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Land Use and Quality of Life in 45 Israeli Cities

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Land Use and Quality of Life in 45 Israeli Cities

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Environmental Health, Science, and Policy

by

Sarah Jeanette Becker

Dissertation Committee:
Professor Oladele Ogunseitan, Chair
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2007

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2007

DEDICATION

To

my parents and brother

Barbara, Leo, and Laurence Becker

for their endless support and encouragement

And to

my friends and colleagues

whose exchange of ideas helped shape this dissertation

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Conference Proceedings/Abstracts

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Becker, S.J. and O.A. Ogunseitan. 2003. Remote sensing of the direction and sustainability of land use change in Israel. *Open Meeting of the Human Dimensions of Global Environmental Change Research Community*, Montreal, Canada.

Becker, S.J. 2003. Land, water, and conflict in Israel: change detection analysis with remote sensing and land-use planning activities in the Jordan River basin. *Greening XII Conference*, University of California, Santa Barbara.

Becker, S.J. and O.A. Ogunseitan. 2001. Climate change, water resources, and environmental conflict in Arab-Israeli peace negotiations. *Global Change Open Science Conference*, Amsterdam, the Netherlands.

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ABSTRACT OF THE DISSERTATION

Land Use and Quality of Life in 45 Israeli Cities

By

Sarah Jeanette Becker

Doctor of Philosophy in Environmental Health, Science and Policy

University of California, Irvine, 2007

Professor Oladele Ogunseitan, Chair

This research tested the hypothesis that a latent construct of quality of life (QOL) in Israel is predictable from key socioeconomic and environmental variables associated with land use across 45 cities. Data were acquired from the Israel Central Bureau of Statistics, the International Policy Institute for Counter-Terrorism, and Landsat 7. The environmental variables included the Normalized Difference Vegetation Index (NDVI) and percent of built land. Demographic and socioeconomic variables included average income per capita (between 672 and 4,569 shekels/month), percent of new motor vehicles (12.24 – 41.15%), median age (12 – 38 years of age), percent of students in each city between 20 and 29 years of age (0.10 – 34.57%), percent of families with 4 or more children (2.32 – 49.38%), population (9,302 – 646,279 inhabitants), and the number of violent terrorist attacks per city (0 – 52 attacks in 1999). The socioeconomic and environmental data were evaluated using correlation coefficients and principal components analysis to characterize QOL. The NDVI showed a weak positive correlation with percent of built land ($r = 0.130$; $p = 0.361$) and strong correlations with average income per capita ($r = 0.579$; $p = 0.000$), median age ($r = .388$; $p = 0.008$),

percent of new motor vehicles ($r = 0.472, p = 0.001$), percent of families with 4 or more children ($r = -0.480; p = 0.001$), and percent of people in each city between 20 and 29 years who are students ($r = 0.532; p = 0.000$). Percent of built land showed a significant relationship with median age ($r = 0.352; p = 0.018$) and percent of new motor vehicles ($r = 0.337; p = 0.024$). Principal components analysis supported the grouping of all socioeconomic variables, but interestingly, NDVI did not cluster with this group. Although NDVI correlates with specific socioeconomic variables, NDVI was not found in this study to be a predictor of QOL in the Israeli cities. These results demonstrate a quantifiable relationship between components of QOL and environmental characteristics that can aid policymakers in planning for emerging problems that impact human lives, such as climate change and drought within the context of variable socioeconomic factors.

CHAPTER 1: INTRODUCTION

STATEMENT OF THE PROBLEM

Violent conflict has been a constant reality for Israel since its establishment in 1948. The land that is now present-day Israel started in 1948 as two countries: Israel and Palestine. Many Arab countries declared war against Israel upon Israel and Palestine's independence. As a result of the war, Jordan and Egypt annexed part of Palestine, while Israel acquired the rest of Palestine. The Arabs who remained in Israel during the war of independence were granted Israeli citizenship and became known as Arab Israelis (MFA, 2001), the Arabs who fled or left by force became known as Palestinians, although the Palestinian Liberation Organization (PLO) considers anyone (Muslims and Jews) "Palestinian" who resided in Palestine before Israel's independence (Palestinian National Charter, 1968). Some of the exiled Palestinians had relatively high standards of living, such as those who lived in Saddam Hussein's Iraq (Doran, 2003), while others lived in refugee camps where they remain (Shiblak, 1996). Other Palestinians live in villages and cities in the present-day West Bank and Gaza Strip.

Israel's subsequent acquisition of land from its Arab neighbors inspired the Palestinians to seek self-determination (Palestinian National Charter, 1968). A leader emerged, Yasser Arafat, who headed the PLO, whose purpose was to liberate Palestine. The U.S. considered the PLO a terrorist organization because of its terrorist attacks against Israel for the purpose of liberating Palestine. Other terrorist groups emerged whose purposes were also Palestinian self-determination (OLRC, 2005). In 1999, the year examined in my study, Yasser Arafat was the head of the PLO and the head of the

Palestinian people and there was still relative peace. Arafat was involved in peace talks with Israel, which failed in 2000 and preceded the second Intifada. In 1999, relative peace reigned with intermittent terrorist attacks (ICT, 2006). The Oslo Accords discussions took place throughout the 1990s and it appeared that there would be peace between Israel and Palestine, however, the intermittent terrorist attacks continued and Israelis faced the possibility of terror. Some cities were more heavily impacted by violent conflict, such as Tel Aviv and Jerusalem, while other cities experienced a much lower frequency of attacks (ICT, 2006).

In conjunction with Israel's security problems, Israel also faces environmental problems. Israel's climate is temperate, but hot and dry in the south and the east (CIA, 2006). Israel has limited arable land and freshwater resources (CIA, 2006). Israel faces the degradation of its groundwater resources from pollution (CIA, 2006). The majority of Israel's residents live along the coast and in the north of Israel. The Negev desert is sparsely inhabited compared to the more temperate climate and arable land zones. High level of individual stress has been associated with inhabiting crowded cities (Stokols, 1992). Therefore, it is important to research the relationship between environmental factors and the quality of life in Israel.

Several socioeconomic variables have been used in other QOL studies (Lo and Faber, 1997). Lo and Faber also included environmental factors in their QOL research. Lo and Faber found that the socioeconomic factors were related as QOL factors. I argue that the presence of conflict impacts QOL as much or more than the other socioeconomic factors. Thus far, there have been no studies which examine the relationship between violent terrorist conflict, socioeconomic factors, and the environment. My research seeks to examine the relationship between QOL and the environment. I seek to do this using remote sensing as a method to study the environment of urban areas as it relates to QOL.

PURPOSE OF STUDY

The purpose of the study is to use principal components analysis and remote sensing to analyze environment quality and QOL variables to determine if and how they are related. I selected Israel to study the relationship between QOL and the environment because conflict is consistently present in Israel and I wanted to see how conflict as a QOL variable related to environmental issues. Lo and Faber (1997) also studied the relationship between QOL and the environment, but without considering conflict, in the urbanized region of Atlanta, Georgia.

OBJECTIVE OF STUDY

My research uses correlational analyses, principal components analysis, and remote sensing in 45 Israeli cities to analyze the environment and QOL variables to determine if and how they are related and if there are patterns among the relationships (see Figure 1 for a map of Israel). The environmental variables are the NDVI and the percent of built land. The QOL variables are the average income per capita, percent of new motor vehicles, median age, percent of people in each city between 20 and 29 years who are students, percent of families with 4 or more children, population, and the number of violent attacks per city. My research tests the following hypotheses:

H1: Cities with a higher percent of built land are more likely to experience terrorist attacks than areas with a lower percent of built land.

H2: Cities with a higher percent of built land are more likely to experience a higher QOL.

H3: Cities experiencing higher NDVI are more likely to experience a higher QOL.

H4: There is a relationship between QOL and the proportion of built land and NDVI within city boundaries.

In this study, correlational analyses were used to test the first three hypotheses and principal component analysis was used to test the fourth hypothesis.

DEFINITION OF TERMS

Quality of life. This study defines quality of life (QOL) using the following socioeconomic variables: average income per capita, percent of new motor vehicles, median age, percent of students in each city between 20 and 29 years of age, percent of families with 4 or more children, population, and the number of violent terrorist attacks per city. Lo and Faber (1997) found that similar socioeconomic variables related to QOL.

Remote sensing. Remote sensing is the use of satellite images to classify land. It has advantages over land surveying because it can cover large areas of land, be used in a time series, and study land uses in the past.

Built land. For this study, built land is a measure of all urban and developed land. Some of the developed land may contain landscaped vegetation if this land is classified as built land in the supplementary imagery that is used to verify the remote sensing analysis. Another study (Shoshany & Goldshleger, 2002) defined 'developed areas' as having houses, commercial, infrastructure, and industrial spaces. Those land uses are included in the land uses that comprise 'built land.'

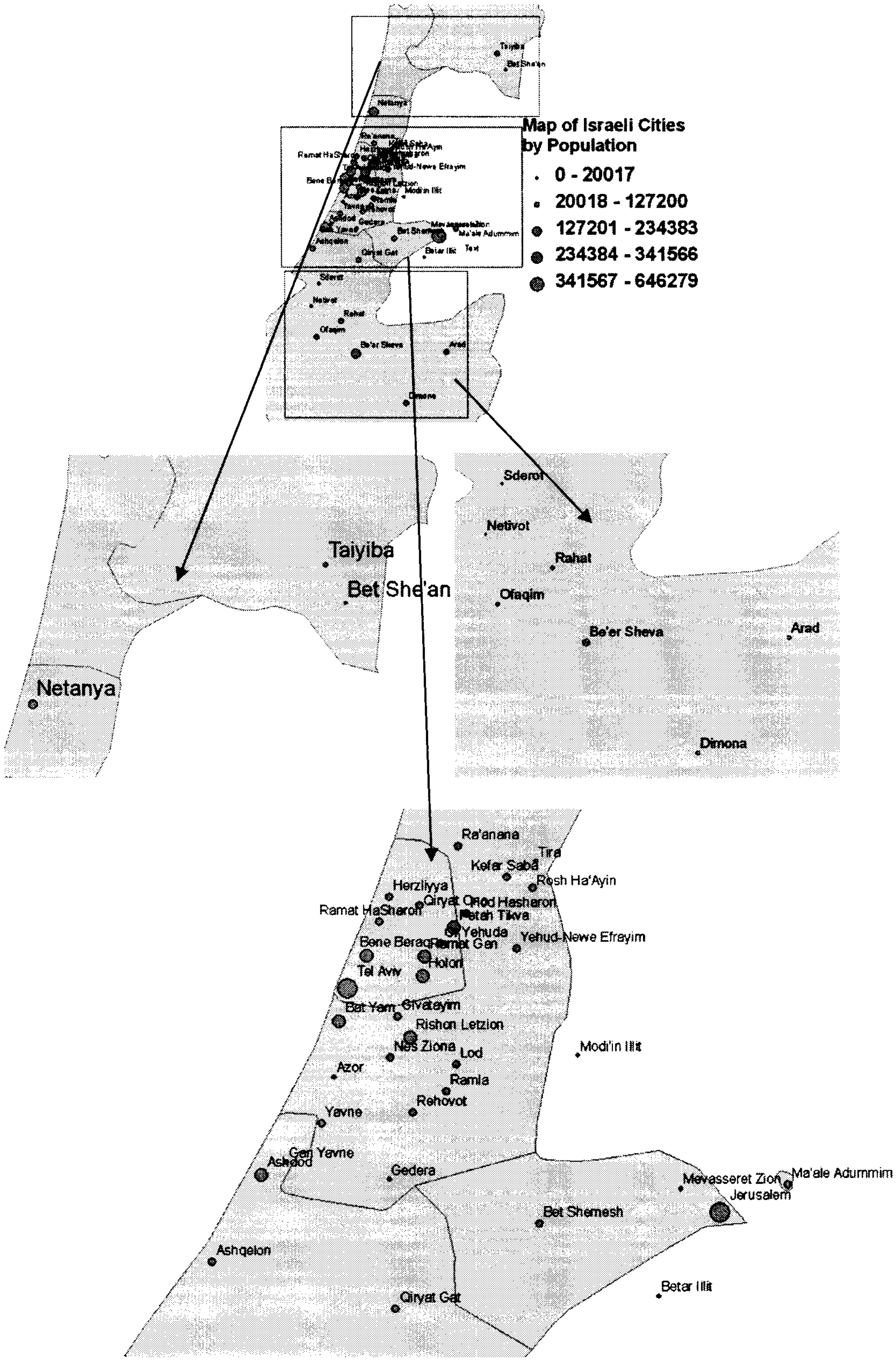
Bare land. Bare land consists of all barren, scrub, undeveloped, agricultural, and vegetative land uses.

NDVI. The Normalized Difference Vegetation Index (NDVI) is a ratio that measures the percent of green cover. It can be used as a measure of environmental quality or as a proxy for built land because built land suggests the absence of green cover. It is measured using remote sensing.

PCA. Principal components analysis (PCA) is a statistical method which finds patterns among variables. This helps determine if there are relationships between the variables that are not obvious using correlation coefficients.

Unsupervised Classification. An unsupervised classification is a classification system where the software that performs the remote sensing clusters the land uses with little input from the user.

Figure 1: Map of Israel showing the cities used in this study with their populations.



CHAPTER 2: BACKGROUND

BACKGROUND

The study of human quality of life (QOL) has been approached through several different scholarly disciplines. QOL is a major topic of research in health and disease analysis (Gill & Feinstein, 1994), rural amenities (Deller et al., 2001), transportation (Frank, 2000), and socioeconomic factors (Lo & Faber, 1997). All of these variables are expected to be relevant to the QOL in Israel. In addition to the commonly studied QOL variables that have been studied in other locations, conflict and fear of conflict impact people's daily activities, from which transportation and bus routes to take, interpersonal debates over human rights treatment, and the ongoing psychological trauma of terrorism.

During the years between the first and second Intifada in Israel, the Israeli and Palestinian governments negotiated a peace settlement that failed and led to the second Intifada. During the years of relative calm, Palestinians reported the belief that their economic conditions had improved and were optimistic about the future (Cragin & Chalk, 2003). Terrorism has also been examined in connection to mental disorders. While a link between mental disorders and terrorism has not been found, there may be a link between an individual who engages in terrorism and developing a mental disorder (Weatherston & Moran, 2003).

Violent conflict impacts not only those who are directly injured or killed in violent attacks, but it also impacts the families and friends of those injured or killed, and everyone in the community. The threat of conflict in Israel mandates that all eligible adults join the army at age 18 with men serving as reservists after their terms end until age 45. Joining the army brings unique challenges to soldiers and their families. The enlistees and families of the enlistees encounter anxiety and emotional trauma, which has been examined in soldiers who experience post-traumatic stress disorder (PTSD) (Dekel & Solomon, 2006; Solomon et al. 1992). Exposure to violent conflict has also been shown to cause PTSD in other groups, which can potentially impact QOL. These groups of people include Palestinian children (Khamis, 2005; Lavi & Solomon, 2005; Baker & Shalhoub-Kevorkian, 1999).

In addition to violent attacks, few studies quantitatively examine the environment in combination with other socioeconomic variables. Bolund and Hunhammar (1999) examined the relationship between "ecosystem services" in urban areas and QOL. They defined ecosystem services as the benefits that humans derive from ecosystems. Homer-Dixon (1999) qualitatively described the relationship between conflict and the environment. Lo and Faber (1997) used quantitative measures to examine the relationship between NDVI, surface temperature, and the percent of built land, and QOL in Atlanta, Georgia. They found a relationship between NDVI and QOL using principal components analysis.

Shafik (1994) sought to examine two opposing views: 1) environmental quality affects human welfare, and higher incomes tend to be associated with environmental degradation; and 2) economic growth tends to result in a steady deterioration of environmental quality. She tested the relationships between environmental indicators—including deforestation, municipal waster, air pollution, lack of access to safe water and urban sanitation, and river water quality—and per capita income. She also hypothesized a relationship between other factors and environmental quality, such as technology, policy, and location-specific characteristics like sampling location (residential vs. commercial, or urban vs. suburban). She found log linear, quadratic, or cubic relationships between environmental quality and per capita income.

Frank (2000) examined the role of transportation in QOL. Increased transportation promotes QOL because it facilitates travel to work and decreases the time spent getting to work. However, Frank (2000) believes that an increase in transportation decreases QOL because it decreases physical activity, which has an association with mortality.

Other studies have examined the relationship between certain environmental and socioeconomic variables. Fung and Siu (2000) used correlations to examine the relationship between remote sensing data and socioeconomic variables. They measured the relationships between the Normalized Difference Vegetation Index (NDVI), urban land uses, purchasing power, economically active population, number of households, population aged 65 or above, degree of crowding, young families, and percentage of home ownership. Millette et al. (1995) used remote sensing to analyze environmental and social change in Nepal. They identified indicators of social and environmental change as expressed in the landscape. They found that the landscape indicators which suggest socioeconomic vitality and environmental stability are agricultural areas with irrigated rice and vegetable production and slopes with bench terraces.

RELATIONSHIP BETWEEN CONFLICT AND ENVIRONMENTAL RESOURCES

There is extensive literature on the relationship between environmental resources and conflict, but statistical evidence between conflict and environmental resources is scant. This section outlines the literature on environmental resources and conflict.

