Evaluating 25 Years of Environmental Change Using a Combined Remote Sensing Earth Trends Modeling Approach: A Northern California Case Study

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This thesis titled
Evaluating 25 Years of Environmental Change Using a Combined Remote Sensing Earth Trends Modeling Approach: A Northern California Case Study

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ABSTRACT

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Evaluating 25 Years of Environmental Change Using a Combined Remote Sensing Earth Trends Modeling Approach: A Northern California Case Study

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Mountain glaciers are an important resource for monitoring how regions are being affected by global environmental changes because their advance and retreat are influenced by fluctuations in precipitation and temperature. Using Mt. Shasta in northern California as the study area, this thesis employed a time-series approach to remote sensing image analysis coupled with a Markov-based procedure to demonstrate how remote sensing can be used to define the environmental trajectories active in the region and project those trends into the future. This experimental approach was applied to a series of yearly images from 1985 to 2010 to examine the long-term implications of environmental change and then the trends were projected forward in varying increments to 2110. The long-term change signal showed that El Nino cycles strongly influenced regional land cover patterns and controlled glacial advance and retreat. When this pattern was projected into the future, two scenarios were observed: 1) growth if El Nino cycles strengthen or 2) recession if El Nino cycles weaken.

Approved: _____________________________________________________________

James K. Lein

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CHAPTER 1: INTRODUCTION

Environmental change is a pressing global issue that displays differing regional effects. Some areas are experiencing more intense droughts. Others are receiving abnormal amounts of rain. Whether they are found in Antarctica or in mountainous regions, it is widely agreed that glaciers are getting smaller as a result of increasing global temperatures and that glacial melt water is contributing to global sea level rise. In response to the changes occurring throughout the world, the USGS recently published the results of a 50-year study on shifting climate and shrinking glaciers in the Pacific Northwest and Alaska (USGS 2009). This study found that while the Pacific Decadal Oscillation (a phenomenon similar to El Nino) has some control over the growth and recession of mountain glaciers, this control is becoming weaker as global temperatures rise. Glaciers in the study area have been losing mass over the last 50 years, and this loss in mass has been accelerating over the last 15 years (USGS 2009). Since glaciers are often a source of drinking water in some places, these results are disturbing.

However, glacial responses to environmental changes can vary from glacier to glacier. No one glacier or group of glaciers is able to represent all glaciers in terms of environmental change trends and therefore the state of each glacier needs to be individually monitored and assessed (Pelto and Riedel 2001). With extreme changes like droughts, floods, fires, sea level rise, and increased storm activity occurring, it is important that environmental changes be studied and monitored across the globe. For instance, at least two glaciers on Mt. Shasta in northern California appear to be experiencing a period of growth rather than recession. When the growth trends, along
with temperature and precipitation data, are projected into the future, two different results occur. The results from one model show the glaciers getting smaller and ultimately disappearing this century. The results from another model result shows that the glaciers will stay approximately the same size and then begin to grow again (Howat et al. 2007). If the glaciers were to disappear, it would have a devastating impact on the water resources in the region. Because of this, environmental monitoring methods need to be employed. With environmental monitoring, the status of the glaciers can be evaluated and projected over time to look for undesirable changes.

Glaciers are also important for determining the effects that global climate patterns are having on a region. They require a certain range of climatic conditions in order to continue to exist and could potentially be thought of as environmental monitors, as they fluctuate in size in response to changing precipitation and temperature trends. If temperatures are warming or precipitation is decreasing in a region that contains mountain glaciers, they would register those changes by shrinking. Because they are so sensitive to outside changes, it is important to monitor them.

Environmental monitoring is often done through the use of change detection analyses. Principal components analysis and Markov chains are two widely used and accepted forms of change detection. Principal components analysis takes the inputs of multiple bands, applies a linear transformation to them, and produces a set of new images ordered in terms of the amount of variance explained in the original data (Eastman and Fulk 1993). This technique is useful for isolating trends within the data or for reducing data dimensionality. Markov chains take two input images, one from an earlier date and
one from a later date, and compute the probability that the pixels in the images will change to a different state at some date in the future (Lein 1989). This technique offers a means of projecting environmental trends into the future to explain what the likely land use patterns will be. The results can be given to planning committees so that they can adjust policies if these changes are undesirable.

Study Questions

Mountain glaciers are experiencing different patterns of advance and retreat in different regions on the planet. The purpose of this research is to demonstrate how remote sensing can be used to analyze environmental change trends and project these trends into the future for the purpose of environmental monitoring. Using Mt. Shasta in northern California as the study focus, the research presented here seeks to examine the following questions:

1) What are the environmental trends taking place in the Mt. Shasta study area?

2) What are the long-term implications in regards to environmental change when those trends are projected into the future?

By employing a time-series approach to remote sensing image analysis coupled with a Markov-based procedure to extrapolate changes into the future, this study demonstrates how long-sequence satellite data can illuminate trends that present challenges to environmental resource management.
CHAPTER 2 – THE IMPORTANCE OF ENVIRONMENTAL CHANGE AND HOW IT CAN BE EVALUATED

Environmental change is an important topic in geographic literature. Regions can experience different environmental changes in response to global stimuli like the El Niño Southern Oscillation or global warming, and these changes often have devastating impacts like intense droughts, flooding, or glacial retreat. The differing impacts in regions around the world lead to a need for environmental monitoring. Environmental monitoring can be done easily and effectively with remote sensing. While there are many possible remote sensing methods that can be employed, principal components analysis and Markov analysis are among the most widely used.

Human Vulnerability to Environmental Change

As environmental conditions shift over time and populations continue to grow, it becomes increasingly important to study the patterns of environmental change and look for trends. Understanding these patterns of change is important for determining human vulnerability, exposure, sensitivity, and adaptive capacity in terms of socio-economic risks, water scarcity, and crop failures (Gergis and Fowler 2009). While it is not agreed upon in the scientific community about how extreme changes have been, it is agreed that regional changes have occurred (Burton 1997). Regional changes can increase or decrease erosion, runoff, flooding, and CO₂ concentrations, promote climate change, and increase or decrease biodiversity (Mas 1999). More people are finding themselves vulnerable with the expansion of urban areas into hazard-prone areas, and vulnerability is exacerbated by environmental changes.
Vulnerability

Vulnerability is the understanding of how susceptible a system is to changes, and its ability to cope with adverse effects from these changes (Adger 2006). It is a complex concept involving many factors such as exposure, sensitivity, and adaptive capacity. Exposure is the magnitude, frequency, and areal extent of the stress being generated (Adger 2006). Sensitivity is the degree to which the system is affected by the stress (Adger 2006). Finally, adaptive capacity is the ability of the system to accommodate the stress (Adger 2006).

Vulnerability and adaptive capacity in the face of environmental change emerged concurrently with the growing awareness that environmental changes were taking place (Smit and Wandel 2006). The use of the term “adaptation” to discuss human systems can be traced back to ecologist and anthropologist Julian Steward, and has since been used in the study of natural hazards, political ecology, and food security (Smit and Wandel 2006). Many different vulnerability theories have emerged, in a variety of disciplines. As an understanding of how environmental changes affect human vulnerability continues to develop, interest has started to turn towards the El Nino Southern Oscillation phenomenon and how it causes regional changes and affects vulnerability around the globe.

El Nino and La Nina

El Nino is a phenomenon that occurs in the Equatorial Pacific when the trade winds weaken or reverse (Sverdrup et al. 2006). The low and high pressure regions in the Pacific Ocean change position, which is called the Southern Oscillation (Sverdrup et al. 2006).
Eventually the trade winds collapse altogether, the body of warm water normally found in the west equatorial Pacific moves to the east, and upwelling shuts down along the coast of Peru, leading to an elevation of sea surface temperatures (Sverdrup 2006). La Nina is the reverse. El Nino tends to cause droughts, flooding, fires, and extreme hurricane activity (Gergis and Fowler 2009). During the time of El Nino, the northern United States experiences warmer winters while the eastern United States experiences more rainfall (Sverdrup 2006). The El Nino and La Nina event phases occur every two to seven years and when the phases occur, they can last 18 to 24 months (Gergis and Fowler 2009).

These events are measured primarily by the NINO3 index, an index that is computed by analyzing sea surface temperature anomalies and their departure from normal monthly sea surface temperatures (Vecchi and Wittenberg 2010). When the NINO3 values are highly positive, El Nino conditions are being detected (Vecchi and Wittenberg 2010).

The role that global changes play in the strength, frequency, and duration of El Nino and La Nina events is widely debated. One study compiled the results of multiple climate reconstructions of past El Nino and La Nina events from ice cores, coral, tree rings, and documented histories into a record of events from A.D. 1525 to 2002. There were 92 El Nino events and 82 La Nina events documented (Gergis and Fowler 2009). The researchers found that the strength, frequency, and duration of El Nino and La Nina events vary over time from weak to extreme (Gergis and Fowler 2009). They also noticed that 55% of these extreme event years since A.D. 1525 occurred during the 20th century,
and that 30% of these event years occur after 1940, indicating that an increase in extreme events has been taking place very recently over the past 50 to 100 years (Gergis and Fowler 2009; Vecchi and Wittenberg 2010). Whether this increase is natural or a result of anthropogenic activity is still up for debate.

