value of anomaly detection per se becomes questionable. However, even in these circumstances it is found that an ordered presentation of the most anomalous regions up to some limit creates a reasonable result. The most anomalous regions did in fact tend to have the most interesting features of the scene as was subjectively judged by manual inspection. For example, if there are many man made objects in the scene which did not categorize well into endmembers, the most anomalous areas tended to be those with non-grey (blue, red, yellow) colors.

We systematically investigated the ten scenes with the most anomalous pixels, and found that they consist of scenes with highly variable areas involving standing water, combined with failure to converge until seed sizes approached 10 square meters (10 pixels). Standing water tended to

encourage highly variable vegetative growth at its borders, and seems to also have intrinsically highly variable radiance in general, perhaps due to glint (specular solar reflection off of the water surface). Since the standing water is in many cases unable to dominate the spectral variance of the scene, the algorithm does not account for the variability.

The summary images generally managed to cover all of the anomalous pixels in these instances, since the anomalous regions tended to be compact and the summary orthophotography samples cover 225 square meters. Other areas with large numbers of anomalies were dominated by complex man-made scenes. As noted above, the anomalies reported tended to be the man-made non-white (colored) objects in the scene.

In summary we find the scene level performance of the algorithm to meet the requirements laid out in the goals for the algorithm.

4.3 Dataset Level Products

The scene level products can be used by an analyst to define dataset level mapping targets. However, the scene level summaries present a relatively myopic view of the dataset, giving a total of 4766 individual constituents in the case of the Terra spring dataset.

The scene level information can be merged to produce dataset level products automatically. A dataset level map of pixel purity and pixel fit distance are available.

The automatic extraction of all the constituents of the entire dataset (as opposed to scenes) and mapping them would be the ideal result of an automated dataset level analysis. We have investigated methods of consolidating the scene level constituents into a dataset level “library” of constituents. The goal was to reduce the thousands of scene level endmembers to something less than 100 (the exact number depending, of course, on the dataset). We also investigated ways to produce automated mapping of the library endmembers, without resorting to unreasonable computation demands.

4.3.1 Targeted Mapping

The scene summaries show orthophotography of the purest example of each constituent to aid identification of the constituent. The distribution observed in the abundance map of the scene can also be used to identify the constituent. If an analyst identifies a constituent he wishes to map at the dataset level, the algorithm can be given the spectrum used to define the endmember to be mapped over the entire dataset. This requires that the entire dataset be re-analyzed with the mapping target spectrum included in the scene classification step. However, there is no need for the analyst to produce a training set using traditional methods; the training is already performed by the scene summary classification algorithm. The labor burden on the analyst is then reduced to choosing what elements presented in the scene summaries are of interest for mapping.

The number of pixels used in the target spectrum depends on the scene context. The number of pixels can be as little as three, or even fewer if the analyst wishes to target an anomaly. All targets mapped in the analyses shown here have three pixel training areas. This is a substantially smaller number than is traditionally used in manual analysis, but the fidelity of the results, evaluated below, seems unaffected.

An example of a mapping target choice and the resulting dataset mapping is illustrated in Figures 4-15 through 4-16. Figure 4-15 shows the visual context of the scene containing the example mapping target, a Joshua tree. Figure 4-16 shows a portion of the scene level summary of the scene. The scene summary contains 8 endmembers. One of the endmembers is clearly Joshua

trees, as shown by the purest pixel orthophotography and the member abundance map showing the small sparse canopy typical of desert shrubbery. This scene also has a separate endmember representing creosotebush.

The target in this case, a Joshua tree, is mapped by default within the scene as part of the scene summary report. The target spectrum is the average of the “seed” pixels found for this endmember (see the algorithm description in Appendix B). In this case there are three seed pixels. This is a much smaller set of pixels than is normally used in a manual analysis training set.

Figure 4-15 is an RGB view of the Joshua tree scene. The scene is a sparsely vegetated desert scene with some man made alteration in the form of roads and mining activity. The inset shows the location of the scene (in red) relative to the entire dataset.

When applied to the entire dataset as a target to be mapped, the abundance of the target is presented over the entire dataset area as an output. This is shown in Figure 4-17.

Figure 4-15. RGB View of Joshua Tree Scene

Figure 4-16 below shows the selected scene summary outputs from the Joshua tree target source. Top Left: The visual scene as seen by the hyperspectral instrument. Top Right: The scene abundance map of the constituent labeled “endmember 3”. Bottom Left: The purest pixel orthophotography of endmember 3. Bottom Right: The spectrum of endmember 3.

Figure 4-16. Summary Outputs from the Joshua Tree Target Source

Figure 4-17 shows the target spectrum abundance over the entire dataset, based on the selection of the endmember shown in Figure 4-16 as a target spectrum. Top: The entire E-W line of the dataset. Bottom: A large portion of the E-W line zoomed to show mapping results. The Joshua

tree abundance is the blue shade in the image. The overlain maroon lines are the scene boundaries. Joshua trees themselves show up as the white dots in the image.

Figure 4-17. Target Spectrum Abundance over the Entire Dataset

As an exercise in mapping several species of desert vegetation using the scene summary endmembers as target spectra, we mapped Joshua tree, creosotebush, and bitterbrush for the E-W portion of the spring Terra dataset. A three color image created using the three species abundances is shown in Figure 4-18. The bitterbrush are seen to follow the washes, and the local landscape is surrounded with a sparse canopy of creosotebush and Joshua trees.

Figure 4-18 below shows from Left: A three color image formed from mapping of Joshua tree (red), Creosotebush (green), and bitterbrush (blue). Right: the same scene in orthophotography for comparison. The bitterbrush is spectrally very similar to creosotebush, being difficult to distinguish using the three color photography. But it is clear that the two species are mapped separately here, as bitterbrush tends to follow the drainage features.

Figure 4-18. Mapping of Joshua Tree (red), Creosotebush (green), and Bitterbrush (blue)

Normally target maps are not presented as abundances, however, but as regions or pixels identified positively as containing the target. The analyst can manually apply a threshold to the abundance map to produce the target map if desired. The threshold to be applied is not a generic quantity, it depends on the goal of the analyst. For example, the threshold can be optimized for mapping purity (high confidence the target is present when identified by the map) or for mapping efficiency (high confidence that all instances of a target are found). Purity and efficiency are generally traded against each other in view of the analytical goals for the map.

Another option is to allow the automated extraction of the target map from the abundances. Two methods of doing this were investigated. The abundance map produces an estimate between zero and one of the portion of the spectrum due to the target. This implies a threshold of 0.5 will identify pixels that contain at least a majority of the endmember by area. We refer to this method as “majority abundance” mapping. This method is relatively conservative, as there are certainly cases where a constituent can be the dominant spectrum in a pixel without having a majority of the abundance. A second method identifies any pixel dominated by the mapped endmember as containing the target constituent. We refer to this method as “plurality abundance” mapping.

These two mapping cases are shown in Figure 4-19. As expected the plurality abundance map has many more pixels than the majority abundance map.

The two maps of Figure 4-19 below show automated Joshua tree maps of the southeastern portion of the Terra spring dataset. The Joshua tree abundance is the blue color map, with an overlay in yellow of the Joshua tree map. The top map is the product of applying a simple majority threshold to the abundance map. The bottom is the product of mapping pixels dominated by the Joshua tree abundance (plurality mapping).

Figure 4-19. Automated Joshua Tree Maps

Mapping of geological endmembers follows the exact same methodology as illustrated above for vegetation endmembers. Since the algorithm is data-agnostic and uses all bands, it makes no distinction concerning the type of terrain. Geological mapping is illustrated in the performance evaluation below.

4.3.1.1 Targeted Mapping Performance

We validated the automated mapping results against manual analysis results. The manual analysis results are from the MANNRRSS expert analyses of botanical and geological content of the datasets.

We chose three vegetation endmembers and three geological endmember for comparison. The vegetation on the north south line is too complex for definitive comparison of endmembers, since it has many species with large variations of senescence. We therefore chose shrub species from the E-W portion of the Terra spring dataset for botanical mapping comparison. For geological comparison we chose the minerals illite, alunite, and kaolinite to compare, since they have broad and easy to discern distributions across the N-S portion of the dataset.

In each case we take the constituent map from manual analysis and the two forms of automated output (simple majority and dominant constituent maps), and calculate the overlap among maps.

Three geological target maps are shown in Figure 4-20. As can be seen, there is a clear but not necessarily exact correlation among the maps. Similarly, the vegetation mapping shown in Figure 4-21 shows that manual analysis and automated analysis give highly correlated results for the three shrub species.

The target maps of Figure 4-20 show three geological constituents along the N-S line of the Terra spring dataset. In all three maps the colors are: Green: Alunite. Blue: Illite. Red: Kaolinite. Left: manual analysis using traditional methods. Middle: Automated target mapping using the pixel plurality method. Right: Automated target mapping using the pixel majority method. Note

that the automated map results have plus symbols representing target presence, whereas the manual analysis result has filled polygonal areas.

Figure 4-20. Target Maps of Three Geological Constituents, N-S Line of Terra Spring Dataset

Figure 4-21 below shows the vegetation maps of three species along the E-W line of the Terra spring dataset. In all three maps the colors are: Green: Creosotebush. Blue: Bitterbrush. Red: Saltbush. Top: manual analysis using traditional methods. Middle: Automated target mapping using the pixel plurality method. Bottom: Automated target mapping using the pixel majority method. Note that due to sparseness of the majority method map, the colored symbols are increased in size in the bottom map.

Figure 4-21. Vegetation Maps of Three Species along the E-W Line, Terra Spring Dataset

In order to more precisely evaluate the mapping fidelity, we evaluated the overlap of the manual and automated mapping results. To create an overlap, the map results were rasterized onto a grid and the number of grid points in common were counted. We can use the manual analyses to allow a meaningful interpretation of the rasterized overlap. Two manual analyses exist for the same mineral for the same dataset: alunite in the spring Terra dataset. Assuming that the fidelity of these two datasets are similar (with possible differences in efficiency due to analyst threshold choices) we can measure the apparent overlap of these two datasets to give an estimate of any misregistration effects. The overlap for the two alunite maps is shown in Table 4-1, which implies that around 50% overlap is expected for two maps that are consistent.

Table 4-1 shows two manual analyses of the alunite content of the N-S line of the spring Terra dataset. The second analysis had 40% as much area as the first analysis, reflecting differing analyst choices of methods and thresholds. The total overlap is around 50% of the smaller dataset for this case.

Table 4-1. Analysis of Alunite Content

	Manual Map 1	Intersection	Manual Map 2
Area (raster pixels)	306095	60399	118445
Area (normalized)	2.58	0.51	1.00

Tables 4-2 and 4-3 show the overlap of the first manual analysis of the minerals alunite and illite. Kaolinite was excluded from the analysis after manual checking. Kaolinite was seen to show a strong variability in the VNIR (visible) portion of the spectrum due to a varying amount of iron oxide present. That is to say: kaolinite, a clay, can be colored red or white. The automated analysis was able to map the components of kaolinite with two target spectra to account for the variability (both components are shown in Figure 4-20), but the overlap results were not completed.

The figure of merit is the overlap, fraction of the smaller map which lies within the larger map. The Plurality method shows a 60% overlap, which is approximately the level of agreement found

between the two manual analyses compared in Table 4-1, which had a very similar total relative area between the maps. The Majority method, which is very conservative (high purity but low efficiency) shows an excellent agreement with 95% overlap of the maps. The alunite maps also showed overlaps of around 50% for both methods. The high overlap of the illite majority method is, in fact, unusual given the results of Table 4-1. This may reflect that the purest regions of illite are large uniform areas (e.g., a quarry) and not spread too widely.

The manual method is apparently more liberal in defining the existence of the mineral all around than either automated mapping method. However, one could consider the Plurality method results to be reasonably close in size to the manual results, especially if one takes into account the second manual analysis which also showed smaller map areas. The majority method, as mentioned above, appears to be very pure but lower efficiency maps.

Table 4-2 lists the results of the overlap of the illite maps. The two automated analyses are overlapped with the manual analysis result for the N-S line of the spring dataset.

Table 4-2. Overlap of Illite Maps

Illite				
Method	Majority		Manual	
Area (pixels)	21099		187269	
Intersection (pixels)		19847	50560	
Area (normalized)	0.26		2.26	
Intersection (normalized)		0.24	0.61	
Intersection (fraction)		0.95	0.61	

Table 4-3 lists the results of the overlap of the alunite maps. The two automated analyses are overlapped with the manual analysis result for the N-S line of the spring dataset.

Table 4-3. Overlap of Alunite Maps

Alunite				
Method	Majority		Manual	
Area (pixels)	6496		306095	
Intersection (pixels)		3682	36071	
Area (normalized)	0.09		4.36	
Intersection (normalized)		0.05	0.51	
Intersection (fraction)		0.57	0.51	

A similar overlap analysis is conducted for the three shrub species mapped for the E-W line of the spring Terra dataset. The results for these are shown in Tables 4-4 through 4-6. These results are more ambiguous. The majority method gives maps that are substantially smaller than the other analyses. This may have to do with the small size of the shrubs giving on average a smaller pixel fill fraction than for geological endmembers. The majority method maps are extremely pure as expected, showing an average overlap with the manual analysis of 65%. The Plurality methods and manual analyses gave similar map areas except for saltbush, which had automated results significantly more conservative than the manual analysis. The overlaps were low, averaging 25%, or half that of the geological maps. While this implies a lower map fidelity, a

manual inspection and qualitative comparison of the shrub species map determined that both maps agreed on the broad distribution of the shrubs, and both suffered confusion at the level of individual shrubs. There was a high level of confusion between Bitterbrush and Creosotebush, for example. In the area of downtown Beatty (in the western leg of the E-W line) there was substantial confusion with various planted vegetation.

Table 4-4 lists the results of the overlap of the bitterbrush maps. The two automated analyses are overlapped with the manual analysis result for the E-W line of the spring dataset.

Table 4-4. Overlap of Bitterbrush Maps

Bitterbrush				
Method	Majority		Manual	Plurality
Area (pixels)	3248		94173	108228
Intersection (pixels)		2293	15894	
Area (normalized)	0.03		1.00	1.15
Intersection (normalized)		0.02	0.17	
Intersection (fraction)		0.71	0.17	

Table 4-5 lists the results of the overlap of the creosotebush maps. The two automated analyses are overlapped with the manual analysis result for the E-W line of the spring dataset.

Table 4-5. Overlap of Creosotebush Maps

Creosotebush				
Method	Majority		Manual	Plurality
Area (pixels)	4805		543837	338294
Intersection (pixels)		1914	47349	
Area (normalized)	0.01		1.61	1.00
Intersection (normalized)		0.01	0.14	
Intersection (fraction)		0.39	0.14	

Table 4-6 lists the results of the overlap of the Saltbush maps. The two automated analyses are overlapped with the manual analysis result for the E-W line of the spring dataset.

Table 4-6. Overlap of Saltbush Maps

Saltbush				
Method	Majority		Manual	Plurality
Area (pixels)	884		98065	19762
Intersection (pixels)		750	8759	
Area (normalized)	0.04		4.96	1.00
Intersection (normalized)		0.04	0.44	
Intersection (fraction)		0.85	0.44	

Based on both the qualitative and quantitative assessment of the mapping results, the automated mapping results can be considered of reasonable fidelity for use in evaluating both geological and botanical content of the mapped area at the dataset level. The automated mapping process

represents a great reduction in analyst time spent producing maps, allowing him to simply choose elements from the scene summaries and leaving the details to the algorithm.

4.3.2 Spectral Library Generation

An idealized automated analysis would produce as a final product a catalog of the geological and botanical content of the dataset. While this goal is perhaps too poorly defined to be achievable, the automated analysis is capable of producing a synoptic overview of the entire dataset in terms of the most spectrally separable constituents of the dataset.