Conflict over environmental resources

Homer-Dixon (1999) defined three types of resource scarcity as supply, demand, and structural scarcities. According to this view, supply scarcity occurs when there is depletion and degradation which produce a decrease in total available resources. Demand scarcity occurs when there is population growth or changes in consumptive behavior. Structural scarcity occurs when there is an imbalance in the distribution of wealth and power. Some groups get more than their fair share of resources, while other groups receive less. Structural scarcity is often a result of class or ethnic relations within a country (Homer-Dixon 1999).

Resource capture is an interaction of supply, demand, and structural scarcities. Powerful groups within a society realize that when a key resource becomes scarce due to supply and demand, they distribute the resource to one group over another, reinforcing structural scarcity. Israel is a key player in resource scarcity with the groundwater supplies in the West Bank (Lowi, 1999). Israel is dependent on the water from the Mountain Aquifer, which is under much of the West Bank and Jerusalem (Lowi, 1999). Israel does not allow for unrestricted Palestinian pumping or access to the aquifer and does not allow building of wells without permits because it fears that the Palestinians might over-pump or pump from too shallow of height causing saline contamination.

Israel does allow the Jewish settlements in the West Bank to receive more than their fair share of the resource pie, the groundwater from the Mountain Aquifer. Palestinian restrictions are so severe that they have lost much of their livelihood in agriculture and have to rely on jobs doing day labor for the Israelis (Homer-Dixon, 1999; Lowi, 1999).

Homer-Dixon (1999) outlined several potential causes of violence from environmental stress. He stated the causes as being from disputes from local environmental degradation, ethnic clashes from population migration, civil strife caused by environmental scarcity affecting economic productivity, scarcity-induced interstate war, and North-South conflicts from global problems. He said that the most likely causes of conflict are ethnic clashes and civil strife. Interstate violence over water will not likely occur. Often interstate violence is spawned by other political, economic or religious issues.

By itself, environmental scarcity is neither a necessary nor sufficient cause of conflict (Homer-Dixon, 1999). Other social, societal and governmental responses can mediate or worsen problems of environmental scarcity. A study on Ethiopia by Green (1995) showed that governmental intervention can assuage environmental scarcity problems or lack of intervention can worsen problems. Between 1984 and 1985, there was severe drought and famine in Africa. Ethiopia was especially affected while the surrounding nations were able to cope due to governmental reaction and actions. In Ethiopia a million people died from lack of food and from disease. The government forced the residents of the areas hardest hit by famine to migrate to other parts of the country. The areas to which the residents moved were inadequately equipped to handle a large influx of new residents. Many died unnecessarily from this forced migration. The government also forced families to move closer to roads so that they could receive governmental services, such as health care and education. Rather than improve the standard of living, this encouraged starvation because farmers had to walk further to reach their fields (Green, 1995).

Two projects that have looked for a link between environmental stress and civil violence were the State Failure Task Force (Esty et al., 1999) and a project by Hauge and Ellingsen (1998). The State Failure Task Force (Esty et al., 1999) found the most efficient ways to distinguish between "failure" states and stable states. The Task Force achieved this through determining the level of material living standards, trade openness, and level of democracy. Material living standards were measured by infant mortality. They did not expect to find a direct correlation between environmental change and state failure but they did believe that environmental change might be significant, negative impact on the factors associated with state failure. Environmental degradation was correlated with infant mortality. This would, in turn, affect state stability. Their findings showed that states with underlying vulnerabilities and limited governmental and social capacity to respond to environmental hazards made them more susceptible to state failure. The environmental variables that they found with statistical significance to infant mortality were soil degradation and deforestation rate. They found that an environmental change initiates an impact on society. The society's ability to cope with the environmental change depends on underlying environmental conditions – the society's vulnerability – and the society's capacity to cope with the change satisfactorily. The higher the capacity, the less likely there will be harm.

The State Failure Task Force cites work by Hauge and Ellingsen (1998) as the only other study which uses statistical tests to measure the direct impact of environmental stress on political violence. Hauge and Ellingsen found that domestic armed conflict is higher in countries with deforestation, land-degradation, and low freshwater availability per capita. Their deforestation and land-degradation results agree with the deforestation and soil degradation results of the State Failure Task Force; however, Hauge and Ellingsen found land-degradation to be the largest motivating factor in conflict, whereas the State Failure Task Force found deforestation to be the largest factor.

EXAMPLES OF CONFLICT OVER ENVIRONMENTAL RESOURCES

Jordan River conflict in the 1950s and 1960s

In the 1950s and 1960s, the Jordan River was a cause of conflict Syria and Israel in the 1950s when Israel began a water development project in the Huleh Basin of Israel. There was further conflict in the 1960s when the Arab nations attempted to divert water from the Jordan River for their use. Israel bombed this project in order to halt its progression (Eberlee, 1998).

Nile River

There has been relatively little violent conflict over the Nile River for a variety of reasons. Egypt and Sudan signed an agreement in 1959, which allocated 55.5 billion cubic meters of Nile water to go to Egypt, 18.5 billion cubic meters of water to go to Sudan, with the rest of the Nile water presumably lost through evaporation and water seepage into Lake Nasser. This agreement suited Egypt and Sudan without considering the other nations further upstream of the Nile River who would try to partake some of the resources pie that Egypt and Sudan kept for themselves. Egypt threatened bombing if other upstream nations tried to allocate some water for themselves. The other upstream riparians had been too busy with civil wars or wars against neighboring nations to proceed with development to procure water from the Nile River. Ethiopia, the biggest threat to diverting Nile waters, had spent the post Cold War years struggling with separatist Eritrean forces and then later a war with independent Eritrea. Sudan has also struggled with non-Muslim separatist forces. The political conflict has overridden conflict that would have otherwise arisen over Egypt's inequity in taking more than its fair share in the resource pie of the Nile River (Klare, 2001).

Currently, political conflict in the Nile region is declining. Ethiopia and Eritrea have a cease-fire agreement. Sudan's opposition groups are talking of peace agreements. Sudan would eventually like to divert more water from the Nile than is allocated in the 1959 treaty with Egypt over water withdrawal rights. With Egypt's growing population, this will become a likely source of conflict since Egypt is struggling to meet the water and food needs of its people. With Egypt's growing size, it needs to feed the population. Egypt already uses every cultivated field, and will need to cultivate more fields to produce enough food. In order to do this, Egypt will need even more water for food production. Egypt is currently trying to achieve the increase in food production without increasing its claim from the Nile River by recycling industrial and urban water in watering its crops. However, with the constantly growing size of the population, Egypt may eventually have to use more than its 55.5 billion cubic meters of Nile water as agreed upon with Sudan in 1959 (Klare 2001).

Egypt is not the only rapidly growing nation in the Nile region. Other nations also face high population growth rates. There is a projected increase in population of 152% between 1998 and 2050 in the Nile basin. The highest projected population increase in Ethiopia with an increase of 213% (WRI, 2000).

Global climate change is also likely to play a role in future water resources in the Nile region. Climate change projections show increased water in the upstream riparian nations caused by increased precipitation in the Central African highlands, including in Ethiopia. In contrast, there will be less water in the lower, drier regions downstream due to increased evaporation. This will be beneficial to the upstream nations but abysmal in Egypt, which would suffer from the increased evaporation (Klare, 2001).

Currently through Egypt has dominion over the Nile water. Until there is more political stability in the region, the water problems will be secondary to the political problems, and Egypt will continue to dominate. Whether Egypt's reign over the water resources will be long or short remains to be seen. Currently Egypt dominates the Nile's resources, just as Israel dominates the Jordan River's resources (Klare, 2001).

Environmental cooperation

Deudney (1999) finds methodological complications in the environmental conflict literature. He feels that environmental conflict researchers do not consider cooperation as a factor of environmental problems. He claims that they only consider conflict as a byproduct of environmental problems. There are other researchers whose stance on environment and cooperation mirror Deudney's stance.

Ali (2003) feels that environmental concerns can lead to conflict but are more likely to lead to cooperation. He believes that environmental problems are likely to create a "sustainable consensus." A sustainable consensus is a contract between two rivals. Heidenreich (2004) further pontificates the point of environmental cooperation. She describes cross border transboundary river project between Bosnia and Herzegovina. She says that the environment can be used as a platform for dialogue and peace in Balkan countries. Dabelko (2006) says that environmental problems can be used for peacemaking. He came up with four conclusions: 1) "The environment plays a role in preventing conflict;" 2) "The environment plays a role as a lifeline during conflict;" 3) "The environment plays a role in ending conflict;" and 4) "The environment plays a role in making peace sustainable and long-lasting."

Cooperation over land uses can also be used to promote cooperation. Rosecrance (1995) argued that Israel and Jordan should have merged and created a shared and common port in Aqaba and Eilat. He also suggested a greater economic openness in disputed territories.

Ali and Grewal (2006) studied an area where there are two projects which mine for minerals. They found that the more successful project embraces flexibility and indigenous ownership rather than by giving money to or trying to buy out the indigenous people. Ali and Grewal say that it is best to let indigenous people retain recognition from the mining company rather than to give them money.

Ray et al. (2001) made suggestions for environmental cooperation. They suggested pest management among Israelis and Palestinians to protect environmental and water quality, wastewater treatment and reuse, and a food for water compromise between

Israel and the Palestinians. Both parties would mutually benefit among these kinds of non-politically loaded cooperation.

EXAMPLE OF ENVIRONMENTAL COOPERATION

Peace treaty with Jordan

The peace treaty with Jordan signed in 1994 was a very important step between Israel and an Arab nation. It could serve as a model for a future treaty that could be signed between Israel and the Palestinians. The Israel Jordan peace treaty overcame difficulties such as the issue of displaced Palestinians living in Jordan. The peace treaty could not have happened if it were not for concessions made on both sides. King Hussein of Jordan relinquished Jordan's claim to the West Bank, as the Palestinians should relinquish their claim to Israel; and while Jordan recovered some of the land claimed by the Israelis, the Israelis have the right to use the land for 25 years after the peace treaty was signed. This could serve as a guide to the Palestinians occupying the West Bank and Gaza Strip who demand for the immediate removal of Jewish settlements. Jordan made the concession that before regaining control of the land, Israel could occupy it in a transition period (MEDEA, 2001).

Solving other, more immediately serious problems with Jordan, allowed Israel and Jordan to improve their relations concerning water. As part of the agreement, Israel gives Jordan a 20 million m^3 of water per year. However, in 1999, after a dry year, Israel was unable to meet the supply that it had promised to Jordan. Jordan still insisted on receiving its supply, even in drought years when the water is not available (MEDEA 2001). Thus far, this has not led to conflict, but lack of conflict due to hydrologic stress could be due to other factors causing conflict in the region unrelated to water scarcity, such as the Palestinian intifada.

REMOTE SENSING, LAND USE, AND THEIR RELATIONSHIP TO QOL ISSUES

Lo and Faber (1997) related remote sensing of land use to QOL. There is a lot of research that relates remote sensing and land use to issues that impact QOL. These studies do not use these factors as QOL indicators but nonetheless link remote sensing to QOL variables. Issues that impact QOL that can be measured using remote sensing are climate and agriculture.

Climate

Climate can impact QOL in different ways, including, the urban heat island effect and extreme weather events such as tornadoes, hurricanes, and cold conditions.

The urban heat island effect occurs in built areas where the temperature is higher than in surrounding rural areas (EPA, 2007). Research has been slow to show the causes of higher temperatures in urban areas (Voogt & Oke, 2003). The EPA further states, "heat islands form as cities replace natural land cover with pavement, buildings, and other infrastructure. These changes contribute to higher urban temperatures in a number of ways: 1) displacing trees and vegetation minimizes the natural cooling effects of shading and evaporation of water from soil and leaves (evapotranspiration); 2) tall buildings and narrow streets can heat air trapped between them and reduce air flow; and 3) waste heat from vehicles, factories, and air conditioners may add warmth to their surroundings, further exacerbating the heat island effect." (EPA, 2007). The urban factors that create heat islands can have both positive and negative impacts on QOL. Heat islands form in urban areas because natural vegetation is replaced by built land, which reflects light differently than vegetative cover. Urban areas have higher solar radiation absorption because they are covered with buildings and impervious surfaces, and thus the heat that is stored during the day is released at night (Weng, 2001a). Other factors go into the development of heat islands, such as those listed by the EPA (2007) above. The replacement of vegetative land with built land may have an impact on QOL, depending on if the advantages of the built land outweigh the disadvantages. In addition, other contributing factors to the heat island effect can diminish QOL. These can include the urban structure and the pollution from the industry that causes the warming. Weng (2001a) examined the Pearl River Delta, China and found that areas of urban development had increased surface temperatures.

De Ridder and Gallee (1998) demonstrated that local climate changed when irrigation improved in Southern Israel. Irrigation improves QOL by allowing food and agricultural production in regions where production otherwise would not be tolerated due to climate or other factors relating to soil quality. De Ridder and Gallee showed that climate change can be associated with a factor that improves QOL.

Agriculture

Agriculture plays a role in QOL in two ways. It provides food to feed a local population and it provides a source of income when the food is exported. Remote sensing has been used to monitor agricultural productivity, crop yield, and NDVI in relationship to agricultural output.

Lobell et al. (2003) used remote sensing to study crop production, yield, and area in Yaqui Valley, an agricultural region in Mexico that produces a large percentage of the world's wheat. They predicted yield using the fraction of absorbed photosynthetically active radiation and simple model. They found high error in multitemporal imagery, but had low error using a single date image. Lobell and Asner (2003) performed decadal analysis of agricultural land in the United States and found that climate contributes more to crop yield than management. This study by Lobell et al. (2003) shows and effective way to monitor crops, which can help mitigate future conflicts, needs over increasing population, and urbanization. Lobell and Asner (2003) then show that management may play a smaller role in crop yield than previously believed and that climate may be a more important factor in crop yield.

Xiuwan (2002) used remote sensing to analyze land use change and its impact on sustainable development in Korea. He used several different classification methods to test accuracy of quantifying land use change in Korea. He selected a mixture of supervised and unsupervised classifications to create the most accurate land use analysis. He used NDVI for vegetation changes. Vegetative land decreased even though NDVI increased. He found that NDVI increased due to expansion in agricultural land. Industrialization and urbanization in his study area has been very fast. This development put strain on water resources, which decreased during his study period. He found that land has changed due to a combination of human activities and natural forces and that these changes impact sustainable development. He concluded that natural resources, ecosystems, and environmental states impact regional and economic development.

Guyer and Lambin (1993) studied land use in Ethiopia and concluded that population growth and food sales to international markets were increasing at too high of a rate and was causing farmers to cease their practice of allowing farmland land to lie fallow after cultivation. They used remote sensing to look at patterns of land use and NDVI among agricultural lands. Weng (2001b) used remote sensing to look at how urban growth causes problems with runoff and water management. He found that urban areas were more likely to flood due to the area's inability to store water.

CHAPTER 3: METHODOLOGY

STUDY AREA

The study area covers 45 cities in the central part of Israel from Taiyiba in the north to Dimona in the south (Fig. 1.1). These 45 cities were selected because of they were defined as "urban localities" by the Israel Central Bureau of Statistics (CBS, 2003). Urban localities contain more than 2,000 residents. These 45 cities had greater than 2,000 residents and were located in the Landsat image in areas that were not obscured by cloud cover (Figure 3.1). The largest city is Jerusalem with a population of 646,279 and the smallest city is Azor with a population of 9,302. Public services contain the largest sector of the Israeli labor force at 31.2% (CIA, 2006). Manufacturing is the second largest sector with 20.2% of the labor force (CIA, 2006). Agriculture, forestry, and fishing is the smallest part of the labor force at 2.6% (CIA, 2006).

Twenty-one percent of the country is below the poverty line and the literacy rate is 95.4% (CIA, 2006). Two major religions, Judaism (76.4%) and Islam (16.4%), make up the majority of people in Israel. Eight percent of the population is Christian, Druze, or unspecified (CIA, 2006). The Jewish residents are of various ethnicities from Israel and all over the world. Hebrew and Arabic are the official languages with English being the most commonly used foreign language (CIA, 2006).

