Effects of two utility-scale solar energy plants on land-cover patterns using SMA of Thematic Mapper data

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Abstract

Due to depleting fossil fuels, many nations are adding renewable resources – such as geothermal, wind, and solar energy – to their energy portfolios. The southwestern United States counts as one of the best places in the world to collect solar energy, and already, Nevada is harnessing the sun's energy on a large scale. Depending on the size and type of the installation and location, there can be various environmental implications due to changes in the land cover change, and sometimes these are potentially negative implications. This study was conducted at two utility-scale solar energy (USSE) plants in Nevada, Nevada Solar One and the Nellis Solar Power Plant. First, the environmental effects of USSE are reviewed. Second, changes in land cover were analyzed for pre-installation, syn-installation, and post-installation in these two facilities from 2004 to 2011. A time series of Landsat 5 thematic mapping (TM) images were used with principal component analysis (PCA), minimum noise fraction (MNF), and spectral mixture analysis (SMA) to estimate the subpixel fraction of each pixel covered by a four-endmember model: high-albedo, low-albedo, shadow, and vegetation. Results showed that PCA-Normalized data had the highest correlation coefficients, which indicates that solar plant construction had no significant effect on the land-cover fraction in the surrounding area of the facilities. On the other hand, results of land-cover analysis of the points located within the facilities showed that the low-albedo fraction increased

and the high-albedo fraction decreased after construction. The shadow fraction decreased slightly after construction, and the fraction of vegetation was close to zero before and after construction; this was due to the plants being constructed in an arid area. This study indicated that except for the long-term effects of USSE plants on the environment, land-cover patterns in the case of high-albedo, low-albedo, shadow, and vegetation altered significantly inside plant areas and did not alter significantly outside.

Keywords

Solar energy, Land-cover change, Environmental impacts, PCA, MNF, SMA,

1. Introduction

With the awareness that fossil fuels are depleting, many nations are adding renewable resources to their energy portfolios, such as geothermal, wind, and solar energy. Although harvesting solar energy has been around for a while, not until recently has this topic gained interest as a renewable energy resource, especially in areas having bright sunshine year-round. The southwestern United States counts as one of the most attractive places in the world to collect solar energy. Already, Nevada is harnessing this energy on a large scale, and several utility-scale solar energy (USSE) plants have emerged that typically are capable of greater than 1 MW.

According to the Solar Energy Industries Association report in 2014, among the U.S. states, Nevada produces 286 watts per person, and stands in the third place after Hawaii and Arizona [1]. Due to its numerous USSE plants, Nevada is emerging among the top states in terms of solar opportunities. These USSE plants, which use varying types of solar farming technologies, generally can be classified into photovoltaic (PV) and concentrating solar power (CSP) [2]. PV cells generate electrical power by converting sunlight into direct current

electricity. On the other hand, CSP technologies use mirrors or reflective surfaces to reflect and concentrate sunlight onto receivers, which collect the solar energy and convert it to heat. Devabhaktuni et al., [3] reviewed various solar power technologies, their applications and challenges. Since these technologies at the utility scale have a large spatial footprint, it is important to understand their potential effects on the environment.

According to Phillips [4] and Tsoutsos et al. [5], the major indirect environmental effects of solar energy comparing with fossil fuels energy consumption that are considered positive are reduced emissions of greenhouse gases, reduced transmission lines from electricity grids, reclamation of degraded land, and improved quality of water resources, among others. In addition, the environmental impacts of PV cell production can also be reduced by converting to more advanced production process [6]. These effects have resulted in increased interest in USSE installations, with many pending permits for installations planned for the future. As more of these plants appear on the landscape, a major challenge is to understand the effects on land use and changes in surface characteristics of the land. These effects depend on the size, type, and location of the installations [4,5], and must be addressed appropriately in energy policies.

During the last decade, many researchers have investigated environmental and human effects of solar energy installations, including on biodiversity, visual impacts relating to the loss of amenities as well as visual intrusion from an aesthetic viewpoint, land use, soil, water resources, human health, fragmentation, and changes in the microclimate. In a study on the positive and negative effects of USSE development on biodiversity, soils, water resources, and human health, Hernandez et al. [2] showed that potential effects on the land-cover by USSE plants are relatively small compared to other energy systems. In a general overview of some environmental effects by solar technology, Tsoutsos et al. [5] graded the potentially negative

effects, such as visual impacts, the routine and accidental release of chemicals, land-use, and work safety and hygiene as well as the effect on the ecosystem and on water resources. They suggested that the potential environmental burdens of solar installations depend on the size and nature of the project, and often are site-specific. They associated most of these burdens with the loss of amenities, such as visual impacts or noise in the case of central systems. Klein and Rubin [7] indicated life-cycle greenhouse gas emissions of using thermal energy storage is 4-9 times less than using natural gas-fired energy backup system at a CSP technology plant.