At the scene level the analyst is presented with summaries representing a reasonably complete summary of a quarter square kilometer of land (at the spatial and spectral resolution of the datasets here). However, extended over a large area this can rapidly become an infeasible amount of information for manual perusal. For example, the Terra spring dataset scene summaries produce over 4700 scene constituents and around 1000 anomalies for presentation. Many of the scene constituents are repeated from scene to scene, and could be combined when presenting a higher level overview.

The mechanics of the algorithm, and the limits of the information used as input prevent the algorithm from providing an exhaustive list of constituents. For example, with the Terra dataset having around 300 spectral bands of information, it becomes mathematically impossible to differentiate among more than 300 spectra using a linear decomposition. In practice this number is smaller; this algorithm limits the dataset level constituent model to 64 endmembers or less.

The overview, referred to as the endmember library for the dataset, is presented much like the scene summary: A map showing the distribution of all the constituents is given, along with the spectra and purest pixel orthophotography of each constituent. This is intended to allow the analyst to quickly digest the major elements of the dataset and perhaps choose scenes to look at more closely or constituents to map.

As an example the spectral library produced for the Terra spring dataset is shown in Figure 4-22. There are a total of 56 spectra found; every pixel of data is then assigned to the constituent that it closest resembles spectrally based on scene level classification data. Figure 22: The 56 spectra of the N-S line returned by the automated extraction process. Left: the whole spectra. Right: A close-up of the 1950-2450 nm spectral wavelengths, which tend to show geological absorption features.

Figure 4-22. Fifty-six Spectra of the N-S Line by Automated Extraction Process

4.3.2.1 Spectral Library Generation Performance

To evaluate this many spectra we separate out three broad classes of constituent for further discussion: geological, botanical, and roofs. These categories are based upon looking at the summary orthophotography and spectra: If there are apparent geological absorption features in the spectrum, if the photograph is centered on vegetation, or if the photograph is of the roof of a structure. See Figure 4-23 for examples of the three classes as they were selected from the dataset library summary. These show typical geological, “roof”, and vegetation constituents. The majority of the spectra can easily be seen to belong to one of these three categories of constituent. Other spectra are unique constituents apparently due to saturation of the instrument, various other forms of groundcover that bear no clear absorption features, etc.

Figure 4-23. Spectra and Orthophotography, Automated Summary, Spring Terra Dataset N-S Line

Figures 4-24 through 4-25 show the spectra and mapped distribution of 10 selected geological endmembers from the library. The library seems to have found and mapped at least four of the nine minerals mapped in the manual analysis: opal/chalcedony, alunite, illite, and kaolinite (green, red, yellow, and gold respectively shown in Figure 4-25). These are in fact the dominant minerals of the N-S line, with the exception of zeolite. Zeolite has a highly variable spectrum, and may not be suited to extraction by the automated method of analysis and summary. To allow a qualitative evaluation of the mineral library map, Figure 4-26 shows a closeup of the library minerals constituent map centered on the hot springs area near the middle of the north-south line. This region is referred to as “sub-area 1” in the geological analysis elsewhere in this report. This region has all four of the minerals mentioned above, and comparing to the manual analysis results for the same area, show a high degree of correlation with manual analysis results.

Figure 4-24. Spectra of Ten Selected Geological Constituents, N-S Line Library

Figure 4-25 shows the mapped distribution of ten selected geological constituents from the N-S spring library. Colors have been chosen to match those of the manual geological analysis results (and do not match those of Figure 24, which are colored as ordered by the automated summary output).

Figure 4-25. Mapped Distribution of Ten Selected Geological Constituents, N-S Spring Library

A closeup of the middle of the N-S line is shown in Figure 4-26 below, showing an area corresponding to the area referred to as “sub-area 1” in the geological analysis. Top: The results of the automated library generation. Bottom: The manual geological analysis results for the. Opal/chalcedony, alunite, illite, and kaolinite are mapped as green, red, yellow, and gold respectively.

Figure 4-26. Closeup of the Middle of the N-S Line, Sub-area 1

In order to provide a quantitative check of the quality of the automated library generation maps, we measured the overlap of the manual and automated illite maps; the results are tabulated in Table 4-7, and shown in Figure 4-27. Based on the overlap observed, we conclude that the manual and library map are consistent. However, the manual map has significantly more pixels mapped than the library map.

Table 4-7. Results of the Overlap of the Manual and Library Maps for Illite

	Library (Automated) Map	Intersection	Manual Map
Area (raster pixels)	123184	64133	187269
Area (normalized)	1.00	0.52	1.52

Figure 27 shows the distribution of illite per the automatically generated library map (blue), per manual analysis (yellow), and their overlap (green). Note that the green region has larger symbols than the other regions for clarity.

Figure 4-27. Illustration of Overlap of the Manual and Library Maps for Illite

The distribution of the selected vegetation endmembers and their spectra are shown in Figures 4-28 through 4-29 show the vegetation found seems to encompass most of the riparian corridor vegetation. Generally the automated spectral library is not efficient at discovering desert shrubbery, perhaps due to the sparse coverage and interfering soil backgrounds of those species.

Figure 4-28. Spectra of Seven Selected Vegetation Constituents from the N-S Line Library

Figure 4-29 shows the mapped distribution of seven selected vegetation constituents from the N-S spring library. Colors do not match those of Figure 4-28, which are colored as ordered by the automated summary output.

Figure 4-29. Mapped Distribution of Seven Selected Vegetation Constituents, N-S Line Library

To evaluate qualitatively the library vegetation mapping result, we compare a restricted area of the N-S riparian corridor with the manual vegetation analysis results. This comparison is shown in Figure 4-30. The color codes have been matched where appropriate: creosotebush, green riparian, senesced riparian, rabbitbrush, cottonwood are white, maroon, cyan, coral, and green respectively. Comparing the five automatically extracted constituents mapped as being in this area, one sees analogues for the green riparian, senesced riparian, and cottonwood. In addition to these, in the automated collection there appears to be two grades of green riparian (maroon and

yellow), and an additional senesced riparian where the vegetation is growing in a salt crusted environment (magenta). The fidelity within the scene appears to be very good, in fact correctly classifying the greenest riparian region (yellow area) as riparian and not cottonwood as the manual analysis does.

Figure 4-30 shows a side by side comparison of a portion of the riparian corridor. Left: the automated mapping result containing five of the seven selected vegetation endmembers. Right: The same scene showing the manually mapped species: creosote, green riparian, senesced riparian, rabbitbrush, cottonwood are white, maroon, cyan, coral, and green respectively.

Figure 4-30. Side by Side Comparison of a Portion of the Riparian Corridor

However, the automated library mapping algorithm did fail to distinguish any of the many species of tree or identify any of the desert shrubs present. This is definitely a limitation of having to restrict the automated result to 64 constituents maximally.

Finally, Figures 4-31 through 4-32 show the spectra and mappings of the eight selected library constituents whose summary orthophotography implied man-made origins (they are all pictures of the roofs of structures). Of the eight mapped constituents, four are mapped uniquely to a single structure, with no other pixels being assigned to that constituent. The other four map beyond just a single structure. The constituent mapped in yellow is a generic constituent for a tin roof, but seems to accurately be restricted to a certain kind of structural roof. The constituent mapped in yellow, a red tiled roof, seems to map to a few areas of the N-S line which have high iron-oxide content (which appear red) including an area around a quarry; these pixels may or may not be the same material as the roof tiles. The constituent mapped in green appears to also be mapped to the purer salt crusts in the scene. The roof mapped in red also maps to some grey desert varnish areas. These last two cases represent examples of the confusion noted in Figure 4-13, where natural objects of neutral coloration and relatively featureless spectra can be mapped together with man-made, uncolored objects.

Figure 4-31. The Spectra of Eight Selected Roof Constituents from the N-S Line Library

Figure 4-32 shows the mapped distribution of eight selected vegetation constituents from the N-S spring library. Colors do not match those of Figure 4-31, which are colored as ordered by the automated summary output.

Figure 4-32. Mapped Distribution of Eight Selected Vegetation Constituents, N-S Spring Library

The library building capability therefore seems to contain mappings and spectra that represent real, relevant constituents of the dataset. When a constituent is identified by the dataset summary, the mapping presented seems to be of reasonable fidelity. The completeness of the summary set of constituents, and the discriminatory ability are limited. It could be argued that the geological constituents represent a relatively complete set based on the observation that the automated mapping found all the major manually mapped constituents. Vegetative manual analysis (complimented with extensive fieldwork to allow identification and discrimination of

training areas) appears to have a much higher level of discriminatory ability. However, as shown above, the automated targeted mapping of scene-level constituents works well for vegetation.

4.4 Repeatability

A claimed benefit of automated analysis is the ability to meaningfully and quantifiably compare results across datasets. The MANNRRSS program acquired two hyperspectral datasets from the same vendor of the same area, providing a well-controlled opportunity to test repeatability of the mapping and library results of the automated algorithm.

4.4.1 Targeted Mapping Repeatability

We tested the repeatability of a mapping result to confirm that the algorithm returns the same result across datasets. Since the repeated datasets are separated by six months, we chose to use a geological constituent, which should be relatively static. Visual inspection of the fall and spring mappings of the kaolinite, illite, and alunite minerals shows broadly similar distributions across the N-S Terra datasets. To estimate quantitatively the repeatability, the overlap areas of the spring and fall illite and alunite maps are summarized in Table 4-8. The illite mineral maps showed excellent overlap, whereas the alunite overlap was smaller. In both maps, the total areas mapped are broadly consistent, with the possible exception of the plurality (looser) mappings of alunite. It is possible that there is some confusion between alunite and kaolinite, as they seem to be relatively mixed for some areas of the maps. Overlap of kaolinite was not measured because of some intrinsic variability in the kaolinite spectrum in the visible wavelengths.

Table 4-8 shows the areas and overlaps of alunite and illite target maps from the fall and spring datasets. The target maps have two methods of mapping, Majority and Plurality. Majority is more conservative and plurality is more efficient. The numbers here have been corrected for any gaps in coverage between fall and spring datasets.

Table 4-8. Areas and Overlaps of Alunite and Illite Target Maps, Fall and Spring Datasets

Illite					
Spring Dataset	Fall Dataset	Spring Area	Overlap	Fall Area	Overlap %
Majority	Majority	18111	11334	16782	68
Plurality	Plurality	68657	28970	47813	61
Plurality	Majority	68657	15056	16782	90
Majority	Plurality	18111	14696	47813	81
Alunite					
Majority	Majority	5527	1036	7054	19
Plurality	Plurality	54445	24935	97657	46
Plurality	Majority	54445	2632	7054	37
Majority	Plurality	5527	3680	97657	67
Average Overlap					59

4.4.2 Library Generation Repeatability

We also ran the automated library generation on both fall and spring datasets and compared the results. The vegetation endmembers found between the two were not well aligned but this is not surprising given the seasonal dependence of vegetation constituents. The vegetation constituents

found in the fall library looked to be broadly representative. The geological constituents found in the N-S line of the dataset for the two datasets were well aligned, on the other hand. The same major minerals were found, including alunite, illite, opal/chalcedony, and kaolinite. In the fall dataset a constituent which appears to correlate well with zeolites was also found. This mineral was not automatically extracted in the spring dataset. These minerals are mapped in Figure 4-33, to be compared to Figure 4-25.

Figure 4-33 shows a mapping of selected geological constituents automatically extracted from the fall dataset. These are to be compared to those in Figure 4-25. The minerals mapped appear to correspond to kaolinite (orange), alunite (red), zeolite (blue), opal/chalcedony (green), and illite (yellow). Cyan may represent a second illite based constituent.

Figure 4-33. Selected Geological Constituents Automatically Extracted; Fall Dataset

We did not try to compare explicit overlap rates of the automated extraction mappings. We conclude that while the mappings are not perfectly repeatable, they are very consistent across the six month timescale separating the fall and spring hyperspectral datasets.

4.5 Change Detection

One of the goals pursued for automated analysis was change detection, since an important function of mapping is to analyze and detect differences over time in an area's makeup.

The most straightforward method of change detection is via comparison of mapped results. We chose not to pursue this method, as it represents a secondary product being analyzed to produce a tertiary product, and would have required producing methods of rationalizing constituent maps across datasets. As can be seen from the inefficiency of the simple overlap calculations above, comparing binary maps at the pixel level is not trivial.

Instead we chose to attempt to use the primary hyperspectral datasets and look for differences in spectra from location to location. This more direct approach should be very good at finding localized changes that significantly impact the spectrum. It would be less efficient at detecting wide area or global changes such as senescence of an entire species of grass.

There were two intrinsic timescales in the dataset for change detection. One timescale is intra-dataset, inter-scene. The data acquisition occurs during a several hour time-span, during which there is substantial overlap of the data as the target area is crossed by the hyperspectral platform. Each square meter of the dataset is in fact sampled twice on average, usually around 15 minutes apart. We analyzed these revisited pixels for spectral change during the intervening time. The second timescale is the inter-dataset time of fall to spring, around six months for these datasets. We also analyzed the spectra between the two datasets to attempt to detect change.

An example of the short term change detection for the Terra spring E-W dataset is shown in Figure 4-34. The scene outlines are shown along with a temperature plot of the spectral difference observed across the area. The color coding is such that red pixels are significantly different. The area encompasses a spring with vegetation in the upper left (that area was used in the example to illustrate automated scene summary), and a portion of the town of Beatty commerce district in the lower left. Some of the areas between scene boundaries are blank and did not get sampled twice in the data collection. The other areas that generally show up with shades of pink, were sampled at least twice and therefore are available for a change measurement. Clearly visible as red are the cars along the road and in the parking lots of the businesses. Their mobility even on short timescales causes them to register well in the short term change detection. The area around the spring also has a clear pattern of change, related to the shadows of the trees. As the sun changes position the shadows move, changing the spectra around the edges of shadow-casting objects such as trees.

Figure 4-34 shows from Top: The significance level of spectral change observed within a subset the Terra E-W spring dataset. Pixels in red are significantly different. Bottom: High resolution photography of the same area to permit identification of change areas.

Figure 4-34. Example of the Short Term Change Detection for the Terra Spring E-W Dataset

The Spring-Fall dataset difference was broadly similar to the short time scale difference. Sensitivity to change appeared to be reduced due to the larger overall difference in radiance from fall to spring, which can tend to wash out differences slightly. None the less the data-set level difference map revealed cars changing location, among other changes. In fact, the scene anomaly shown in Figure 4-8, a small plastic bag, shows up as one of the 853 pixels marked as being significantly different between fall and spring. Someone must have removed the bag.

The other significantly different pixels tended to be the areas of salt encrustation and some of the taller reeds. The area does have a large change in the salt crust over the seasons as the rainy season washes one year's salt away and deposits the next.

To illustrate the seasonal change map, a portion of the N-S difference is shown in Figure 4-35. The areas of greatest change in the scene correlate well with the visible salt crusts in the orthophotography and some of the reeds on the creek bed on the right of the image. The area to

the left of the road has large areas of grasses which were manually measured to have had a significant green-up between fall and spring. This is not evident in this difference map. In general, aside from the reed beds, the difference detection algorithm was insensitive to green-up and senescence, probably due to this having been a relatively global change between the scenes and therefore ignored as a global radiance difference by the algorithm.

Figure 4-35 shows from Top: The significance level of spectral change observed over a portion of the N-S flight line. The difference measurements are change across the spring to fall datasets. Pixels in red are significantly different. Bottom: High resolution photography of the same area to permit identification of change areas.

Figure 4-35. Seasonal Change Map, a Portion of the N-S Flight Line Difference

4.6 Algorithm Portability

The algorithm producing these results was designed around the idea of being data agnostic. During development care was taken to use methods that involved only statistical first principles to define algorithm behavior, rather than ad-hoc or heuristic methodologies adapted from the dataset at hand for development. As a test of this, we acquired a dataset of the Aviris instrument and ran the algorithm over several scenes.