DATA

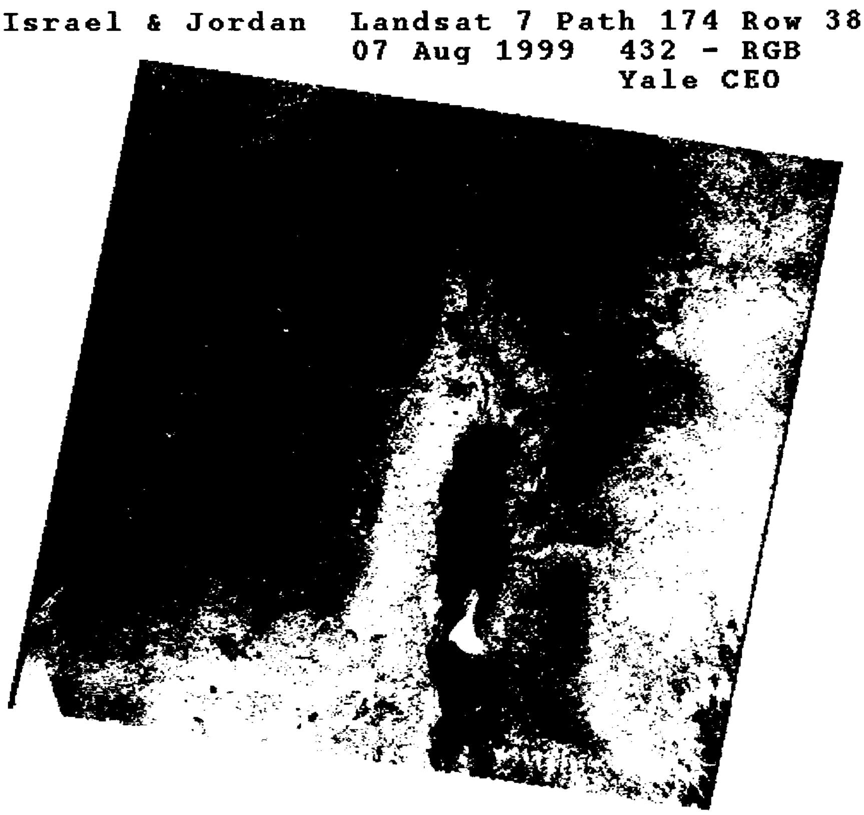
There were five sources of data for this research. The data came from the Landsat Enhanced Thematic Mapper 7 (Figure 3.1), Google Earth, Maps.walla.co.il, the Israel

Central Bureau of Statistics (CBS), and the International Policy Institute for Counter-Terrorism (ICT) at the Interdisciplinary Center in Herzliyya, Israel.

The Landsat image of Israel was acquired on August 7, 1999 (Figure 3.1). A summer image was selected because it was not obscured by cloud cover. An image was selected from 1999 because 1999 was near the end of a period of relative peace. During the 1990s, there peace negotiations occurred between the Israelis and the Palestinians. There were still low levels of terrorist conflict among the Israelis and Palestinians, but this conflict was not triggered by any particular event. The Second Intifada, which began in 2000, was triggered by a series of events that included failed peace negotiations, Ariel Sharon's visit to the Temple Mount, and incitement by Arab leadership. In 1999, the violence was more likely due to inequalities and resentment between the Palestinians and the Israelis and not from a specific motivating factor. The particular Landsat scene was selected because it was from the summer and contained no cloud cover in most of the image. Lo and Faber (1997) selected an image from midyear to coincide with the socioeconomic data. For my research, a winter image could have been better to distinguish between vegetative and built land uses, which arose as a difficulty in the summer image due to the spectral similarity between built and bare land uses. My research agrees with Lo and Faber's (1997) reason for selecting a midyear image and did not select a winter image because of the socioeconomic data.

Imagery from Google Earth, Maps.walla.co.il, and the CBS were obtained as reference images. The satellite images from Google Earth had twice the resolution as the Landsat image. The Google Earth pixels were 15 meters by 15 meters. The images from Maps.walla.co.il and CBS were thematic land use maps.

Figure 3.1: Landsat 7 image of Israel, August 7, 1999. The cloud cover in the northwest corner of the image appears white.



Socioeconomic data were obtained from the CBS and ICT. The variables from CBS were average measured by locality and were income per capita, percent of new motor vehicles, median age, percent of people in each city between 20 and 29 years who are students, percent of families with 4 or more children, and population. The variable from the ICT was the number of terrorist attacks per locality. CBS obtained the data from the National Insurance Institute (NII), Ministry of Labor and Social Affairs (MLSA), and Ministry of Religious Affairs (MRA) (CBS, 2003). The CBS defined locality as a "permanently inhabited place" that has 40 or more permanent inhabitants, has an independent administration, is not within the boundaries of another locality, and whose establishment was authorized by planning institutions. The CBS included in its report data for localities that had 2,000 or more residents. It chose socioeconomic data that existed for all types of geographical units that exist in Israel. These included kibbutzim (collective rural cooperatives), moshavim (semi-collective cooperatives), and regional councils. I solely used data on the urban locality level.

The CBS (2003) calculated average income per capita was measured by the following equation:

$$\frac{(A*B)+(C*D)+G}{P}$$

where A is the average monthly wage per employee residing in the locality in 1999; B is the number of employees residing in the locality; C is the income of the self-employed based on tax collection, divided by 12; D is the number of self-employed residing in the locality; G is the total income from all benefits paid by the NII and MRA in 1999 divided by 12; and P is the total population of the locality. These data came from the NII and MRA.

My study uses population rather than population density, which Lo and Faber used (1997). Shoshany and Goldshleger (2002) studied population density in Israel and found that population densities in developed areas were higher than those in the total district area. This means that for my project, I cannot use or calculate the population density for each city because development is clustered in a small area in many cities where the Israeli government designated the municipal boundaries far outside the developed areas. Thus, population density would appear artificially low and is not sufficiently accurate for this study.

The percent of new motor vehicles was estimated by the total number of private cars and trucks up to 4 tons made during or after 1995 dived by the total number of private cars and trucks in a locality in 1999. These data came from the CBS.
The median age in each city was and the percent of families with 4 or more children, estimated as a percentage of the total number of families receiving child allowances, were based on NII data. The percent of people in each city between 20 and 29 years who are students is calculated from the total number of residents between 20-29 years old in a locality. This came from the CBS.

The ICT collected data on terrorist and guerilla attacks from around the world (ICT, 2006). My research only used data that were from the pre-1967 borders of Israel, with the exception of Betar Illit, Ma'ale Adummim, and Modi'in Illit, which are located in the West Bank. Ma'ale Adummim is located within the municipal boundaries of eastern Jerusalem that were captured after 1967. Israel considers eastern Jerusalem to be part of Israel and not the West Bank. Others consider Ma'ale Adummim to be part of illegally seized land and a settlement (ARIJ, 1997). Betar Illit, Ma'ale Adummim, and Modi'in Illit were included in my study because the CBS included these cities with other cities that were included in the pre-1967 borders and did not pair them with other West Bank cities. The violent attack data were aggregated by city in order to be in the same unit as the other socioeconomic data.

Two cities from my study, Rahat and Taiyiba, consisted of a Muslim majority. These cities were among the poorest cities in my study and scored lower on many of the QOL data that were examined for this study. The median ages in these two cities were also low. This could be attributed to the large number of children in each family (CBS, 2003). I did not include more Arab cities in my study because many of them are located in the north of Israel beyond the boundary of the satellite image that I used or are located in parts of the satellite image that were obscured by cloud cover. The data that the CBS provided did not include Arab villages that were in the Palestinian territories. I excluded these cities from the research. Due to the dearth of consistent available data on Arab cities, I do not make any conclusions on the differences between QOL in the Arab and Jewish cities.

The city boundaries were provided by the CBS in the same CBS images that provided the thematic land use classifications. The borders were used to trace and clip the city borders on the Landsat image using remote sensing software from PCI Geomatics. The process of drawing the city borders on the satellite image is called digitization. The borders were drawn on the Landsat image according to the borders from the thematic maps. The land uses from the Landsat image were identified on the thematic maps, and thus it was possible to delineate the borders on the Landsat image using the land uses as markers.

CLASSIFICATION OF REMOTE SENSING AND ENVIRONMENTAL DATA

Two environmental variables were derived from the Landsat data: 1) land use and 2) the normalized difference vegetation index (NDVI).

Remote Sensing of Land Use

A Landsat 7 satellite image of Israel was selected from Path 174, Row 38 taken on August 7, 1999. The coordinates were 31 45 48 N and 35 33 27 E on Degree/Minute/Scale coordinates. Its entity identification number is 7174038109921950. It was provided by the Center of Earth Observation (CEO) at Yale University. CEO acquired the image from the EROS Data Center. This satellite image was selected because it had low cloud cover in the majority of the image. The northwest part of the image was contaminated with clouds, and thus many cities in that part were excluded from analysis. The software used for the analysis was from PCI Geomatics.

Background on Landsat satellite as a remote sensing instrument

The first Landsat satellite was launched in 1972. It was initially called the Earth Resources Survey Satellite, or ERTS-A, and was renamed ERTS-1 when it reached orbit. ERTS-B was launched in 1975, and was renamed Landsat 2 when it reached orbit. ERTS-1 was renamed Landsat-1 at that point as well. Landsat 1 operated until 1978 (Taranik, 1978). Landsat 3 was launched in 1978, Landsat 4 was launched in 1982, Landsat 5 was launched in 1984, Landsat 6 was launched in 1993 (but failed to orbit, thus data attainment was never achieved), and Landsat 7 was launched in 1999. Landsats 1 – 3 carried return beam vidicon cameras, Landsats 1 – 5 carried multispectral scanners (MS), Landsats 4 – 5 carried thematic mappers, and Landsats 6 – 7 carried enhanced thematic mappers (USGS, 2003a). The multispectral scanner scans the earth in a 185-kilometer swath. It uses an oscillating mirror and fiber optic sensor array. Its resolution is 80 meters and has radiometric coverage in four spectral bands ranging from green in the visible spectrum to near-infrared (USGS, 2003b), or 0.5 – 1.1 microns (USGS, 2002). Data collection from multispectral scanners ceased in 1992.

The thematic mapper (TM), on board Landsats 4 and 5, absorbs in seven spectral bands (compared to the MS, which only has four bands) ranging from 0.45 – 12.50 microns with a resolution of 30 meters, with the exception of band 6, which has a resolution of 120 meters (USGS, 2002) (Table 3.1). The scenes are approximately 170 x 183 kilometers (USGS, 2003c).

The enhanced thematic mapper (ETM), on board Landsat 7, absorbs eight spectral bands, ranging from 0.45 – 12.50 microns with a resolution of 30 meters, except for band 6, which has a resolution of 60 meters, and band 8, which has a resolution of 15 meters (USGS, 2002).

Table 3.1: Thematic mapper spectral bands and their description of what landscape features they detect based on their wavelengths (from Lillesand & Kiefer, 2000).

Band	Wavelength (μm)	Nominal spectral location	Principal applications
1	0.45 – 0.52	Blue	Designed for water body penetration, making it useful for coastal mapping. Also useful for soil/vegetation discrimination, forest type mapping, and cultural feature identification.
2	0.52 – 0.60	Green	Designed to measure green reflectance peak of vegetation for vegetation discrimination and vigor assessment. Also useful for cultural feature identification.
3	0.63 – 0.69	Red	Designed to sense in a chlorophyll absorption region aiding in plant species differentiation. Also useful for cultural feature identification.
4	0.76 – 0.90	Near Infrared	Useful for determining vegetation types, vigor, and biomass content, for delineating water bodies, and for soil moisture discrimination.
5	1.55 – 1.75	Mid Infrared	Indication of vegetation moisture content and soil moisture. Also useful for differentiation of snow from clouds.
6	10.4 – 12.5	Thermal Infrared	Useful in vegetation stress analysis, soil moisture discrimination, and thermal mapping applications.
7	2.08 – 2.35	Mid Infrared	Useful for discrimination of mineral and rock types. Also sensitive to vegetation moisture content.

Image preprocessing—geometric correction. Images also need to be corrected due to systematic and nonsystematic geometric distortions. Systematic distortions are caused by scan skew, mirror scan velocity, panoramic distortion, platform velocity, earth rotation, and perspective geometry; while nonsystematic distortions are caused by altitude and attitude (Bernstein & Ferneyhough, 1975; Bernstein, 1983; Jensen, 1986). Some of these errors can be corrected using knowledge of platform ephemeris and internal sensor distortion, while others can be corrected using ground control points (points on the earth where image and map coordinates can both be identified). Systematic distortions (except for earth rotation) can be corrected with platform ephemeris and internal sensor knowledge; while nonsystematic distortions can be corrected using ground control points (Jensen, 1986). Landsat corrected these distortions.

Image preprocessing—radiometric normalization. Before change detection analysis, the data from different images must be radiometrically corrected and normalized. Radiometric correction amends for errors in detector response (Jensen, 1986). Detector response errors that occur can manifest as line dropouts, striping, and line start problems. A line dropout occurs when a detector does not operate during a scan resulting in a zero brightness value for every pixel in a line for a particular band. Since it is not possible to restore the nonexistent data, it is possible to use the brightness information from the preceding and proceeding bands to create a value for the nonexistent band. The values for the nonexistent band are created using the following equation:

$$BV_{ijk} = Int\left(\frac{BV_{i-1,j,k} + BV_{i+1,j,k}}{2}\right)$$

where i is the line, j is the pixel, k is the band, the output for the missing line is BV_{ijk}, the output for the preceding line is $BV_{i-1,j,k}$, and the output for the proceeding line is $BV_{i+1,j,k}$. Every pixel in line from a bad scan can use this method to fill in for missing pixels (Guindon, 1984).

Striping occurs when detector goes out of adjustment and creates a reading with a contrast value greater than other detectors of the same band. The data need to be restored to the same contrast as the other detectors of the scan. A histogram is created to determine which scan lines of each of the detectors over a homogenous scene, such as water, to determine which band is out of contrast. If a detector has a median or mean that is significantly different from the other detectors, it is probable that it needs adjustment. Correction using a bias or a more severe gain can be employed to minimize error. Bias correction makes an additive or subtractive adjustment and a more severe gain makes a multiplicative adjustment (Jensen, 1986).

"Line start" problems occur when a scanning system fails to scan at the start of a scan line or when the detector fails to collect data along the line. The first pixel of a band could be located on the wrong line. If it commonly is located on that line, it is simple to adjust the pixel to the proper line. However, if the displacement is random, it is almost impossible to adjust the misplaced pixel (Jensen, 1986).

Landsat corrected these distortions before distribution. I received the corrected image.

Image preprocessing—atmospheric corrections. I performed an atmospheric correction on the image to correct for haze and solar effects and other atmospheric artifacts in the satellite image that did not reflect actual land use. The atmospheric correction calibrates the image according to a standard calibration file, solar zenith and azimuth angles (information available in metadata files). The correction algorithm was the atcor2 algorithm which was developed by Richter (1996a; 1996b; and 1998). This algorithm is used for flat terrain and allows the user to specify the parameters for the type of environment where the satellite image is located. The elevation was set to 0.2 kilometers and the date and pixel size of the image were input to August 7, 1999 and 30 meters^2. The calibration file was C:\Geomatica_V91\atcor\cal\landsat7\etm_standard1.cal. The Atmospheric Definition Area was "desert," the Condition was "dry," and the Thermal Atmospheric Definition was "Arid." To determine the correction parameters, an auxiliary file that came with the satellite image provided the sun azimuth angle. Knowledge of the sun azimuth angle allowed the software to calculate the solar zenith angle. Visibility and adjacency were kept at the default of 30.0 km and 1.0 km.

Selection of cities from the satellite image. Forty-five cities were selected in Israel for remote sensing analysis (Table 4.1). I selected them if the CBS provided additional socioeconomic data. Some cities were excluded from remote sensing analysis due to high cloud cover in the northwest corner of the image (Figure 3.1). The clouds also created shadows rendering analysis unfeasible.

The cities were clipped from the satellite image using the "new shapes" tool. The user outlined the city borders and the clipped them using the clipping/subsetting feature. The Israel Central Bureau of Statistics made these boundary data available to the public via the internet.

NDVI. Researchers have demonstrated the relationship between NDVI and variables that relate to QOL, such as urbanization and climate (Zhou et al., 2004), food production (Guyer and Lambin, 1993), and crowding (Fung and Siu, 2000). The NDVI is a ratio based index employing the red and near infrared (NIR) bands (Chen et al., 1998) and is one of the most commonly used methods for analyzing vegetation cover (Tucker et al., 1998). It is useful in studying vegetative vigor in arid environments. Measuring vegetation in arid environments is difficult due to the high proportion of land without vegetative cover, such as land covered by rock, soil, and litter. The NDVI counters this problem by using both the red and NIR bands (Chen et al., 1998). The red band absorbs chlorophyll, while the NIR reflects plant materials (Tucker, 1979). This can be used to estimate percent green cover (Chen et al., 1998) and is calculated by the following formula (Rouse et al., 1974):

$$\mathrm{NDVI} = \frac{NIR - red}{NIR + red}$$

where NIR = the brightness value in the near infrared band (band 4), and red = the brightness value in the red band (band 3).

The NDVI ranges between –1.0 and +1.0. Typical NDVI values for vegetation are 0.1 –0.6 for vegetation (higher values indicate denser vegetation); below 0 for clouds, snow, and water; and approximately 0 for developed land uses, bare rocks and soils. Snow and water reflect red more strongly than NIR and result in negative values. Bare rocks and soils reflect red and NIR about equally.

The mean NDVI for each city was determined. Each mean NDVI value was integrated with the other socioeconomic data for each city.

Green cover and the percent of urban land have been shown to have a relationship with QOL variables (Lo and Faber, 1997). Lo and Faber classified urban land as "commercial or industrial or both" and "transportation" but excluded residential land uses. They said that "commercial or industrial or both" and "transportation" negatively impact QOL, but that residential land is desirable and does not negatively affect QOL. For my study, residential land is not separate from the built land percentage for each city. In other countries, residential land contains mixed land use types from high density to low density housing. Low density housing often contains greenscaping to enhance the beauty and desirability of the location (Kloss and Calarusse, 2006). Israel contains a high level of high density housing (Alterman, 2002), thus residential housing was included in the percent of built land, even though Lo and Faber (1997) say that residential land contributes to a higher QOL. However, in the final results for my study, the mean NDVI for each city was found to have a slight positive correlation with the percent of built land. Lo and Faber (1997) found that greenness has a negative correlation with built land, but this was not found to be true in my study. This could be attributed to the greenscaping in the urban areas, which my study classified as built land.