Furthermore, Turney and Fthenakis [8] compared the intensity of land use for life-cycles of PV power from the installation and operation of USSE plants with that for coal power. Using two kinds of metrics, transformation and occupation, they found that as the age of the power plant increased, the land-use intensity of PV power became significantly smaller than that for a coal power plant. Horner and Clark [9] used harmonization process to provide a standard method to calculate solar land-use energy intensity by reducing, characterizing and explicating of it for PV and CSP technologies. Murphy et al. [10] showed the off-site land-use energy intensity is less than 1% of the on-site land-use for PV and CSP technology. In order to assess the environmental and human effects of USSE plants, Phillips [4] applied a mathematical model of sustainability to the results of Turney and Fthenakis [8]; results indicated that installation and operation phases of utility-scale PV solar plants could be considered as sustainable at a strong level.

Results of research by Hernandez et al. [11] on land-use efficiency of USSE installations in California indicated that allocated land was used more for PV schemes (85%) than for CSP (15%). In addition, PV installations were in greater abundance than CSP installations; however, the type of technology used had no effects on land-use efficiency (Wm^{-2}). On the other hand,

land-use efficiency on private land was greater than that on public land. To sum up, environmental and human effects of USSEs, both for PV and CSP installations, depended on the size and nature of the project, and were relatively small compared to other energy systems, especially coal power.

USSE plants have an effect on fragmentation of the countryside as well. This effect, in the case of an installation on the ground, refers to the potential loss of the identity elements typical of the region (e.g., cultivability). According to Chiabrando et al. [12], "...fragmentation is often seen as a negative factor and is opposed to nature conservation, as it is in the case of natural areas, since it causes a decrease of the biodiversity." USSE plants also have an effect on microclimates. With PV systems, this happens due to the temperature that is reached by the PV panels during operation as a result of heating caused by sunlight. The temperature of the panels can increase up to 70°C, which can cause changes by heating the air surrounding the plant. Armstrong et al. [13] studied the effects of solar energy generation technologies on microclimatic changes and consequently on ecosystem carbon cycling and greenhouse gas emissions.

USSE plants occupy many square kilometers of desert area, thus affecting the thermal balance, which, according to Gunerhan et al. [14], "may destroy some species living in this kind of harsh environment." This effect could play a big part in choosing the type and location of a solar power plant. Hernandez et al. [15] examined land, energy and environmental compatibility for PV and CSP technology in California and they identified diverse sites for small and utility-scale solar energy that could meet the state energy demand three to five times over. De Marco et al. [16] identified suitable areas for USSE with respect to the analysis of the legislation. They examined the effects of existing solar installation on CO₂ sequestration and on avoided CO₂.

Beylot et al. [17] compared the environmental effects of utility-scale PV installations that were grid-connected and ground-mounted, using four scenarios for life-cycle assessment (LCA). They found that dual-axis trackers have more of an effect on ecosystem quality than other types, and this was influenced mainly by land occupation. In fact, they found that power plants with dual-axis trackers needed more space between each element of the PV field because that would provide wider shade than fixed and single-axis trackers. In 2014, Qian studied the impact of land-use and land-cover change as a factor of changing in the regional surface energy balance on changes in surface solar radiation [18]. Their study was conducted in eastern China from 1979-2008 based on diurnal temperature range in various stations. They reported the reduction in surface solar radiation at most stations due to land-use and land-cover change.

The thermal balance of an area can be assessed by remote sensing methods. Over the last few decades, many remote sensing applications have been developed to assess changes in land cover, land use and also potential areas for solar plant installation. Chen et al. [19] provided a statistical example on vegetation estimation, based on multivariate statistical modeling and using remote sensing data. They selected the reflectance of data from four bands of a Huan Jing (HJ-1) charged-coupled device, six vegetation indexes, three principal components from principal component analysis (PCA), and three variables from tasseled-cap transformation to correlate with measured vegetation coverage. According to the results, this method had relatively high precision with environments having various densities of vegetation. Mahtta et al., [20] mapped potential areas for solar plant installation (CSP and PV) using remote sensing techniques considering land slope and solar radiation in India. Calvert et al., [21] reviewed the status of the application of geographic information science and remote sensing techniques to decrease the uncertainties about renewable energy development.

When classifying multi-spectral images, each pixel often contains a mixture of land-cover categories. One useful technique for estimating the proportion of each pixel that is covered by a series of known cover types is by spectral mixture analysis (SMA). Lu and Weng [22] applied an SMA approach to solve the mixture problem with low-resolution data, and provided better classification results than traditional maximum-likelihood classifiers. To estimate impervious surfaces, Wang et al. [23] compared the performance of four methods by using linear SMA for spectral-data treatment in the central area of Shanghai, China. Regarding endmember extraction for SMA, Mei et al. [24] proposed an algorithm to integrate spectral similarities and spatial context. Similarly, Plaza et al. [25] presented an automated method for unsupervised determination of pixel purity from multi-dimensional datasets. Song [26] used Bayesian SMA to determine the effects of endmember variability on the estimation of sub-pixel vegetation fractions.