Porting the algorithm required literally no change to the algorithm code. Since the publicly available Aviris dataset is relatively small, only scene level outputs were produced and evaluated. In all cases the results were promising and seemed to be of higher fidelity than the results of the Terra dataset analysis. Unfortunately the data had no high resolution orthophotography so detailed evaluation of constituent and anomaly selection was difficult.

As an example, portions of the scene summary from a well known scene from Cuprite, NV are shown in Figures 4-36 through 4-39. Figure 4-36 shows Left: Aviris Cuprite Scene in Visible Colors. Right: Automated Scene Summary Classification

Figure 4-36. Example Scene: Cuprite NV Visible Colors vs Automated Scene

Figure 4-37 shows the radiance spectra extracted by the automated scene analysis, corresponding to the mapping produced in Figure 4-36. A closeup of the 1950-2450 nm wavelengths shows the different mineralogical absorption features.

Figure 4-37. Radiance Spectra Extracted by the Automated Scene Analysis

Figure 4-38 shows the pixel fit distances for the Cuprite scene. There are anomalies found in the scene: the bright area to the right seems to have saturated the instrument, and along the roads there are several apparently man-made anomalies.

Figure 4-38. Pixel Fit Distances for the Cuprite Scene

Figure 4-39 shows a selected constituent from the Aviris Cuprite scene. Left: The pixel abundance for this constituent. Right: The spectral radiance of this constituent. This constituent appears to be the mineral alunite.

Figure 4-39. Selected Constituent from the Aviris Cuprite Scene

We were unable to explicitly evaluate the constituents found by the algorithm. There appears to be at least two kaolinite spectra (with differing iron oxide content), alunite, buddingtonite, dickite, chalcedony, calcite, muscovite, and several mixtures. Figure 4-40 shows the abundance distributions found for all 16 components.

Figure 4-40. Abundance of All Sixteen Constituents Found in the Cuprite Scene

One possible cross check is found by comparing the automated and a manual abundance result for three of the minerals: alunite, kaolinite, and buddingtonite. A manual analysis found in a training manual for hyperspectral analysis was used for comparison (www.ittvis.com/Envi/docs/tutorials/Geologic_Hyperspectral.pdf). A side by side comparison is shown in Figure 4-41, showing excellent agreement for these three minerals.

Figure 4-41 below shows from Left: A snapshot of a tutorial on hyperspectral analysis. The tutorial analysis used HyMap data. Note that the minerals are mislabeled. The buddingtonite and alunite labels are reversed. Right: A similar picture of the three minerals created using the abundance maps of the scene summary. The larger blue region on the bottom of the left picture is not present in the right; for that area the automated analysis extracted a kaolinite constituent with different iron oxide content.

Figure 4-41. Side by Side Comparison Showing Excellent Agreement for Compared Minerals

Another comparison can be made with [Fred A. Kruse, Comparison of AVIRIS and Hyperion for Hyperspectral Mineral Mapping, Presented at the 11th JPL Airborne Geoscience Workshop, 4-8 March 2002, Pasadena, CA]. Figure 4-42 shows a comparison of six minerals as presented in that paper, and as classified by using the automatically extracted abundances. Note that some classification thresholds have been manipulated to best match the image from the paper. Thresholds were generally set to abundances of 25% or more.

Figure 4-42 from Left: A class map made from the automated abundance maps of Cuprite, using the Aviris dataset. Right: A figure from the publication listing six minerals mapped manually. The automatically extracted endmembers were mapped to colors that match those of the publication, and appear to correspond well with the author's manual mapping methods.

Figure 4-42. Comparison Classification Using the Automatically Extracted Abundances

Generally the scene summary appears to be accurate and complete (given the constraint of 16 maximum constituents). It is definitely competitive with manual procedures.

The algorithm is not immune to certain instrumental variations, however. We tried and failed to run the algorithm over publicly available datasets from the Hyperion instrument. There appear to be serious quality issues in their data which defeat the protections the algorithm has in place to combat instrumental issues; this causes highly non-linear artifacts to dominate the algorithm results. Similarly, we were unable to get satisfactory results from the SpecTIR spring dataset. While generally of good quality, the data had a very large number of saturated pixels; saturated pixels are highly nonlinear in response, which overwhelmed the statistical analysis of the data. If we had been provided a map of saturated pixels we could have masked these effects; no such map was provided by the vendor, however. A clear limitation of the algorithm is that the instrument must obey the assumption of linearity and relatively Gaussian noise. Variations from sensor to sensor and some nonlinearity are acceptable and accounted for by mechanisms within the algorithm, but the Hyperion and SpecTIR datasets suffered from severe global nonlinearities.

4.7 Automated Hyperspectral Analysis Conclusions

The results presented here show that an automated analysis of hyperspectral data can successfully extract the major components of the area being imaged and produce a synoptic overview and library with little or no human involvement. The automated methods require no ground support work or reflectance corrections to the data.

These include maps of the constituent locations, and, if available, imagery of the purest example of a constituent. We have demonstrated an ability to produce more detailed and finer granularity summaries of individual imagery scenes of the dataset, including quantified maps of constituent pixel abundance, maps of pixel anomalousness, and a spectral and photographic summary of purest examples of the constituents. We have demonstrated an ability to produce high fidelity maps of any of the scene level constituents with no need for definition of training areas or extraction of purest pixels. Finally, we have demonstrated an automated change detection capability that successfully operates over minutes to years timescales.

We have demonstrated that the algorithm developed to accomplish this is portable to a completely different instrument and landscape and dataset with no modification to any of its parameters or methods.

These results are a promising start and show that there is a lot of leeway to reducing the amount of human effort needed to gain visibility into the large and highly complex datasets produced by hyperspectral imagers.

How the automated capabilities presented here would advance the goals of the typical remote sensing analysis has not been fully explored, but we believe these tools would be of great use in analyst workload reduction in large datasets with most traditional remote sensing tasks.

5.0 CONCLUSIONS

The MANNRRSS program has provided valuable insights into using remote sensing as a natural resource management tool. The datasets collected and produced for the program will continue to be useful as a highly detailed baseline of the geological and botanical state of the Oasis valley and area around Beatty, NV.

The duplicate hyperspectral coverage, ancillary airborne datasets, and extensive field work afforded by the program allowed the production of high quality mineral and vegetation mapping, as well as the exploration of novel analysis techniques using combined datasets. The experience gained during the program by the partnership of Desert Research Institute; University of Nevada, Reno; and Sierra Nevada Corporation gives valuable insight into what is available and what is cost effective in data collection options when designing future remote sensing programs.

We list some of the choices faced in remote sensing data collection, and their impacts here:

5.1 Hyperspectral Spatial Resolution

Spatial resolution is one of the principal cost drivers of remote sensing data collection for airborne platforms. The one meter spatial resolution taken using the airborne sensors provided the ability to do high resolution local scale mineralogical maps. It allowed relatively sensitive detection of man made disturbances and, when combined with repeated hyperspectral datasets of the same areas, sensitive change detection of mineralogical change. Spatial resolution was shown to directly impact the scale of vegetation that is able to be mapped: with one meter resolution, vegetation as small as 0.5 square meters can be discerned.

At significantly lower spatial resolution one can use space based sensors. These sensors, typically 5-10 meters, were shown here to still allow some district level mineralogical mapping and coarse vegetation vigor. These space based sensors are, however, still multispectral and do not allow vegetation species or accurate mineralogical mapping.

5.2 Hyperspectral Spectral Resolution

The 10 nanometer spectral resolution requested from the vendors proved adequate to accurately perform mineralogical maps. Vegetative species mapping was less successful, but was probably not hindered by lack of spectral resolution. This choice is not a strong cost driver, mainly affecting data volumes and efforts that scale with volume such as processing times. It should be noted that the majority of the analysis here was performed on 5 nanometer data provided by Terra.

The studies on lower resolution instruments show that multispectral data is not able to adequately map mineralogical or vegetation. They were, however, able to map vegetation vigor and change at a coarse scale.

5.3 Reflectance Correction of Hyperspectral Data

The utility of reflectance corrected data for manual hyperspectral analysis is unquestioned. It allows better analyst identification of salient spectral features for mapping, and qualitative feedback on the data quality. Achieving a high quality correction incurs quite a large percentage of the cost of collection due to vendor supplied effort to apply it and iterate with the customer until an adequate correction is achieved.

We found that a high quality, large area, diffuse ground calibration target with coincident ground collected spectra must be in the collection area of the hyperspectral dataset. Achieving an accurate reflectance spectrum free of artifacts required these inputs.

The effort at automation showed however that high quality automated mapping can be done of all relevant geological and vegetative species mapped here using the uncorrected radiance datasets as inputs.

5.4 Georegistration

All datasets taken were requested to have one meter georectification applied to them. Both vendors achieved this precision with commercial interial navigation units. The ability to register the maps at this level directly allowed the coregistration of ancillary datasets and the coregistration of the change detection datasets. For these activities it is crucial, and comes at relatively small added cost. The fusion of geographical information into GIS information systems is a revolution that is currently underway in many other fields beyond remote sensing, and any dataset gathered for a remote sensing program will be required to be able to contribute to the synergy a GIS system can provide.

5.5 Ancillary Data: LIDAR

By default a ten meter digital elevation model is available for most areas of the United States from the USGS. The high precision (15 cm) digital elevation model afforded by a LIDAR dataset allowed several studies to be performed that otherwise would not have been possible. Man made disturbance identification, high precision fault finding, and vegetation stress with respect to slope were example studies performed here which were made possible by the LIDAR dataset. In general, the fusion of high precision elevation information with other data allowed novel and unexpected studies to be easily performed, and thus increased the value of the primary remote sensing data. Simultaneous acquisition of LIDAR and a second ancillary dataset, high precision orthophotography, came at a marginal cost of around 30%.

5.5.1 Ancillary Data: High Precision Orthophotography

A 15 cm spatial resolution, georectified orthophotography dataset was collected alongside the spring hyperspectral dataset. While not used directly in any analysis mentioned above, the value of this dataset cannot be overstated. This dataset allowed the visual identification of items in the hyperspectral dataset, especially for meter scale objects. The use of the orthophotography as the background of mapping outputs allowed enhanced contrast and greatly aided visualization of the dataset. It allowed visual confirmation of mapping results. It was crucial to the useability of the automated analysis outputs, as it allowed the analyst to identify the constituents being mapped by the algorithm.

5.6 Automation

This program demonstrated an algorithm that was capable of automatically ingesting the radiance hyperspectral dataset and creating a mapping of the major constituents of the area being imaged, all without human intervention. In particularly it appeared to identify, extract, and map with reasonable fidelity all the major geological constituents identified for manual analysis. It also demonstrated how this tool could be used as an aid to an analyst, greatly simplifying scene constituent identification and targeted mapping of interesting features.

Since analysis of remote sensing data is very labor intensive and not highly repeatable, any large remote sensing program will need to explore how to streamline data analysis. While collection costs tend to scale well for cost effectiveness (mobilization costs are a large part of the cost for small programs) analysis costs, unless automated or simplified, will scale linearly. The automated analysis, by using radiance data directly, also removes the ground support effort needed for accurate reflectance calibration, which could become a major cost driver for large scale imaging projects.

5.7 Outlook

MANNRRSS has paved the way for any future remote sensing programs that may require the identification, mapping, and tracking of the status of large areas of land. The data products collected and produced for this program will provide a lasting and useful survey of the area around Oasis valley and Beatty, NV.

6.0 ACKNOWLEDGMENTS

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APPENDIX A VEGETATION TRANSECT DATA

A.1 Location of Vegetation Transect Data

Characterization of six unique plant communities that occurred within the study area is shown in Figure A-1 below and detailed in Table A-1. Plant species in six transects varying from 30 to 50 m in length by 2 to 5 m in width were identified at the species level (Hickman, 1993).

Figure A-1. Six Unique Plant Communities within Study Area

Table A-1. Plant Communities Characterized in the Study Area

Tran	Community Type	Dominant Species	Dominant Growth Form	Elevation (meters)	Cover	Species	Cover Diversity Index
1	Low elevation Mojave Desert	Menodora/ Creosotebush	Evergreen shrubs	1213	28.74	17	1.681
2	High elevation Mojave Desert	Bladder sage/ Green rabbitbrush	Deciduous shrubs	1285	54.23	16	2.0647
3	Native wetland	Wildrye/Saltgrass/ Bullrush	Perennial grasses	1119	84.46	7	1.5467
4	Alkaline meadow	Saltgrass/ Greasewood	Perennial grasses and shrubs	1107	100	4	0.2202
5	Alkaline wetland	Saltgrass/ Nutsedge	Perennial grasses	1071	55.42	6	1.0125
6	Natural Spring	Cottonwood/ Cattail	Trees and perennial grasses	1023	100	7	1.3876

Table A-2. Perennial Plant Species Found in Vegetation Transects

common name	Genus	species	Family	Origin	growth form
Goldenhead	<i>Acamptopappus</i>	<i>shockleyi</i>	Asteraceae	native	deciduous shrub
White bursage	<i>Ambrosia</i>	<i>dumosa</i>	Asteraceae	native	deciduous shrub
Fourwing saltbush	<i>Atriplex</i>	<i>canescens</i>	Chenopodiaceae	native	deciduous shrub
Shadscale	<i>Atriplex</i>	<i>confertifolia</i>	Chenopodiaceae	native	deciduous shrub
Green rabbitbrush	<i>Chrysothamnus</i>	<i>viscidiflorus</i>	Asteraceae	native	deciduous shrub
Rubber rabbitbrush	<i>Chrysothamnus</i>	<i>nauseosus</i>	Asteraceae	native	deciduous shrub
Blackbrush	<i>Coleogyne</i>	<i>ramosissima</i>	Rosaceae	native	deciduous shrub
Brittlebush	<i>Encelia</i>	<i>virginensis</i>	Asteraceae	native	deciduous shrub
Goldenbush	<i>Ericameria</i>	<i>cooperi</i>	Asteraceae	native	deciduous shrub
Buckwheat	<i>Eriogonum</i>	<i>fasciculatum</i>	Polygonaceae	native	deciduous shrub
Hop-sage	<i>Grayia</i>	<i>spinosa</i>	Chenopodiaceae	native	deciduous shrub
cheesbush	<i>Hymenochlea</i>	<i>salsola</i>	Asteraceae	native	deciduous shrub
winterfat	<i>Krascheninnikova</i>	<i>lanata</i>	Chenopodiaceae	native	deciduous shrub
Anderson wolfberry	<i>Lycium</i>	<i>andersonii</i>	Solanaceae	native	deciduous shrub
spiny menodora	<i>Menodora</i>	<i>spinescens</i>	Oleaceae	native	deciduous shrub
Bladder sage	<i>Salazaria</i>	<i>mexicana</i>	Lamiaceae	native	deciduous shrub
greasewood	<i>Sarcobatus</i>	<i>vermiculatus</i>	Chenopodiaceae	native	deciduous shrub
smooth horsebush	<i>Tetradymia</i>	<i>glabrata</i>	Asteraceae	native	deciduous shrub
Fremont cottonwood	<i>Populus</i>	<i>fremontii</i>	Salicaceae	native	deciduous tree
white willow	<i>Salix</i>	<i>alba</i>	Salicaceae	introduced	deciduous tree
Nevada Mormomtea	<i>Ephedra</i>	<i>nevadensis</i>	Ephedraceae	native	evergreen shrub
Green ephedra	<i>Ephedra</i>	<i>viridis</i>	Ephedraceae	native	evergreen shrub
creosotebush	<i>Larrea</i>	<i>tridentata</i>	Zygophyllaceae	native	evergreen shrub
pygmy-cedar	<i>Peucephyllum</i>	<i>schottii</i>	Asteraceae	native	evergreen shrub
bitterbrush	<i>Purshia</i>	<i>mexicana</i>	Rosaceae	native	evergreen shrub
Desert paintbrush	<i>Castilleja</i>	<i>chromosa</i>	Scrophulariaceae	native	perennial forb
Larkspur	<i>Delphinium</i>	<i>parishii</i>	Ranunculaceae	native	perennial forb
Desert trumpet	<i>Eriogonum</i>	<i>inflatum</i>	Polygonaceae	native	perennial forb
desert mallow	<i>Sphaeralcea</i>	<i>grossulariaefolia</i>	Malvaceae	native	perennial forb
wire lettuce	<i>Stephanomeria</i>	<i>pauciflora</i>	Asteraceae	native	perennial forb
Desert needle grass	<i>Achnatherum</i>	<i>speciosum</i>	Poaceae	native	perennial grass
Nutsedge	<i>Cyperus</i>	<i>laevigata</i>	Cyperaceae	native	perennial grass
Saltgrass	<i>Distichlis</i>	<i>spicatus</i>	Poaceae	native	perennial grass
Great Basin rye	<i>Leymus</i>	<i>cinerius</i>	Poaceae	native	perennial grass
bullrush	<i>Scirpus</i>	<i>nevadensis</i>	Cyperaceae	native	perennial grass
alkalai sacaton	<i>Sporobolus</i>	<i>airoides</i>	Poaceae	native	perennial grass
cattail	<i>Typha</i>	<i>latifolia</i>	Typhaceae	native	perennial grass
arrow-grass	<i>Triglochin</i>	<i>concinna</i>	Juncaginaceae	native	perennial grass