Unsupervised classification. In the unsupervised classification, the data or pixels of the image are grouped into categories of similar spectral properties. These clusters of pixels are compared to ground truth data to determine what land uses the clusters represent (Lillesand & Kiefer, 2000). The software determines where the clusters of land uses are. The user determines what land uses these clusters are. The land uses for each city were classified using a k-means unsupervised classification. Between 10 and 32 initial clusters were grouped together to maximize the ability to distinguish between land use classes. The clusters were then aggregated to 3 classes: bare, built, and a class which contained pixels outside of the city boundaries. The land use classes were verified using the ancillary data provided by CBS, Google Earth, and Maps.walla.co.il. Accuracy analyses were performed on 250 pixels that were randomly placed by the unsupervised classification algorithm. Each pixel was identified as 'built' or 'bare' according to its corresponding location on ancillary maps. To perform the accuracy check, the photointerpreter compared the pixel in the satellite image to the reference data to determine if the software had assigned the pixel to the correct land use class. All vegetative and bare land uses were grouped into the same bare land use class. Issues arose because of the spectral similarity between built land uses and bare land uses that included undeveloped land with low vegetative cover. Those pixels were spectrally similar and there was often confusion between those pixels.

The reference images were taken from the 1) the Israel Central Bureau of Statistics, which provides a detailed thematic land use map of Israel (http://gis.cbs.gov.il/website/landuse_2002/mavo/main.html); 2) the Ministry of the

Environment, which provides aerial photographs of Israel (http://gis.sviva.gov.il/); and 3) Google Earth, which provides satellite images of Israel at a 15x15 meter resolution.

Error Matrices. Error matrices were generated for each city. The error matrices showed how select pixels were classified and misclassified. The columns represented the reference data and the rows represented the classified data. The diagonal in matrix represented the number of correctly classified pixels. The column totals were used to calculate the producer's accuracy, the row totals were used for the user's accuracy, and the Kappa coefficient uses all totals (Lillesand & Kiefer, 2000).

Kappa. To measure the photointerpreter's accuracy in analyzing the satellite image and assigning land use types, the Kappa coefficient of agreement was used. Kappa has been found to be more accurate in judging change versus no change than other statistical methods (such as producer's accuracy and user's accuracy) (Fung & LeDrew, 1988).

The Kappa coefficient of agreement measures the actual agreement minus the chance agreement. It is the proportion of agreement after chance is removed for total map accuracy (Rosenfield & Fitzpatrick-Lins, 1986). It is calculated for each error matrix from each band of comparison and is a measure of how the classification performs compared to the reference data (Fung & LeDrew, 1988). The Kappa coefficient of agreement test statistic is (Ward, Phinn, & Murray, 2000):

$$K = \frac{\text{(observed accuracy - chance agreement)}}{\text{(1 - chance agreement)}}$$

where K = Kappa.

Cohen (1960) first determined K is calculated using the following formula:

$$K = (p_o - p_c)/(1 - p_c)$$

in which $p_o =$ the proportion of units which agree, p_c = the proportion of units for the expected chance agreement, and $p_o = \Sigma p_{ii}$, $p_c = \Sigma(p_{i+}p_{+i})$, $p_{ij} = X_{ij}/N$, where N = the total number of counts in a matrix, and X_{ij} = the number of count in a the ijth cell (Rosenfield & Fitzpatrick-Lins, 1986). The values range between 0 and 1. A value of 1 indicates perfect agreement. A value of 0 indicates that agreement is no better than chance (Rosenfield & Fitzpatrick-Lins, 1986). When obtained agreement equals chance agreement, $K = 0$; when there is perfect agreement, $K = 1$ (Cohen, 1960). Kappa is calculated according to an agreement matrix of proportions (Table 3.2).

Table 3.2: Cohen's (1960) agreement matrix of proportions.

			Judge A		
	Category	**1**	**2**	**3**	p_{iB}
	1	.25 (.20)*	.13 (.15)	.12 (.15)	.50
***Judge* B**	**2**	.12 (.12)	.02 (.09)	.16 (.09)	.30
	3	.03 (.08)	.15 (.06)	.02 (.06)	.20
	p_{iA}	.40	.30	.30	$\sum p_i = 1.00$

$p_0 = .25 + .02 + .02 = .29$
$p_c = .20 + .09 + .06 = .35$

* Parenthetical values are proportions expected on chance association. Chance for Category 1 is calculated multiplying the amount of units that Judge A placed in Category 1 (.40) by the amount of units that Judge B placed in Category 1 (.50); thus (.40)(.50) = .20. In satellite image analysis applications, Judge A would be replaced with reference (or ground truth) data, and Judge B would be replaced with the interpretation data.

Cohen (1960) introduced Kappa for applications in clinical and social psychology to measure interrater reliability between two judges in determining, e.g., mental health conditions, and whether the judges' agreement would occur by chance or was actual agreement. Kappa differs from χ^2 because χ^2 measures association. Association may or may not imply agreement between the two judges.

Congalton and Mead (1983) applied Cohen's Kappa to consistency and correctness between photointerpreters. Their accuracy analysis was based on "an appropriate sampling scheme" and "an adequate number of samples". Instead of using the results from two judges to calculate Kappa as Cohen (1960) did, Congalton and Mead (1983) used reference data and interpretation results to determine Kappa. The reference data acted as the first judge, while the interpreter determining the specific land use acted as the second judge.

Congalton and Mead (1983) calculated conditional agreement coefficients between one photointerpreter and the reference data for each category of data. For example, their categories were pine, cedar, oak, and cottonwood. They calculated categorical Kappas for each category. This allowed them to find the level of agreement that the photointerpreter had between each category and its reference data. Reference data can be obtained from either aerial photographs (e.g. Congalton and Mead, 1983; Ward et al., 2000) or ground truth data (e.g. Reese et al., 2002). Ground truth data are best suited for determining present land uses and not land use change over time. Only if there were historical ground truth data for the years of interest, would ground use data be a viable option in change detection analysis. Otherwise, using aerial photographs taken during the appropriate years can serve as the reference data when determining Kappa. The research performed for this study used a variety of reference data.

Producer's accuracy. The producer's accuracy studies errors of omission where a pixel is excluded from its correct land use class. The producer's accuracies for each city were determined by dividing the number of correctly classified pixels by the column total. The column total was the number of training pixels for each land use class. The producer's accuracy showed how well the reference pixels were classified for each land use (Lillesand & Kiefer, 2000).

User's accuracy. The user's accuracy examines errors of commission where a pixel is included in the wrong category. The user's accuracies for each city were calculated by dividing the number of correctly classified pixels by the row total. The row total was the number of pixels that were categorized into that land use class. The user's accuracy indicated how well the pixel assigned to a given land use class actually represents that class on the ground (Lillesand & Kiefer, 2000).

Overall accuracy. The overall accuracy is calculated by dividing the total number of correctly classified pixels by the total number of reference pixels (the row total) (Lillesand & Kiefer, 2000).

SOCIOECONOMIC DATA USED IN QUALITY OF LIFE ANALYSIS

This study used several variables to measure QOL. They were: 1) the average income per capita; 2) percent of new motor vehicles; 3) median age; 4) the percent of people in each city between 20 and 29 years who are students; 5) the percent of families with 4 or more children; 6) population; and 7) and the number of violent attacks per city. The data were collected in 1999 on the city level by the CBS and ICT in Israel. Lo and Faber (1997) selected similar socioeconomic variables, however, some of their variables were not available for Israel. Nonetheless, the variables that I selected still showed evidence to support the hypothesis. The variables selected for Israel are believed to have a large impact on the daily QOL that the residents face.

USING STATISTICAL ANALYSES AND PRINCIPAL COMPONENTS ANALYSES TO EVALUATE THE ENVIRONMENTAL AND QOL DATA

Principal components analysis (PCA) was used to integrate the environmental and QOL data. PCA is a method to reduce related or unrelated variables into related factors. PCA is often used in remote sensing to create image components that are unrelated to each other. It compresses the information from a larger number of bands from seven into two or three bands (Townshend, 1984). The first two or three components explain a high proportion of variance from the original data, while the remaining components explain less and can be omitted. In my research, PCA was not used to reduce the data within the satellite image, it was used to determine the relationship between the socioeconomic (average income per capita, percent of new motor vehicles, median age, percent of people in each city between 20 and 29 years who are students, percent of families with 4 or more children, population, and the number of violent attacks per city) and remote sensing (the percent of built land and NDVI) data. SPSS software performed the PCA.

PCA is an improvement over simple correlation coefficients and correlation matrices. My study used nine variables, which produced 81 correlations in a correlation matrix. It was necessary to interpret the 81 correlations and then to find if there was a pattern or relationship among the correlations. Kline (1994) suggests asking what accounts for the correlations. Knight et al. (1994) created functioning and motivation scales to measure drug treatment readiness. They formulated a series of questions and analyzed the questions using principal components analysis. They found that questions grouped together into relatable patterns. For example, questions that asked about depression loaded most strongly onto the same factor.

CHAPTER 4: RESULTS

SUMMARY OF RESULTS

Forty-five cities were analyzed with a K-Means Unsupervised Classification to determine the percent of built land and the percent of undeveloped land in each city. The forty-five cities are shown in Table 4.1. The analysis of the 45 cities and their corresponding census data revealed two components: 1) median NDVI, average income per capita, percent of new motor vehicles, median age, percent of people in each city between 20 and 29 years who are students, and the percent of families with 4 or more children; and 2) conflict, population, and the percent of built land in a city. The first component grouped socioeconomic variables and NDVI while the second component grouped non-socioeconomic variables. These two physical remote sensing variables grouped in different principal components.

Table 4.1: Forty-five cities in Israel were analyzed using remote sensing to determine the percent of built land and the NDVI.

CITY	% OF BUILT LAND	MEDIAN NDVI
Arad	5.76	.105
Ashdod	31.68	.164
Ashqelon	21.58	.187
Azor	52.44	.223
Bat Yam	70.51	.157
Be'er Sheva	54.63	.116
Bene Beraq	73.18	.154
Bet She'an	46.18	.182
Bet Shemesh	24.78	.223
Betar Illit	32.71	.176
Dimona	13.53	.107
Gan Yavne	13.17	.244
Gedera	23.68	.229
Givatayim	78.84	.215
Herzliyya	48.09	.251
Hod HaSharon	40.75	.268
Holon	59.29	.171
Jerusalem	40.78	.167
Kefar Saba	54.72	.250
Lod	44.30	.189
Ma'alé Adummim	6.94	.111
Mevasseret Zion	52.52	.223
Modi'in Illit	31.01	.169
Nes Ziona	27.09	.275
Netanya	50.88	.197
Netivot	65.98	.130
Ofaqim	34.10	.114
Or Yehuda	37.33	.232
Petah Tikva	35.92	.223
Qiryat Gat	30.97	.152
Qiryat Ono	67.72	.270
Ra'anana	42.97	.268
Rahat	20.30	.107
Ramat Gan	66.04	.231
Ramat HaSharon	32.48	.252
Ramla	39.19	.195
Rehovot	28.32	.232
Rishon Letzion	17.64	.189

Rosh Ha'Ayin	28.31	.165
Sderot	63.08	.170
Taiyiba	23.85	.202
Tel Aviv	67.13	.202
Tīra	38.32	.230
Yavne	29.99	.202
Yehud-Newe Efrayim	59.98	.250

The overall accuracies ranged from 71.721% to 97.177%. The producer's accuracies ranged from 43.333% to 100.000% in the built and 19.355% to 97.080% in the bare land uses. The user's accuracies ranged from 33.333% to 91.837% in the built and 35.294% to 97.794% in the bare land uses. Overall Kappa coefficients ranged from 0.558 to 0.945. Individual Kappa coefficients ranged from 0.2565 to 0.9507 for bare and 0.2346 to 0.8653 built land uses. Different cities had different levels of accuracy. The accuracy levels were lower in some cities due to spectral similarities between land uses. The built and bare land uses were most commonly confused. The class with pixels outside of the city boundaries was not commonly confused with the built and bare pixels with the exception of when the test pixels in the accuracy analysis were on the border of the land use types. A discussion of the error matrices and the accuracy statistics for each city are presented in the appendix.

RESULTS OF HYPOTHESIS TESTING

H1: Cities with a higher percent of built land are more likely to experience terrorist attacks than areas with a lower percent of built land.

The percent of built land showed a strong but statistically insignificant negative correlation with the number of violent attacks in the 45 Israeli cities in 1999 (r = -0.770, p = 0.230) (see Table 4.3 for the correlation matrix). The statistical insignificance could be due to the low number of violent attacks in Israel in 1999. The Second Intifada started in 2000, during which violent terrorist attacks occurred almost daily. Israel was still relatively peaceful in 1999. Terrorist attacks occurred in 1999, but at a lower level than the following year. The negative correlation indicates that when there is a higher percentage of built land in a city there is less terrorism. Therefore, the hypothesis is rejected.

The municipal boundaries are outside of the built-up areas in many cities. The percent of built land may concentrate in certain parts of the city within the municipal boundaries and leave other areas of open space that may be designated for future growth or other land uses. However, one expects that where there is built land, there are people. Where there are people, there should be violent terrorist attacks. The population had a weak statistically insignificant positive correlation with the percent of built land (r = 0.193, p = 0.205), but had a strong almost statistically significant positive correlation with violent attacks (r = 0.923, p = 0.077). In Israel terrorist attacks are more closely associated with population than with built land. This could be due to the diffuse municipal boundaries.

H2: Cities with a higher percent of built land are more likely to experience a higher QOL.

Built land showed statistically significant correlations with median age (r = 0.352, p = 0.018) and the percent of new motor vehicles (r = 0.337, p = 0.024). These are not strong positive correlations, but they are significant. This implies that there is a positive relationship between these QOL variables and the percent of built land.

The other variables show weaker correlations and do not show statistical significance with built land, with the exception of the strong negative relationship between built land and conflict, as discussed above.

Median age was significantly or strongly associated with QOL in all variables except population. This suggests that other variables, like median age, are stronger predictors of QOL than built land, but built land still showed a significant relationship with some QOL variables.

The results confirm the hypothesis because they show that cities with a higher amount of built land are more likely to experience higher QOL. This was not true for all variables but it was true for two variables.

H3: Cities experiencing higher NDVI are more likely to experience a higher QOL.

NDVI showed positive statistically significant correlations with the average income per capita (r = 0.579, p = 0.000), median age (r = 0.388, p = 0.008), the percent of students between 20 – 29 years old (r = 0.532, p = 0.000), and the percent of motor vehicles (r = 0.472, p = 0.001). NDVI showed a negative statistically significant correlation with the percent of families with four or more children (r = -0.480, p = 0.001). It showed weak and insignificant correlations with the percent of built land (r = 0.139, p = 0.361), population (r = -0.076, p = 0.622), and violent attacks (r = 0.010, p = 0.990). The statistically significant correlations between NDVI and the socioeconomic variables suggest that green cover is desirable and more prevalent among people with a higher income who can afford to pay for green cover in a country where water is scarce. These higher income people are older, have smaller families, are more educated, and can afford to purchase other nonessential items such as motor vehicles.

The significant results between NDVI and several QOL variables confirm the hypothesis that cities with higher NDVI values are more likely to experience higher QOL.

H4: There is a relationship between QOL and the proportion of built land and NDVI within city boundaries.

This hypothesis was tested using PCA. The first two principal components had eigenvalues that were greater than 1, and thus two principal components were obtained from the data (Table 4.2). The eigenvalues explain the percent of variance. In this research, the cumulative percent of variance for the first two components was 93% with 75.7% for the first component and 17.5% for the second component. Using the varimax rotation, the first component had 5 positive and 4 negative loadings (Table 4.4). The 5 positive loadings were average income per capita, median age, percent of students between 20 – 29 years old, percent of new motor vehicles, and percent of built land. The 4 negative loadings were the percent of families with 4 or more children, population, violent attacks, and NDVI. There were 8 positive loadings and 1 negative loading on the second component. The positive loadings were average income per capita, median age, population, percent of students between 20 – 29 years old, percent of new motor vehicles, percent of built land, NDVI, and violent attacks. The negative loading was the percent of families with 4 or more children. The communalities showed high variance for all of the variables, except for the NDVI whose communality showed a moderately high variance (Table 4.5).

Eight of the variables loaded more strongly onto the first factor. Those variables were average income per capita, percent of new motor vehicles, median age, percent of people in each city between 20 and 29 years who are students, percent of families with 4 or more children, population, the number of violent attacks per city, and the percent of urban land. One variable—NDVI—loaded more strongly onto the second factor (Table 4.4). Most variables that loaded strongly onto the first factor derived from the CBS and ICT and relate to QOL. The exception was the percent of built land which derived from remote sensing. This related remote sensing to QOL variables and showed a relationship between the built environment and QOL. Notably, the loading of the percent of the percent of urban land and violent attacks showed a relationship between the built environment and conflict.