The provided review of literature showed remote sensing methods can be used to assess land-cover changes due to USSE construction. Fragmentation of the countryside as well as changes to microclimates and the thermal balance are some negative effects from USSE plants that could lead to changes in the land cover. Moreover, it is widely accepted that almost all kinds of vegetation are sensitive to thermal change. Thus, due to the lack of literature concerning long-term effects of USSE plants on land-cover changes, this research focuses on the effects of USSE generation facilities on land-cover trends, using remote sensing data. Specifically, the effects on land cover by two USSE installations in an arid environment is examined, Nevada Solar One and the Nellis Solar Power Plant, both installed in southern Nevada within the last decade. This study measured the long-term effects using changes in the land-cover surroundings and within the facility. To understand effects of solar-facility construction on this type of environment, changes

in land-cover trends were classified as pre-installation and post-installation of the plants, based on changes in high-albedo, low-albedo, vegetation, and shadow fractions. The significance of this research is analysis of long-term effects of USSE plants on land cover using remote sensing techniques. These effects are analyzed inside and outside the plant areas.

The paper is organized as follows. In section 1, the present state of literature is reviewed. Section 2 describes the study areas and is followed by section 3, which explains the remote sensing data requirements. Methodology is described in section 4. Results and discussions are given in section 5 and is followed by the summary and conclusion in section 6.

2. Study Area

Nevada Solar One and Nellis Solar Power Plant were selected for this study because of their location and solar energy techniques; one plant is located inside an urban area (Nevada Solar One) and the other is located outside the urban area (Nellis Solar Power Plant). In addition, one uses PV techniques (Nellis Solar Power Plant) and the other uses CSP techniques (Nevada Solar One). This study of two types of power plants demonstrates approach and methodology while identifying their effect on land cover.

2.1 Nevada Solar One

Nevada Solar One (NS-1) is a concentrated solar power plant with a footprint of 1.62 km² in the Eldorado Valley near Boulder City, Nevada. The effect on land cover is studied over a rectangular area ~127 km² around the facility. It has been built within the City's Energy Resource Zone, which requires renewable generation as part of plant development permits. This plant uses parabolic concentrators with mirrors to focus the sun's energy onto oil-carrying receiver tubes. The heated oil is used to boil water into steam in order to drive a turbine power generator. This

plant uses proprietary technology to track the sun's location and to concentrate rays during peak demand hours. The solar plant provides mixed power, using 98% concentrated solar and 2% natural gas. Electricity production is more than 130 gigawatt hours per year [27]. NS-1 construction began in February 2006, and operations started in June 2007.

Figure 1 compares two aerial images of NS-1 both during construction in 2006 (Fig. 1a) and after completion in 2010 (Fig. 1b). In Figure 1a, the land for the upper plant section has been prepared for the construction in 2006. In Figure 1b, the solar panels have been installed in the upper section and panels in the lower section are getting installed in 2010. In order to investigate changes in land-cover characteristics further, Points 1A and 2A were selected for further analysis and comparison using the proposed methods. Point 1A is located within the facility areas and Point 2A is located outside of the facility.

Figure 1. Nevada Solar One in a) 2006 and b) 2010.

2.2 Nellis Solar Power Plant

Nellis Solar Power Plant (NSPP), a photovoltaic power plant, spreads over 0.57 km² within Nellis Air Force Base located in northeast of Las Vegas in Clark County, Nevada. The effect on

land cover is studied over a rectangular area $\sim 7.76 \text{ km}^2$ around the facility. PV cells generate electrical power by converting sunlight into direct current electricity. The system contains approximately 70,000 PV panels that employ an advanced single-axis sun-tracking system. NSPP generates more than 25 gigawatt hours of electricity annually, and supplies more than 25% of the power at the Nellis Air Force Base [28].

NSPP construction began in April 2007, and operations started in October 2007. Figure 2 compares two aerial images of NSPP, including before construction in 2006 and after completion in 2010. In Figure 2a, the land has been prepared for the construction in 2006. Figure 2-b shows the solar panels completely installed in 2010. Similar to NS-1, in order to further investigate the changes in land-cover characteristics, Points 1B and 2B were selected for further analysis using the proposed methods. Point 1B is located within the facility area and Point 2B is located outside of the facility.

Figure 2. Nellis Solar Power Plant in a) 2006 and b) 2010.

3. Remote Sensing Data

This research used aerial imagery from the Landsat 5 thematic mapper (TM) as well as from the National Agriculture Imagery Program (NAIP). TM imagery from Landsat 5 was used to estimate land-cover changes, and the higher resolution NAIP imagery was used to validate the results.

3.1 Data from Landsat 5 Thematic Mapper

Landsat 5 is a low-earth-orbit satellite, recognized as the longest operating mission in history for an Earth-observing satellite. Its payload includes the thematic mapper instrument, which has orbited the planet more than 150,000 times and has transmitted over 2.5 million images. TM images consist of seven spectral bands, including visible, near-infrared, thermal, and mid-infrared bands. Bands 1, 2 and 3 are visible, Bands 4 and 5 are near-infrared, Band 6 is thermal, and Band 7 is mid-infrared. Available since 1984, this multi-channel data is used extensively to differentiate land-cover types and study trends [29–31]. This long-term data provides an opportunity to perform time-series analyses in order to understand the effects of large-scale solar power plants.