Table A-3. Plant Species Cover within Six Sampled Communities

genus	species	Total Cover (Live and Dead)						Relative Cover (Live and Dead)					
		tran 1	tran 2	tran 3	tran 4	tran 5	tran 6	tran 1	tran 2	tran 3	tran 4	tran 5	tran 6
<i>Menodora</i>	<i>spinescens</i>	28.2401						39.30					
<i>Atriplex</i>	<i>confertifolia</i>	6.3971			0.3809	1.1398	1.0878	8.90			0.30	1.53	1.14
<i>Hymenoclea</i>	<i>salsola</i>	5.5407	0.3817					7.71	0.94				
<i>Ephedra</i>	<i>nevadensis</i>	4.3306	3.3573					6.03	8.25				
<i>Peucephyllum</i>	<i>schottii</i>	3.3824	0.3563					4.71	0.88				
<i>Chrysothamnus</i>	<i>viscidiflorus</i>	1.3334	2.8484					1.86	7.00				
<i>Grayia</i>	<i>spinosa</i>	0.7102	0.9142					0.99	2.25				
<i>Lycium</i>	<i>andersonii</i>	0.6272	1.6482					0.87	4.05				
<i>Larrea</i>	<i>tridentata</i>	20.4282						28.44					
<i>Krascheninnikova</i>	<i>lanata</i>	0.2503						0.35					
<i>Eriogonum</i>	<i>fasciculatum</i>	0.3955	0.1693					0.55	0.42				
<i>Tetradymia</i>	<i>glabrata</i>	0.0173	0.7069					0.02	1.74				
<i>Acamptopappus</i>	<i>shockleyi</i>	0.0334						0.05					
<i>Ambrosia</i>	<i>dumosa</i>	0.1402						0.20					
<i>Castilleja</i>	<i>chromosa</i>	0.0005						0.00					
<i>Ericameria</i>	<i>cooperi</i>	0.0283						0.00					
<i>Eriogonum</i>	<i>inflatum</i>	0.0027						0.00					
<i>Salazaria</i>	<i>mexicana</i>		12.2691						30.16				
<i>Coleogyne</i>	<i>ramosissima</i>		5.9757						14.69				
<i>Encelia</i>	<i>virginensis</i>		1.0204						2.51				
<i>Purshia</i>	<i>mexicana</i>		6.4786						15.93				
<i>Achnatherum</i>	<i>speciosum</i>		0.0239						0.06				
<i>Delphinium</i>	<i>parishii</i>		0.0079						0.02				
<i>Ephedra</i>	<i>viridis</i>		4.516						11.10				
<i>Sphaeralcea</i>	<i>grossularifolia</i>		0.0016						0.00				
<i>Chrysothamnus</i>	<i>nauseosus</i>			6.6445			3.4715			3.15			3.62
<i>Distichilis</i>	<i>spicatus</i>			58	118.75	40.9977	3.7694			27.47	94.64	54.97	3.94
<i>Cyperus</i>	<i>laevigata</i>			12.5		26.0752	30.6305			5.92		34.96	31.98
<i>Leymus</i>	<i>cinerius</i>			74.5			15.2367			35.28			15.91
<i>Scirpus</i>	<i>nevadensis</i>			44.5						21.08			
<i>Sporobolus</i>	<i>airoides</i>			12.5						5.92			
<i>Salix</i>	<i>alba</i>			2.5						1.18			
<i>Atriplex</i>	<i>canescens</i>					0.9896						1.33	
<i>Populus</i>	<i>fremontii</i>						40						41.77
<i>Sarcobatus</i>	<i>vermiculatus</i>				4.6908						3.74		
<i>Stephanomeria</i>	<i>pauciflora</i>				0.6607	0.0763					0.53	0.10	
<i>Typa</i>	<i>latifolia</i>						1.5708						1.64
<i>Triglochin</i>	<i>concinna</i>					5.3						7.11	
	total plant cover	71.8581	40.6755	211.145	124.482	74.5786	95.7667	99.98	100.00	100.00	99.21	100.00	100.00
	total species	17	16	7	4	5	7						
	Percent Cover	28.74	54.23	84.46	100.00	59.66	136.81						
	transect area (m ²)	250	75	250	125	125	70

Figure A-2. Spatial Distribution of Plant Canopies in Transect 1, *Menodora/Larrea*

Figure A-3. Spatial Distribution of Plant Canopies in Transect 2, Salazaria/Chrysothamnus

Figure A-4. Spatial Distribution of Plant Cover in Transect 3, Native Marsh

Figure A-5. Spatial Distribution of Plant Cover in Transect 4, Saltgrass Greasewood

Figure A-6. Spatial Distribution of Plant Cover in Transect 5, Saltgrass/Nutsedge

APPENDIX B AUTOMATED ANALYSIS ALGORITHMS

B.1 Algorithm Development

A set of algorithms was developed for the automated analysis of hyperspectral imagery as part of the MANNRRSS program. The goals of the efforts were as follow:

- Create an automated analysis capability using gain corrected radiance datasets as input. No reflectance or other atmospheric correction should be used.
- Create an automated method for extracting the spectral signatures of the principal constituents of the hyperspectral data. Create scene level summaries of spatial distribution and abundance of principal constituents, their spectra, and samples of high resolution orthophotography of the constituents.
- Evaluate the data for anomalies which do not fit the constituent model. These anomalies will consist of spectra that are statistically very different from any of the identified constituents or their possible combinations, but were not abundant enough to be considered a scene constituent. Provide high resolution orthophotography of the anomalous areas.
- Create an automated method for mapping a constituent across the entire dataset. The operator need only identify what constituent to map, by selecting a scene-level constituent.
- Create a data-set level constituent model from the scene level constituents. This is an automated data-set level mapping of the most abundant/significant constituents.
- Analyze multiple datasets for differences, creating a map of the statistical significance of changes seen in hyperspectral datasets. Summarize the statistically significant differences using orthophotography.

B.2 Algorithm Features

Some features that the algorithm will have follow:

- Have as little operator (analyst) inputs to the process as possible. Analyst judgment is to consist only of command choices of what constituents are interesting and evaluating the quality of the outputs.
- Use all bands of the inputs dataset. That is, use no dimensionality reduction. Traditionally a subset of bands, those deemed to contain the majority of the signal of interest, have been selected for analysis. This reduction desensitizes the algorithms to rare or anomalous data, which goes against the goals of this work. The “curse of dimensionality” is a frequently cited issue with hyperspectra data; this comes from a lack of true understanding of the datasets and is not a true burden on using hyperspectral data. We believe that this curse is instead an opportunity and should be fully exploited.
- Use no spatial information. The pixels are all treated independently, with no spatial component of the data taken into account. This allows no assumptions concerning the size, texture, or distribution of the dataset constituents.

An overarching principle of the algorithm development is that it be data agnostic: the algorithm is to make no assumptions about the instrument and imagery contents. All of the algorithmic

behaviors and actions should be derived from statistical first principles. This implies, of course, a statistical model of the data: that the instrument responds linearly to signals, that noise is Gaussian in nature, consistent across the sensor elements, and scales as some power law of the signal amplitude. The data can violate these assumptions to some degree; the algorithm will be designed to be robust to some level of nonlinearity, nongaussianity, and nonuniformity.

We worked towards these goals by implementing from scratch an analysis capability written in MATLAB. This appendix will describe some of the details of the resulting algorithms. The performance of the algorithm is documented in the main text above.

B.3 Automated Classification

The fundamental input to the classification algorithm is the hyperspectral dataset. This dataset should only be corrected for low level instrumental effects. That is, dark frame subtracted and gain corrected. The dataset should not be georectified: the georectification process usually has a “backfill” procedure to fill in missed pixels with the nearest neighbors. These extra pixels are not statistically independent.

The data do not need any reflectance correction. Since the algorithm has no need for reflectance information to distinguish among endmembers, the correction would only be needed to compensate for atmospheric effects on the radiance spectra. These effects, including path length variations in absorption and path radiance variation, are accounted for statistically in the whitening process.

We will refer to the hyperspectral dataset generically as a “datacube”, to reflect the fact that the data is three dimensional (having two spatial dimensions and one spectral dimension).

Automatic classification has three basic steps:

- Whitening: Deriving an estimate of the noise in the data, and transforming the datacube so that this noise is decorrelated and of unit variance.
- Endmember extraction: Using an iterative linear spectral unmixing, extract the clusters of purest pixels that represent the constituents of the scene.
- Scene classification: Use results of linear unmixing to classify pixels by which endmember has abundance plurality. Identify anomalies.

These steps are detailed below. We will assume the reader is familiar with standard methods in hyperspectral analysis and some statistical properties of noise.

B.3.1 Whitening

The first step is whitening. This procedure is meant to transform the data cube’s bands into a basis where each dimension has noise that is uncorrelated and has unit variance.

Preparing the Data Cube

The data cube needs to be split into scenes. This is a relatively mechanical aspect of data manipulation. Larger scenes are better since the algorithm depends on the statistics of large samples to estimate the noise matrix. The limit to scene size is either computer resources or the granularity desired in classification (larger scenes tend to have coarser constituents found).

There is a minimum scene size. If a hyperspectral sensor has N spectral bands, the noise matrix for the whitening transformation is a symmetric, $N \times N$ matrix. This matrix has $N(N+1)/2$

independent covariance entries, or measurands for the noise estimator. A minimum scene size needs to allow the algorithm to have a few pixels per noise covariance, since we need at least a few degrees of freedom per measurand to ensure an accurate measurement. For example, for a sensor of 300 bands like those used for MANNRRSS, the covariance matrix has 50 thousand measurands, requiring a few hundred thousand pixels to accurately estimate the noise matrix.

The rest of the algorithm occurs purely at the scene level, each scene analysis being completely independent of the others. There is no attempt to relate noise or signal across scenes at this stage. Going from scene to dataset level analysis is the subject of automated library generation, discussed below.

Signal Scaling

The data are also scaled by a power law before continuing. The whitening process is meant to allow the assumption that noise everywhere in the scene is constant, independent of signal amplitude. This scaling is required to have the noise amplitude be independent of signal amplitude. The exact scaling depends on the sources of noise. Noise in some systems (most audio/rf systems) is intrinsically independent signal amplitude. In other systems, noise will tend to increase with signal size. For example, in counting experiments the noise is proportional to the square root of the signal. To regain the independence of noise to signal amplitude in a counting experiment, taking the square root of the counts causes the noise level to be constant (with respect to the scaled signal). CCDs, the technology underlying hyperspectral sensors, are fundamentally photon counting so there is some expected signal dependence to the noise. However, an exact scaling of 0.5 for the signal is not necessarily appropriate, as amplifiers and other parts of the system do not follow counting noise statistics.

We estimated the appropriate scaling for the data based on empirical measurement of the apparent scaling of pixel fit distances versus radiance scaling. “Pixel fit distances” are the distances, measured in the whitened space, of a pixel from the nominal signal composition of the pixel, as will be detailed below in the description of the classification step of the algorithm. If the scaling is correct, one would expect there to be no correlation between the fit distance of a pixel and its total radiance. We found that scaling by a power of $\frac{3}{4}$ (0.75) is appropriate to remove the radiance dependence of the noise. This is approximately halfway between the constant noise and counting statistics noise discussed above. The same scaling factor was used for all analyses, irrespective of which dataset or sensor was being analyzed. It appears that the scale factor chosen is very relatively global across sensors, since the same decorrelation seen in Figure B-1 was observed globally.

Figure B-1 shows scatter plots of pixel fit distance versus pixel radiance, for three signal scalings. The goal is to have no correlation between signal size (radiance) and noise size (which scales with fit distance). Left: square root scaling (appropriate for counting statistics). Middle: $\frac{3}{4}$ power scaling (used in this algorithm). Right: No scaling. Scaling the radiance by a power of $\frac{3}{4}$ appears to remove any correlation.

Figure B-1. Scatter Plots of Pixel Fit Distance versus Pixel Radiance for Three Signal Scalings

Fiducial Cuts

The last part of signal cube preparation is applying any fiducial cuts on the data. These refer to selections meant to exclude portions of the cube that contain no signal. These include the bands in the wavelength ranges with strong water absorption: 1350-1420 and 1810-1950 nm. These bands, due to the lack of any true signal, tend to be dominated by path radiance. The presence of path radiance, acting as an uncompensated pedestal in the presence of very low noise, can cause these bands to become very prominent interferers in the whitened data cube.

Extracting a Noise Matrix

We need to extract an estimate of the noise from the data cube itself. The datacube has both noise and signal, however, so the signal needs to be suppressed before a noise matrix can be measured. The normal method to accomplish this is called the “shift difference” technique. This technique, illustrated in Figure B-2, uses the assumption that the signal in a datacube is highly correlated spatially. Therefore the difference among adjacent pixels is dominated by noise. So a reasonably accurate measurement of noise can be achieved by looking at the statistics of the differences among neighboring pixels across the scene.

Figure B-2 shows an illustration of the shift difference technique. A hyperspectral scene is shifted by one row and column (left) and subtracted from itself to produce a difference image (middle), whose covariance matrix is then considered the noise (right).

Figure B-2. Illustration of the Shift Difference Technique

The statistical noise is not the only correlation we want to account for in our whitening matrix, however. The use of radiance rather than reflectance as input data means that the spectra across the scene may have varying path lengths to the ground, which may translate into varying path radiance and atmospheric absorption. These are potentially systematic variations across the scene that we want to consider to be “noise” and suppress using the whitening matrix. For a downward looking sensor platform like those used for MANNRRSS, the viewing angle geometry provides a systematically changing path length to the ground from the center to the side of the sensor. We use this variation to estimate the path length contribution to the noise matrix.

We modified the shift difference technique to explicitly account for these two separate sources for the final whitening matrix. The original shift difference, to account for random noise, is measured by shifting the scene along the direction of travel (along columns of data), subtracting the difference, and measuring the resulting variance. Each column is treated separately to produce a column noise covariance matrix. These column noise matrices are averaged for a statistical noise estimate. Then, the covariance of the column mean radiance is measured, representing the systematic variance of the data due to atmospheric path length variation. These statistical and systematic covariance matrices are then summed to produce the whitening matrix.