Results from models show that the strength of El Nino events has possibly changed as a result of variations in the shape of the Earth’s orbit over the past 6000 years, while other results from the fossil record show that El Nino variability existed around 130,000 years ago and that it can persist during glaciations (Vecchi and Wittenberg 2010). Models attempting to determine future trends predict that increases in global CO$_2$ levels are expected to intensify the precipitation anomalies caused by El Nino (Meehl 1997; Gergis and Fowler 2009); this means that areas where precipitation increases as a result of the El Nino events will likely experience even more rain and flooding. Areas that generally undergo a decrease in precipitation as a result of the events will likely experience even less precipitation and more droughts and fires. Some models even predict that El Nino activity will decrease as a result of increased CO$_2$ (Vecchi and Wittenberg 2010). Regardless of the causes and consequences of El Nino variability, variability exists, and it can cause adverse effects across the globe. This makes monitoring and predicting the trends very important.

**Glacial Response to Environmental Change**

Continental glaciers are not the only bodies of ice that respond to environmental changes. Mountain glaciers tend to reflect the influences of these changes as well, specifically in regards to precipitation and temperature, perhaps even more so than
continental glaciers because they require a certain range of climatic conditions at a smaller spatiotemporal scale to continue to exist (Owen et al. 2009). If mountain glaciers melt as a result of environmental changes, they can be responsible for a variety of hazards including glacial lake outburst floods, slope failures, farmland abandonment, reduction in reservoir longevity, changes in river channels, and finally global sea level rise (Owen et al. 2009). Mountain glaciers around the world are shrinking in response to changing climatic conditions (Owen et al. 2009). However, responses to climate vary from glacier to glacier, meaning no one glacier can represent all glaciers in terms of environmental change trends and therefore each glacier needs to be individually monitored (Pelto and Riedel 2001).

An example of how mountain glaciers can vary by location is a study conducted by Pelto and Riedel (2001) on glaciers in the North Cascades, Washington. This study found that mountain glaciers in that particular region lost mean glacial thickness from 1984 to 1994, but appeared to regain glacial thickness slightly from 1995 to 2000, with variations in these patterns depending on what side of the precipitation divide the glaciers were located on (closer to or farther away from the ocean). A different study conducted by Molnia (2007) on mountain glaciers in Alaska found that a significant amount of these glaciers have been in retreat since the Little Ice Age in response to a documented rise in regional temperatures. While about 98% of these Alaskan glaciers seem to be in retreat, some are actually advancing, while others fluctuate between retreat and advance.

Glaciers located on Mt. Shasta in northern California appear to have a different response to rising global temperature trends. A study by Howat et al. (2007) documented
that the glaciers on Mt. Shasta have not retreated like the other glaciers in the Cascades region. By studying two of active glaciers, Whitney and Hotlum, on Mt. Shasta through the use of aerial photography from 1920 to 2003 and ice-penetrating radar, they found that despite some glacial retreat in the early part of the 20\textsuperscript{th} century, Whitney and Hotlum glaciers have actually advanced despite the temperature trends and that their volumes have stayed relatively stable. They determined that glacial conditions on Mt. Shasta are controlled more by precipitation than they are by temperature.

The precipitation trends appear to be partially controlled by the Pacific Decadal Oscillation, as well as El Nino and La Nina cycles. The El Nino cycles cause increased winter precipitation in the region of Mt. Shasta, while the glaciers to the north receive a decrease in winter precipitation. Using two different models, one using trends documented in their study and the other using trends predicted by climate model known as RegCM2.5, Howat et al. obtained differing results. The first model scenario showed that the two glaciers would start growing by the year 2040. The second model scenario showed that Whitney Glacier would shrink 65-75\% by 2080 and the Hotlum Glacier would be completely gone by 2065. These results appear to be controlled by the model data inputs with precipitation being the dominating factor in the first model and temperature being the dominating factor in the second model.

Using Remote Sensing to Study Environmental Change

An easier way to examine environmental changes is through the use of remote sensing. Remote sensing is an analysis technique made possible in the 1970s by advancements in computer and satellite technology. It is the science and art of obtaining
data and analyzing it without actually being in contact with the surface (Jensen 2005). Sensors on board satellites or airplanes measure the amount of electromagnetic radiation being either reflected or absorbed from objects on the earth (Jensen 2005). This information is recorded by the sensor into a pixel as a digital number, which represents the level of brightness (Jensen 2005). Objects with higher brightness levels are reflecting more electromagnetic radiation, while objects with lower brightness levels are absorbing more electromagnetic radiation (Jensen 2005). These individual pixels make up the remotely sensed image (Jensen 2005). Analysts can then process the image data and analyze its usefulness. The usefulness of the data depends on what the analyst is specifically looking for and trying to study.

Remote sensing can be a powerful tool for environmental analysis. Large amounts of data can be processed fairly quickly through a variety of commercial or open-source software. The processing speed allows analyses and classifications of data to be repeated with ease or adjusted until the results are as accurate as possible (Gao 2009). It does not matter who is operating the software. As long as the inputs are the same, the results should be same (Gao 2009). It is important to note that the results will not necessarily be the same across different software or if the analyst alters or misses a step. Even the smallest error can produce a large variation.

Remote sensing also does not necessarily require field work, as ground truth verification can be conducted using a higher resolution image or a software package like Google Earth, making it a safe and efficient way to examine the environment. However, the high-quality images required for certain analyses can be expensive to obtain or
restricted to governmental purposes only, and image analysis requires intensive training in order for an understanding of the data and the software to be acquired (Gao 2009).

Analyzing Change

The analysis of remotely sensed imagery has been used in many studies of environmental change, environmental change detection, and vulnerability assessments due to changes. Change detection is a form of multi-temporal remote sensing where multiple images from multiple time periods are compared on a pixel to pixel basis to determine what has changed (Gao 2009). Changes in radiance values associated with changes in land cover are often large and easily distinguishable from changes due to sun angles and atmospheric conditions (Mas 1999). Remote sensing data also provide a way for environmental changes to be quantified by type, amount, and location (Wu et al. 2006).

A variety of change detection techniques have been developed to study land use and land cover change as it relates to environmental change (Fan et al. 2008). Markov chains (Brown et al. 2000; Fan et al. 2006; Wu et al. 2006) and principal components analysis (Eastman and Fulk 1993; Roberts et al. 1994; Li and Kafatos 2000) have been employed in many studies to look for and analyze patterns. Other techniques for monitoring land cover changes include image differencing, vegetative index differencing, and post-classification change differencing (Mas 1999).

Image Differencing

Image differencing consists of subtracting one image at one date from another image acquired on another date (Gao 2009). Image ratioing is similar but divides one
image from one date by another image from a different date (Gao 2009). Since each pixel records only one digital number, changes can be quantified in this method. If changes have not occurred, the pixel values should be the same in both images. As a result, in image differencing, areas of no change will show up in the resulting image as values of zero. Areas of no change in image ratioing will show up as values of one. Any changes that have occurred between the two images will show up as positive or negative numbers in image differencing, and whole or decimal numbers in image ratioing (Gao 2009).

From here, the analyst has to decide which changes are important by setting a threshold for change versus no change, and figure out what changed. Both methods are easy to implement and have their own limitations. For instance, results from image differencing can be skewed by variations from sun illumination and seasonal differences, and the nature of change can be difficult to detect (Gao 2009). Image ratioing can also be skewed by variations from sun illumination and seasonality, but it is easier to detect change relationships with this method (Gao 2009).

Vegetative Index Differencing

Vegetative index differencing often uses the normalized difference vegetation index (NDVI) to analyze changes. In this method, two bands from one image can be divided by each other to produce an NDVI band. With two NDVI bands from two different dates, the user can perform image ratioing to determine where changes have occurred (Gao 2009). This method produces meaningful results because a special NDVI classification scheme has been developed and it is widely used. The user simply compares the results to the NDVI classification scheme to see what has changed.
Post-classification Change Detection

In post-classification change detection, the user classifies the pixels in each remotely sensed image into different land cover classes. These codes can correspond to anything as long as they make sense and are meaningful to the analyst. Land cover codes simplify the information contained in the images. Once the images have been classified, the analyst can compare the land cover types found in each image to each other to look for increases or decreases in land cover types (Gao 2009).

Principal Components Analysis

Principal components analysis differs from the above mentioned methods. It is a form of image transformation used to reorganize the information contained within image bands in terms of importance (Gao 2009). It is used to identify the most informative image bands and reduce the number of images needed to display information (Gao 2009). It can also be used to isolate trends within the dataset. To do this, a linear transformation is applied to a series of image bands in order to create a new set of images ordered in terms of the amount of variance explained in the original data (Eastman and Fulk 1993). Each image in this new, ordered set is a called a component. The first component contains the most variance contributed to the image series, and could be considered to be the average characteristic of the input images. The remaining components illustrate change elements within the image set, organized by decreasing magnitude (Eastman and Fulk 1993). PCA is the most widely used approach to study El Nino events (Gergis and Fowler 2009). Problems exist though in giving meaning to these components. It is up to the individual researcher to make decisions about what components are important and
what components represent noise based upon their interpretation of the study area and
data and the problems being addressed in the research (Roberts et al. 1994).