Of the eight variables that loaded most strongly onto the first factor, three also showed strong loadings onto the second factor with loadings of 0.500 or greater (Table 4.4). NDVI was the only variable that loaded strongly onto the second factor but not on the first factor (Table 4.2). Those three variables were the percent of new motor vehicles, the percent of urban land, and the average income per capita. The strong loadings onto the second factor indicate that there is a relationship, albeit a less strong one, between those variables and with NDVI.

This confirms the hypothesis which shows that there is a relationship between QOL and the percent of urban land in Israel. The high loadings of some QOL variables on the second principal show a relationship between QOL and NDVI, thus both hypotheses were confirmed.

Lo and Faber (1997) performed a study that related QOL and remote sensing data. They found that data grouped into two clusters. One cluster was environmental nature and one was socioeconomic in nature. The socioeconomic cluster contained one environmental variable, NDVI. Lo and Faber used this to show a relationship between green cover and QOL. The same holds true for my study. My second component strongly loaded NDVI and strongly loaded other socioeconomic factors showing a relationship between the environment and QOL.

Table 4.2: Clustering of variables around each component.

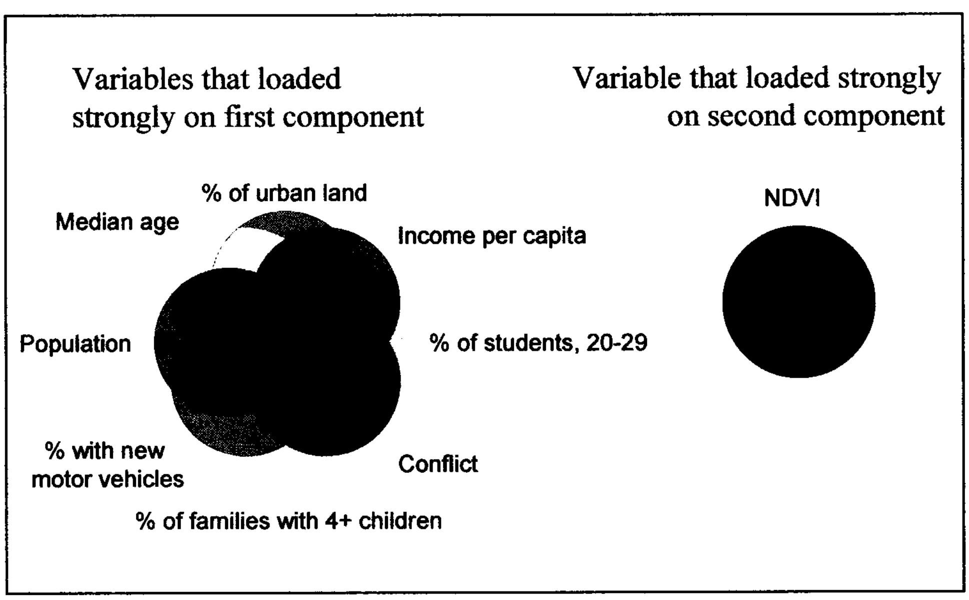


Table 4.3: Correlation matrix of variables.

Correlations

		1999%urban	1999MeanNDVI	1999 avg. income per capita	% of families w/4 children and over	Median age	Population	% of students, 20-29	% of new motor vehicles	conflict 8/7/98-8/7/00
1999%urban	Pearson Correlation	1.000	.139	.240	-.214	.352*	.193	.203	.337*	-.770
	Sig. (2-tailed)	.	.361	.112	.158	.018	.205	.180	.024	.230
	N	45	45	45	45	45	45	45	45	4
1999MeanNDVI	Pearson Correlation	.139	1.000	.579**	-.480**	.388**	-.076	.532**	.472**	.010
	Sig. (2-tailed)	.361	.	.000	.001	.008	.622	.000	.001	.990
	N	45	45	45	45	45	45	45	45	4
1999 avg. income per capita	Pearson Correlation	.240	.579**	1.000	-.838**	.811**	.036	.894**	.830**	-.676
	Sig. (2-tailed)	.112	.000	.	.000	.000	.814	.000	.000	.324
	N	45	45	45	45	45	45	45	45	4
% of families w/4 children and over	Pearson Correlation	-.214	-.480**	-.838**	1.000	-.925**	-.020	-.683**	-.656**	.975*
	Sig. (2-tailed)	.158	.001	.000	.	.000	.896	.000	.000	.025
	N	45	45	45	45	45	45	45	45	4
Median age	Pearson Correlation	.352*	.388**	.811**	-.925**	1.000	.159	.727**	.667**	-.926
	Sig. (2-tailed)	.018	.008	.000	.000	.	.296	.000	.000	.074
	N	45	45	45	45	45	45	45	45	4
Population	Pearson Correlation	.193	-.076	.036	-.020	.159	1.000	.057	.196	.923
	Sig. (2-tailed)	.205	.622	.814	.896	.296	.	.710	.198	.077
	N	45	45	45	45	45	45	45	45	4
% of students, 20-29	Pearson Correlation	.203	.532**	.894**	-.683**	.727**	.057	1.000	.790**	-.890
	Sig. (2-tailed)	.180	.000	.000	.000	.000	.710	.	.000	.110
	N	45	45	45	45	45	45	45	45	4
% of new motor vehicles	Pearson Correlation	.337*	.472**	.830**	-.656**	.667**	.196	.790**	1.000	-.725
	Sig. (2-tailed)	.024	.001	.000	.000	.000	.198	.000	.	.275
	N	45	45	45	45	45	45	45	45	4
conflict 8/7/98-8/7/00	Pearson Correlation	-.770	.010	-.676	.975*	-.926	.923	-.890	-.725	1.000
	Sig. (2-tailed)	.230	.990	.324	.025	.074	.077	.110	.275	.
	N	4	4	4	4	4	4	4	4	4

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4.4: Principal components analysis component loadings.

Rotated Component Matrix[a]

	Component	
	1	2
% of new motor vehicles	.769	.612
% of students, 20-29	.937	.249
Population	-.888	.375
% of families w/4 children and over	-.974	-.200
Median age	.902	.318
1999%urban	.819	.524
1999 avg. income per capita	.724	.657
1999MeanNDVI	-5.68E-02	.876
conflict 8/7/98-8/7/00	-.991	2.063E-02

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Table 4.5: Principal components analysis communalities.

Communalities

	Initial	Extraction
% of new motor vehicles	1.000	.967
% of students, 20-29	1.000	.940
Population	1.000	.929
% of families w/4 children and over	1.000	.988
Median age	1.000	.914
1999%urban	1.000	.946
1999 avg. income per capita	1.000	.956
1999MeanNDVI	1.000	.771
conflict 8/7/98-8/7/00	1.000	.982

Extraction Method: Principal Component Analysis.

STATISTICAL ANALYSES OF REMOTE SENSING

This section contains the statistical results of the remote sensing analyses of each city. Forty-five cities were analyzed with a K-Means Unsupervised Classification to determine the percent of built land and the percent of undeveloped land in each city.

Two land use classes were quantified using remote sensing: built and bare land. The percent of built land was the variable that was used in the principal components analysis. The percent of built and bare land were determined for each city using the Landsat 7 satellite. The cities' borders were determined from the Israel Central Bureau of Statistics' thematic map of Israel. Each city's border was delineated and with the land uses also thematically mapped. The city boundaries were provided by the CBS in the same CBS images that provided the thematic land use classifications. The borders were used to trace and clip the city borders on the Landsat image using remote sensing software from PCI Geomatics.

Arad

The percent of built land in Arad was 5.76% based on the unsupervised classification and the verification using reference imagery from the CBS. The rest of the land was undeveloped or farmland. The median NDVI was 0.105 for all pixels. The remote sensing analyses quantified two land use classes: built and bare. The class designated as "no values" was used by the software program to designate land areas that were outside of the city borders.

The PCI Geomatics software generated the error matrix (Table 4.6). The error matrix was used to calculate the producer's, user's, and overall accuracies, and the Kappa statistic. In doing the accuracy analysis, the software heavily sampled among the no values and bare land uses, but only sampled a few pixels among the built land uses.

The image shows some of the inaccuracies in performing the unsupervised classification (see Figure 4.1). There were regions in the image that were bare and undeveloped that were assigned to the built land use class. In addition to this, there was a region in the image that was bare that was assigned to no value pixel class. The actual land cover type was water, which should have been assigned to bare/undeveloped.

Figure 4.1: The images are of Arad before and after undergoing an unsupervised classification. In panel B, red signifies built land uses, beige signifies bare and undeveloped land, and gray is the land outside city borders, as defined by the Israeli Central Bureau of Statistics.

A B

The producer's accuracy shows the percentage of land use class being correctly classified (Lillesand & Kiefer, 2000). The producer's accuracies for the land uses in Arad were high and showed the pixels were assigned to the correct land use classes (Table 4.7).

The user's accuracy shows when a pixel is omitted from its correct land use (Lillesand & Kiefer, 2000). The user's accuracies for the no value and bare land use classes were high and showed that the pixels were not omitted from their correct land use classes. The user's accuracy for the built land use was low because when performing the unsupervised classification accuracy check, the model tested for accuracy in only two built land use pixels. The two built land use pixels were assigned to the correct class, but four bare land use pixels were erroneously designated as built land (Table 4.7).

The overall accuracy of the K Means Unsupervised Classification analysis was 97.177% (Table 4.7). This value was artificially inflated by the high number of ground truth sampling in areas outside of the city, as selected by PCI Geomatics's software. The producer's and user's accuracies and the individual Kappa statistics are a more truthful measure of photointerpeter accuracy.

The Kappa statistic of 1.0000 for the no values field shows that there was perfect agreement between the photointerpreter and the reference data for the image. The Kappa statistic of 0.3279 for the built land use signified that the photointerpreter showed accuracy of 0.3279 greater than what would be expected by chance interpretation (chance alone = 0). In Arad, the bare land use showed near perfect agreement between the photointerpreter and the reference image.

Table 4.6: An accuracy assessment was performed to create an error matrix. The error matrix for Arad shows how each pixel was classified and what its actual land use class was. The error matrix was then used to calculate the accuracy statistics.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	106	0	0	106
Built	0	2	4	6
Bare	3	0	133	136
Totals	109	2	137	248

Table 4.7: The accuracy statistics for Arad include the overall accuracy, producer's accuracy, user's accuracy, and Kappa statistics.

Accuracy Statistics			
Overall Accuracy: 97.177%		**95% Confidence Interval (94.915% 99.440%)**	
Overall Kappa Statistic: 0.945%		**Overall Kappa Variance: -0.026%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	97.248% (93.718% 100.778%)	100.000% (99.528% 100.472%)	1.0000
Built	100.000% (75.000% 125.000%)	33.333% (-12.720% 79.387%)	0.3279
Bare	97.080% (93.896% 100.264%)	97.794% (94.958% 100.630%)	0.9507

Ashdod

The percent of built land in Ashdod was 31.68%. The median NDVI was 0.164. The producer's accuracies for the bare and no value land uses in Ashdod were high and showed the pixels were assigned to the correct land use classes. The producer's accuracy for the built land use class was over 50% correct. The incorrect pixels were mostly likely to be assigned to the bare land use class. The user's accuracies for the no value and bare land use classes were high and showed that the few pixels were omitted from their correct land use classes. The user's accuracy for the built land use was over 50%. The built land use pixels that were omitted from the built land use class were erroneously assigned to the bare land use class. The overall accuracy was 87.555% (see Tables 4.8 and 4.9).

There are inaccuracies in the unsupervised classification. There were bare land uses that were spectrally similar to built land uses and were classified as built according to the unsupervised classification algorithm. This can be seen in Figure 4.2. The unclassified image is on the left. The built land uses (classified as red) are on the left side of the image with a little on the right side. In the classified image, there are bare land uses that are classified as built.

The Kappa statistic of 0.9048 for the no values field shows that there is good agreement between the photointerpreter and the reference data for the image. The Kappa statistic of 0.5950 for the built land use signifies that the photointerpreter showed accuracy of 0.5950 greater than what would be expected by chance. The Kappa statistic of 0.7876 for the bare land use class showed close agreement between the photointerpreter and the reference image.

Figure 4.2: The unclassified image of Ashdod is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

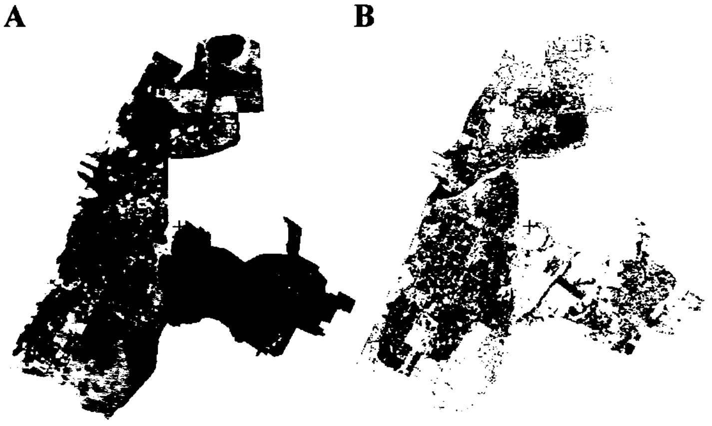


Table 4.8: Error matrix for Ashdod.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	142	0	6	148
Built	1	22	11	34
Bare	0	10	57	67
Totals	143	32	74	249

Table 4.9: Accuracy statistics for Ashdod.

Accuracy Statistics			
Overall Accuracy: 88.755%		**95% Confidence Interval (84.630% 92.880%)**	
Overall Kappa Statistic: 0.800%		**Overall Kappa Variance: -0.005%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	99.301% (97.585% 101.016%)	95.946% (92.431% 99.461%)	0.9048
Built	68.750% (51.128% 86.372%)	64.706% (47.172% 82.240%)	0.5950
Bare	77.027% (66.767% 87.287%)	85.075% (75.796% 94.353%)	0.7876

Ashqelon

The percent of built land in Ashqelon was 21.58 and the median NDVI was 0.187. The producer's accuracy shows that there is 55% accuracy for built land uses and over 83% accuracy for bare land uses. The user's accuracies for built land use were 41% and 89% for the bare land use. The low user's accuracy for the built land use class could have been due to the confusion in assigning built land uses to the bare land use class. There is little signature separability between built and bare land use pixels, which causes confusion between the photointrepeter and the classification data. Evidence of the signature similarity between the bare and built land use pixels can be seen in Figure 4.3. The software algorithm also assigned many bare land use pixels to the build land use class (see Tables 4.10 and 4.11). The overall accuracy was 88.400%. The overall accuracy could have been inflated by the large number of accuracy pixels that the computer algorithm selected from the area of the satellite image where there were no pixels.

The Kappa statistic of 0.9676 for the no values field shows that there is overall good agreement between the photointerpreter and the reference data for the image. The Kappa statistic of 0.3559 for the built land use class shows that there is poor agreement between the photointrepreter and the reference data, but it is still better than what would be expected by chance alone. The Kappa statistic of 0.8196 for the bare land use class showed high agreement between the photointerpreter and the reference image.

Figure 4.3 shows the unclassified and classified images of Ashqelon. The classified image shows the areas of built and bare land uses. In many areas, built and bare pixels were misclassified. This occurred in areas where there was sand and vegetation. Built land uses were also erroneously classified as bare.

Figure 4.3: The unclassified image of Ashqelon is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

A **B**

Table 4.10: Error matrix for Ashqelon.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	130	0	2	132
Built	2	11	14	27
Bare	1	9	80	90
Totals	133	20	96	249

Table 4.11: Accuracy statistics for Ashqelon.

Accuracy Statistics			
Overall Accuracy: 88.400%		**95% Confidence Interval (84.230% 92.570%)**	
Overall Kappa Statistic: 0.797%		**Overall Kappa Variance: -0.003%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	97.744% (94.845% 100.644%)	98.485% (96.022% 100.948%)	0.9676
Built	55.000% (30.696% 79.304%)	40.741% (20.355% 61.126%)	0.3559
Bare	83.333% (75.357% 91.309%)	88.889% (81.840% 95.937%)	0.8196

Azor

The percent of built land in Azor was 52.44 in 1999. The median NDVI was 0.223. The producer's accuracy is 68% and the user's accuracy is 73% for built land uses and 69% and 65% for the bare land uses. The overall accuracy is 90%. The Kappas for the no values class is 0.9600, 0.6829 for the built class, and 0.5966 for the bare class (Table 4.13). The error matrix (Table 4.12) shows built and bare land uses were confused. This occurred because of the spectral similarity between some bare and built land cover types.

Figure 4.4 shows the unclassified and classified images of Azor. In parts of the image, there is confusion between the bare and built land uses, but the overall accuracy is high with high Kappa values and producer's and user's accuracies.

Figure 4.4: The unclassified image of Azor is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

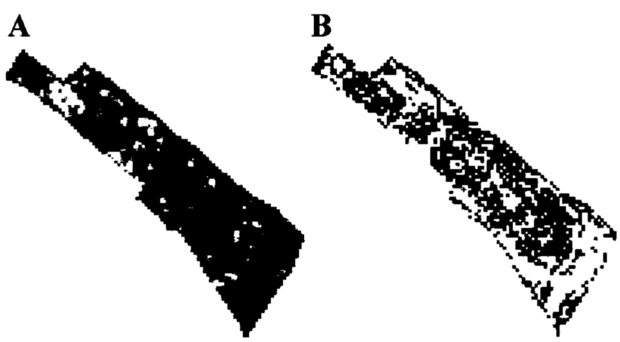


Table 4.12: Error matrix for Azor.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	170	2	0	172
Built	1	28	9	38
Bare	0	11	20	31
Totals	171	41	29	241

Table 4.13: Accuracy statistics for Azor.