Standard TM data products are available as digital numbers (DN), which are converted to spectral radiance at the sensor's aperture, using the following equation [32]:

$$L_{\lambda} = \left(\frac{LMAX_{\lambda} - LMIN_{\lambda}}{Q_{calmax} - Q_{calmin}} \right) (Q_{cal} - Q_{calmin}) + LMIN_{\lambda} \quad (1)$$

Where:

L_{λ} = Spectral radiance at the sensor's aperture [W/(m² sr μ m)]

Q_{cal} = Quantized calibrated pixel value [DN]

Q_{calmin} = Minimum quantized calibrated pixel value corresponding to $LMIN_{\lambda}$ [DN]

Q_{calmax} = Maximum quantized calibrated pixel value corresponding to $LMAX_{\lambda}$ [DN]
 $LMIN_{\lambda}$ = Spectral at-sensor radiance that is scaled to Q_{calmin} [W/ (m² sr μm)]
 $LMAX_{\lambda}$ = Spectral at-sensor radiance that is scaled to Q_{calmax} [W/ (m² sr μm)]
Spectral radiance data can be converted to surface reflectance (ρ) data to reduce scene-to-scene variability. Chander et al. [32] provided an equation to convert the spectral radiance at the sensor's aperture to the top-of-atmosphere (TOA) reflectance of the Earth.

Recently, the U.S. Geological Survey (USGS) has released climate data records (CDR), which provides surface reflectance data of TM. Because this current research began before the release of the CDR data, however, spectral radiance images were calculated from DN images. In this research, spectral radiance images were used to estimate land-cover change. Pure pixels were selected from the same images for the SMA process, and were validated based on a high-resolution image. After the normalization process, which will be described in methodology section, spectral radiance images and surface reflectance images were identical.

Both study sites were covered by Landsat TM scenario for Path 39 and Row 35. From March 2004 to February 2011, 114 images were acquired from the USGS Earth Resource Observation Systems (EROS) Data Center (EDC). These images were analyzed visually in order to isolate 76 cloud-free images appropriate for further processing. All bands had a spatial resolution of 30 m, except for thermal infrared, which was 120 m. Thermal infrared was not used during data processing.

3.2 Data from the National Agriculture Imagery Program

The National Agriculture Imagery Program acquires aerial imagery during the agricultural growing seasons in the continental U.S. [33], at 1-m resolution. The frequency bands that are

available are natural colors – red, green, and blue (RGB). However, beginning in 2007, some states have been delivering four bands of data, RGB as well as near infrared. In this research, NAIP imagery acquired during May 2010 was used for verification of the results. This imagery was obtained from the website for W.M. Keck Earth Science & Mining Research, from which data from 2006, 2009, 2010, and 2013 were available (<http://keck.library.unr.edu/>) [34].

4. Methodology

Data processing and analysis primarily consisted of 1) a data treatment step to reduce the dimensions of the Landsat imagery, 2) data unmixing in order to retrieve information of sub-pixel land-cover, and 3) trend analysis to estimate changes in the land-cover. Figure 3 shows the flowchart of these applied methods.

Figure 3. Flowchart of the methods used for data treatment of the Landsat 5 imagery.

4.1 Data Treatment Techniques

In order to convert correlated Landsat 5 TM imagery bands into a set of linearly uncorrelated variables, two methods were applied that include both principal component analysis (PCA) [35,36] and minimum noise fraction (MNF) [37]. These methods basically involve a constrained rotation of data in a multi-dimensional space. In PCA, variance represents the information, and the data rotation is performed such that variance is maximized along fewer dimensions. The data projections along these dimensions are called principal components. Similarly, the MNF rotates the data to achieve minimum noise along fewer dimensions. The data projections along these dimensions are called minimum noise components. Both PCA and MNF transform Landsat 5 TM imagery such that the information of the transformed imagery is concentrated into fewer bands. These transforms are tested over arid regions to identify the most applicable methods for land-cover analysis of solar facilities.

The PCA and MNF transforms were used with both original data and normalized data. For original data, spectral radiance images are the input without any change; normalized data, on the other hand, is converted to get the zero mean (zero-centering) and the unit variance (normalization) for each band. The terms 'original' and 'normalized' are used to identify the results of these two input data variations. The PCA and MNF transforms were implemented using MATLAB R2014a. MNF had the lowest noise fraction in the last component, whereas PCA had the largest variance in the first component. In this research, a TM cloud-free image, acquired on July 18, 2007, had been selected to find endmembers using PCA and MNF components. Thus, PCA and MNF techniques both were applied to the image. Table 1 lists the percentage of the total variance explained by each principal component in the PCA bands, and the noise fraction of each MNF band.