A debate exists over the best way to conduct a PCA for time series analysis.
Roberts et al. (1994) documents the arguments for using standardized versus
unstandardized components. Many people claim that the standardized components
method is superior for time series analysis (Mas 1999; Eastman and Fulk 1993). In this
method, all of the input images are forced to carry the same weight and have equal
importance as each other, and a correlation matrix is calculated from the Z-scores of each
image used. It is thought that this method causes output images to contain more
information. Eastman and Fulk (1993) used standardized components and PCA to study
changes over 36 months in AVHRR-derived NDVI images of Africa with much success.
Using this method, they were able to identify seasonal changes and even changes related
to El Nino. Li and Kafatos (2000) conducted a similar study over an 11-year period on
vegetation response to El Nino in the United States. One of their component results
showed a possible relationship between vegetation variability and precipitation and
temperature trends influenced by El Nino as well.

Roberts et al. (1994) argues that NDVI images are already standardized and
therefore do not need to be standardized by PCA. Because they do not need to be
standardized, unstandardized components should be used for time series analysis using
NDVI imagery. They argue also that real-world reflectance values become lost through
the use of standardized components, and the changes in reflectance values are needed to
understand vegetation changes. To illustrate these points, they conducted a study of the
Everglades in south Florida using 21 time-sequential AVHRR-derived NDVI images to look at the effects of global warming and hurricanes to the area with some success. Since both methods give successful results, the decision of which to use is ultimately up to the analyst, what imagery they are using, and what patterns they are trying to capture.

Markov Analysis

Another common method in remote sensing to study landscape changes is the use of Markov analysis. While the above methods focus on what changes occurred during the past, this method focuses on what changes can be predicted into the future if the changes that have occurred continue to occur. It is useful for making long-term preparation plans and policy changes if the changes predicted are undesirable.

This method uses two images, one from an earlier time period and one from a later time period, and determines the probability that a pixel at one state and one time period will still be at that state or at a different state at the next step of the sequence, based on the changes that occurred between the two input images (Lein 1989). In mathematical terms, an image cell \([C]\) at one point in time \([t]\) and one state \([S_1]\) has a set of probabilities \([P_1, P_2, P_3 \ldots P_n]\) that the cell \(C\) will either move to another land use/land cover state or remain in the same state \([S_1, S_2, S_3 \ldots]\) at a later time \([t + 1]\), given that it was in state \(S\) at time \(t\) (Lein 1989). This is done by a computation of a transition probability matrix, which calculates the transition probabilities from each cover class to all of the other cover classes in the image (Eastman 2009).

It assumes that land use/land cover changes are stochastic (randomly determined) processes and that different land use/land cover categories are the different states of the
chain (Weng 2002). Markov analysis shows the possible magnitudes and directions of environmental changes, regardless of whether the trend persists or not (Fan et al. 2008). In the past, Markov analysis input images consisted of field surveys, maps, or aerial photography, but advances in satellite remote sensing have improved the use and efficiency of Markov analyses (Fan et al. 2008).

This method has been used in a wide variety of studies in conjunction with other methods. For instance, Fan et al. (2008) used Markov chains with GIS, cellular automata models, and change detection to determine how land use and land cover was changing in the Pearl River Delta of China over a 5 year period, and then projected those trends 10 years into the future to determine how change was likely to proceed. They found that forest changed to farmland, farmland changed to urban, and given these trends, urban expansion was likely to increase in the future as more land transitioned to urban. Another study by Wu et al. (2006) that studied land use changes in Beijing used Landsat imagery, GIS, regression analysis, and Markov chains. They used a classification scheme consisting of 6 classes and Markov chains to determine how land use was likely to change twenty years in the future. Their methods predicted that urban land would increase significantly and a lot of agricultural land would be lost. Both studies’ results have further applications in the world of urban planning. They could help decision makers modify policies before too much usable land is lost to urban expansion.
CHAPTER 3 – MT. SHASTA AND SURROUNDING REGION

The study area of Mt. Shasta and the surrounding region was chosen because of the mountain glaciers located on Mt. Shasta. Based on the assumption that mountain glaciers reflect changes in regional and global climate, it was hoped that patterns of change would be displayed in the glaciers on Mt. Shasta. This area was also chosen because of California’s rising state population, drier climate, and inadequate amount of water resources for its population.

Geographic Location

The study area is Landsat 4-5 TM Path 45 Row 31, is approximately 170 km north-south by 183 km east-west (EROS 2010), and is located in a region of northern California and southern Oregon. Portions of the counties of Siskiyou, Modoc, Shasta, Trinity, and Humboldt in California and Josephine, Jackson, and Klamath in Oregon are included in the study area, as well as the cities of Medford, Ashland, Grants Pass, Klamath Falls, Altamont, Weed, Yreka, and Castella. The study area location is depicted in Figure 1.
Geologic Setting

The study region lies in the southernmost portion of the Cascades Range. There are several volcanoes located in the region, including Medicine Lake and Mt. Shasta. Mt. Shasta is the focus for this study, and it is a stratovolcano around 4,316.6 meters in elevation and the second highest peak in the Cascades Range (Blodgett et al. 1996). It is made up of four different overlapping cones and considered to be active (Blodgett et al. 1996). The last known eruption was in 1786 (Wood and Keinle 1990). As a result of the
volcanic activity, the area around Mt. Shasta, specifically Shasta Valley, contains debris avalanche deposits that are approximately 300,000 years old, and also andesitic air fall tephra, pyroclastic flows, and lahar deposits (Brantley and Glicken 1986). In addition to the deposited volcanic materials in the area, five glaciers are located on Mt. Shasta, including Whitney glacier. There is an estimated 1.4 billion cubic meters of ice and snow located on the volcano (Blodgett et al. 1996). This glacial ice provides the primary water source (Cold Creek Springs at 1341.12 meters on Mt. Shasta) for the City of Mt. Shasta (City of Mt. Shasta 2011).

Regional Climate

This area of the United States typically has wet winters and dry summers (Trouet et al. 2009). Oregon typically receives more precipitation and is generally cooler than California (Gleason 2011). During the month of August, precipitation is often below 1.3 centimeters in California and around 1.3 centimeters in Oregon (Gleason 2011). As a result of the low precipitation, fires frequently occur during the summer (Trouet et al. 2009). In addition to these conditions, more winter snowfall tends to occur during El Nino years as the Pacific winter storm track moves south towards central California (Howat et al. 2007).

Socioeconomic Conditions

According to data from the US Census Bureau, displayed in Figure 2, this area of California is characterized by an increasing population. By doing simple ratio calculations in Microsoft Excel using population growth projections for the state of California and state of Oregon from the year 2000, it can be seen that the population is
expected to keep increasing. According to the United States Census Bureau, the population is predominately white and between the ages of 18 and 65, with poverty levels above the national average (U.S. families below poverty level: 9.9%; U.S. Individuals below poverty level: 13.5%), as can be seen by Table 1 and Figure 3.

Figure 2: The current and projected population trends in the study area.
Table 1: This table illustrates the socioeconomic status of the population in the study area.

<table>
<thead>
<tr>
<th>County</th>
<th>% Families Below Poverty Level</th>
<th>% Individuals Below Poverty Level</th>
<th>% Unemployed</th>
<th>% Under 18</th>
<th>% Over 65</th>
</tr>
</thead>
<tbody>
<tr>
<td>Siskiyou</td>
<td>11.0</td>
<td>15.4</td>
<td>10.6</td>
<td>21.0</td>
<td>19.4</td>
</tr>
<tr>
<td>Modoc</td>
<td>13.7</td>
<td>15.8</td>
<td>7.1</td>
<td>20.4</td>
<td>19.8</td>
</tr>
<tr>
<td>Shasta</td>
<td>11.6</td>
<td>15.4</td>
<td>10.5</td>
<td>23.0</td>
<td>15.8</td>
</tr>
<tr>
<td>Trinity</td>
<td>8.5</td>
<td>15.1</td>
<td>10.9</td>
<td>17.4</td>
<td>26.8</td>
</tr>
<tr>
<td>Humboldt</td>
<td>12.2</td>
<td>18.2</td>
<td>7.9</td>
<td>20.2</td>
<td>13.0</td>
</tr>
<tr>
<td>Josephine</td>
<td>13.2</td>
<td>17.3</td>
<td>9.2</td>
<td>20.5</td>
<td>21.7</td>
</tr>
<tr>
<td>Jackson</td>
<td>13.9</td>
<td>9.3</td>
<td>7.9</td>
<td>21.9</td>
<td>17.4</td>
</tr>
<tr>
<td>Klamath</td>
<td>17.6</td>
<td>13.8</td>
<td>8.9</td>
<td>23.1</td>
<td>16.4</td>
</tr>
</tbody>
</table>

Figure 3: This chart depicts the average percent of each race reported in the study area.
CHAPTER 4 – REMOTE SENSING METHODS

Analysis employed an experimental time-series analysis approach in which several remote sensing methods were combined to discover what environmental trends could be observed in the results and to examine the long-term implications of environmental change when the trends were projected into the future. Images were subjected to such corrective measures as image subsetting and standardization of all of the images to a base image with a series of ground control points. Principal components analysis was applied to the series of bands from each year to reduce the amount of data, and unsupervised classification was applied to the first component produced for each year in ENVI. Classes produced by the unsupervised classification were regrouped into more meaningful classes, and these images were processed with the Area Calculation tool, Markov Modeler, and Earth Trends Modeler in IDRISI with interesting results. The basic process is illustrated by the methodology flow chart in Figure 4.
Figure 4: Methodology flowchart.