Accuracy Statistics			
Overall Accuracy: 90.456%		**95% Confidence Interval (86.539% 94.373%)**	
Overall Kappa Statistic: 0.789%		**Overall Kappa Variance: 0.227%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	99.415% (97.980% 100.850%)	98.837% (96.944% 100.730%)	0.9600
Built	68.293% (52.829% 83.756%)	73.684% (58.367% 89.001%)	0.6829
Bare	68.966% (50.403% 87.528%)	64.516% (46.060% 82.972%)	0.5966

Bat Yam

The percent of built land in Bat Yam was 70.51 and the median NDVI was 0.157. The overall accuracy was high. The producer's and user's accuracies were high the built land use class and were lower for the bare land use class. The Kappas for the no values and built land use classes were high at above 90% and 60%. The Kappa for the bare land use class was lower at 0.44 but was still higher than what would be expected by chance agreement (Table 4.15). The low accuracy statistics for the bare pixels could be attributed to the lower number of pixels sampled in the accuracy assessment (Table 4.14).

Figure 4.5 shows classified and unclassified images of Bat Yam. In the lower left portion of the picture there are pixels designated as built land use pixels that are bare in the reference imagery. There are also pixels that contain low density built land uses. Some of these pixels are designated as built and some as bare.

Figure 4.5: The unclassified image of Bat Yam is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

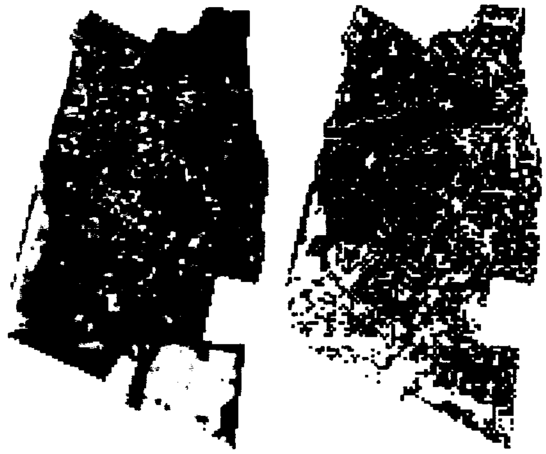


Table 4.14: Error matrix for Bat Yam.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	74	0	5	79
Built	2	109	22	133
Bare	4	11	18	33
Totals	80	120	45	245

Table 4.15: Accuracy statistics for Bat Yam.

Accuracy Statistics			
Overall Accuracy: 81.707%		**95% Confidence Interval (76.673% 86.742%)**	
Overall Kappa Statistic: 0.699%		**Overall Kappa Variance: 0.000%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	92.500% (86.103% 98.897%)	93.671% (87.669% 99.673%)	0.9062
Built	98.833% (30.696% 79.304%)	81.955% (75.043% 88.867%)	0.6477
Bare	40.000% (24.575% 55.425%)	54.545% (36.041% 73.050%)	0.4437

Be'er Sheva

The percent of built land in Be'er Sheva in 1999 was 54.63% and the median NDVI was 0.116. The overall, user's, and producer's accuracies were high reflecting that most pixels were assigned correctly in the accuracy assessment (Table 4.17). Few pixels were identified incorrectly. The Kappas were also high indicating high agreement between the classified and reference data (Table 4.16). Figure 4.6 shows the unclassified and classified images for Be'er Sheva and that most built pixels were assigned to built land uses and most bare pixels were assigned to bare land uses. There was signature separability between the two land uses in Be'er Sheva. This signature separability was reflected in the high accuracy statistics.

Figure 4.6: The unclassified image of Be'er Sheva is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

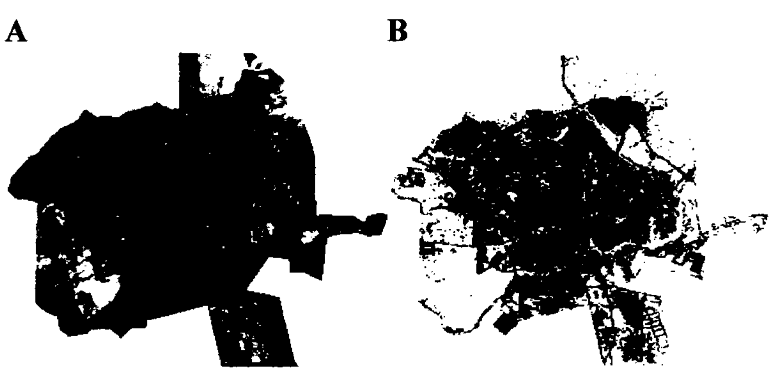


Table 4.16: Error matrix for Be'er Sheva.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	104	0	4	108
Built	1	70	10	81
Bare	2	9	48	59
Totals	107	79	62	248

Table 4.17: Accuracy statistics for Be'er Sheva.

Accuracy Statistics			
Overall Accuracy: 89.516%		95% Confidence Interval (85.502% 93.531%)	
Overall Kappa Statistic: 0.838%		Overall Kappa Variance: 0.001%	
Class Name	Producer's Accuracy (95% Confidence Interval)	User's Accuracy (95% Confidence Interval)	Kappa Statistic
No values	97.196% (97.601% 100.791%)	96.296% (92.272% 100.321%)	0.9349
Built	88.608% (80.968% 96.274%)	86.420% (78.342% 94.498%)	0.8007
Bare	77.419% (66.205% 88.633%)	81.356% (70.571% 92.141%)	0.7514

Bene Beraq

The percent of built land in Bene Beraq was 73.18%. The median NDVI was 0.154. The overall accuracy, and the user's and producer's accuracies for built land uses were high. The user's accuracy was high for bare land uses. The producer's accuracy was low for the bare land use. The Kappas were high (Table 4.19). Seven out of 248 pixels were sampled by the software in the accuracy assessment among bare and undeveloped pixels (Table 4.18). This number is low in producing a reliable accuracy assessment. However, the low number could not be easily increased because of the high percentage of built land and the low percentage of bare and undeveloped land. This can be seen in Figure 4.7, which shows the high percentage of built land in red.

Figure 4.7: The unclassified image of Bene Beraq is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

A B

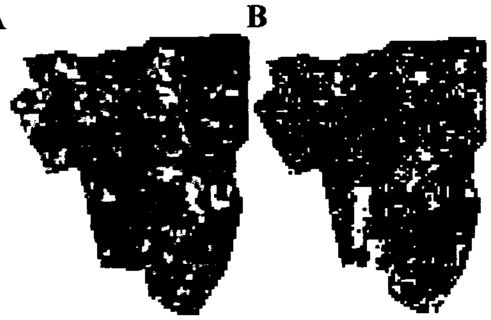


Table 4.18: Error matrix for Bene Beraq.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	76	8	1	85
Built	13	131	12	156
Bare	0	2	5	7
Totals	89	141	18	248

Table 4.19: Accuracy statistics for Bene Beraq.

Accuracy Statistics			
Overall Accuracy: 85.484 %		**95% Confidence Interval (80.898% 90.070%)**	
Overall Kappa Statistic: 0.719%		**Overall Kappa Variance: -0.006%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	85.393% (77.494% 93.293%)	89.412% (82.282% 96.541%)	0.8349
Built	92.908% (88.316% 97.499%)	83.974% (77.897% 90.052%)	0.6286
Bare	27.778% (4.308% 51.248%)	71.429% (30.819% 112.038%)	0.6919

Bet She'an

The percent of built land in Bet She'an was 46.18% and the median NDVI was 0.182. The overall, producer's, and user's accuracies were high reflecting a high accuracy in the accuracy assessment in identifying land use pixels. The Kappa coefficients were also high indicating agreement between the pixels and the reference data (Tables 4.20 and 4.21).

Figure 4.8 shows the unclassified and classified images for Bet She'an. Many of the misclassifications were where the PCI Geomatics unsupervised classification algorithm misidentified the bare land pixels for built land use pixels because the spectral values for the some of the built and bare land uses were spectrally similar.

Figure 4.8: The unclassified image of Bet She'an is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

Table 4.20: Error matrix for Bet She'an.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	91	0	6	97
Built	0	51	18	69
Bare	6	14	57	77
Totals	97	65	81	243

Table 4.21: Accuracy statistics for Bet She'an.

Accuracy Statistics			
Overall Accuracy: 81.224%		**95% Confidence Interval (76.130% 86.319%)**	
Overall Kappa Statistic: 0.718%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	93.814% (88.505% 99.124%)	93.814% (88.505% 99.124%)	0.8976
Built	78.426% (67.698% 89.225%)	73.913% (62.827% 84.999%)	0.6449
Bare	70.370% (59.809% 80.932%)	74.026% (63.582% 84.470%)	0.6120

Bet Shemesh

The percent of built land in Bet Shemesh in 1999 was 24.78% and the median NDVI was 0.223. The accuracy and Kappa statistics were high indicating agreement between the reference and classified data and high accuracy in correctly identifying the pixels' land uses (Table 4.23).

Figure 4.9 shows the unclassified and classified images for Bet Shemesh. The area that was misclassified that was not adequately sampled in the accuracy assessment (see Table 4.22) was in the northeast part of the image. Bare land uses were assigned as built land. The high accuracy statistics do not reflect this region of misclassification because not enough accuracy assessment pixels were taken in this region.

Figure 4.9: The unclassified image of Bet Shemesh is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

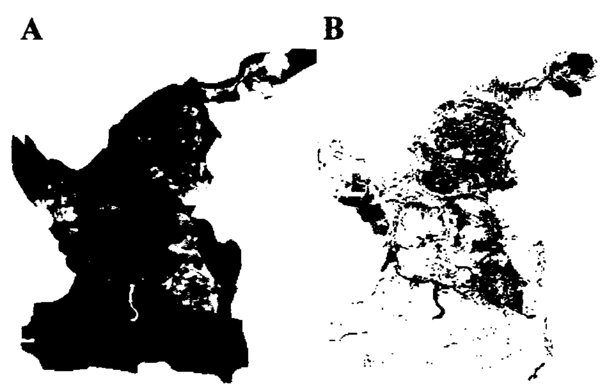


Table 4.22: Error matrix for Bet Shemesh.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	127	0	4	131
Built	0	23	6	29
Bare	5	6	78	89
Totals	132	29	88	249

Table 4.23: Accuracy statistics for Bet Shemesh.

Accuracy Statistics			
Overall Accuracy: 91.200%		95% Confidence Interval (87.488% 94.912%)	
Overall Kappa Statistic: 0.849%		Overall Kappa Variance: -0.000%	
Class Name	Producer's Accuracy (95% Confidence Interval)	User's Accuracy (95% Confidence Interval)	Kappa Statistic
No values	96.212% (92.577% 99.848%)	96.974% (93.619% 100.275%)	0.9353
Built	79.310% (62.843% 95.778%)	79.310% (62.843% 95.778%)	0.7660
Bare	88.636% (81.437% 95.836%)	87.640% (80.241% 95.040%)	0.8093

Betar Illit

The percent of built land in Betar Illit in 1999 was 32.71%. The median NDVI was 0.176. Figure 4.10 shows Betar Illit. The accuracy statistics (Table 4.25) were high, based on the 245 pixels that were sampled for verification based on the ancillary imagery. The parts where there was misclassification in the image were where bare pixels were misclassified as built pixels (see Table 4.24 for misclassified pixels; Figure 4.10). This occurred in localized clusters in the image and was not greatly sampled in the accuracy assessment and thus not reflected in the high accuracy and Kappa statistics.

Figure 4.10: The unclassified image of Betar Illit is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

Table 4.24: Error matrix for Betar Illit.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	91	5	6	102
Built	4	29	7	40
Bare	14	12	77	103
Totals	109	46	90	245

Table 4.25: Accuracy statistics for Betar Illit.

Accuracy Statistics			
Overall Accuracy: 79.435%		**95% Confidence Interval (74.204% 84.667%)**	
Overall Kappa Statistic: 0.678%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	83.486% (76.057% 90.916%)	89.216% (82.706% 85.726%)	0.8076
Built	63.043% (48.008% 78.079%)	72.500% (57.412% 87.588%)	0.6624
Bare	85.556% (77.737% 93.347%)	74.757% (65.882% 83.632%)	0.6038

Dimona

The percent of built land in 1999 in Dimona was 13.52%. The median NDVI was 0.107. All accuracy statistics were high (see Table 4.27). There were some bare pixels that were designated as built, but in Dimona the misclassification of bare land use pixels was low and signature separability between built and bare land uses was high (Table 4.26; Figure 4.11). There was high signature separability between the built and bare land uses in this city. The developed land had a higher NDVI than the bare land and there was little confusion between the two land use types in the accuracy assessment.

Figure 4.11: The unclassified image of Dimona is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

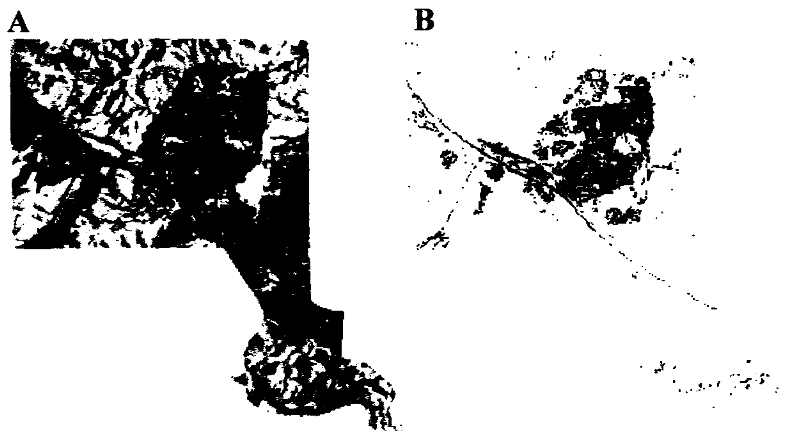


Table 4.26: Error matrix for Dimona.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	124	0	3	127
Built	0	14	2	16
Bare	1	4	102	107
Totals	125	18	107	250

Table 4.27: Accuracy statistics for Dimona.

Accuracy Statistics			
Overall Accuracy: 96.000%		**95% Confidence Interval (93.371% 98.629%)**	
Overall Kappa Statistic: 0.928%		**Overall Kappa Variance: -0.000%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	99.200% (97.238% 101.162%)	97.638% (94.603% 100.673%)	0.9528
Built	77.778% (55.794% 99.672%)	87.500% (68.170% 106.830%)	0.8653
Bare	95.327% (90.861% 99.794%)	95.327% (90.861% 99.794%)	0.9183

Gan Yavne

The percent of built land in Gan Yavne in 1999 was 13.17%. The median NDVI was 0.244. Tables 4.28 and 4.29 shows the error matrix and accuracy statistics. The overall accuracy and the producer's and user's accuracies for the no values and bare land uses were high. The unsupervised classification accuracy assessment sampled heavily outside of the city borders and among bare land use pixels. It sampled very little among the built land use pixels, which resulted in a wide confidence interval among built pixels. There was also a high degree of error in the producer's accuracy, which could be attributed to the small number of sampled pixels and to the high number of reference pixels that were classified as bare that were built in the reference data (Tables 4.28 and 4.29).

In spite of the low sampling accuracy among the built land use pixels, the unsupervised classification appeared to cluster the land uses satisfactorily, as is shown in Figure 4.12. There appeared to be little misclassification and there were no parts of the image that had large clusters of misclassifications.

Figure 4.12: The unclassified image of Gan Yavne is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

A B

Table 4.28: Error matrix for Gan Yavne.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	135	0	4	139
Built	0	8	4	12
Bare	4	10	81	95
Totals	139	18	89	246

Table 4.29: Accuracy statistics for Gan Yavne.

Accuracy Statistics			
Overall Accuracy: 91.057 %		**95% Confidence Interval (87.288% 94.826%)**	
Overall Kappa Statistic: 0.834%		**Overall Kappa Variance: -0.008%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	97.122% (93.983% 100.261%)	97.122% (93.983% 100.261%)	0.9338
Built	44.444% (18.711% 70.178%)	66.667% (35.828% 97.506%)	0.6404
Bare	91.011% (84.507% 97.515%)	85.263% (77.609% 92.918%)	0.7691

Gedera

The percent of built land in Gedera was 23.68% in 1999. The median NDVI was 0.229. The overall accuracy was high. The producer's and user's accuracies were high for the no values and the bare/undeveloped land use classes. The producer's and user's accuracies were low for the built land use class. The Kappa coefficients for the built and bare land uses were low but were still considered to be classified correctly greater than what would be expected by chance alone (Tables 4.30 and 4.31).

As seen in Figure 4.13, many bare land use pixels were designated as built in the unsupervised classification. There was a variety of bare land uses in Gedera and some of them were spectrally similar to the built land uses, especially those with similar reflectivities to the built land uses. Many bare land uses had high vegetative cover and according to Figure 4.13, these highly vegetative bare land covers were not likely to be classified in the unsupervised classification algorithm. The bare and undeveloped land uses with low vegetative cover were more likely to be misclassified as built in Gedera.