The assumptions being used are:

- Systematic pixel variations are well represented by the columnwise (across path) variation of the scene.
- Statistical pixel variations are well represented by variations between neighboring pixels.
- Signal is not correlated with the dataset columns. For example, there is no endmember in the scene that is varying systematically along the direction of travel.

The last assumption may fail if the platform happens to be flying along a linear feature such as a road. This was not observed to be an issue in general, however, because the number of columns involved lends robustness to the result. The modified shift difference process is illustrated in Figure B-3. A side benefit of this technique is the removal of any whisk to whisk variation that may exist in a push-broom hyperspectral sensor, an instance of which was used for MANNRRSS collections.

Figure B-3 shows an illustration of the modified shift difference estimate of the whitening matrix. A hyperspectral scene radiance is shifted by one row (top left) and subtracted from itself to produce a difference image, whose covariance matrix is calculated column by column. The mean of these covariance matrices is then considered the noise (top middle). The column mean radiances are found (bottom left), and their covariance matrix calculated (bottom middle). The final whitening matrix is the sum of the two covariance matrices (right).

Figure B-3. Illustration of the Modified Shift Difference Estimate of the Whitening Matrix

Masking Bad Channels

An assumption of the statistical model being used is that all pixels of a scene have the same noise covariance matrix. Underlying the pixels of a scene are the hyperspectral sensor's CCD wells, each of which potentially has a unique noise signature. The algorithm needs to mask and remove from the data any sensor elements which don't conform to the overall noise statistics. If a sensor element with unusual statistics is left in the dataset, this pixel will introduce artifacts into the spectra selected as endmembers. Sensing elements need to look statistically "normal" in a scene.

In a pushbroom sensor, the CCD elements are the columns (along-travel) and the bands of the datacube. Rows are composed of successive readings from the CCD elements. For this reason bad sensor elements can often be seen in hyperspectral analyses as "stripes" in the dataset.

To get a measure of how compatible an element is with the overall statistics, we look at the measurements of the elements in the noise whitened space, and measure the variance of those measurements. (Each scene has as many independent measurements per sensor element as there are rows in the scene, several hundred in the case of a typical Terra scene). In the absence of signal, the variance of the measurements from an individual sensor element should equal one. In the presence of signal, the variance will be greater than one due to variations among signals. However, if signal variations are not correlated with sensor elements (a similar assumption is already operating in the noise extraction procedure) each element will see the same mixture of noise and signal variance, so the net effect of a signal's presence should be a global increase in the size of the variances. We can therefore rely on the distribution of the population of variances across the CCD to identify outliers. Outliers in variance have incompatible statistics and are removed.

This procedure is illustrated in Figure B-4. We chose to discard any sensor element whose variance is more than three times the median of all sensor element variances. In the case

illustrated, the median variance of each pixel is around 2.7, leading to the masking of any elements with a variance of more than around 8. As noted above, the variance being larger than one is due to the presence of signal. There is a red curve overlain on this histogram to show the noise model prediction of the noise-only distribution of variances, which should follow a normalized chi-square distribution of degree of the number of rows in the scene. The bimodality of the distribution is an artifact of the geometry of the scene, but any scene induced features to the distribution are washed out and very small relative to the cutoff. The right half of Figure B-4 illustrates graphically the sensor surface and shows how the outliers really do show up as randomly distributed hot spots. It was later discovered that these elements were generally already masked by the vendor: they provided data that interpolated over these elements but the interpolation algorithm used introduced statistical artifacts.

Figure B-4 shows an illustration of defining the sensor mask, i.e., identifying sensor elements that are statistically incompatible with the noise whitening matrix. Left: A histogram of the noise whitened measurement variance of each sensor element. Right: An “image” of the CCD showing the outliers in the variance distribution.

Figure B-4. Illustration of Defining the Sensor Mask

Once a bad sensor element is removed, the overall noise statistics of the sensor will change, since the odd statistics of the bad element were included in the previous estimate. We therefore iterate the bad element ID process until no more bad elements are identified and convergence on a consistent population is achieved. The procedure is observed to remove around 0.1% of the sensor elements for the Terra datasets. This is a small fraction of the data collected by the instrument, but excluding them is essential to the success of the rest of the automated extraction algorithm.

Once the mask of bad sensor elements has been identified, they need to be removed from the dataset. In practice this means that data from noisy sensor elements must be replaced via interpolation, since the algorithm is incapable of ignoring individual sensor elements.

The simplest interpolation is to replace the data from adjacent elements: either adjacent columns in the scene or adjacent spectral bands. Interpolation using adjacent columns was the method used by the hyperspectral vendor, for example, to compensate for bad sensors. However, the average radiance of the adjacent columns may not match the average radiance of the affected column. As shown in Figure B-5, this simple “left-right average” interpolation can cause

discontinuities in the spectrum, which will still become outliers in the noise model. We used an alternate method of interpolation which used the left-right column average to get a shape of the spectrum across the bad elements, but added a linear offset to allow the spectral boundaries to match smoothly for the affected column.

Figure B-5 shows the interpolation across a row of six bad elements (all in the same column and in six adjacent bands). Red is the original data, blue are the adjacent column spectra. Simple left-right averaging produces the cyan curve, which leaves discontinuities in the spectrum. The magenta interpolation adds a linear offset to the left-right average to allow smooth boundaries of the interpolated region. The middle three red and cyan values matching is not a coincidence; this is due to the vendor having already applied a simple interpolation algorithm to those three elements.

Figure B-5. Interpolation Across a Row of Six Bad Elements

Modifying Noise Matrix Eigenvalues

The final step in producing the final whitening matrix is eigenvalue normalization. Due to the limited number of samples being used to estimate the parameters of the noise covariance matrix, there is some uncertainty in the true values of those measurands. Some of the measurement errors will fluctuate to low values; underestimating the variance of the noise in that direction. If we apply a whitening to a dataset which underestimates some of the noise values, this will tend to enhance some noise fluctuations to the point where they can be incorrectly identified as statistically significant, corrupting the algorithm results. When one is talking of measuring 50 thousand parameters (or, more importantly, several hundred eigenvalues) each with a tens of

degrees of freedom, some of these fluctuations will be significantly low. The algorithm therefore needs to ensure that the noise estimates are reasonable.

Figure B-6 illustrates this phenomenon with a couple of toy data models. We simulated data cubes of 200 bands with unit noise on each band (“white noise”), and then measured the noise covariance matrix for those cubes. One cube consisted of 1000 pixels, the other of 100,000 pixels. These cubes represent having 10 and 1000 degrees of freedom per measurand respectively. The underlying “true” eigenvalue spectrum for both cubes is a constant value of one, but due to measurement uncertainty there are a range of measured values.

Figure B-6 shows the spectrum of eigenvalues recovered from a white noise source of 200 bands for a cube with 1000 pixels and 100,000 pixels. These illustrate the expected fluctuations in the measured versus true eigenvalues (noise variances) in the scene extracted whitening matrix, which typically has a few tens of degrees of freedom per measurand.

Figure B-6. Spectrum of Eigenvalues Recovered from a White Noise Source

The spectrum of measured values is predictable based on statistical theory; they should follow a chi squared cumulative distribution with the number of degrees of freedom of the measurands of the covariance matrix. And indeed this is the case in Figure B-6 for the toy model, which also predicts that the expected fluctuations span down to a factor of 1/3 the true noise for the case of 10 degrees of freedom. Even for the case of 1000 degrees of freedom there is a noticeable deviation of measured to actual eigenvalues.

Knowing we can model the measured eigenvalue spectrum allows us to apply a correction to the spectrum to bring them more in line with the true eigenvalues. To estimate the true noise

eigenvalues, we use the low tail of the covariance matrix eigenvalues. This process is illustrated in Figure B-7. The eigenvalue spectrum of a whitening matrix is shown on the left. The smallest eigenvalues, on the left side of the plot, will be dominated by noise (signal is present in the larger variance bands), so we expect the lower end tail to have a uniform underlying variance spectrum, like the white noise model. The right side of the figure has a closeup of this region. In red is a best fit to a chi square model of 92 degrees of freedom (which is the number of degrees of freedom for the matrix measurements for this scene). We only fit the lower half of the curve, since that half has no signal. The top edge of the fitted curve is then the “true” minimal white noise level of the data, in this case 0.32.

Figure B-7 shows from left: The eigenvalue spectrum of a whitening matrix for a scene of the Terra dataset. Right: A closeup of the low value tail of the eigenvalue spectrum, showing the measured values (blue), the theoretical fit for measuring white noise with the population statistics used (red), and the estimated “true” population noise eigenvalue.

Figure B-7. Process To Estimate the True Noise Eigenvalues

We then modify the whitening matrix to bring these lowest eigenvalues up to the minimum noise estimated from the fit. In general, around 30 of the bands, 10 percent of the total, are affected by this correction. The corrections can be up to a factor of two, which is significant when the whitened distance metric is relied upon so heavily elsewhere in the algorithm, where distance is equated with the log likelihood of statistical consistency.

Apply Whitening Matrix

We then use the corrected whitening matrix to rotate and rescale the scene data. The rotation matrix is the diagonalizing matrix of the whitening matrix, and the scaling is the square root of the eigenvalues of the whitening matrix. That is, the covariance matrix C can be diagonalized, written as

$$C = VDV^{-1} = (VD^{1/2})I(D^{1/2}V^{-1})$$

Where D is a diagonal matrix (of eigenvalues) and V is an orthogonal matrix of columnwise eigenvectors. Rewriting the diagonalizations as a pair of transforms wrapping the identity matrix (representing the whitened space), we make an equivalence to get the pixel data S into the whitened space (S') and find the transformation matrix T :

$$S' = TS = (VD^{1/2})^{-1} S;$$

$$\mathbf{T} = (\mathbf{V}\mathbf{D}^{1/2})^{-1} = (\mathbf{D}^{1/2})^{-1}(\mathbf{V})^{-1} = \mathbf{D}^{-1/2}\mathbf{V}^T$$

What this new basis $\mathbf{T}$ transforms to, is of the same dimensionality as the original data cube. The number of dimensions is the number of bands, in which space each spatial pixel measurement is a point. Figure B-8 illustrates a radiance in the original and transformed bases.

Figure B-8. Radiance Spectrum Before and After the Whitening Transformation.

Whitening is crucial, since in a whitened dataset the distances among the pixels become a statistical likelihood metric. That is, the separation of two pixels with identical signal content and whitened noise follow a well defined distribution. This distance follows a “Chi” distribution with degrees of freedom of the number of bands (the dimensionality) of the space. Figure B-9 illustrates this distribution.

Figure B-9 shows from left: The expected pixel separation in whitened space of 329 bands for pixels with the same signal content and white noise. Right: The likelihood versus separation for the two pixels being consistent with the same underlying signal.

Figure B-9. Separation of Two Pixels Follow a Well Defined Distribution (“Chi” Distribution)

Spaces with hundreds of dimensions behave in counterintuitive ways: The expected separation of two measurements in two dimensions peaks at zero separation: you expect two measurements of the same point to lie on top of each other. In higher dimensions, the chi probability says that the

expected separation of two measurements is approximately the square root of the dimensionality of the space, with very little variation. The left half of Figure B-9, showing the distribution for 329 bands, shows that the expected distance is 18 with only a few percent variation. The probability of being closer than 15 is essentially zero, and the probability of being further than 21 is as well. The right half of Figure B-9 shows the likelihood of consistency as distances increase: it drops precipitously beyond 21, even when the number of effective trials in the data is in the millions. The ability to exploit this tight constraint on distances in a whitened metric space will be used extensively by the algorithm.

Note that the “noise” as measured here by the shift difference method includes some signal variation, which will impact the sensitivity of the algorithm to some signals. The exact nature of the desensitization depends on the scene and signal geometry. For example, a constituent whose spatial distribution is highly textured, and has many boundaries, will be affected disproportionately, as the shift difference will encode the boundaries into the noise covariance matrix. E.g. dense but clumped vegetation will have many boundaries with the host landscape and may not be statistically distinguishable from the landscape.

Most of the effort put into the development of the whitening algorithm had to focus on the prevention of false alarms at the potential expense of sensitivity. The algorithm is easily captured by statistical anomaly, as can be seen by the discussion of Figure 9.

B.3.2 Endmember Extraction

After whitening the dataset, endmember extraction is performed. The model used for the signal is linear superposition: a pixel contains a linear combination of the “pure” spectral components of the scene. These pure elements, called endmembers, represent the true constituents of the dataset. This assumption has been shown to be reasonable for most hyperspectral datasets, given the assumption that the endmembers are macroscopic. If mixing of endmembers occurs on scales comparable to spectral wavelengths, non-linear effects can dominate the superposition of mixed endmembers. In practice the linearity assumption will simply cause the algorithm to classify nonlinear mixtures of endmembers as a different endmember.

The geometry of the dataset in this model is a simplex: the simplest volume element possible. That is, in three dimensions, a tetrahedron, so this form is sometimes called a hyper-tetrahedron. The endmembers lie on the vertices of the simplex, and all possible linear combinations lie in the interior of the simplex. The task of the algorithm is to find the vertices of the simplex, which then fully describe the geometry of the simplex. The simplex is always convex: the vertices always lie on “outward” pointing extrema.

Given a set of endmembers, the dataset can be “unmixed” using linear spectral unmixing. This procedure assigns to each pixel in the dataset a set of coefficients describing the amount of each endmember to contribute to a sum which best represents the pixel. This best sum, a point lying somewhere within the simplex, will not exactly coincide with the pixel’s location, but rather the closest point available in the simplex’s subspace. The remaining distance, sometimes called the “orthogonal subspace projection” distance, represents how close the measured pixel lies to the simplex, and how likely it is, given the noise model, to truly be a measurement of a point in the simplex. This distance is referred to as the “fit distance”, since it is exactly analogous to the root sum of squares (RSS) of residuals in a linear regression. It is expected to follow a chi distribution of the number of degrees of freedom, where the number of degrees of freedom is the number of

bands (the dimensionality of the space) minus the number of endmembers (the dimensionality of the simplex).

Two issues arise with linear spectral unmixing. The first issue is that real spectral mixtures must constrain the sum coefficients to be positive (an endmember cannot contribute to a spectral sum subtractively). Applying a positivity constraint on the unmixing solution is usually called for, to avoid unnatural unmixing solutions. The cost of this, however, is that the computation times increase dramatically as there is no closed form solution to the minimization problem with positivity constraints, thus requiring iterative solutions to unmixing. The second issue is whether to constrain the unmixing to a brightness constraint: that all the spectral power observed in a pixel be accounted for by the sum of endmembers. This represents a “sum to one” constraint on the unmixing sum coefficients. In geometric terms it represents forcing all the pixel unmixing solutions to lie on the surface rather than in the volume of the simplex. In terms of hyperspectral radiance, it represents not allowing for brightness variations in endmembers across the scene.

To find the vertices of the simplex we use a slightly modified version of an algorithm developed in [Neville, R. A., Staenz, K., Szerdedi, T., Lebfefre, J. Hauff, P. “Automatic Endmember Extraction from Hyperspectral Data for Mineral Exploration”, Proceeding of the Fourth International Airborne Remote Sensing Conference, Vol II pp 891-897, Ottawa, Ont. Canada, 1999], which they called “iterative error analysis”. The algorithm is iterative in that it performs a linear spectral unmixing of a hypothesized set of endmembers, and then searches for the worst fitting pixels in the unmixing to define, or seed, the next endmember which becomes one of the hypothesized set. This iteration proceeds until convergence.

The algorithm requires: an initial hypothesis to begin the iteration, definition of how many pixels to group to form the next endmember seed, definition of how to define the boundaries for pixel grouping, and a convergence definition. In the original algorithm, these quantities were heuristic: they began iterating by searching for seeds among the brightest pixels, they found that having 10 pixels within 1 degree in spectral angle were valid seed definitions, and convergence after no seed were found in the set of pixels further than 1000 (arbitrary radiance units) fit distance.