Image Acquisition and Calibration

In order to conduct this environmental change study, images needed to be obtained. The United States Geological Survey has an excellent image database at http://glovis.usgs.gov. Here, Landsat images are available for free public download. If images are not available for immediate download, users can request them to be made available by filling out an electronic form. USGS emails the user when the image is
available, usually within a few days. Users can choose between the Landsat 7 SLC off, Landsat 7 SLC on, Landsat 4-5 TM, Landsat 4-5 MSS, and Landsat 1-3 MSS collections.

For this study, the Landsat 4-5 TM collection was used because it had nearly 30 years of images available and no known sensor errors, unlike the Landsat 7 satellite, which had an instrument malfunction in 2003 (EROS 2011). Landsat 4-5 TM images are processed with Standard Terrain Correction (Level 1T), resampled with cubic convolution, and projected using UTM-WGS 84 (EROS 2010). Images from Path 45 Row 31 (the Landsat image with Mt. Shasta located in it) were used.

In order to prevent errors resulting from seasonal changes, a preliminary examination of the data available in GloVis was conducted, and it was determined that August of each year had the highest number of relatively cloud-free imagery available. For this reason, August 1st was chosen as the ideal anniversary date. However, in the world of satellite imagery, the perfect anniversary date is not always obtainable. Clouds and haze can appear in the image or the satellite may not have flown over on that day. For this reason, most of the images do not fall on the ideal anniversary date. Instead, images were used from different days during the month of August, and a few images even had to be obtained from June, July, and September, when the original downloaded data from August was shown to have clouds obscuring the areas of interest in the study area. Vegetation and sun angle differences can be reduced if images from the same time of year are used (Mas 1999). Images beyond the 4-month range were not used. In total, twenty-five images were downloaded, one from each year from 1985 until 2010. These are referenced in Table 2. A twenty-five year period was chosen because at the time of
download, there were twenty-eight years of images, and twenty-five was the closest even time period. Images were downloaded and saved to the hard drive.
Table 2: This table depicts the image dates used in the study and their corresponding reference codes. Dates outside of the ideal August anniversary date are highlighted in yellow.

<table>
<thead>
<tr>
<th>Image Date</th>
<th>GloVis Image Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>August 16, 1985</td>
<td>L5045031_03119850816</td>
</tr>
<tr>
<td>August 19, 1986</td>
<td>L5045031_03119860819</td>
</tr>
<tr>
<td>August 6, 1987</td>
<td>L5045031_03119870806</td>
</tr>
<tr>
<td>August 24, 1988</td>
<td>L5045031_03119880824</td>
</tr>
<tr>
<td>August 11, 1989</td>
<td>L5045031_03119890811</td>
</tr>
<tr>
<td>June 27, 1990</td>
<td>L5045031_03119900627</td>
</tr>
<tr>
<td>August 1, 1991</td>
<td>L5045031_03119910801</td>
</tr>
<tr>
<td>August 19, 1992</td>
<td>L5045031_03119920819</td>
</tr>
<tr>
<td>August 6, 1993</td>
<td>L5045031_03119930806</td>
</tr>
<tr>
<td>August 9, 1994</td>
<td>L5045031_03119940809</td>
</tr>
<tr>
<td>August 12, 1995</td>
<td>L5045031_03119950812</td>
</tr>
<tr>
<td>August 14, 1996</td>
<td>L5045031_03119960814</td>
</tr>
<tr>
<td>August 17, 1997</td>
<td>L5045031_03119970817</td>
</tr>
<tr>
<td>August 4, 1998</td>
<td>L5045031_03119980804</td>
</tr>
<tr>
<td>July 22, 1999</td>
<td>L5045031_03119990722</td>
</tr>
<tr>
<td>August 25, 2000</td>
<td>L5045031_03120000825</td>
</tr>
<tr>
<td>August 28, 2001</td>
<td>L5045031_03120010828</td>
</tr>
<tr>
<td>August 31, 2002</td>
<td>L5045031_03120020831</td>
</tr>
<tr>
<td>August 18, 2003</td>
<td>L5045031_03120030818</td>
</tr>
<tr>
<td>September 21, 2004</td>
<td>L5045031_03120040921</td>
</tr>
<tr>
<td>August 23, 2005</td>
<td>L5045031_03120050823</td>
</tr>
<tr>
<td>August 26, 2006</td>
<td>L5045031_03120060826</td>
</tr>
<tr>
<td>August 13, 2007</td>
<td>L5045031_03120070813</td>
</tr>
<tr>
<td>August 15, 2008</td>
<td>L5045031_03120080815</td>
</tr>
<tr>
<td>August 18, 2009</td>
<td>L5045031_03120090818</td>
</tr>
<tr>
<td>August 5, 2010</td>
<td>L5045031_03120100805</td>
</tr>
</tbody>
</table>
Once the images were downloaded, they had to be pre-processed prior to analysis. Without pre-processing, pixels could be misaligned, resulting in the appearance of change in an area where change did not actually occur. To ensure proper image overlay, each image had to be registered to the 1985 base image. To register the images, files were imported into the ENVI 4.7 software and then saved as ENVI standard composite files, with the thermal band, band 6, omitted from the composite. Then “Select GCPs: Image to Image” was selected. To save time, the machine was allowed to pick 50 ground control points for each image without supervision. Even so, the number of ground control points still varied, but never fell below 25. Next, “Warp from GCPs: Image to Image” was selected and each image was warped to the base image.

Next, a subset of the study area had to be created. It was necessary to create a subset rather than use the whole image because the edges of the Landsat images are uneven and this introduces errors into the analysis. The ENVI software does not allow the user to select a parallelogram-shaped image like the Landsat image. Instead, only a square-shaped study area can be selected so the user must be selective on what to include. It is impossible to subset most of the entire image. For this study, the focus was on Mt. Shasta so that area was included in the subset. There are some lakes to the north and east portions of the image, as well as some urban areas that were included as well. Lakes to the south and an urban area to the west could not be included in the study due to the subset shape. A subset of the 1985 image was created first and then was used to subset the rest of the images.
Data Reduction and Classification

*Principal Components Analysis*

The ENVI Principal Component Analysis (PCA) module was used on each subset image to compress each image from six correlated bands of information into three uncorrelated output bands. According to PCA theory, the first band contains the highest percentage of variance (a measure of how far values lie from an expected mean), represent the main qualities of all six bands compressed into one band, and reduce noise (anomalously high or low pixel values) in the data. The other bands produced would contain less variance and more noise.

The ENVI software gives the option of calculating forward principal components (PC) rotations and reverse PC rotations. For this study, the forward PC rotation was used, along with the use of the Correlation Matrix. The forward PC rotation calculates new statistics, performs the linear transform on the data using a Covariance or Correlation Matrix, and produces the output bands, while a reverse PC rotation takes calculated statistics and transforms the PC images back to their original form. A Correlation Matrix was used because the input bands were of raw imagery and from the same image and therefore needed to be weighted the same. While the user can specify any number of output bands, three output bands were produced and the first output PC band for each year was used.

After the PC rotations were conducted on the subsets, each PC band 1 image for each year was examined for areas of interest in the study area. This visual examination revealed some notable changes over the twenty-five year time horizon that will be
discussed in a later chapter. Subsets of areas with notable change were created to be analyzed with the Markov Modeler and Area tool.

*K-Means Unsupervised Classification*

Because of the PC rotations, the original reflectance values were lost. In order to run some of the upcoming analyses and also make it easier to make sense of the images produced from the PC rotations, the resultant pixels had to be grouped into classes. This was done through the use of K-Means Unsupervised Classification in the ENVI software. “Unsupervised classification” simply means that the computer software was allowed to group like pixels together into classes based on image statistics without the user defining classes first. Instead, the user examines the results of the K-Means Classification and determines what each class probably represents based on reasoning and knowledge of the study area. This is a quick and useful method for separating pixels into classes.

To place pixels into classes, the K-Means Classification module in ENVI calculates class means and then clusters pixels into the nearest class using minimum distance. The user defines how many iterations, or how many times, the software will run through the image recalculating class means and classifying pixels. The user can also specify a distance threshold that needs to be met in order for a pixel to be grouped to a certain class, a standard deviation threshold, and a pixel change threshold, or the number of pixels a class changes by during each iteration. The software continues to run the module until the user-defined number of iterations is reached or the number of pixels in each class changes less than the pixel change threshold.
For this analysis, the number of iterations was set to 1,000. It is better to set a high number of iterations because the software automatically stops when the pixel change threshold is reached. Setting a low number of iterations could cause the software to stop before the pixel change threshold is reached and the resulting classes may not be as accurate as the user would like. The change threshold was left at the default value of 5.00. The Maximum Stdev from Mean and Maximum Distance Error options were left blank, which was the default setting. The K-Means Classification module was used five times for each yearly image with varying class numbers. The class numbers were: 5, 7, 10, 15, and 20. A variety of class numbers was used so that there would be many possibilities available from which to define classes.