Figure 4.13: The unclassified image of Gedera is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

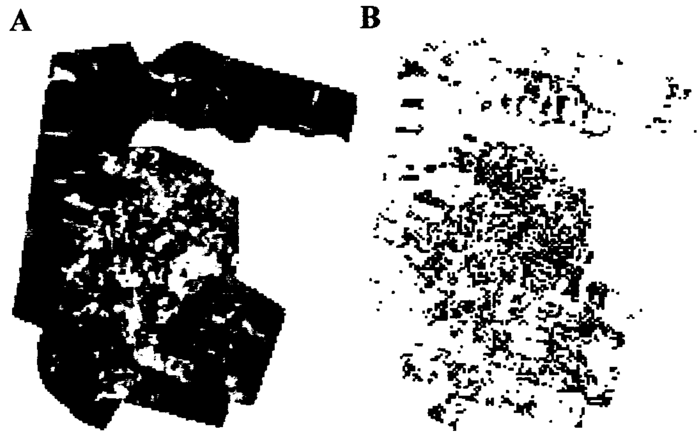


Table 4.30: Error matrix for Gedera.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	92	1	6	99
Built	0	11	13	24
Bare	9	21	95	125
Totals	101	33	114	248

Table 4.31: Accuracy statistics for Gedera.

Accuracy Statistics			
Overall Accuracy: 79.839%		95% Confidence Interval (74.644% 85.034%)	
Overall Kappa Statistic: 0.660%		Overall Kappa Variance: 0.000%	
Class Name	Producer's Accuracy (95% Confidence Interval)	User's Accuracy (95% Confidence Interval)	Kappa Statistic
No values	91.089% (85.038% 97.141%)	92.929% (87.375% 98.484%)	0.8807
Built	33.333% (15.734% 50.932%)	45.833% (23.815% 67.851%)	0.3752
Bare	83.333% (76.053% 90.613%)	76.000% (68.113% 83.887%)	0.5558

Givatayim

The percent of built land in 1999 in Givatayim was 78.84% and the median NDVI was 0.215. Givatayim is in an urban highly developed area and is right outside of Tel Aviv. It is surrounded by other cities and does not have a lot of undeveloped land. Figure 4.14 shows the classified and unclassified images for Givatayim. The red shows the high level of built land in Givatayim.

The high percentage of built land made the accuracy assessment sampling low in the bare land uses. Thus, the Kappa statistic and the producer's and user's accuracies were low for the bare and undeveloped land uses in Givatayim. The producer's and user's accuracies were high for the built and no values land uses. Kappa was high for the no values and was just above 0.5 for the built land use pixels. The overall accuracy was high (see Tables 4.32 and 4.33).

Figure 4.14: The unclassified image of Givatayim is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

Table 4.32: Error matrix for Givatayim.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	82	8	1	91
Built	9	98	24	131
Bare	1	10	6	17
Totals	92	116	31	239

Table 4.33: Accuracy statistics for Givatayim.

Accuracy Statistics			
Overall Accuracy: 77.824%		**95% Confidence Interval (72.348% 83.300%)**	
Overall Kappa Statistic: 0.616%		**Overall Kappa Variance: 0.000%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	89.130% (82.227% 96.034%)	90.110% (83.427% 96.793%)	0.8392
Built	84.483% (77.463% 91.503%)	74.809% (66.994% 82.625%)	0.5105
Bare	19.355% (3.834% 34.876%)	35.294% (9.636% 60.952%)	0.2565

Herzliyya

In 1999, Herzliyya was 48.09% developed and had a median NDVI of 0.251. It had high overall, producer's, and user's accuracies. The Kappa statistics were also high indicating agreement between the reference and the classified data (Table 4.35). A small number of pixels were misclassified (Table 4.34). The built and bare land use pixels were confused almost equally.

Figure 4.15 shows the unclassified and classified images. There was a lot of confusion between land uses because the land uses were spectrally inseparable.

Figure 4.15: The unclassified image of Herzliyya is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

Table 4.34: Error matrix for Herzliyya.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	127	2	2	131
Built	3	44	10	57
Bare	2	19	40	61
Totals	132	65	52	249

Table 4.35: Accuracy statistics for Herzliyya.

Accuracy Statistics			
Overall Accuracy: 84.739%		95% Confidence Interval (80.071% 89.406%)	
Overall Kappa Statistic: 0.750%		Overall Kappa Variance: 0.000%	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	96.212% (92.577% 99.848%)	96.947% (93.619% 100.275%)	0.9350
Built	67.692% (55.554% 79.831%)	77.193% (65.423% 88.963%)	0.6914
Bare	76.932% (64.510% 89.336%)	65.574% (52.831% 78.317%)	0.5649

Hod HaSharon

The percent of built land in 1999 in Hod HaSharon was 40.75%. The median NDVI was 0.268. The accuracy statistics are shown in Table 4.37. They show high producer's and user's accuracies for the bare land uses and pixels that have no value. The producer's and user's accuracies for the built land uses are low. This could be attributed to a high number of bare land use pixels that were designated as built and a high number of built land use pixels that were designated as bare. This is evident in the error matrix (Table 4.36). There was a variety of bare and undeveloped land use covers, which led to the confusion of the photointerpreter and the difficulty in designating the clusters in the unsupervised classification (see Figure 4.16 for imagery generated by the unsupervised classification).

Figure 4.16: The unclassified image of Hod HaSharon is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

Table 4.36: Error matrix for Hod HaSharon.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	121	0	4	125
Built	4	15	26	45
Bare	5	17	56	78
Totals	130	32	86	248

Table 4.37: Accuracy statistics for Hod HaSharon.

Accuracy Statistics			
Overall Accuracy: 77.419%		**95% Confidence Interval (72.014% 82.825%)**	
Overall Kappa Statistic: 0.626%		**Overall Kappa Variance: -0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	93.077% (88.329% 97.825%)	96.980% (93.315% 100.285%)	0.9327
Built	46.875% (28.022% 65.728%)	33.333% (18.449% 48.218%)	0.2346
Bare	65.115% (54.462% 75.771%)	71.795% (61.167% 82.423%)	0.5682

Holon

The percent of built land in Holon in 1999 was 59.29%. The median NDVI was 0.171. The accuracy statistics (Table 4.39) are high, but just over a quarter of the bare land use pixels were designated as built (Table 4.38) and almost a fifth of built land use pixels were designated as bare.

Figure 4.17 shows the unclassified and classified images for Holon. In the unclassified image, the lower half of the central part of the image is bare and is covered in sand and other undeveloped land covers. In the classified image on the right, it is evident that this part of the image erroneously shows many built (red) pixels in the undeveloped areas. The same pixel misclassification occurred in the lower right corner of the image too.

Figure 4.17: The unclassified image of Holon is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

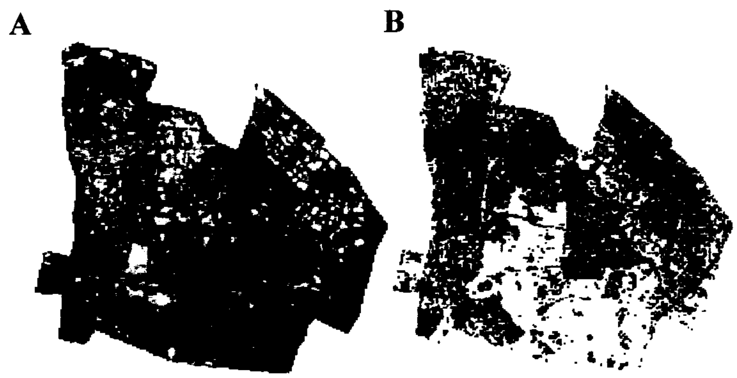


Table 4.38: Error matrix for Holon.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	86	1	4	91
Built	1	84	16	101
Bare	2	9	47	58
Totals	89	94	67	250

Table 4.39: Accuracy statistics for Holon.

Accuracy Statistics			
Overall Accuracy: 86.800%		**95% Confidence Interval (82.404% 91.196%)**	
Overall Kappa Statistic: 0.799%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	96.629% (92.318% 100.941%)	94.505% (89.274% 99.737%)	0.9147
Built	89.362% (82.597% 96.127%)	83.168% (75.376% 90.960%)	0.7303
Bare	70.149% (58.446% 81.853%)	81.034% (70.083% 91.986%)	0.7409

Jerusalem

The percent of built land in Jerusalem was 40.78% and the median NDVI was 0.167. The accuracy and Kappa statistics were high (Table 4.41), with the user's accuracy for the bare land uses being the lowest. Many bare land use pixels were assigned to the built land use class (Table 4.40). This is especially noticeable in the west side of Jerusalem, where the land on the outer edge of the city boundary is bare but was assigned built land use pixels by the unsupervised classification (Figure 4.18).

Figure 4.18: The unclassified image of Jerusalem is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

A B

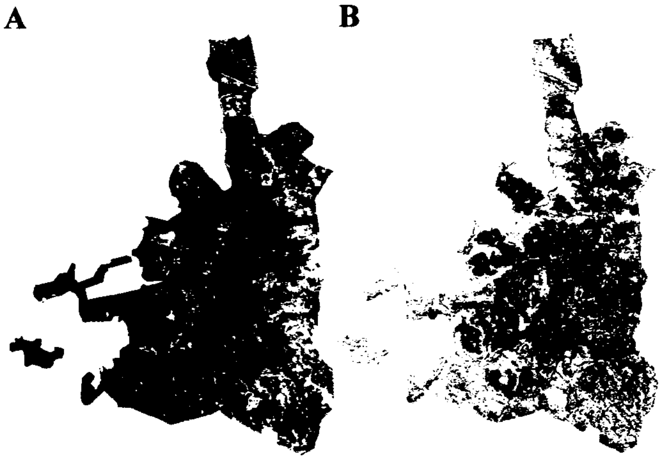


Table 4.40: Error matrix for Jerusalem.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	139	0	2	141
Built	0	36	9	45
Bare	4	21	37	62
Totals	143	57	48	248

Table 4.41: Accuracy statistics for Jerusalem.

Accuracy Statistics			
Overall Accuracy: 85.484%		**95% Confidence Interval (80.898% 90.070%)**	
Overall Kappa Statistic: 0.751%		**Overall Kappa Variance: -0.003%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	97.203% (94.150% 100.255%)	98.582% (96.275% 100.888%)	0.9665
Built	63.158% (49.758% 76.558%)	80.000% (67.202% 92.798%)	0.7403
Bare	77.083% (64.151% 90.015%)	59.677% (46.660% 72.695%)	0.5000

Kefar Saba

The percent of built land in Kefar Saba in 1999 was 54.72%. The median NDVI was 0.250. The accuracy and Kappa statistics were high (Table 4.43) with little misclassification of land use pixels. The bare land use pixels were more likely than the other pixels to be misclassified (Table 4.42). This occurred to in areas where the bare land uses were spectrally similar to the built land uses and is evident in Figure 4.19.

Figure 4.19: The unclassified image of Kefar Saba is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

Table 4.42: Error matrix for Kefar Saba.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	133	1	3	137
Built	1	54	10	65
Bare	4	7	35	46
Totals	138	62	48	248

Table 4.43: Accuracy statistics for Kefar Saba.

Accuracy Statistics			
Overall Accuracy: 88.800%		**95% Confidence Interval (84.691% 92.909%)**	
Overall Kappa Statistic: 0.813%		**Overall Kappa Variance: -0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	96.377% (92.897% 99.857%)	97.080% (93.896% 100.264%)	0.9348
Built	87.097% (77.946% 96.248%)	83.077% (73.192% 92.962%)	0.7750
Bare	72.917% (59.303% 86.530%)	76.087% (62.673% 89.501%)	0.7040

Lod

The percent of built land in 1999 in Lod was 44.30%. The median NDVI was 0.189. The accuracy statistics are shown in Table 4.45. They show that while the user's and producer's accuracies for the built and bare land uses are over 59% correct, the Kappas are low but the accuracy is still greater than what would be expected by chance. As with the other cities, the error matrix (Table 4.44) shows that there was confusion in differentiating between built and bare land use pixels. The pixels were still identified correctly more than 50% of the time.

Figure 4.20 shows the unclassified and classified images for Lod. The greatest difficulty in distinguishing built and bare land pixels arose in bare pixels that were spectrally similar to built pixels. Many bare pixels that had a high reflectance in band 3 were identified as built pixels. Many built pixels also had a high reflectance in band 3. Bare pixels that had low reflectance in band 3 were likely to be identified as bare pixels.

Figure 4.20: The unclassified image of Lod is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

Table 4.44: Error matrix for Lod.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	111	0	3	114
Built	1	38	28	67
Bare	3	19	45	67
Totals	115	57	76	248

Table 4.45: Accuracy statistics for Lod.

Accuracy Statistics			
Overall Accuracy: 78.226%		95% Confidence Interval (72.888% 83.564%)	
Overall Kappa Statistic: 0.661%		Overall Kappa Variance: 0.001%	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	96.522% (92.738% 100.305%)	97.368% (93.991% 100.745%)	0.9509
Built	66.667% (53.551% 79.782%)	56.716% (44.106% 69.327%)	0.4380
Bare	59.211% (47.504% 70.917%)	67.164% (55.173% 79.155%)	0.5266

Ma'alé Adummim

The percent of built land in 1999 in Ma'alé Adummim was 6.94%. The median NDVI was 0.111. The accuracy statistics and Kappa values (Table 4.47) are high, with the exception of the built Kappa. The built Kappa and user's and producer's accuracies are based on 5 reference pixels and 8 classified pixels (Table 4.46), which is a small number of pixels to do an accuracy assessment. However, the percentage of built land was low so there were few built from which to select for an accuracy assessment (see Figure 4.21 to see the built and bare land use pixels).

Figure 4.21: The unclassified image of Ma'alé Adummim is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

A B

Table 4.46: Error matrix for Ma'alé Adummim.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	142	0	1	143
Built	0	4	4	8
Bare	6	1	91	98
Totals	148	5	96	249

Table 4.47: Accuracy statistics for Ma'alé Adummim.

Accuracy Statistics			
Overall Accuracy: 95.181%		**95% Confidence Interval (92.320% 98.042%)**	
Overall Kappa Statistic: 0.905%		**Overall Kappa Variance: -0.042%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	95.946% (92.431% 99.461%)	99.301% (97.585% 101.016%)	0.9828
Built	80.000% (34.938% 125.062%)	50.000% (9.102% 90.898%)	0.4898
Bare	94.792% (89.826% 99.757%)	92.857% (87.248% 98.466%)	0.8838

Mevasseret Zion

The percent of built land in Mevasseret Zion was 52.52% in 1999. The median NDVI was 0.223.The user's and producer's accuracies for Mevasseret Zion were above 70% for the built and bare land use pixels (Table 4.49). The Kappa statistics were also high for each land use type. Because there was approximately an equal number of built and bare land use pixels, the accuracy assessment sampled in each land use type almost equally (Table 4.48). The two land use types were also spectrally dissimilar. Many of the built land use exhibited different reflectances from the bare land uses. The large number of pixels sampled in each land use and the spectral dissimilarity allowed for a more correct unsupervised classification and the photointerpretation. There was some misclassification of pixels, as can be seen in the bare areas outside of the built region of the city (Figure 4.22).

Figure 4.22: The unclassified image of Mevasseret Zion is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

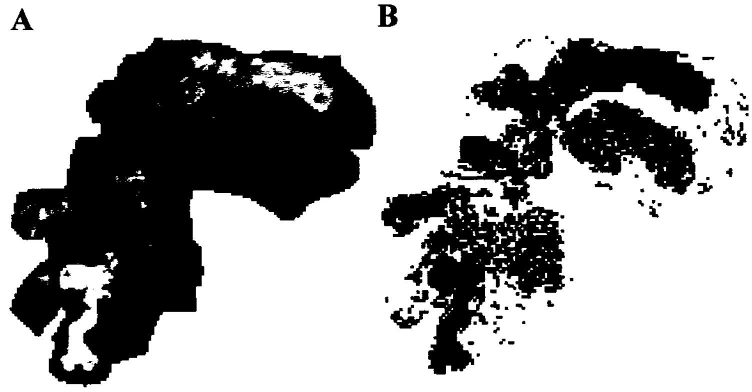


Table 4.48: Error matrix for Mevasseret Zion.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	112	0	10	122
Built	0	54	9	63
Bare	3	14	45	62
Totals	115	68	64	247

Table 4.49: Accuracy statistics for Mevasseret Zion.

Accuracy Statistics			
Overall Accuracy: 84.400%		**95% Confidence Interval (74.702% 89.098%)**	
Overall Kappa Statistic: 0.758%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	97.391% (94.034% 100.739%)	91.803% (86.526% 97.081%)	0.8482
Built	79.412% (69.066% 89.758%)	85.714% (76.280% 95.149%)	0.8038
Bare	70.313% (58.338% 82.287%)	72.581% (60.670% 84.492%)	0.6315

Modi'in Illit

The percent of built land in 1999 in Modi'in Illit was 31.01%. The median NDVI was 0.169. Tables 4.50 and 4.51 show the error matrix and the accuracy statistics. The accuracy statistics for Modi'in Illit were high and there was very little misassignment of pixels in the assessment, except in areas where the bare land uses were spectrally similar to the built land uses. The pixels with no values were assigned to the wrong class and several bare pixels were assigned no values. This often happens when the software chooses pixels at land use edges when selecting pixels for the accuracy assessment.