Table 1. PCA Band Variances and MNF Bands Noise Fractions

Band Number	PCA-Original		PCA-Normalized		MNF-Original	MNF-Normalized
	Total Variance (%)	Eigenvalues	Total Variance (%)	Eigenvalues	Noise Fraction	Noise Fraction
Band 1	94.3341	1444.5980	89.8667	5.3920	0.8271	0.1168
Band 2	4.1613	63.7245	7.4157	0.4449	0.2522	0.0798
Band 3	1.1043	16.9105	1.7782	0.1067	0.1891	0.0694
Band 4	0.2154	3.2986	0.5798	0.0348	0.1169	0.0434
Band 5	0.1796	2.7505	0.2406	0.0144	0.0828	0.0390
Band 6	0.0053	0.0814	0.1188	0.0071	0.0446	0.0326

The first three components of PCA-Original and PCA-Normalized covered 99.6% and 99.06% of the variance, respectively; the last three components of MNF-Original and MNF-Normalized carried 24.4% and 11.5% of the noise, respectively.

The transformation of TM imagery into fewer bands for most of the information can be used continuously in further analysis, such as for target identification, image classification, and subpixel retrieval. Often, pure pixels (containing a single land cover called an endmember) exhibit extreme values in these bands, whereas mixels (pixels containing multiple endmembers) exhibit intermediate values, depending on the level of mixing. As shown in Figures 4 and 5, the PCA and MNF components were graphed as scatter plots to identify the endmembers identified as extreme corners (vertices) in these plots [25,38] (Boardman 1994; Plaza et al. 2002). Figure 4 shows the 2-D scatter plot of PCA-Original- and -Normalized datasets and Figure 5 shows the 2-D scatter plot for MNF-Original and -Normalized datasets. The types of the pixels at the extreme vertices in the scatter-plots were determined by linking the pixels back to the image-feature space.

Figure 4. 2-D scatterplot of the first three principal components of PCA (July 18, 2007).

Figure 5. 2-D scatterplot of the last three principal components of MNF (July 18, 2007).

Four endmembers were identified, including high albedo (HA), low albedo (LA), vegetation (VG), and shadow (SH). High albedo represents land covers that reflect most of the light, such as concrete roofs and sand. Low albedo is associated with land covers that absorb most of the light and appear relatively dark colored to the eyes, such as asphalt and water bodies. For each endmember type, at least 20 representative pixels were selected. Thus, spectral signatures of HA, LA, VG, and SH land-cover types were extracted using four variations of data treatment, including PCA-Original, PCA-Normalized, MNF-Original, and MNF-Normalized.

Spectral signatures of endmembers can be used to retrieve subpixel land cover of mixels by means of a process of unmixing. Several techniques have been developed, including linear spectral unmixing, fuzzy classification, and automatic subpixel detection. In this research, spectral mixture analysis was used to retrieve subpixel land cover.

4.2 Spectral Mixture Analysis

Often, a pixel contains a mixture of land-cover categories. In fact, the number of pure pixels that contain only one feature or class is small. Nevertheless, the value of a pixel with a mixed land cover depends on the ensemble of responses for each constituent land-cover. SMA has been extensively employed for land-cover mapping using TM data [26,39,40]. This technique seeks to determine the likely composition of constituent land-cover types or endmembers to produce the measured pixel value,

$$b^i = f_1^i \cdot \rho_1^i + f_2^i \cdot \rho_2^i + \cdots + f_N^i \cdot \rho_N^i + e, \quad (2)$$

where b^i is measured i^{th} band spectral radiance of a pixel with N endmembers. The ρ^i and f^i are spectral reflectance and subpixel aerial fraction of an endmember, respectively; and e is the residual error. Such relationships for an imagery with K bands result in a system of equations that can be written in matrix form as

$$\mathbf{b} = \bar{\rho}\mathbf{f} + \mathbf{e}, \quad (3)$$

where $\bar{\rho}$ is a K by N matrix with rows corresponding to K bands and columns corresponding to N endmembers. The symbols $\mathbf{f}$ and $\mathbf{e}$ are column vectors of subpixel aerial fraction of endmembers and the residual errors, respectively. The SMA approach poses two conditions on the subpixel land-cover fractions given by:

$$\sum_{n=1}^N f_n = 1 \quad (4)$$

and

$$0 \leq f_n \leq 1, n = 1, 2, \dots, N \quad (5)$$

Equations (3), (4), and (5) were solved for each cell to estimate fractions such that residual error R is minimized [41]. The Nedler-Mead method (available in MATLAB 2014a), used to minimize the residual, is a multidimensional, unconstrained, nonlinear minimization for finding the minimum of a scalar function of several variables [42].

4.3 Validation

For validation, the SMA results were compared with land cover based on high-resolution NAIP imagery. Subpixel fractions were retrieved for a TM image acquired on May 10, 2010, and compared to classification of an NAIP image acquired on May 7, 2010. The comparison was made over a randomly selected rectangular area within the City of Las Vegas. The NAIP image was classified using a supervised image-classification tool in ArcGIS 10.2.2 for the same four endmembers used in SMA. Pixels representing the endmembers were manually selected for the image-classification process. Additionally, land-cover fractions of all TM image pixels were calculated using SMA. As mentioned earlier, NAIP imagery has a 1-m resolution and TM images have a 30-m resolution. Thus, pixels of each TM image included 900 NAIP pixels. Therefore, two land-cover datasets were calculated for the land-cover fractions of the TM images and the NAIP imagery. In order to compare TM image results with NAIP imagery results, four types of data were used as input for the SMA process: PCA-Original, PCA-Normalized, MNF-Original, and MNF-Normalized. The correlation coefficient was calculated to determine the relationship between image classification and SMA results.