Defining Classes

The resultant K-Means Unsupervised Classification images were then compared to Google Earth images to try to determine what land cover types each class represented. The ENVI software has a Cursor Location Value tool which gives the latitude and longitude coordinates at whatever location the cursor is pointed to. This makes it easy to type coordinates into Google Earth directly to see what is on the ground at each location.

Ultimately, the images with only 5, 7, and 10 were determined to be too broad and generalized to be of much use for this study and 20 classes was determined to be too many, so the image with 15 classes was chosen. Even with the use of 15 classes, there were still pixels that could be considered forest and water or ice and bare ground grouped into the same classes. There were also areas of ridge shadows that had the same digital number values as water. This made it impossible to have perfect class categories. As a
result, generalized classes were used and a certain amount of error and uncertainty was accepted.

Two attempts were made to produce generalized classifications. The first attempt grouped pixels into four classes and the second attempt grouped pixels into five classes. Google Earth was used to aid in the decision-making of how classes were regrouped. Ultimately, the second attempt at classification was chosen as it did not generalize areas of barren ground into ice or areas of vegetation into water. A fifth class was added and the generalized classes were redistributed accordingly. As a result, less bare ground was included in the ice category and less vegetation was included in the water category. Table 3 shows the attempts to name each class. Some additional subsets were made from the reclassed images that showed only the area surrounding Mt. Shasta. This was necessary so that the areas of glacial ice for each year could be compared across time. The change in glacial ice was assumed to be the most important water resource to track and project into the future.
Table 3: Classification Attempts

<table>
<thead>
<tr>
<th>Class</th>
<th>Attempt 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>Ice, Natural Bare Ground</td>
</tr>
<tr>
<td>Class 2</td>
<td>Human-Modified Bare Ground</td>
</tr>
<tr>
<td>Class 3</td>
<td>Human-Modified Vegetation</td>
</tr>
<tr>
<td>Class 4</td>
<td>Natural Vegetation</td>
</tr>
<tr>
<td>Class 5</td>
<td>Water, Natural Vegetation</td>
</tr>
</tbody>
</table>

This table depicts the class categories that were chosen for the analysis. Class 1 represents Ice (pixels that were considered to be representative of glacial ice) and Natural Bare Ground (pixels that were considered to be without vegetation naturally and had the same pixel values as those that were ice). Class 2 represents Human-Modified Bare Ground (pixels that were considered to mostly have had their vegetation removed by humans – includes areas that appear to have been subjected to clear cutting – while some pixels could still have been naturally bare of vegetation). Class 3 represents Human-Modified Vegetation (pixels that appear to have been modified for agricultural purposes by humans). Class 4 represents Natural Vegetation (pixels that appear to be forested). Class 5 represents Water (pixels that were considered representative of water bodies) and Natural Vegetation (areas of forested land that were of the same pixel value as water).

Analytical Modeling

To continue with the analysis, the files were exported from ENVI to IDRISI. This was done because even though ENVI is a powerful software, IDRISI had different modeling approaches that were pertinent to this environmental investigation, such as the Markov modeler and a different method of principal components analysis.

Area Calculation

To assess how much each class changed per each year, and to identify any noticeable trends, the Area Calculation tool was used. The Area Calculation tool in
IDRISI gives the user the option to select an output format of an image of the area, an attribute values file, or a tabular file. In addition, the area can be designated to be cells, hectares, acres, square meters, square feet, square kilometers, or square miles. For this project, attribute values files in square meters were calculated for each image. This produced an .avl file that could be opened using Microsoft Excel. The area results of each class for each year were combined into one Excel spreadsheet where graphs could be produced. Area was calculated for the K-Means reclassified images and the subsets of Mt. Shasta. The results were an important part of the analysis of the study area.

Earth Trends Modeler

The Earth Trends Modeler is a relatively new feature to this version of IDRISI and therefore has not been used in many analyses. This modeler allows the user to take a series of images across time and analyze them for trends or perform PCA. In order to do this, the user must first specify the name of the project and create a Time Series File for their images. In order to create the Time Series File, the user must first create a Raster Group File. A Raster Group File is simply all of the images to be analyzed organized into a specific group that IDRISI can recognize. This group file is specified in the Time Series File creator. The user must also enter in the dates on which the first and last images in the series were collected, specify whether they were collected annually, monthly, etc., and create a title for the series. The Time Series File can then be saved and added to the project. If a proper Working Folder is not designated at the beginning of using IDRISI, IDRISI will not add the Time Series File to the project.
Once the user has taken care of the initial set-up, the analysis can be performed. The user can choose from doing the following: a Series Trend Analysis, a Seasonal Trend Analysis, a Principal Components Analysis, Empirical Orthogonal Teleconnections, a Fourier PCA Spectral Analysis, or Linear Modeling. For this thesis, the K-Means reclassified images were experimentally subjected to the PCA option to see if meaningful results could be produced. The idea was to perform a principal components analysis on a principal components analysis and see if any evidence could be found that links the changes in each image to El Nino and La Nina events. The first principal components analysis in ENVI was used to compress the bands, while the second principal components analysis in IDRISI was used to compress time.

The user gets the chance to choose to use a correlation matrix or a covariance matrix, and also how many components the software will produce. In this case, the default option of correlation matrix was selected, along with 13 components. The standardized components and correlation matrix were chosen again so that all of the input images would be weighted the same and given equal importance. This number of components was chosen because higher numbers of components produced error messages saying that there was not enough variance contained in certain images to produce all of the components requested.

Once the software finishes with the processing, the results can be displayed in the “Explore Space/Time Dynamics” and the “Explore PCA/EOT/Fourier PCA/Wavelets” tabs. In the first tab, the user can create a three-dimensional visualization of the input images that can be played as a loop. In the second tab, the user can look at a graph that
shows how much variance each year contributed to each component, and it places a trend line on the data. Output images of each component are produced as well so that the user can see which areas in the study area produced what level of variance.

**Markov Modeler**

The use of the Markov Modeler in IDRISI was another important part of the analysis of the study area. The Markov Modeler takes two land cover images, an image from an earlier time period and an image from a later time period, and computes the probability of each land cover type being found at a specified time in the future. It produces three outputs: a text file that shows the probability that each land cover will change to each of the other categories, a text file that shows how many pixels are expected to change, and an image for each land cover type showing the probability that the land class will be found there in the future.

This thesis was mainly concerned with the likelihood that Mt. Shasta would still have glacial ice, given the current environmental trends, far into the future. It was also concerned with the rate of change, and if varying the input images caused the trends to change or if the results were still relatively the same.

In the modeler, the user is given the option to choose an earlier land cover image and a later land cover image, and specify the number of time periods between these images. Different combinations were used. These included the 1985 and 2010 images (25 time periods), the 1990 and 2010 images (20 time periods), the 1995 and 2010 images (15 time periods), the 2000 and 2010 images (10 time periods), and the 2005 and 2010 images (5 time periods). The user then has to specify the number of time periods to
project forward from the second image. For each time period combination, 5, 10, 15, 25, 50, 75, and 100 time periods were projected forward, making the future years 2015, 2020, 2025, 2035, 2060, 2085, and 2105. The “Background cell option” and “Proportional error” settings were left at their default settings of “Assign 0.0” and “0.0,” respectively.

The Markov Modeler was used to calculate land cover class probabilities on the first and second attempt classifications of the K-Means images, and the Mt. Shasta subsets.

Because this project is mainly concerned with the availability of water resources in the future, the results of classes 1 and 5 from the second classification attempt were analyzed in depth. The resulting text files were saved to the hard drive, while the probabilities of the glacial ice and the bodies of water from the resulting images were recorded into an Excel sheet.
CHAPTER 5 – OBSERVED ENVIRONMENTAL TRENDS

After utilizing the Area calculation tool, Earth Trends Modeler, and Markov analysis, the results were analyzed. Basic visual analysis revealed that urban areas have grown, glacial ice and water bodies grow and recede, and clear cutting has increased. It was found with the Area calculation tool that the glacial ice on Mt. Shasta and the water body, Lake Shastina, appear to grow and recede in response to El Nino and La Nina, with a noticeable negative trend in area over time for Lake Shastina. The glacial ice remains stable for now. With Earth Trends Modeler, human modification and El Nino and La Nina appear to contribute to most of the changes noticed in the study area. Finally, Markov analysis shows two distinct trends in glacial ice change, as well as possible trends in other changes of land cover.

Image Examination Results

Visual examination of the PC images yielded some notable changes that have occurred over the past twenty five years.

1) Urbanization

   o Urban areas appeared to have grown steadily. This observation is supported by data obtained from the US Census for the study area section. Population has continued to grow over the years and is projected to continue growing into the future. A steady increase in population could put a strain on the water resources in the area.
2) Changes in Glacial Ice
   o The glacial ice on Mt. Shasta appeared to change in size each year by growing or receding. This is discussed later in the results of the Markov Modeler and Area summary.