In the whitened space, these quantities can be defined more rigorously rather than left as heuristic parameters.

- Initial iteration endmember: The starting endmember for the iteration is the scene average, the center of the pixel distribution. This will allow the next seed selected to be the endmember farthest from the scene average. After the first iteration, the scene average endmember is removed from the endmember list.
- Seed size: The minimum number of pixels required to group together to form an endmember. This number is initially three, but is not a free parameter. The value three represents the smallest set of pixels we use to declare a unique scene constituent, relegating smaller area objects to be analyzed as anomalies if they are truly spectrally outliers. The free parameter is actually the number of endmembers to search for maximally. If convergence is not achieved before this maximum number, the seed size is doubled (increasing the coarseness of the scene classification by using larger area seeds) until convergence is achieved. We observed over the MANNRRSS datasets that convergence almost always occurred within 3-6 pixel seed sizes, however a pair of complex scenes required 96 pixel seeds for convergence. The average spectrum of the seed pixels is used as the next endmember.

- Seed pixel grouping: The conditions for grouping pixels together to form a seed are that they are close enough in the whitened distance metric to be consistent with being from the same signal. This distance was chosen to be the confidence interval given by the number of pixels in the scene: the maximum distance expected for a pixel to fluctuate given the scene's pixel count. E.g. in the Terra hyperspectral datasets used in MANNRRSS, 329 dimensions with scenes of 250,000 pixels, this distance is 21.36. Any set of N pixels within this distance of a center pixel can become a seed, where N is the seed size requested. Center pixels, those that nucleate a seed, are searched in order of descending pixel fit distance until a seed is formed (or pixels are exhausted, which was never observed).
- Convergence: The set of endmembers is defined to have converged when the next endmember seed found has a fit distance smaller than the confidence interval calculated as defined above, but for the number of degrees of freedom of the fit rather than the number of bands. The algorithm could also fail to find a seed due to pixel exhaustion, but this was never observed. A limit is placed on the number of endmembers searched for. If this number is exceeded, convergence has failed and seed size is increased (see above). This limit to the number of endmembers is constrained. It is constrained by either the number of bands available, since there need to be at least as many bands as endmembers (and preferably many more), or by computational needs. In practice we limit convergence to 16 or less endmembers in our analyses, as discussed below in the description of classification.

There are a few more subtleties in the endmember extraction algorithm. As mentioned above, the linear spectral unmixing may have two constraints applied. One is the positivity constraint, enforcing that the solution for each pixel's endmember sum coefficients be positive. We found that the nature of the simplex and the iterative convergence algorithm never needed this constraint, since the convexity of the simplex geometry naturally enforced this. Any negative abundances in the unmixing result are set to zero before the fit distances are calculated.

We did enforce a sum to one (brightness) constraint, but observed that this made almost no difference to the results. It did allow shadowed areas to be considered a separate endmember; and sometimes allowed two uncolored but different brightness endmembers (e.g., black versus white cars) to be differentiated. The former is useful: a scene with a large dark area allows the path radiance to be accounted for as an endmember; this will increase the accuracy of the resulting unmixing. The latter is an issue for man-made objects mainly.

The fit distance calculation is also not trivial. The fit distances resulting from unmixing may not follow the chi distribution exactly: at first this is due to the endmembers not accurately describing the scene. But towards convergence, where fit distance accuracy is more important from a statistical point of view, the distribution may not match exactly, as shown in Figure B-10.

The left side of the figure shows the seed average fit distance for a set of endmembers found in iterative extraction of a typical scene. The steadily decreasing fit distance of the seeds shows the steadily better scene description being found by the endmembers extracted. This scene converged after 14 endmembers. The spike from the first to the second endmember is due to the scene average being removed from the endmember list after the first iteration.

The right half of the Figure B-10 shows, in red, the fit distance distribution for all pixels in the scene after convergence. Note that the median of the distribution implies 221 "effective" bands,

not the 329 bands that are actually in the instrument. Also, the standard deviation of the distribution is slightly broader than that expected for a chi distribution of 206 degrees of freedom (shown in blue in the figure). The lower number of bands and slightly larger standard deviation of the fit results are not surprising, given the fact that the instrument and scene may not strictly follow the statistics implied by the whitening matrix derived (see above).

In view of this actual distribution of fit distance, applying a convergence cutoff blindly using $329 - 14 = 315$ bands, with a $1/250,000$ confidence interval, makes little sense. We therefore derive the cutoff distance using the observed distribution: We find how many standard deviations the cutoff would be for the appropriate chi distribution, and apply that standard deviation cut to the fit distance convergence criterion. In this case, for example, the chi distribution with 206 degrees of freedom has a $1/250,000$ likelihood interval of 17.6, or 7.2 standard deviations above the median. Applying this to the median and standard distribution of the observed fit distances after 14 endmembers gave a convergence cutoff of 21.4, which the 15th endmember fit distance did not exceed.

Figure B-10 from left: The seed pixel average fit distance for the endmembers found during endmember extraction. The convergence can be seen as the steadily decreasing fit distance. Right: The fit distance distribution, in red, for all scene pixels after convergence (14 endmembers for this scene). The blue curve is a chi distribution with degrees of freedom based on the observed median fit distance.

Figure B-10. Fit Distances Resulting from Unmixing May Not Follow Chi Distribution Exactly

The effective number of bands being less than 329 is probably a measure of the amount of entanglement of signal in the whitening matrix (see discussion above). It is generally assumed in hyperspectral instruments that there are far fewer independent bands than there are spectral bands, and this may reflect that phenomenon. The distribution of effective degrees of freedom across datasets is strikingly coherent (Figure B-11), so this measure may not provide useful diagnostics of scene quality. Use of the fit distance distribution as a figure of merit for algorithm performance merits further exploration.

Figure B-11. A Histogram of the Effective Number of Bands Across the Terra Spring Dataset.

B.3.3 Classification

After the endmember extraction has successfully converged, the results of the linear spectral unmixing are used to produce a set of rule images. These rule images are referred to as abundance images, since they have a number between zero and one for each endmember and each pixel to represent the fraction of the pixel that endmember consists of.

Classification is given for a simple plurality abundance for the pixel. As noted above, applying the brightness (sum to one) constraint to the spectral unmixing can find shadows as separate endmembers. These are identified and removed from the rule images used for classification. To identify shadows, we found that an endmember with radiance less than half that of the endmember mean radiance should be classified as shadow.

The example scene endmembers and classification are shown in Figures B-12 through B-13.

Figure B-12 shows the endmembers extracted for an example scene. One endmember is shadow, and is not used in the scene classification.

Figure B-12. Endmembers Extracted for an Example Scene

Figure B-13 shows from Left: An example scene in visual colors. Middle: An abundance (rule) image for one of the endmembers, a vegetation endmember. Right: An example scene classified. Color coding matches that of Figure B-12.

Figure B-13. Example Scene Endmembers and Classification

An additional step of the classification step is to catalog the endmember contents by recording the location of the purest pixel (highest abundance pixel for a given endmember). This purest pixel is generally, but not necessarily, a seed pixel.

Additional outputs are given from the algorithm at this point, including the abundance maps, the purity (maximum abundance per pixel), the classification maps, fit distance maps (see below) and the purest pixel locations and if available high resolution orthophotography of an area centered on the purest pixel (for visual identification of scene contents).

The limit of 16 endmembers for scene summary classification may seem arbitrary, but it represents a realistic limitation of the algorithm. While in theory one can differentiate as many constituents as there are bands, in practice this is not the case. The fit distance distribution would imply that there are at least 200 bands useable for signal discrimination. This is many times 16. The limiting factor for classification is due to limited signal to noise. In the distance whitened space, the typical signal is around 43 units long, as shown in Figure B-14.

Figure B-14 shows the whitened lengths of all scene level constituents found in the Terra spring dataset. The average length is 43 units, with some as short as 13 units long.

Figure B-14. In the Distance Whitened Space, the Typical Signal is Approximately 43 Units Long

When interpreting the linear spectral unmixing results as abundances, there is some natural spread in abundance due to noise fluctuations. These fluctuations are the projection of the noise onto a specific direction (that of the constituent), which means that they will have a magnitude proportional to a chi distribution of one degree of freedom. For an average signal radiance of around 40, this represents an average abundance fluctuation of around 2.5% (0.025 in abundance units). However, if there are fifteen chances for fluctuation, then the expected maximum

fluctuation is 3.4 times that, or 8.4%. This means that in classifying a pixel by plurality with 16 endmembers, there can be significant uncertainty in the abundances being used. The uncertainties get worse with larger number of constituents, and will eventually dominate the result. This implies that meaningful classification maps with these signal-to-noise ratios are only really available for 15-20 endmembers or less.

A more sophisticated analysis of the effect of signal to noise ratio on abundance mapping would probably allow the imposition of a threshold for classification. The simply plurality of abundance may not reflect a statistically significant abundance in all pixels: for 16 endmembers, a seven percent abundance could conceivably cause classification of the pixel, which may not be the analyst's goal in classification.

B.3.4 Anomaly Identification

One byproduct of the classification step is a final fit distance distribution for the scene. As noted above, this distribution follows closely but not exactly the chi distribution expected from the noise model.

Some pixels in the scene may not conform well to the model of a linear combination of the extracted endmembers. These pixels are referred to as anomalies, and generally will contain a constituent that is fundamentally different than those extracted automatically. We can apply a likelihood cutoff to the fit distances of the pixels and classify those exceeding the cutoff to be anomalies.

The search for anomalies, in order to be efficient, needs to apply a cutoff as low as possible. This cutoff needs to be compatible, however, with a reasonable false alarm rate. To increase the sensitivity, we apply a further correction to the fit distances to account for sensor element variation. During the data whitening phase truly anomalous sensor elements were removed from the dataset. However, there will continue to be intrinsically different noise statistics across the sensor. We remove sensor element to element variation by normalizing fit distances to the scene mean column to column. This implies, again, that any anomalies are not correlated with sensor columns.

Figure B-15 shows the fit distances of the example scene, where on the left is the raw fit distances after unmixing. The sensor to sensor noise variation is clearly evident as slight variation in the column to column fit distance. The middle and right parts of the figure show a normalized fit distance, where the column to column variation of means has been removed. The resulting fit distance map and distribution are much cleaner, allowing a lower threshold to apply. We apply a threshold using the same technique as used in the convergence criterion in the endmember extraction. However, to achieve a low enough false alarm rate, we increase the number of standard deviations (7.2 in the example above) by 10%. This allows a small buffer zone between the expected statistics of one false alarm per scene to be effectively zero false alarms per scene.

Figure B-15 from Left: a map of scene fit distances after unmixing. The vertical stripes are due to varying sensor element noise statistics. Middle: The same fit distance map after removal of variations in the mean fit distances. Right: The distribution of fit distances after column normalization. To be compared to the distribution shown in the right half of Figure B-10.

Figure B-15. Fit Distances of the Example Scene

A last step in anomaly detection is to remove a large source of false alarms: glint. Glint tends to cause saturation of the sensor, and would be trivial to remove if the dataset provider had provided flags to mark saturation. However, in the MANNRRSS datasets we had no ancillary saturation information and had to apply a maximum radiance cutoff. This cutoff was heuristically applied by observing the fit distance versus brightness, as shown in Figure B-16.

Figure B-16 shows a scatter plot of fit distance versus brightness for a scene. The brightest parts of the scene were due to glint, and show a high proportion of anomalousness. We masked pixels with a brightness greater than 1.65×10^5 from anomaly detection to avoid glint and saturation. Compare with the middle scatter plot of Figure B-1.

Figure B-16. Fit Distance versus Brightness

Figure B-16 also shows another form of false alarm in anomalies: shadows. The scene depicted has several pixels of deep shadow, which are anomalous because the radiance of those pixels is dominated by path radiance. We again heuristically provided a lower limit to anomaly detection to avoid deep shadow anomalies. Whereas the glint pixels should be generically suppressible by detecting instrument saturation, shadows need to be identified by some other means.

An example of a found anomaly is shown in Figure B-17. Figure B-17 shows from Left: The scene in visible colors. Middle: The scene fit distance map; the anomaly is in the lower left portion of the map. Upper Right: The anomalous spectrum and the closest matching constituent spectrum. Lower Right: A region of the high precision orthophotography centered on the anomalous pixels, showing the anomaly to be a piece of mining equipment.

Figure B-17. Example of a Found Anomaly

A dataset level anomaly map can also be produced. In order to allow meaningful mapping across the scenes, the dataset level anomaly map is given in terms of number of standard deviations a pixel lies above the mean fit distance (after all the corrections applied above to the scene fit distance). The resulting map can be interpreted as mapping the significance of the local spectral deviation from the constituent model.

B.4 Mapping

The products from the scene classification are considered to be the fundamental pieces of a scene summary: a list of scene constituents, maps of their abundance, a scene classification into those constituents, and a list of anomalies. However, much of hyperspectral analysis needs classification and abundance maps that span across a dataset (multiple scenes). The automated

analysis approached this need in two ways, by analyst targeted mapping across the data, and by an automated dataset level summary capability (see “Library Generation”, below).

Traditional mapping methods generally use a “matched filter” technique. This technique performs well if given a good target spectrum. It suffers from two drawbacks. One, the output is in the form of a “rule image” of arbitrary normalization. An analyst is needed to interpret the meaning of the resulting image. Second, the fidelity of the algorithm depends heavily on the scene contents. The algorithm can only maximize the target response relative to the scene noise (generally measured using the shift difference technique). The most accurate mapping capabilities need to be given the other constituents of the scene, to allow the matched filter to maximize the response in the space that is orthogonal to other signal components. Few analysts are willing to try to exhaustively extract the endmembers from each scene to target the constituent of interest. The automatically extracted endmembers, then, provide a natural environment in which to apply targeted mapping.

The targeted mapping capability is therefore a simple additional step after endmember extraction. Any target endmembers are appended to the list of endmembers, and another unmixing is performed. First, we need to ensure that none of the automatically extracted endmembers represent one of the targets: they would then be redundant in the unmixing. If any of the automatically extracted endmembers are within the cutoff distance (the $1/N_{\text{pixel}}$ confidence interval distance, like the seed nucleation distance definition in the iterative endmember extraction) of any of the target spectra, those endmembers are removed from the list before unmixing.

The collection of endmembers after targets are appended may no longer be a convex simplex in the whitened space. We therefore need to apply the positivity constraint to the unmixing of targeted mapping spectra. This greatly increases the computation time, but is observed to give accurate results.

The target spectrum itself needs to be in units of radiance, the same units as the input pixel dataset. It therefore needs to be extracted from the dataset itself. We generally used the scene summary endmember definitions as target spectra in analysis. If wanted, some manual form of target spectrum extraction could be used, such as defining training areas or using a pixel purity index tool.

If the automatically extracted endmembers are used, the target spectra are usually defined by only three pixels, which is a substantially smaller number than is normally used. We observed very good results using these spectra. Since the seed pixels are by their nature extremely pure, they probably represent a better estimate of the true target spectrum compared to a larger but coarser sample. The purity of the sample more than offsets the statistical uncertainty of the spectrum due to small sample size: in large numbers of dimensions even a $1/\sqrt{3} \rightarrow 40\%$ reduction in target pixel uncertainty is enough to accurately map abundances, where distances are so constrained. The target pixel has a one sigma uncertainty volume that is infinitesimally small $\sim (1/\sqrt{3})^{329}$ compared to the single pixel uncertainty volume.

In principle, any anomaly of interest to the analyst could also be mapped, using the anomalous spectrum as a target. We did not pursue this in any of the analysis of the MANNRRSS dataset, but note it as a possibility.