4.4 Trend Analysis

In order to analyze the effects of the construction of USSE plants on land-cover patterns, time-series data were classified as pre-installation, syn-installation, and post-installation data. In addition, the average land-cover fraction of each land-cover type was calculated for pre-installation, syn-installation, and post-installation. Because some land covers followed an annual periodic pattern, the averaging method was used to minimize the annual trends effects.

5. Results and Discussion

In this section, the results of subpixel land-cover estimation and their temporal analysis with respect to solar installations are presented. First, a brief comparison of four data treatments is discussed to identify a suitable treatment for selecting endmembers and applying SMA. Second, the fractional area maps of four endmembers produced by SMA are presented and discussed at the two study sites. Finally, the pre- and post-installation fractional area maps are compared to estimate the effects of solar facilities on land-cover patterns.

5.1 Comparisons of Data Treatment Techniques

In order to identify a suitable treatment for selecting endmembers, the SMA results were validated using NAIP imagery acquired on May 7, 2010. To do so, a random rectangular area was selected within the City of Las Vegas. Figure 6a displays the area on which the validation process was applied. The image in Figure 6b was obtained from the image classification process for the four showing classes (in the legend), which were manually determined. Commercial building roofs and high-reflectance soils were classified as high-albedo, and roads and water bodies were classified as low-albedo. Shadow was mainly represented by the shadows of large buildings. As shown in Figure 6b, SMA was applied on the closest available Landsat imagery, acquired on May 10, 2010, in the same area on the first four bands of PCA and the last four bands of MNF, based on the four endmember types obtained from Figures 4 and 5.

Figure 6. a) NAIP imagery (7 May 2010) of a random area in the City of Las Vegas b) Classified image.

Figure 7 shows the relationship between the estimated fractions of each endmember by SMA and NAIP imagery classifications. According to Figure 7, high-albedo, low-albedo, and vegetation can be estimated with higher correlation coefficient by PCA-Normalized ($r = 0.58$ to $r = 0.79$). In addition, MNF- Original shows the highest correlation coefficient for vegetation ($r = 0.81$). The calculated fractions for shadow have low-correlation coefficients. The possible reason might be that a shadow moves along the ground throughout the day, and the NAIP imagery and the Landsat images were not taken at the same time of day, therefore, the fraction of shadow in the NAIP imagery differs from that of the Landsat images.

Figure 7. Relationship between the estimated fractions of each endmember by NAIP imagery classification and applied methods (7 May 2010).

Figure 8 shows component-based signatures of endmembers for PCA-Normalized and MNF-Original. The first band of PCA (PCA1) and the last band of MNF (MNF6) clearly represent the endmembers. In contrast, endmember values of PCA's last band (PCA4) and MNF's first band (MNF3) were in the lower range and were relatively hard to recognize.

Figure 8. Reflectance characteristics of the endmembers for PCA-Normalized and MNF-Original (7 May 2010).

5.2 Trend Analysis

According to the correlation coefficients obtained in Figure 7, PCA-Normalized and MNF-Original datasets were selected as the data preparation methods used to apply SMA on Landsat 5 TM images from 2004 to 2011. SMA was applied to 76 cloud-free PCA-Normalized and MNF-Original images (Landsat 5 TM). The calculation process was pixel by pixel, and the result of each pixel was independent of the other pixel results.

The mathematical process was applied to satisfy Equation (2) with the constraint equations, (3) and (4). Accordingly, the summation of the endmember fractions in each pixel must be equal to 1; however, the results showed some errors for certain pixels. One way to determine errors was to find the summation of the four fractions and set the acceptable range as high and low limits for the data. As a result, 1.1 and 0.9 were assumed as the high and low limits, respectively. An unreliable pixel was defined as a pixel with a summation either less than 0.9 or greater than 1.1. Therefore, the ratio of number of unreliable pixels to all pixels was calculated for the two solar plants.

Figure 9 shows the percent of error in each area for the two datasets. According to Figure 9, the calculated results by PCA-Normalized had less error percentage to compare with MNF-Original. The average percentage error for PCA-Normalized results at Nevada Solar One and the Nellis Solar Power Plant area were 3.09% and 6.81%, respectively; the average percentage error for MNF-Original results were 29.09% and 32.86%, respectively. A possible reason for the lower errors in Nevada Solar One was that this facility was located out of town, and so the pixels were not filled by complicated and mixed endmembers. The Nellis Solar Power Plant is located within a urban area; therefore, pixel structures were more complicated than in the desert. Further,

the results of SMA on PCA-Normalized had a higher number of errors during winter and summer and a lower number of errors in fall and spring; in contrast, the error plot of MNF-Original did not have a specific pattern. Consequently, SMA on PCA-Normalized resulted in the highest accuracy.

Figure 9. Percentage of error in calculated land-cover fractions from 2004 to 2011.