3) Changes in Water Bodies
   o Water bodies appeared change in size each year by either growing or receding. This is discussed in a later section.

4) Changes in Forested Lands
   o Areas of clear cutting that appeared in the study area appeared to increase in number over time. An internet search with the keywords: “northern California” and “clear cutting” produced a number of websites illustrating the controversy of the effects of clear cutting in the area, and a company called Sierra Pacific Industries, that is responsible for clear cutting. These search results supported the assumption that an increase in clear cutting was being observed in the imagery.

Links to External Processes

The areal calculation yielded important results for the Mt. Shasta subset images, and the glacial ice on Mt. Shasta was deemed the most significant aspect of the study area. In these images, as much cloud cover as possible, as well as areas outside of the extent of the glacial ice, were cropped out, leaving only the farthest reaching extents of the glacial ice. The Area calculation outputs that were saved as text files were imported into Excel so that changes in area could be compared across time. In these results, it
appears that the area of the glacial ice increases and decreases over time in response to El Nino and La Nina. El Nino and La Nina years are displayed in Table 4.
Table 4: This table of El Nino and La Nina event years was created from data obtained from NOAA (2011).

<table>
<thead>
<tr>
<th>El Nino or La Nina Event</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>La Nina</td>
<td>1984 – 1985</td>
</tr>
<tr>
<td>La Nina</td>
<td>1988 – 1989</td>
</tr>
<tr>
<td>La Nina</td>
<td>1995 – 1996</td>
</tr>
<tr>
<td>La Nina</td>
<td>1998 – 2000</td>
</tr>
<tr>
<td>La Nina</td>
<td>2000 – 2001</td>
</tr>
<tr>
<td>El Nino</td>
<td>2004 – 2005</td>
</tr>
<tr>
<td>El Nino</td>
<td>2006 – 2007</td>
</tr>
<tr>
<td>La Nina</td>
<td>2007 – 2008</td>
</tr>
<tr>
<td>El Nino</td>
<td>2009 – 2010</td>
</tr>
<tr>
<td>La Nina</td>
<td>2010 – 2011</td>
</tr>
</tbody>
</table>

Periods of increased glacial ice seem to occur during El Nino events, and periods of decreased glacial ice seem to occur during La Nina events. However, it appears that
not everyone is in agreement as to which years were actual El Nino events and which years were actual La Nina events.

Starting at the beginning, a slight increase in glacial ice area was observed from 1985-1986, followed by a decrease in 1987. From 1984 to 1985, a La Nina event was observed by NOAA (2011), causing 1985 to have a lower amount of glacial ice. Then the years 1986 and 1987 were characterized by a weak El Nino event (NOAA 2011; Viles and Goudie 2003), which caused ice to increase relative to 1985. Glacial ice decreases during the period of 1987 to 1988 as a La Nina event appears from 1988 to 1989 (NOAA 2011; Gergis and Fowler 2009).

After this, glacial ice increases again from 1988 to 1990. It would be expected that an El Nino event occurred during this time, but instead, NOAA (2011) and Viles and Goudie (2003) record a La Nina event. It also cannot be confirmed that another La Nina event occurred from 1990 to 1992 when glacial ice decreased, even though the pattern of ice supports this conclusion. NOAA (2011) reports average conditions until an El Nino event from 1991 to 1992, Viles and Goudie (2003) report an El Nino starting in 1990, and Gergis and Fowler (2009) report an El Nino from 1991 to 1992. This could be due to the fact that this El Nino event was a weak event or perhaps the Pacific Decadal Oscillation was having some influence.

Glacial ice area stays relatively low until about 1994. From 1994 to 1995, glacial ice area increases dramatically. During this time, a strong El Nino event was reported by NOAA (2011). From 1995 to 1997, the area of glacial ice decreases. It appears that there was a La Nina event from 1995 to 1996 (NOAA 2011). The years 1997 and 1998 show
the largest increase of glacial ice in this study period. These are the years that NOAA (2011) recorded the strongest El Nino event of the 20th century. From 1998 to 2000, glacial ice area appears to decrease. During this time a strong La Nina event was recorded by NOAA (2011). Glacial ice continues to decrease from 2000 to 2001 during another La Nina event (NOAA 2011).

This was followed again by an increase in glacial ice from 2001 to 2004. El Nino events were reported by NOAA (2011) for 2002 to 2003 and 2004 to 2005. The 2004 El Nino event was characterized as a very weak event (Gergis and Fowler 2009), yet it still appeared to be reflected in the glacial ice changes. From 2005 to 2006, there is an increase in glacial ice which appears to correspond with the 2006 to 2007 El Nino event (NOAA 2011). From 2006 to 2008, there is a decrease in glacial ice. La Nina conditions are reported for 2007 to 2008 (NOAA 2011). Glacial ice increases again from 2008 to 2009 as another El Nino event is reported (NOAA 2011). From 2009 to 2010, the ice continues to increase as El Nino persists (NOAA 2011). The study set ends here, but as La Nina conditions are being reported for 2011, it would be expected that if a Landsat image from August 2011 is examined, the area of glacial ice would be on the decline. The trends in area are displayed below in Figure 5.
A linear regression trendline was added to the dataset. It was expected that due to global rising temperatures, the glacial ice would exhibit a negative trend. However, it appears that the ice is relatively stable for now, which is what Howat et al. (2007) found as well. The ice could be appearing stable for now because 25 years is not enough time to display a true trend across time. If this study was continued and more images were added, perhaps a true positive or negative trend in area would establish itself.

Because of the influence that El Nino and La Nina events have on Mt. Shasta, Mt. Shasta could potentially be thought of as a “barometer” or response signature for environmental changes for this region of northern California and southern Oregon. The glacial ice is almost directly influenced by El Nino and La Nina events. By studying the
patterns in the ice and establishing trends, El Nino and La Nina events could be better monitored.

Secondary Connections

Lake Shastina, one of the lakes that appeared to grow and shrink over time, was cropped out and imported into IDRISI to see if El Nino/La Nina event trends were observed here as well. Lake Shastina is located slightly to the northwest of Mt. Shasta. The analysis of the area trends of Lake Shastina was done primarily for future research recommendations and confirmation of the El Nino/La Nina event trends illustrated above.

Lake Shastina seems to be influenced by the presence of El Nino and La Nina events as well, but the influence seems to be more extreme. The area of the lake water fluctuates dramatically. Not all of the fluctuations match up perfectly to these events, however. Also, when a linear regression trendline was added to the dataset, a negative trend was observed, indicating that even though the lake water fluctuates in area, the area is getting smaller overall. Something else may be exhibiting more control than El Nino and La Nina events on the lake water area. Some potential factors could be increasing populations around the lake or fluctuations in regional precipitation during the summer months. It is recommended that further research be conducted on this lake and other lakes in the area. A decrease in lake water means a decrease in drinking water for the region, and in a region with increasing population trends, this could spell disaster for future generations. The trends in Lake Shastina can be observed in Figure 6.
Earth Trends across Time

To understand the trends across time in the image series, the Principal Components Option of the Earth Trends Modeler in IDRISI was used. The PCA in IDRISI was conducted on the K-Means surfaces. The software produced twelve components images and graphs of variance trends. Using this image specific information, shifts over time could be observed.

Dominant Trend

This surface explains 72.07% of the variance observed across time in this series of images. Therefore, the image result is the average characteristics observed in the study area. It is what one would expect to see at any given time during the month of August. The results are displayed below in Figure 7.

Figure 6: Area of Lake Shastina over time.
Figure 7: Dominant Trend. This surface is what one would expect the region to look like during the month of August.
Secondary Shifts

This surface explains 2.707% of the variance in the images across time, after the dominant influence is removed. When the graph of variance contributed by each year is analyzed, it appears that the amount of variance each image contributes increases over time. When portions of the surface are zoomed in on, one can observe the areas of clear cutting contributing to the variance. This makes sense as the amount of clear cutting seems to increase as time goes by. Changing agricultural trends seem to contribute as well to this particular component. The surface is illustrated below in Figure 8.
Figure 8: The secondary shift. The portion of the surface illustrating clear cutting influences has been cropped out and enhanced.
Residual Trends

This surface contributes 2.443% to the total variance across time after the first two components have been removed. While cloud cover from the 1990 image explains some of the variance observed, changes in Lake Shastina and changes in glacial ice also emerge. These patterns are displayed in Figure 9.
Figure 9: Changes in water body and glacial ice size.

*Agricultural Trajectory*

This surface contributes only 1.384% of the variance after the influences from the other components have been eliminated. Based on the PC image produced and the component graph, it is believed that the patterns being observed are those of agricultural changes and changes induced by the increased clear cutting. It is assumed that
agricultural changes and clear cutting are being observed because the areas contributing
the most positive and negative reflectance values are those where agriculture and clear
cutting were taking place. These patterns are illustrated below by Figure 10.