The output of the mapping is a dataset-level abundance map, and a dataset level classification map. The abundance map can be used by the analyst as a traditional “rule image” for applying a

threshold for classification. Since the abundance map is in units of pixel fraction, one simple threshold to apply is a majority of the pixel, i.e., a threshold of 0.5. We refer to this as an automatically generated “majority” map. The mapping algorithm also produces a classification map based on the target endmember having a plurality of the pixel (the same rule used in scene based analysis to classify a pixel.) We refer to this second method as a “plurality” map. Majority mapping tends to be conservative: lower efficiency for identifying a pixel as containing the target, but high purity, or rate of correctly identifying the target as being present. Plurality tends to be more efficient, but less pure.

While an arbitrary number of target spectra can be accommodated by the algorithm for simultaneous mapping, the signal to noise levels (see discussion above in classification) and computational complexity of the positivity constraint limited practical mapping to around five targets simultaneously.

B.5 Library Generation

A top level goal of the algorithm development was to produce a dataset level summary of the spectral constituents. The scene level summaries of the MANNRRSS datasets produced thousands of constituents and localized abundance maps. The challenge in going to dataset level products is dealing with changing data conditions and therefore differing whitening matrices from scene to scene.

The method applied to extract a dataset level set of constituents builds on the scene level results. The seed pixels from each scene level constituent are accumulated into a dataset-level purest pixel collection. In addition, the scene level whitening matrices are averaged over the dataset.

The collection of seed pixels are then whitened using the averaged noise matrix, and given to the iterative endmember extraction algorithm. The only differences in the iteration are:

The maximum number of endmembers is constrained to be 64

The brightness constraint is not applied (no sum-to-one constraint on the unmixing coefficients).

The lack of brightness constraint reflects the fact that the brightness of endmembers at the dataset level is likely to fluctuate as solar radiance or atmospheric conditions change. The result is a dataset level collection of constituents, produced from the purest scene level pixels.

Rather than attempt to map these dataset level endmembers by linear spectral unmixing over all pixels in the dataset, these dataset level endmembers are used to create a super-classification of each scene level classification: for each scene level constituent, the set of pixels classed as being dominated by the constituent are assigned to the closest matching dataset level constituent. The distance calculation of constituents occurs in the scene-level whitened space; i.e., for each scene the dataset level constituents are transformed using the local whitening matrix. In this way with very little computation every pixel in the dataset can be matched to one of the dataset level constituent.

The fidelity of the automatic dataset level extractions are explored in the main document above.

B.6 Difference Detection

A final goal of the automation algorithm was to allow automated difference detection. Difference is defined as a statistically significant change to a location’s radiance spectrum across two datasets. The two datasets are not necessarily at the same geometric spacing, and can be

separated by arbitrary amounts of time. This means that the radiance spectrum of scenes being compared can be very different. We did not attempt to perform detection across different sensors (different spectral resolution), but this could be performed by resampling one instrument's spectral bins to the other.

To measure a spectral change with these constraints in mind, the difference computation itself is deceptively simple: using an averaged whitening matrix (the sum of the matrices of the two scenes being compared), whiten both scenes with this average matrix, and calculate the whitened metric distance between pixels in the two datasets. This gives a population of spectral "distances" between the two datasets. This difference is corrected for sensor variation by normalizing across column means, as is done for fit distances in the anomaly search algorithm.

The significance of a difference is computed as the number of standard deviations above the mean of the distribution a difference lies. The mean of this distribution is almost always larger than what can be attributable to spectral noise; much of the difference is presumably due to radiance shifts among the two datasets. It should be noted that this method relies on reasonably large pixel statistics in the two scenes being compared. Therefore two scenes or datasets which just "graze" each other should not have a difference measurement associated with it, or should have a significance penalty applied. In the implementation of the algorithm here, no such limits were applied, and caused some false alarms in scenes with little overlap.

The remaining problem is which pixels between datasets are to be matched. Given two datasets, the first task is to attempt to coregister them. In the case of MANNRRSS, the typical georegistration accuracy was around one meter. This implies that between two datasets, there could be one pixel coregistration uncertainty at each point. For difference detection, we use a shotgun approach: we measure the difference between a "primary" dataset, and every pixel in the local 3x3 area of the "secondary" dataset. The minimum difference is taken as the distance value for that "primary" pixel.

It should be noted that this method treats the two datasets being compared asymmetrically, hence the primary and secondary designation. The method is more sensitive to a locally different pixel in the primary dataset. That is, if a car appears in the primary dataset but not in the secondary, it will be noted as missing in the local neighborhood of pixels in the secondary dataset. However, if the car only appears in the secondary dataset, the primary pixels will generally be able to find a close match in the local (unchanged) area around the car. In effect, there is a "blind spot" to change in the secondary dataset which is the size of the coregistration error. Performing the difference measurement in both directions and taking the maximum, while intensive, is the most sensitive method of change detection.

The main issues in difference detection are the large amounts of bookkeeping of matching together scenes in the datasets, multiple measurements of the same location in each dataset, scene boundaries, etc. The intermediate products of the change detection are a large number of "sigma" significance measurements each with a location. The final product of the mapping is registering all of these local measurements to a one square meter pixel output map. The larger of two or more measurements in the same output pixel is the final result; if no difference measurement occurred in a given square meter, the map is left blank.

The performance of change detection is discussed in the main document above. The change detection methodology of using the global difference distribution of the pixels to extract the significance of a local pixel difference manifests itself as an insensitivity to global change. For

example, the senescence or growth of vegetation on a seasonal basis was largely missed by the difference detection. On the other hand, local change at the few pixel level was found with reasonable sensitivity. A typical change detection output is shown in Figure B-18. On the Left: A change map (white is none, red is 12 sigma) showing the spring to fall change in a part of the MANNRRSS north-south flight lines. Right: The same area in the spring orthophotography. Change that was detected: a car passing along the N-S road (near bottom), the appearance of the fall calibration targets (middle left of image), and disappearance of salt crust (large area upper right, lower right).

Figure B-18. Difference Detection Example

The change detection algorithm is a relatively immature effort compared to other algorithms presented here; further work is needed to allow more precise and targeted change detection. For example, an obvious area to look for change detection is in the dataset level mapping products discussed above.

B.7 Speed

A key concern of the automated algorithm is how computationally intensive it is. For example, real-time production of the scene summary product would have obvious implications for the utility of this algorithm. Similarly, the latency between an analyst defining a target and the production of a dataset level map has impacts on the algorithm utility. In the discussion below, timing results are based on the algorithm being run in a single threaded MATLAB command line environment with a 2.6 GHz Xeon processor. The numbers here are rough guides; no systematic benchmarking or speed evaluations were performed.

The scene level endmember extraction takes around 25-50 times longer to compute than the collection of the data being analyzed (five-ten hours per flightline, which represent around 12 minutes of collection each). This number goes down dramatically if the whitening matrix calculation is simplified: The iterative identification and removal of bad sensor elements at each scene dominates the computation time. Removal of this step from the scene level calculation is a realistic option given that bad sensor elements can be presumably found once per dataset or monitored using other processes. The scene summary computation time without bad sensor ID is around ten times the collection time.

This computation time is tantalizingly close to real time, considering that in these estimates no optimizations were attempted (disk access and memory IO appeared to be clear bottlenecks).

The dataset level calculations are relatively quick: it took only a few minutes to complete classification of the entire Terra spring dataset (526 scenes, 57 square kilometers). Of course, the scene level products are needed as input to this process.

Finally, the mapping process was about as slow as the scene level analysis. However, there is no clear path forward to reducing this time. The increased computational complexity is due to the need to apply a positivity constraint to the unmixing, which requires an iterative algorithm to converge to the best fit solution. If this constraint were removed, a mapping process is competitive with collection time given scene level inputs completed. We observed clearly better mapping results, however, with the positivity constraint in place. We did not attempt to evaluate the fidelity of a non-constrained mapping for real time use; that is an area of potential further work.

Given the complexity of the algorithm described here, the computational tractability of the procedure is surprising. Further attempts to benchmark and optimize the algorithm for speed may warrant attention.

B.8 Magic Numbers

An important goal of the algorithm was to allow trivial portability to other sensor and geographic locations. To do this, we designed the algorithm around statistical assumptions and avoided any algorithm behavioral choices that could not be derived from that model and extracted from the dataset itself. A risk of designing an algorithm of this complexity using a given sensor and a given dataset is unwittingly tailoring the algorithm to the dataset at hand. In order to mitigate that risk, we attempted to track violations of the above design philosophy. Quantities showing up in an algorithm that do not follow this, that are heuristically or empirically optimized, are referred to as magic numbers.

The magic numbers identified as potential portability risks are:

- The bad sensor element cut: A cut on the whitened variance of a sensor element scene measurements. Sensor elements whose variance are more than three times the mean are marked as bad and removed from the scene. This value of three was chosen empirically based on observed distributions like that shown in Figure B-4.
- The power scale: The power law chosen to scale the radiance data to cause the noise variance to be independent of total radiance. This value, 0.75, was chosen empirically based on observed distributions like that found in Figure B-1.
- Shadow definition: Unusually dark endmembers are declared to be a shadow endmember, and removed from the classification result. The threshold, being half the mean radiance of the scene endmembers, was chosen by manually surveying some obvious shadow endmembers.
- Anomaly cut scaling: We scaled the threshold for anomaly detection. The threshold nominally calculated is the number of standard deviations above median that represents a statistical confidence interval of one occurrence per scene. We found empirically that false alarms are below one per scene at around 1.1 times this number of standard deviations. This inflation of the threshold is due to imperfections in the noise model.
- Anomaly minimum radiance cut: We applied radiance thresholds to pixels that were above the anomaly threshold, to eliminate glint and shadow anomalies. The glint is

probably evident using instrumental saturation, but the lower bound for declaring shadow, which we set at a scaled radiance of 26,000, was based on observed distributions like that in Figure B-16. This number is not truly independent from the shadow definition mentioned above.

We have reason to believe that the repercussions of all these magic numbers are minimal; none the less further work to remove these is probably worthwhile. In each case there are probably first principle based or data driven ways to arrive at the values.

To estimate the success of our efforts we performed a portability test of the algorithm to a different sensor and different geography (the Aviris Cuprite, NV radiance dataset). The algorithm, with no modification, performed very well. The detailed results of that effort are described in the main text above.

The algorithm needs more stringent testing under other conditions. In particular, the algorithm has not been pushed to function in either adverse atmospheric conditions or in side looking modes.

B.9 Automated Analysis Conclusion

We have described an algorithm designed for automation of several aspects of the MANNRRSS program analysis goals. While some success has been met, further effort is required to understand the true utility of the algorithm applied to a real remote sensing problem, and how it may complement traditional methods of analysis to ease the labor burden of the analyst.

We believe that through careful design we have created an algorithm that succeeds surprisingly well at extracting through statistical analysis the major and salient components of a hyperspectral dataset and formatted them as a succinct synoptic set of outputs easily consumed by humans. Given the speed and performance of this algorithm, it's application to semi-realtime quick-look may be a feasible route for further study. Additionally, it could be used as an onboard filter and compression algorithm for situations where the high data rate of the hyperspectral instrument overwhelms the ability to record or transmit data from an instrument in the field. This would allow the use of hyperspectral data's unique capabilities to be used in realtime situational awareness applications.

APPENDIX C VENDOR SUPPLIED DOCUMENTS

The embedded documents were provided by the remote sensing data providers as part of their contracted deliverables. These documents contain details of the collection instrument, methodologies and data processing. To view documents in their entirety, double click on the document.

C.1 Terra Remote Sensing, Spring 2007 Collection Final Report

5.0 Results

5.1 Geometric Correction

Boresight calibration was based on 6 passes over the airport in Beatty, NV. Navigation data has been processed and is provided both in a raw form and in ENVI mapping files. All flightlines have been geo-rectified to a 1m lidar-generated DEM.

5.1.1 Spatial gaps

Due to heavy turbulence during acquisition there are several small gaps in between flightlines (*Figure 3*). The extents of these gaps can be seen in the mosaic provided with the delivered data. The majority of the gaps are in the east-west block.

Re-flights on the second day of acquisition intended to cover gaps were curtailed due to military airspace restrictions.

In all but one case, gaps are well below the NRCAN standard of 2% linear gap per flightline pair. In the worst case, there was a 2.5% linear gap (*Figure 4*).

Figure 3: Small gaps between flightlines

C.2 Terra Remote Sensing, Fall 2007 Collection Final Report

C.3 SpecTIR Corporation, Spring 2007 Collection Report

SpecTIR
Spectral Technology and Innovative Research

SpecTIR Standard Delivery Form

SpecTIR Contract #: 1062-3000

SpecTIR Job Name: Sierra Nevada Corp. Mannrrss II

Sensor:

☐

SpecTIR V

☒

SpecTIR VS

Processed data are provided using the following standardized directory structure and naming conventions. Items may or may not be included on this deliverable media depending upon the contracted Scope of Work.

☒

QL – Three-band composite, “quicklook” image files in either JPEG or TIFF format, included as a convenient means of referencing images/flightlines.

☒

RAD – Processed calibrated radiance data with matching ENVI header files. Radiance data units and scaling factors are included in the header files for each processed flight line. Standard units are $\text{mW}/\text{cm}^2/\text{steradian}/\text{m}$ scaled by a factor of 1000. This means that for an pixel value of 4500, the actual radiance value is $4.500 \text{ mW}/\text{cm}^2/\text{steradian}/\text{m}$.

☒

REF – Polished ATCOR/MODTRAN derived reflectance images, matching ENVI header files, and associated processing log files. The ATCOR output reflectance data are polished using a SpecTIR proprietary program based on a Savitsky-Golay algorithm with refined handling of atmospheric absorption features associated with CO₂ and water. ATCOR process-generated log files for each flight line are included providing information on all input parameters used in the generation of these data.

☒

IGM GLT – ENVI compatible IGM and GLT files that provide pixel level georectification/georeferencing for the associated radiance and/or reflectance files. The IGM files are named as “*_IGM.dat”, while the GLT files are named “*_GLT.dat”. GLT files can be used to georeference radiance and/or reflectance data using the “Georeference from GLT” option under the ENVI “Map” menu. IGM files provide mapped UTM coordinate values in raw unrectified image space, and can be used to link tabular field data and observations to the unresampled, raw data space. Subdirectories may be present if multiple resolution IGM/GLTs were generated per client request.

☐

GEO – Fully rectified, navigated spectral data cubes of radiance and/or reflectance data. Subdirectories may be present if multiple resolution IGM/GLTs were generated per client request, or if a mosaic product was included in the scope of work (SOW).

☒

DOCS – This directory may contain subdirectories related to flight planning, flight collection logs, calibration report and any ancillary documentation deliverables as identified in the SOW.

C.4 SpecTIR Corporation, Spring 2007 Collection Quality Assurance Report

Quality Assurance Report

Date: 07/27/07

Client Name: Sierra Nevada Corporation

Project Name: MANNRRSS II

Report Overview: This Quality Assurance Report is provided to satisfy the SDRL A005 Quality Event deliverable outlined within the project scope of work (SOW).

Table 1 of the SOW the specific requirements for the final processed data. The data supplied meets these requirements.

Findings:

Instrument Parameters: The ProspectIR-VS instrument was used to collect the input data. This instrument's design meets the specified underlying sensor system performance requirements outlined in the SOW.

Swath width	320 pixels
Spectral region ¹	400-2460 nm
Radiometric resolution	12 bit VNIR , 14 bit SWIR. Data stored as 16 bit integers.
Band-to-band registration	VNIR and SWIR are internally absolute at 0.0 pixels; < 0.5 pixel between VNIR and SWIR bands
Spectral Smile ²	< 0.2 nm VNIR < 1 nm SWIR
Image Keystone ³	< 0.2 nm VNIR < 0.5 nm SWIR
Signal to Noise Ratio	800:1 (Peak)

Table 1: ProspectIR-VS Sensor Specifications

Collection Parameters: The data collection design was configured to collect pixels at a spatial resolution of 1 meter GSD at nadir with a spectral resolution of approximately 10nm as specified.