The time series of endmember changes, obtained from SMA on PCA-Normalized, were plotted for Points 1A and 1B within the two facilities areas (Figures 10 and 12), and Points 2A and 2B for outside of the facilities (Figures 11 and 13).

Figure 10. Time series of land-cover types at Point 1A, located inside Nevada Solar One.

Figure 11. Time series of land-cover types at Point 2A, located outside Nevada Solar One

Figure 12. Time series of land-cover types at Point 1B, located inside the Nellis Solar Power Plant.

Figure 13. Time series of land-cover types at Point 2B, located outside the Nellis Solar Power Plant.

For clarity, high-albedo and low-albedo fractions were plotted separate from vegetation and shadow fractions. Mean fraction values of endmembers for pre-installation, syn-installation, and post-installation at Points 1A, 2A, 1B, and 2B were calculated (Table 2).

Table 2. Mean values of Endmembers for Pre-installation, Syn-installation, and Post-installation at Points 1A, 2A, 1B, and 2B.

Point	Endmember	Pre-Installation	Syn-Installation	Post-Installation
Point 1A	HA	18.47	39.18	19.13
	LA	53.01	46.05	63.12
	SH	25.98	14.77	16.38
	VG	2.53	0.001	1.36
Point 2A	HA	20.31	19.6	18.53
	LA	46.5	48.84	50.77
	SH	30.46	29.47	30.42
	VG	2.73	2.08	0.27
Point 1B	HA	28.58	28.99	18.19
	LA	26.37	26.05	42.3
	SH	44.91	44.84	39.43
	VG	0.14	0.12	0.07
Point 2B	HA	28.99	29.93	26.72
	LA	21.34	22.53	21.86
	SH	49.54	47.54	50.9
	VG	0.13	0.001	0.53

The results for Point 2A, which is located outside of Nevada Solar One at a distance of 1500 m from Point 1A, show that the endmembers fractions were not affected by solar-facility construction (Figure 11). In other words, the mean value of the endmember fractions for pre-installation, syn-installation, and post-installation did not change significantly (Table 2). In Point 2A, low-albedo had the highest fraction and vegetation had the lowest fraction. The low value of the vegetation fraction seems logical because the facility is located in an arid area with a low

amount of vegetation. In addition, the dominant land-cover type in the area is shrubland and barren, which is represented as a combination of mostly low-albedo, high-albedo, shadow, and a small amount of vegetation.

The time series plot of endmember types at Point 1A, located inside Nevada Solar One, showed different behavior (Figure 10). The low-albedo fraction increased after the construction, and decreased during the construction. Furthermore, the high-albedo fraction increased during construction, and then slightly decreased after the installation of the solar panels. Similarly, the shadow fraction decreased after construction; again, there was no significant change for the vegetation fraction for pre-construction and post-construction. Solar panels are relatively dark objects, and are constructed to absorb sunlight. Thus, a slight reduction of high-albedo and increase of low-albedo was expected after construction. During construction, because the surface is being prepared for installation of the solar panels, shrub removal, the land cover would be bare soil, which is brighter when compared to shrubland. Therefore, high-albedo is increased and low-albedo is decreased during the construction phase.

Figure 12 and 13 show similar results for the Nellis Solar Power Plant. Figure 12 shows the changes for the time series of the endmember types for Point 1B within the facility's area, and Figure 13 for Point 2B outside of the facility. The low-albedo fraction increased and the high-albedo fraction decreased after construction at Point 1B within the facility (Table 2). The shadow fraction decreased slightly after the construction, and the fraction of vegetation was close to zero before and after the construction at Point 1B. Figure 13 displays the time series of the endmember changes at Point 1B, which was located 850 m from Point 2B. According to the plots, the endmember fractions in areas outside of the facility did not change significantly by the construction of the solar facility.

In order to compare the endmember fractions during pre- and post-construction in the entire area, the mean value of each endmember fraction in each pixel for pre-construction was subtracted from the post-construction value of that pixel. Figure 14 show the results for Nevada Solar One and Figure 15 for the Nellis Solar Power Plant. The following equation summarizes the operation:

$$\Delta F = F_{pre} - F_{post} \quad (6)$$

Where ΔF is image of land cover change, F_{pre} is the mean value of endmember fraction for pre-construction, and F_{post} is the mean value of endmember fraction for post-construction.

In Figures 14 and 15, the gray color represents a zero value, which means that no changes occurred in those pixels between pre- and post-construction in terms of the corresponding endmember type. Moreover, darker color indicates lower values, which represent an increase of the fraction after the installation. Similarly, brighter color indicates higher values, which means that the fraction of the endmember decreased after construction. It can be seen that the color of the pixels that include solar panels for low-albedo is darker than any other areas (Figures 14 and 15), which means that the fraction of low-albedo surface increased after construction. The plant borders are relatively bright because the soil had been disturbed; however, no solar panel was installed there to absorb the light and increase the low-albedo. Equally, the colors of bordering pixels are darker than other areas in high-albedo, which indicates an increase of high-albedo fractions. It shows that disturbed or bare soil reflects the sunlight more than the solar panels.