Figure 10: Agricultural Trajectory. Some of the main contributors to changes in
reflectance values have been cropped out from the main image and enhanced. The
enhanced image on the left illustrates the agricultural changes, while the enhanced image
on the right illustrates the areas of clear cutting.
Vegetative Pulse

The next two surfaces contribute 1.197% and 1.169% of the total variance observed respectively. It is possible that the vegetation changes observed in these two components are El Nino/La Nina signatures. Some of the changes in variance contributed for each year correspond to La Nina years. In the first surface, the changes appear to be taking place mostly in the northern part of the study area while in the second surface, the changes appear to take place mostly in the southern portion. These patterns are depicted below in Figure 11 and Figure 12.
Figure 11 – Vegetative change trends.
Figure 12: Vegetative change trends.
Interpretation of the General Trends

It appears that the patterns in variance observed from changes in agriculture and clear cutting from Component 2 are the most significant changes that are occurring in the study area. As the amount of variance contributed by each year increases over time, it appears that these changes are getting stronger. It is therefore interpreted that humans are impacting the land more than the environment in certain regions located within the study area, and the effects of clear cutting should be studied further. Component 7 also supports the notion that humans are having a significant impact as most of the variance from this component can be explained by agricultural changes and clear cutting.

The second most significant pattern occurring in the study area is the pattern observed in Component 3 of the changing glacial ice and lake size. Because it is believed that these changes are controlled by El Nino and La Nina, it is interpreted that these influences have a strong impact particularly on bodies of ice and small bodies of water. The amount of variance contributed by Lake Klamath at the northernmost end of the study area for this component was not significant, perhaps because it might take a stronger event to affect such a large lake.

Finally, Components 9 and 10 show that while El Nino and La Nina are influencing the region, they are affecting water and ice more than they are affecting vegetation. If changes in vegetation from the El Nino and La Nina events were significant, they would have displayed in the earlier components instead of the later components.
Projecting Into the Future

When the entire study area was subjected to the Markov Analysis, the following results emerged.

1) Transition to Ice

- The first Markov result that was analyzed was the number of cells expected to transition to Class 1 (Ice) over time. This number includes the number of cells predicted to be Class 1 plus the number of cells from the other classes that transitioned to Class 1. This result produced two noticeable trends – glacial ice recession and glacial ice expansion – over time. It is difficult to determine what these trends can be attributed to. The recession trend appears to be associated with El Nino input images. The year 1990 exhibited El Nino symptoms, 1995 was a strong El Nino year, and 2010 was an El Nino year. This does not make much sense as glacial ice tends to expand during El Nino. It could be possible to attribute this trend to strengthening effects from global temperatures overriding the increased precipitation from El Nino. The expansion trend makes a little more sense. It could be attributed to trends that would be exhibited when going from a non-El Nino or weak El Nino year to an El Nino year. The year 1985 was neutral, 2000 was a La Nina year, 2005 was a weak El Nino year, and 2010 was an El Nino year. Glacial ice would be expected to expand when going from a time of decreased precipitation to a time of increased precipitation. These trends are depicted in Figure 13 below.
Figure 13: Illustrating the trends of Class 1 over time.

2) Steady State
   - The next Markov result illustrates the probability that the pixels originally labeled as Class 1 (ice) will remain in Class 1 over time. This result only shows Class 1 and does not show the probabilities of any of the other classes changing to Class 1 over time. As can be seen, the probability of a pixel staying Class 1 over time that was originally Class 1 decreases. These trends do not appear to reflect any trends from El Nino or La Nina. They could potentially reflect trends from increasing global temperatures. These results are alarming in that the probability that the about of
landcover that was originally ice is expected to decrease from about a 60 to 80\% in 2015 chance down to a 10 to 30\% chance in 2110. If environmental changes keep occurring at the rate they are occurring, most of the glacial ice may be gone by 2110. This trend is displayed in Figure 14.

Figure 14: Displaying the probability that Ice will remain Ice over time.

3) Ice to Barren
   - The next result shows the probability that Class 1 (Ice) will change to Class 2 (Bare ground) over time. Class 2 was the class that Class 1 had the highest overall probabilities of transitioning into over time when compared to the other classes. The probability that ice will be bare ground
appears to increase until about mid-century and then decrease over time. These trends do not appear to reflect any influences from El Nino or La Nina. Additional research would be needed to see if these trends might reflect changes in the Pacific Decadal Oscillation. These results, however, are alarming in terms of water resources if most of the glacier may disappear over time and change into bare ground. The trends are displayed in Figure 15.

Figure 15: This chart displays probability that Ice will change to Bare Ground over time.
4) Barren to Ice

- The next result shows the probability of Class 2 (Bare Ground) changing to Class 1 over time. These results were picked to show the probability that Class 2 (Bare Ground) would go back to being Class 1 (Ice) over time. These results appear to follow the trends outlined in Figure 15. The probability that Bare Ground will go back to being Ice is very low, though. There is only about a 10 to 30% chance that this will happen, indicating that oscillations may occur as a result of El Nino and La Nina changes, but overall land cover is not expected to transition back to ice over time. These results are depicted in Figure 16.

![Probability of Class 2 (Clearcutting, Bare Ground) Changing to Class 1 (Ice) Over Time](image)

Figure 16: Showing the probability that Class 2 will change back to Class 1 over time.
5) Transition to Vegetation

- The next result shows the probability that Class 1 (Ice) will transition to Class 3 (Vegetation). As it can be seen, Ice has a relatively low probability of transitioning to Vegetation over time. However, more and more Ice is expected to transition to Vegetation over time. Perhaps with warming temperatures, vegetation could occupy new elevations that could not be previously occupied due to the area being too cold or covered in ice. The trends are depicted in Figure 17.

Figure 17: Showing the probability that Class 1 will change to Class 3 over time.
6) Vegetation to Ice

- The next result shows the probability that Class 3 (Vegetation) may change to Class 1 (Ice) over time. The probability that Vegetation may transition to Ice is about the same as the probability that Ice may transition to Vegetation over time. Perhaps this means that the two land cover types will oscillate back and forth over time especially towards the later part of the century. The results are shown below in Figure 18.

![Figure 18: Showing the probability of Class 3 changing back to Class 1 over time.](image-url)
7) Extrapolated Trending

- The final result shows the changes in area over the 25-year study period, with the trends from Figure 5.10 added. Like Howat et al. (2007), two potential trends – recession and expansion of the glacial ice – were predicted. This shows that similar results can be obtained from this simple method, compare to more complicated modeling methods. These trends could be linked to changes related to El Nino and La Nina. The input images from 1985, 2000, and 2005 are all times when glacial ice area is relatively low compared to the glacial ice area during the 2010 El Nino year and could reflect what would be expected if there is transition from a non-El Nino or weak El Nino year to an El Nino year. There would be an increase in glacial ice. The input images from 1990 and 1995 are from years when there was either a strong El Nino or a potential El Nino and the 2010 image represents a weaker El Nino year. This trend could reflect what would be expected when transitioning from a strong El Nino year to weak El Nino year. There would be a decrease in glacial ice. These trends are displayed below in Figure 19.
Figure 19: Showing the current trend in glacial ice area and the projected trends.

Validation of the Markov Model

In order to verify the results of using the Markov modeler to predict future land cover classes, an accuracy assessment had to be conducted. This accuracy assessment used the K-Means images from 1990 and 2000 as the input images in the Markov modeler to predict the land cover classes that would appear in 2010. The predicted land cover classes were then compared to the actual land cover classes that appeared during 2010.

To compare the predicted and actual land cover classes of 2010, 300 ground control points were randomly chosen in the actual 2010 image and the class type for each
Figuring out the land cover class types in the Markov modeler output images was more difficult. The Markov modeler produced an output image for each class type, along with the probability that each pixel would be that class. Because there were five classes, there were five output images. The 300 ground control points had to be found in each of these output images, and the probability of these points being a certain class as recorded. After all of this information was recorded, the actual predicted class for each point was determined to be the class with the highest probability variable recorded. This process was very lengthy, but it yielded the results needed for an accuracy assessment. The error matrix for the actual and predicted 2010 images is recorded in Table 5.

Table 5: The error matrix for the accuracy assessment of the actual and predicted 2010 images.