A Service Disabled – Veteran Owned – Small Business

APPENDIX D LIST OF DATA PRODUCTS

This appendix is a placeholder for a future table of data products of the program. Contractual obligations require us to make the data products available and this list will be provided as the program develops.

D.1 Primary Data Products

Primary data products are those delivered by the vendors who collected the hyperspectral and ancillary data sets. A list of the filetypes can be found in Table D-1. Further detail on these data can be found in Appendix C. Wild cards (asterisks) in the filename refer to the portion of the filename that varies with location of the data.

File datatypes are listed in Table D-1. There are four types of data:

- **DAT:** Image data file, band interleaved data. These files have two parts, a “.dat” binary data file and a “.hdr” header portion describing the contents of the file (compatible with ENVI image reading software.)
- **ASCII:** Text files, usually self documented columns of numerical data.
- **TIFF:** Tiff images, sometimes with georeferenced information in the header.
- **Shapefile:** A standard vector “shapefile”, compatible with ESRI ArcGIS software.
- **Grid:** A standard grid (raster) file, compatible with ESRI ArcGIS software.

To locate the particular hyperspectral data files by coverage area, the vendors provided ESRI shapefiles with databases to map polygonal geographic outlines to filenames. These are “all_lines_index”, “BlockOutlines_Poly”, and “0925_Hyperoutlines” in the Table D-1 below for SpectIR, Terra spring, and Terra fall datasets respectively. The LIDAR and high resolution orthophotography files are divided by UTM square kilometer.

Table D-1. List of Primary Data Products

Filename	Description	Data type
Spectir		
*_rad	Ungeoregistered calibrated radiance for each flight box (all channels)	DAT
*_pol_rect	Georegistered and calibrated polished reflectance for each flight box (all channels)	DAT
*_pol_ref	Ungeoregistered calibrated polished reflectance for each flight box (all channels)	DAT
*_rad_rect	Outlines of individual flight box	ESRI shapefile
*_rad_GLT	Geometric look-up tables for each flight box	DAT
*_rad_IGM	Internal geometry models for each flight box	DAT
*_rad_rect_QL	Georectified three channel color-infrared composites for each flight box	TIFF
all_lines_index	Outlines of all flight box	ESRI shapefile
Terra		
*_REF*_GEO	Georegistered calibrated reflectance, multiple 2GB files (all channels)	DAT
*_RAD*_GEO	Georegistered calibrated radiance, multiple 2GB files (all channels)	DAT
REF	Ungeoregistered calibrated reflectance, multiple 2GB files (all channels)	DAT
RAD	Ungeoregistered calibrated radiance, multiple 2 GB files (all channels)	DAT
BlockOutlines_Poly	Outlines of all 2 GB file locations	ESRI shapefile
0925_Hypeoutline_Poly	Outlines of all 2 GB file locations	ESRI shapefile
*_*_nav	Navigation file for each flightline	ASCII
*_*_IGM	Internal geometry models for each flight box	DAT
*_*_GLT	Geometric look-up tables for each flight box	DAT

*_DROPLINES	Dropline pixel maps for each flightbox	DAT
SAT	Saturated pixel map for each 2 GB file	DAT
temp_hill	Lidar-derived hillshade	ESRI grid
clip14411	Lidar-derived digital elevation model	ESRI grid
scene1	Lidar-derived hillshade	TIFF
clip14411	Lidar-derived digital elevation model	TIFF
1441_Beatty_*_*_15cm	Georegistered high resolution orthophotography (UTM square km files)	TIFF
1441_*_*_CXYZI	LIDAR raw point clouds (UTM square km files)	ASCII
1441_*_*_1mDEM	LIDAR 1-m DEM points (UTM square km files)	ASCII

D.2 Secondary Data Products

Secondary data products are those created by the analysis efforts described in this document, and are also made available as part of the MANNRRSS II program. A list of some of the products created during the program and made available are listed in Table D-2.

Data types are as the same as those described in section D.1. In addition, the following data types are also listed:

- ERDAS img: An ERDAS Imagine image file, compatible with ESRI ArcGIS software.
- GeoTIFF: A georeferenced TIFF image file.
- PDF: An Adobe Acrobat image file.

All geological analysis maps are based on the Terra fall 2007 dataset unless otherwise noted. All vegetation and automated analysis maps are based on the Terra spring 2007 dataset unless otherwise noted.

Table D-2. List of Secondary Data Products

Filename	Description	Data type
<u>Vegetation analysis</u>		
E-W_bitterbrush	bitterbrush map for east/west flightbox	ESRI shapefile
E-W_saltbush	saltbush map for east/west flightbox	ESRI shapefile
E-W_creosotebush	creosotebush map for east/west flightbox	ESRI shapefile
E-W_senesced riparian	senesced riparian map for east/west flightbox	ESRI shapefile
E-W_cottonwood	cottonwood map for east/west flightbox	ESRI shapefile
E-W_green riparian	green riparian map for east/west flightbox	ESRI shapefile
E-W_rabbitbrush	rabbitbrush map for east/west flightbox	ESRI shapefile
N-S_cottonwood	cottonwood map for north/south flightbox	ESRI shapefile
N-S_willow	willow map map for north/south flightbox	ESRI shapefile
N-S_russian olive	russian olive map for north/south flightbox	ESRI shapefile
N-S_rabbitbrush	rabbitbrush map for north/south flightbox	ESRI shapefile
N-S_saltbush	saltbush map for north/south flightbox	ESRI shapefile
N-S_creosotebush	creosotebush map for north/south flightbox	ESRI shapefile
N-S_bitterbrush	bitterbrush map for north/south flightbox	ESRI shapefile
N-S_green riparian	green riparian map for north/south flightbox	ESRI shapefile
N-S_senesced riparian	senesced riparian map for north/south flightbox	ESRI shapefile
N-S_tamarisk	tamarisk map for north/south flightbox	ESRI shapefile
ndvi_pct_chg	raster data expressing % change of NDVI values between spring and fall	TIFF
pct_chg_ctnwd	raster data expressing % change of NDVI values between spring and fall for cottonwood trees in N-S flightbox only	ERDAS img

Geologic analysis

N-S_alunite	Alunite map for north/south flightbox	ESRI shapefile
N-S_kaolinite	Kaolinite map for north/south flightbox	ESRI shapefile
N-S_illite	Illite map for north/south flightbox	ESRI shapefile
N-S_chlorite	Chlorite map for north/south flightbox	ESRI shapefile
N-S_goethite	Goethite map for north/south flightbox	ESRI shapefile
N-S_dolomite	Dolomite map for north/south flightbox	ESRI shapefile
N-S_calcite	Calcite map for north/south flightbox	ESRI shapefile
N-S_opal_chalcedony	Opal/Chalcedony map for north/south flightbox	ESRI shapefile
N-S_zeolite	Zeolite map for north/south flightbox	ESRI shapefile
N-S_mirabilite	Mirabilite map for north/south flightbox	ESRI shapefile
E-W_kaolinite	Kaolinite map for east/west flightbox	ESRI shapefile
E-W_illite	Illite map for east/west flightbox	ESRI shapefile
E-W_chlorite	Chlorite map for east/west flightbox	ESRI shapefile
E-W_goethite	Goethite map for east/west flightbox	ESRI shapefile
E-W_dolomite	Dolomite map for east/west flightbox	ESRI shapefile
E-W_opal_chalcedony	Opal/Chalcedony map for east/west flightbox	ESRI shapefile
E-W_zeolite	Zeolite map for east/west flightbox	ESRI shapefile
N-S_alunite_alt	Alunite map for north/south flightbox, independent analysis	ESRI shapefile
N-S_kaolinite_alt	Kaolinite map for north/south flightbox, independent analysis	ESRI shapefile
N-S_illite_TRS	Illite map for north/south flightbox, analysis of TerraRS fall dataset	GeoTIFF
N-S_illite_Spectir	Illite map for north/south flightbox, analysis of SpecTIR spring dataset	GeoTIFF
Aster_4.7_4.6_4.10	ASTER image using band ratios R: 4/7, G: 4/6, B: 4/10	DAT
Aster_7.6_6.5_6.4	ASTER image using band ratios R: 7/6, G: 6/5, B: 6/4	DAT
Aster_4.5	ASTER image using band ratio 4/5	DAT
Linear_features	Linear features map of the flight boxes	ESRI shapefile
Hillshade_anomalies	Hillshade anomalies	ESRI shapefile
Slope_intensity	Slope intensity map	GeoTIFF
Analysis_subset_vaughan	Alteration center analysis by Greg Vaughan	DAT
Analysis_subset_morken	Alteration center analysis by Todd Morken	DAT
Contour_lines_5	Contour line shapefile with 5 meter spacing	ESRI shapefile
spec_res 5	Spectral resolution analysis with 5 nm data	DAT
spec_res 10_av	Spectral resolution analysis with 10 nm AVIRIS data	DAT
spec_res 10_pro	Spectral resolution analysis with 10 nm Prospectir data	DAT
spec_res 17	Spectral resolution analysis with 17 nm HyMap data	DAT
spat_res 1	Spatial resolution analysis with 1 meter Prospectir data	DAT
spec_res 5	Spatial resolution analysis with 5 meter Prospectir data	DAT
spec_res 10	Spatial resolution analysis with 10 meter Prospectir data	DAT
spec_res 15	Spatial resolution analysis with 15 meter Prospectir data	DAT

Automated analysis

endMembers_*	Scene level endmember abundances, includes fit distance as last band	DAT
endMembers_*	Scene level endmember radiance spectra, compatible with ENVI library ASCII format	ASCII
classified_*	Scene level classification maps	DAT
sceneSummary_*	Scene level summaries, document form	PDF
Anomaly_N-S_Spring	Anomalousness map, spring north/south flight line	DAT
Anomaly_E-W_Spring	Anomalousness map, spring east/west flight line	DAT
Anomaly_N-S_Fall	Anomalousness map, fall north/south flight line	DAT

Joshuatree_E-W	Joshua Tree map, fractional abundance, for east/west flight box	DAT
Joshuatree_E-W_plurality	Joshua Tree map, plurality method, for east/west flight box	DAT
Saltbush_E-W	Saltbush map, fractional abundance, for east/west flight box	DAT
Saltbush_E-W_plurality	Saltbush map, plurality method, for east/west flight box	DAT
Creosotebush_E-W	Creosotebush map, fractional abundance, for east/west flight box	DAT
Creosotebush_E-W_plurality	Creosotebush map, plurality method, for east/west flight box	DAT
Bitterbrush_E-W	Bitterbrush map, fractional abundance, for east/west flight box	DAT
Bitterbrush_E-W_plurality	Bitterbrush map, plurality method, for east/west flight box	DAT
Alunite_N-S	Alunite map, fractional abundance, for north/south flight box	DAT
Alunite_N-S_plurality	Alunite map, plurality method, for north/south flight box	DAT
Illite_N-S	Illite map, fractional abundance, for north/south flight box	DAT
Illite_N-S_plurality	Illite map, plurality method, for north/south flight box	DAT
Kaolinite_N-S	Kaolinite map, fractional abundance, for north/south flight box	DAT
Kaolinite_N-S_plurality	Kaolinite map, plurality method, for north/south flight box	DAT
Alunite_N-S_fall	Alunite map, fractional abundance, for north/south flight box, Terra fall 2007 dataset	DAT
Alunite_N-S_plurality_fall	Alunite map, plurality method, for north/south flight box, Terra fall 2007 dataset	DAT
Illite_N-S_fall	Illite map, fractional abundance, for north/south flight box, Terra fall 2007 dataset	DAT
Illite_N-S_plurality_fall	Illite map, plurality method, for north/south flight box, Terra fall 2007 dataset	DAT
Kaolinite_N-S_fall	Kaolinite map, fractional abundance, for north/south flight box, Terra fall 2007 dataset	DAT
Kaolinite_N-S_plurality_fall	Kaolinite map, plurality method, for north/south flight box	DAT
Library_N-S_spring	Dataset level classification map, north/south flight box, Terra spring 2007 dataset	DAT
Library_N-S_spring	Dataset level endmember radiance spectra, compatible with ENVI library ASCII format	ASCII
Library_E-W_spring	Dataset level classification map, east/west flight box, Terra spring 2007 dataset	DAT
Library_E-W_spring	Dataset level endmember radiance spectra, compatible with ENVI library ASCII format	ASCII
Library_N-S_fall	Dataset level classification map, north/south flight box, Terra fall 2007 dataset	DAT
Library_N-S_fall	Dataset level endmember radiance spectra, compatible with ENVI library ASCII format	ASCII
Diff_N-S_spring_spring	Spectral change map, north/south flight box, within Terra spring 2007 dataset	DAT
Diff_E-W_spring_spring	Spectral change map, east/west flight box, within Terra spring 2007 dataset	DAT
Diff_N-S_fall_fall	Spectral change map, north/south flight box, within Terra fall 2007 dataset	DAT
Diff_N-S_fall_spring	Spectral change map, north/south flight box, Terra fall 2007 with respect to Terra Spring 2007	DAT
endMembers_cuprite	Scene level endmember abundances, includes fit distance as last band, Aviris Cuprite dataset	DAT
endMembers_cuprite	Scene level endmember radiance spectra, compatible with ENVI library ASCII format, Aviris Cuprite dataset	ASCII
classified_cuprite	Scene level classification maps, Aviris Cuprite dataset	DAT
sceneSummary_cuprite	Scene level summaries, document form, Aviris Cuprite dataset	PDF

APPENDIX E LIST OF REFERENCES

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APPENDIX F LIST OF ACRONYMS AND ABBREVIATIONS

Acronym/Abbreviation	Description
ABLE	Arthur Brant Laboratory for Exploration Geophysics
ASD	Applied Spectral Devices
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
ATCOR	Atmospheric Correction Software Utility
AVIRIS	Airborne Visible/Infrared Imaging Spectrometer
CCD	Charged-Couple Device
CIR	Color Infrared
DEM	Digital Elevation Model
DOE	Department of Energy
DRI	Desert Research Institute
E/W	East/West
EM	Electromagnetic
EMS	Electromagnetic Spectrum
ENVI	Environment for Visualization
FOM	Field of Merit
GIS	Geographic Information System
GPS	Global Positioning System
GSD	Ground Sample Distance
HSI	Hyperspectral
HyMap	HyVista Mapper
IFOV	Instantaneous Field of View
IMU	Inertial Measurement Unit
INS	Inertial Navigation System
LAI	Leaf Area Index
LandSat TM	LandSat Thematic Mapper
LiDAR	Light Detection and Ranging
m	meter
MANNRRSS	Management of Nevada's Natural Resources with Remote Sensing Systems
mm	Millimeter
μm	Micrometer
MNF	Minimum Noise Fraction
MSI	Multispectral
N/S	North/South
NaN	not a number
NASA	National Aeronautics and Space Administration

Acronym/Abbreviation	Description
NDVI	Normalized Difference Vegetation Index
NIR	Near-infrared
nm	nanometer
NPTEC	Nonproliferation Test and Evaluation Complex
NTS	Nevada Test Site
NTTR	Nevada Test and Training Range
PDT	Pacific Daylight Time
PPI	Pure Pixel Index
RGB	Red, Green, Blue
ROI	Region of Interest
RS	Remote sensing
SAM	Spectral Angle Mapper
SNC	Sierra Nevada Corporation
SNR	Signal-to-noise
SWIR	Shortwave-infrared
TIR	Thermal-infrared
um	Unit of Measure
UNR	University of Nevada-Reno
USGS	United States Geological Survey
UTM	Universal Transverse Mercator (cartography)
VIS	Visible
VIS/NIR	Visible/near-infrared
VNIR	Visible/near-infrared