Figure 14. Mean difference of pre- and post-installation at Nevada Solar One for a) high-albedo, b) low-albedo, c) shadow, and d) vegetation.

Figure 15. Mean difference of pre- and post-installation at the Nellis Solar Power Plant for a) high-albedo, b) low-albedo, c) shadow, and d) vegetation.

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529 Moreover, in the shadow images, the solar panels areas are brighter than other areas. The
530 decrease in the shadow fraction occurred due to installation of the solar panels. According to
531 Figure 7, the correlation coefficient of shadow was low; thus, the shadow fraction images do not
532 have high accuracy. Generally, in Nevada Solar One, rows of parabolic concentrators with
533 mirrors are used to exploit the sun's energy. Because the concentrators track the sun's location,
534 they are built at regular spaces to catch the sunlight with the maximum efficiency. Thus, it is
535 expected that shadow exists in the distance between the concentrators. In contrast, the Nellis
536 Solar Power Plant uses photovoltaic solar panels. In this case, the solar panels were installed
537 separately (not in rows) and relatively close to each other. Therefore, the fraction of shadow in
538 the area of the Nellis Solar Power Plant should be less than for Nevada Solar One.

539 Vegetation fractions did not change significantly from pre- to post-construction.
540 Consequently, the color of the endmember image for vegetation, which represents changes due
541 to solar-facility construction are almost the same all over the areas, and even the facilities are
542 relatively hard to distinguish in Figures 14 and 15. The reason is that the facilities were
543 constructed in arid areas, therefore, the amount of vegetation is negligible from the beginning of
544 construction onwards. According to Figures 14 and 15, it was expected that this method will
545 reveal a halo of impacted pixels in the immediate vicinity of solar installations. The output
546 revealed no such halo. Nevertheless, we conjecture that such effect will be profound in areas
547 with higher vegetation. It means that, based on the aforesaid analysis, the effect of solar facility
548 construction on land-cover patterns in neighboring area is negligible in this area (especially
549 Figure 14 that shows NS-1 which has been built outside the urban area).

550

6. Summary and Conclusions

In this paper, the effect of two USSE installations on land cover in an arid environment was studied. This study was conducted at Nevada Solar One and the Nellis Solar Power Plant in the southwest region of the U.S., both installed within the last decade. The effects were measured using changes in the land-cover types surrounding and within each facility.

Two common methods for spectral data treatment were tested: principal component analysis (PCA) and minimum noise fraction (MNF). According to the validation process, PCA-Normalized and MNF-Original datasets were selected as the data-preparation method. Land-cover types were defined based on a two-band scatter plot of pixels. The common endmembers in all the scatter plots were determined as high-albedo, low-albedo, shadow, and vegetation. In order to understand effect of solar facility construction on the environment, the changes for land-cover trends were compared using pre- and post-installation land-cover fractions.

SMA was applied on PCA-Normalized and MNF-Original of Landsat 5 TM images from 2004 to 2011 in the two areas. The average percentage error plot for PCA-Normalized and MNF-Original in Nevada Solar One area and the Nellis Solar Power Plant showed that the PCA-Normalized method had a higher accuracy. Land-cover analysis of the points located close but outside of the facilities (Point 2A and Point 2B) showed that the mean value of endmember fractions for pre-installation, syn-installation, and post-installation did not change significantly. On the other hand, results of land-cover analysis of the points located within the facility showed that the low-albedo fraction increased and the high-albedo fraction decreased after construction. The shadow fraction decreased slightly after construction, and the fraction of vegetation was close to zero before and after the construction, due to the plants being constructed in an arid area.

The results of this paper generally appertain to the effects of USSE installations on land-cover trends in arid environments. The results might be different in other areas, especially where the vegetation fraction was higher. In addition, endmember types that indicated that various classes of land-cover types could be different in other studies. For example, low-albedo could represent water bodies and asphalt, even low these two land-cover types could be defined individually as endmembers. This study indicated that except for the long-term effects of USSE plants on the environment, land-cover patterns in the case of high-albedo, low-albedo, shadow, and vegetation altered significantly inside the solar plant areas.

Due to increasing trends in USSE plant construction, it is important to understand its short- and long-term effects on the environment and land cover. The significance of this research is determination of land-cover change caused by construction of USSE plants. It provides useful insight into their effects on land cover at two plants in Nevada.

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Appendix A. Table of acronyms

CDR	Climate data record
CSP	Concentrating solar power
DN	Digital numbers
HA	High albedo

594	LA	Low albedo
595	LCA	Life-cycle assessment
596	MNF	Minimum noise fraction
597	NAIP	National agriculture imagery program
598	NS-1	Nevada solar one
599	NSPP	Nellis solar power plant
600	PCA	Principal component analysis
601	PV	Photovoltaic
602	RGB	Red green blue
603	SH	Shadow
604	SMA	Spectral mixture analysis
605	TM	Thematic mapper
606	TOA	Top-of-atmosphere
607	USSE	Utility-scale solar energy
608	VG	Vegetation
609		

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