<table>
<thead>
<tr>
<th>Thematic Map Classes (Markov)</th>
<th>Ground Truth Classes</th>
<th>2010 K-Means Image</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 4</th>
<th>Class 5</th>
<th>Sum (Thematic Map Classes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>56</td>
<td>16</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>73</td>
<td>300</td>
</tr>
<tr>
<td>Class 2</td>
<td>22</td>
<td>54</td>
<td>6</td>
<td>4</td>
<td>0</td>
<td>86</td>
<td></td>
</tr>
<tr>
<td>Class 3</td>
<td>6</td>
<td>16</td>
<td>43</td>
<td>7</td>
<td>4</td>
<td>76</td>
<td></td>
</tr>
<tr>
<td>Class 4</td>
<td>2</td>
<td>2</td>
<td>8</td>
<td>34</td>
<td>9</td>
<td>55</td>
<td></td>
</tr>
<tr>
<td>Class 5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>Sum (ground truth pixels)</td>
<td>86</td>
<td>88</td>
<td>58</td>
<td>45</td>
<td>23</td>
<td>300</td>
<td></td>
</tr>
</tbody>
</table>
The error matrix was used to calculate 1) classification accuracy, 2) user accuracy, 3) producer accuracy, 4) error of commission, and 5) error of omission with the following results:

1) Classification Accuracy = \(\frac{56+54+43+34+10}{300} = \frac{197}{300} = 0.6567 = 65.67\%\)

2) User Accuracy
   
a. Class 1 = \(\frac{56}{73} = 0.7671\) = 76.71%
   
b. Class 2 = \(\frac{54}{86} = 0.6279\) = 62.79%
   
c. Class 3 = \(\frac{43}{76} = 0.5659\) = 56.59%
   
d. Class 4 = \(\frac{34}{55} = 0.6182\) = 61.82%
   
e. Class 5 = \(\frac{10}{10} = 1\) = 100%

3) Producer Accuracy
   
a. Class 1 = \(\frac{56}{86} = 0.6512\) = 65.12%
   
b. Class 2 = \(\frac{54}{88} = 0.6136\) = 62.79%
   
c. Class 3 = \(\frac{43}{58} = 0.7414\) = 74.14%
   
d. Class 4 = \(\frac{34}{45} = 0.7555\) = 75.55%
   
e. Class 5 = \(\frac{10}{23} = 0.4348\) = 43.48%

4) Error of Commission
   
a. Class 1 = \(\frac{16+1+0+0}{73} = \frac{17}{73} = 0.2329\) = 23.29%
   
b. Class 2 = \(\frac{22+6+4+0}{86} = \frac{32}{86} = 0.3721\) = 37.21%
   
c. Class 3 = \(\frac{6+16+7+4}{76} = \frac{32}{76} = 0.4342\) = 43.42%
   
d. Class 4 = \(\frac{2+2+8+9}{55} = \frac{21}{55} = 0.3818\) = 38.18%
e. Class 5 = (0+0+0+0)/10 = 0/10 = 0.000 = 0%

5) Error of Omission

a. Class 1 = (22+6+2+0)/86 = 32/86 = 0.3488 = 34.88%

b. Class 2 = (16+16+2+0)/88 = 34/88 = 0.3864 = 38.64%

c. Class 3 = (1+6+8+0)/58 = 15/58 = 0.2586 = 25.86%

d. Class 4 = (0+4+7+0)/45 = 11/45 = 0.2444 = 24.44%

e. Class 5 = (0+0+4+9)/23 = 13/23 = 0.5652 = 56.52%

A value of 85% or greater for the overall accuracy, user accuracy, and producer accuracy would have been ideal. The values that were achieved were well below that. However, given the fact that this was an evaluation of a prediction compared to what land cover types actually occurred, the values are impressive.
CHAPTER 6 – IMPLICATIONS AND FUTURE AREAS OF STUDY

Environmental change is a popular topic in the realm of geography. Changes vary from region to region with differing effects. Some areas experience more flooding while others experience more droughts. Mountain glaciers appear to recede in some areas while advancing in others. El Nino and La Nina appear to exhibit some control over how environmental change manifests itself from region to region. As there are so many factors contributing to environmental change, it is important to study each region. No one region can represent the entire globe, just like no one glacier can represent all glaciers. In this study, environmental change was examined using a time-series remote sensing approach with Earth Trends Modeler and a Markov-based procedure to demonstrate how remote sensing can be used to isolate environmental trends that can be a challenge for environmental resource management.

When Mt. Shasta and the surrounding region were examined with remote sensing technology, it appeared that El Nino and La Nina had a strong effect on the glacial ice. The ice appears to recede and advance as a result of which El Nino phase is in effect, indicating that the glacial ice could potentially be used as a “barometer” for environmental change for this region of northern California and southern Oregon. Patterns from El Nino also manifested themselves in several different components, indicating that El Nino phases are having some obvious effects on the overall region and are also having some minor effects as well. Finally, when environmental changes are predicted with the Markov Modeler, two dominant trends emerge. One is an increase in glacial ice. The other is a decrease in glacial ice. Howat et al. (2007) received similar
results from their models, indicating a relatively simple procedure could produce similar results to a more complicated one.

When the rest of the classes in the probability matrices are examined, it appears that the areas that were originally ice are expected to decrease in probability of being ice over time. Ice is most likely going to transition to bare ground in the future, with little probability of transitioning back to ice. Some ice will transition to vegetation, and it is almost equally likely that the vegetation can transition back to ice over time, making it appear that these two land cover types will oscillate back and forth. Overall, most of the results show that the area of ice is expected to decrease over time and this should be taken into account when making decisions about water resources. As poverty levels in the area are higher than the national average and the area experiences population increases, there may be a lot of vulnerable people in the future.

When the region is examined as a whole, it appears that humans are having a rather large influence as well. Clear cutting appeared in the second component result, and the amount of variance contributed by each image to the component increased over time. In the images, the amount of clear cutting increases over time. Clear cutting could have some potential negative effects as albedo increases when bare ground is exposed, and this could contribute to an increase in regional and global temperatures. When Lake Shastina was examined, it appeared that lake increased and decreased in size as a result of El Nino and La Nina effects. However, this does not seem to be the dominant control on the lake size. Changes in precipitation could be affecting how much water is available, as well as
the increase in regional population. This region is naturally dry, and an increasing population means more water resources are being consumed.

However, this analysis is based on 25 years, rather than 30 or more years of data. If more images could be added to the dataset, a more accurate picture of the patterns of environmental change could be depicted. Also, it is important to note that environmental conditions at the time of image collection affect the results of the Markov Modeler. If only two input years are used, as is customary in most change detection studies, and the region being examined experiences oscillations in environmental conditions due to El Nino and La Nina, the results of the Markov Modeler could be skewed. Glaciers may be expected to keep receding at an alarming rate or continue to expand based on what phase of the El Nino cycle the area is in, when in fact conditions may oscillate back and forth.

Therefore, results of most modeling programs should be taken with a grain of salt when making planning decisions. The outcome may not reflect what may actually be happening, or if the analyst has a hidden agenda, the results could be skewed in favor of certain policies.

**Future Areas of Study and Limitations of the Software**

While researching the study area for this project, it was found that clear cutting increased over time. When clear cutting was researched via a search engine, multiple articles popped up, indicating a controversy between the logging company, Sierra Pacific Industries, and the people of northern California. Sierra Pacific Industries argues that their clear cutting practices are sustainable because they are planting trees in place of the ones they cut down, and that they are reducing wildfire potential because they are
removing fuel for fires (Sierra Pacific Industries). Meanwhile, environmentalists are arguing that clear cutting is not sustainable, that they are essentially planting a monoculture, that they are using alarming amounts of herbicides and fertilizers, and as environmental changes occur (less snowfall, drier conditions), they are going to cause more wildfires (Waggoner 2007). This dispute would be interesting to research in terms of environmental justice issues, ecological issues, sustainability issues, and it has the potential to be supplemented with remote sensing evidence.

In addition, the effects of changing the input images in the Markov Modeler should be examined, as different environmental conditions can skew the results projected into the future. If someone were to only use the 1985 image and the 2010 image to project changes into the future, it would appear that glacial ice was increasing over time, regardless of whether it actually was. Likewise, if someone would have only used the 1995 image and the 2010 image, it would appear that glacial ice is decreasing rapidly over time.

This is important to note because most people conducting environmental assessments like this only project forward from two input images. They do not normally use multiple images like this study did. If an environmental planner were receiving a report containing the results of only the 1985 and 2010 images, they would see that glacial ice is increasing, when in fact it may just be the result of an El Nino/La Nina oscillation. This would give them false hope and they may not make necessary water resource conservation preparations. Likewise, using only the results from the 1995 and
2010 image would cause unnecessary alarm. More research should be done on the effects of putting different types of input images into modeling software.

Although the analysis and modeling of change is an important scientific activity, there are often methodological issues that are difficult to resolve. For example, when conducting PCA, the order of when the study area subset is created and when the PCA is conducted affects the results of the PC bands produced. Initially in this study, the PC rotation was conducted prior to producing a subset of the study area. This produced PC bands that had predominately low pixel values and therefore appeared darker in color, with the exception of a few years that had predominately high pixel values and a lighter appearance. The images with higher pixel values and lighter appearance also looked like they were the inverse of the lower pixel values and darker in appearance images. By this, it is meant that in the lighter images, the glacial ice would appear black and with low pixel values, while the lake would appear white and with high pixel values. In the predominately darker images, this would be flipped. This is illustrated in Figure 20.
Figure 20: This image depicts the “inverse effect” the PC rotation had on images from different years.

It was originally hoped that the images that appeared anomalously lighter would correlate with El Nino events. However, when the images were subset before the PC rotation, more PC bands appeared to have predominately high pixel values and a lighter appearance. This indicates that the edges of the original Landsat images were being taken into consideration in the PC rotation and were skewing the results. Therefore, it is important to subset the image prior to PC rotation.

When combining classes to produce simplified classes, another complication arose. The “inverse effect” that was noticed in the PC rotation results also affected the K-Means classification results. It was noticed that the classes were flipped for certain years, and this had to be taken into account. The years 1985, 1988, 1990, 1991, 1993, 1994,

While there are some difficulties when using environmental modeling, the results are still important. This study showed that Mt. Shasta can be thought of as a “barometer” for environmental changes, and in one possible future trend scenario, it may lose glacial ice. The region should continue to be monitored, and that can be made possible with this simple yet effective experimental method.
REFERENCES