Figure 4.23 shows the unclassified and classified images. These images show the there are built land use pixels away from the central part of the image where the actual built land is located.

Figure 4.23: The unclassified image of Modi'in Illit is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

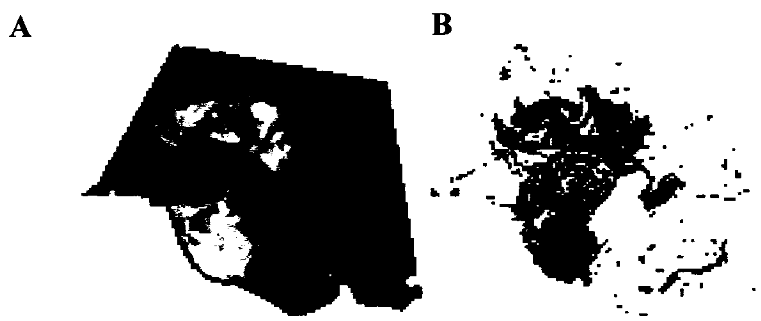


Table 4.50: Error matrix for Modi'in Illit.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	78	1	8	87
Built	0	45	4	49
Bare	8	10	90	108
Totals	86	56	102	244

Table 4.51: Accuracy statistics for Modi'in Illit.

Accuracy Statistics			
Overall Accuracy: 85.887%		**95% Confidence Interval (81.352% 90.422%)**	
Overall Kappa Statistic: 0.784%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	90.698% (83.977% 97.418%)	89.655% (82.681% 96.629%)	0.8416
Built	80.357% (69.058% 91.656%)	91.837% (83.150% 100.524%)	0.8946
Bare	88.235% (81.492% 94.978%)	83.333% (75.842% 90.825%)	0.7169

Nes Ziona

The percent of built land in Nes Ziona in 1999 was 27.09%. The median NDVI was 0.275. Tables 4.52 and 4.53 shows the error matrix and accuracy statistics. While the accuracy statistics for the no values and bare/undeveloped land uses were high, the accuracy values were lower for the built land uses. There were built land use pixels that were interpreted as bare and there were bare pixels that classified as built. Figure 4.24 shows the classified and unclassified images. The unclassified image shows a variety of bare and undeveloped land use types, some of which could be confused with built land. The built land also contained areas that appeared to bare, such as areas with urban vegetation, which were interpreted by the photointerpreter as bare, but as built by the unsupervised classification algorithm.

Figure 4.24: The unclassified image of Nes Ziona is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

A B

Table 4.52: Error matrix for Nes Ziona.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	123	1	5	129
Built	1	21	13	35
Bare	3	8	73	84
Totals	127	30	91	248

Table 4.53: Accuracy statistics for Nes Ziona.

Accuracy Statistics			
Overall Accuracy: 87.500%		**95% Confidence Interval (83.182% 91.818%)**	
Overall Kappa Statistic: 0.789%		**Overall Kappa Variance: 0.000%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	96.850% (93.419% 100.282%)	95.349% (91.327% 99.317%)	0.9047
Built	70.000% (51.935% 88.065%)	60.000% (42.341% 77.659%)	0.5450
Bare	80.220% (71.486% 88.954%)	86.905% (79.095% 94.714%)	0.7931

Netanya

Netanya was 50.88% built and had a median NDVI of 0.197 in 1999. The error matrix and accuracy statistics are shown in Tables 4.54 and 4.55. They show a high interpretation accuracy with the user's accuracy for built land uses, the built Kappa, and the producer's accuracy for bare and undeveloped land uses being lower than the other statistics. Many bare land use pixels were classified as built in the unsupervised classification. These pixels included the coastline which was covered in sand (see Figure 4.25). Other bare land uses pixels were also classified incorrectly. These pixels should have been assigned to the bare land use class. There were also areas of low development that contained built and bare land use types. These areas were erroneously assigned to the incorrect land uses in some cases.

Figure 4.25: The unclassified image of Netanya is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

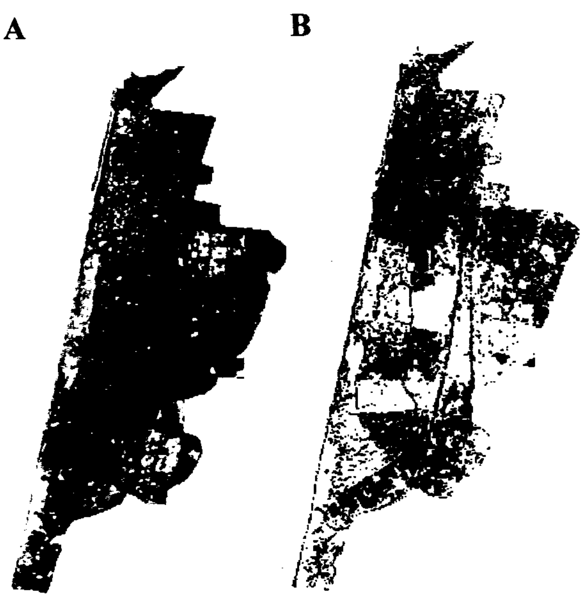


Table 4.54: Error matrix for Netanya.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	133	0	3	136
Built	1	43	18	62
Bare	3	7	41	51
Totals	137	50	62	249

Table 4.55: Accuracy statistics for Netanya.

Accuracy Statistics			
Overall Accuracy: 87.149%		**95% Confidence Interval (82.791% 91.506%)**	
Overall Kappa Statistic: 0.785%		**Overall Kappa Variance: -0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	97.080% (93.896% 100.264%)	97.794% (94.958% 100.630%)	0.9510
Built	86.000% (75.382% 96.618%)	69.355% (57.073% 81.637%)	0.6166
Bare	66.129% (53.542% 78.716%)	80.392% (68.515% 92.269%)	0.7389

Netivot

Netivot was 65.98% built and had a median NDVI of 0.130 in 1999. The accuracy statistics were high, with the exception of the built Kappa and the bare producer's accuracy (Table 4.57). More than half of bare land use pixels sampled in the accuracy assessment were classified as built (Table 4.56). Many of the bare land use pixels exhibited spectral similarities to the built land use pixels, thus making interpretation difficult. Many of the built pixels had a high NDVI but were still within the built region according to reference imagery. They were designated as built which could have led to the designation of many bare pixels to the built land class outside of the built areas.

There were areas that contained both built and bare land use types. The unsupervised classification over-assigned these areas to the built land use class, when large parts of those areas were bare (Figure 4.26).

Figure 4.26: The unclassified image of Netivot is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

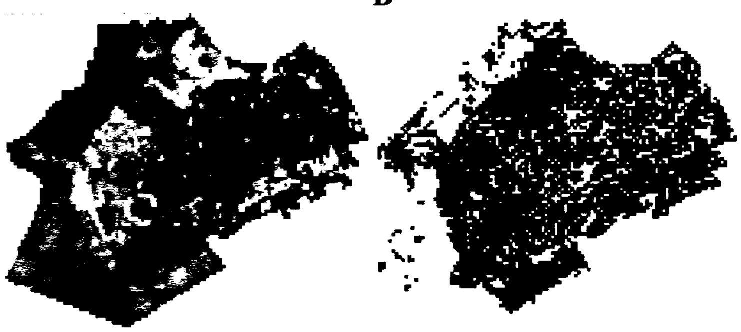


Table 4.56: Error matrix for Netivot.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	91	5	4	100
Built	1	89	29	119
Bare	1	3	24	28
Totals	93	97	57	247

Table 4.57: Accuracy statistics for Netivot.

Accuracy Statistics			
Overall Accuracy: 82.591%		95% Confidence Interval (77.660% 87.522%)	
Overall Kappa Statistic: 0.725%		Overall Kappa Variance: 0.001%	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	97.849% (94.364% 101.335%)	91.000% (84.891% 97.109%)	0.8556
Built	91.753% (85.763% 97.742%)	74.790% (66.568% 83.012%)	0.5849
Bare	42.105% (28.410% 55.800%)	85.714% (70.967% 100.461%)	0.8143

Ofaqim

The percent of built land in 1999 in Ofaqim was 34.10%. The median NDVI was 0.114. The error matrix and accuracy statistics are shown in Tables 4.58 and 4.59. They show confusion between the built and bare pixels, but their correct identification was over 60% for each accuracy statistic. There were parts of the image that contained sparse development. These areas were more likely to be assigned to bare land uses, but there bare land uses that were assigned to built land uses. The bare land uses that were incorrectly classified as built by the software algorithm had higher NDVI values than other bare land uses that were not misclassified. The east side of the city area contained a lot of land that was undeveloped but contained built land pixels (Figure 4.27).

Figure 4.27: The unclassified image of Ofaqim is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

A B

Table 4.58: Error matrix for Ofaqim.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	79	0	1	80
Built	0	38	17	55
Bare	3	21	86	110
Totals	82	59	104	245

Table 4.59: Accuracy statistics for Ofaqim.

Accuracy Statistics			
Overall Accuracy: 82.857%		95% Confidence Interval (77.934% 87.781%)	
Overall Kappa Statistic: 0.735%		Overall Kappa Variance: 0.001%	
Class Name	Producer's Accuracy (95% Confidence Interval)	User's Accuracy (95% Confidence Interval)	Kappa Statistic
No values	96.341% (91.668% 101.015%)	98.750% (95.690% 101.810%)	0.9812
Built	64.407% (51.342% 77.472%)	69.091% (55.969% 82.213%)	0.5929
Bare	82.692% (74.941% 90.444%)	78.182% (70.009% 86.355%)	0.6209

Or Yehuda

Or Yehuda was 37.33% built in 1999 and had a median NDVI of 0.232. Its error matrix and accuracy statistics are shown in Tables 4.60 and 4.61. Many of the pixels were classified as bare that were built according to the reference data. Many built pixels were classified as bare. These led to lower producer's and user's accuracies for the built land uses than for the bare land uses. The confusion could have been caused by the mixture of built and bare land uses that were interspersed within the same areas (see Figure 4.28). The Kappas were also low, but the classification accuracies were still greater than what would have been expected chance.

Figure 4.28: The unclassified image of Or Yehuda is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

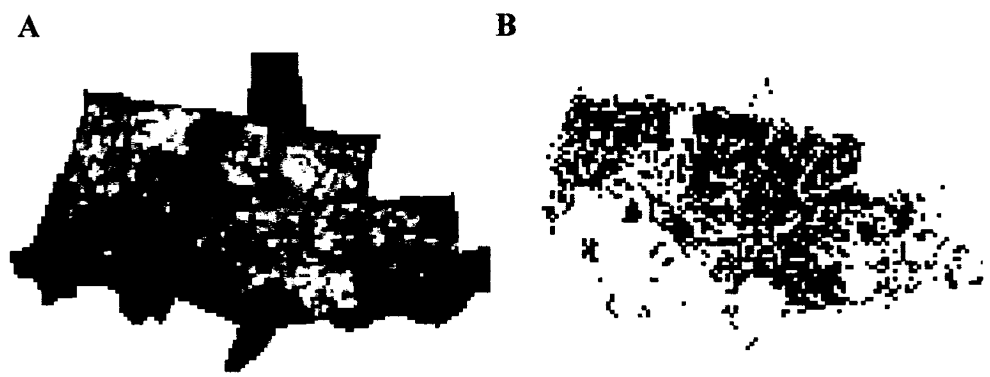


Table 4.60: Error matrix for Or Yehuda.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	102	2	12	116
Built	1	28	14	43
Bare	8	20	60	88
Totals	111	50	86	247

Table 4.61: Accuracy statistics for Or Yehuda.

Accuracy Statistics			
Overall Accuracy: 76.923%		**95% Confidence Interval (71.466% 82.380%)**	
Overall Kappa Statistic: 0.634%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	91.892% (86.363% 97.420%)	87.931% (81.572% 94.290%)	0.7808
Built	56.000% (41.241% 70.759%)	65.116% (49.708% 80.525%)	0.5626
Bare	69.767% (59.479% 80.056%)	68.182% (57.882% 78.482%)	0.5119

Petah Tikva

Petah Tikva was 35.92% built in 1999 and had a median NDVI of 0.223. The accuracy statistics were high (Table 4.63) but they still showed that there was confusion between the built and bare land uses. There were many bare areas that were classified as built and there were built areas that were classified as bare (Table 4.62). The areas that were classified as built that were bare or undeveloped had NDVI values that are typical of built land uses. The pixels that were classified as bare that were built tended to have high NDVI values that are common among vegetative land covers.

Figure 4.29 shows the unclassified and classified images for Petah Tikva. Parts where it is evident that the pixels were misclassified are the roadways. Some of the roads contain all built pixels, but others have gaps where the pixels are bare.

Figure 4.29: The unclassified image of Petah Tikva is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

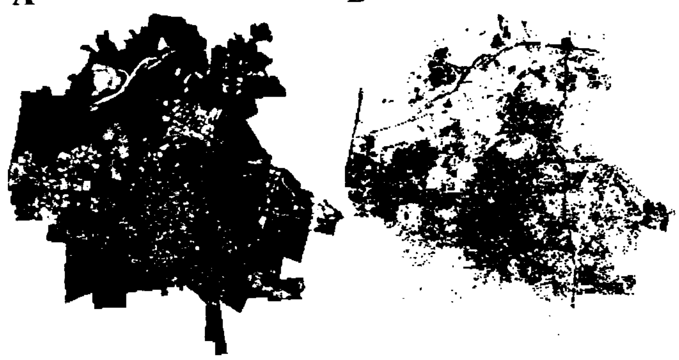


Table 4.62: Error matrix for Petah Tikva.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	104	0	2	106
Built	0	45	13	58
Bare	5	15	65	85
Totals	109	60	80	249

Table 4.63: Accuracy statistics for Petah Tikva.

Accuracy Statistics			
Overall Accuracy: 85.600%		**95% Confidence Interval (81.048% 90.152%)**	
Overall Kappa Statistic: 0.779%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	95.413% (91.027% 99.799%)	98.113% (95.051% 101.175%)	0.9665
Built	75.000% (63.210% 86.790%)	77.586% (65.992% 89.181%)	0.7051
Bare	81.250% (72.072% 90.428%)	76.471% (66.865% 86.077%)	0.6540

Qiryat Gat

Qiryat Gat was 30.97% built and had a median NDVI of 0.152 in 1999. The error matrix and accuracy statistics are in Tables 4.64 and 4.65. They show that many bare land use pixels were designated as built. As with other cities, the regions of the image that were misclassified as built were spectrally similar to built land uses among land that was developed. Many built land use pixels were also designated as bare. However, the statistics indicate that many pixels in the accuracy assessment were identified correctly.

Figure 4.30 shows the unclassified and classified imagery for Qiryat Gat. Many roadways in the unsupervised classification were misclassified as bare. The roads surrounding bare land were misclassified as built. Some of the roads had higher NDVI values than what would be expected for paved land. The verification imagery was not of high enough resolution to determine if the roads had vegetative cover or if the pixels had partial vegetative cover.

Figure 4.30: The unclassified image of Qiryat Gat is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

A B

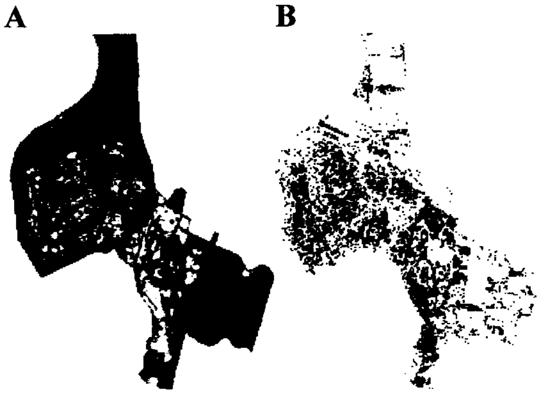


Table 4.64: Error matrix for Qiryat Gat.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	144	0	4	148
Built	0	24	7	31
Bare	4	17	49	70
Totals	148	41	60	249

Table 4.65: Accuracy statistics for Qiryat Gat.

Accuracy Statistics			
Overall Accuracy: 87.149%		**95% Confidence Interval (82.791% 91.506%)**	
Overall Kappa Statistic: 0.770%		**Overall Kappa Variance: -0.007%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	97.297% (94.347% 100.248%)	97.297% (94.347% 100.248%)	0.9334
Built	58.537% (42.237% 74.836%)	77.419% (61.088% 93.751%)	0.7297
Bare	81.667% (71.042% 92.291%)	70.000% (58.550% 81.450%)	0.6048

Qiryat Ono

Qiryat Ono was 67.72% built and had a median NDVI of 0.270 in 1999. It's error matrix and accuracy statistics are shown in Tables 4.66 and 4.67. There was a lot of misclassification of pixels within Qiryat Ono. In the accuracy assessment, many of the no values pixels were on edges of built and bare land use pixels and were classified incorrectly in those land use types. This caused the user's and producer's accuracies and Kappa statistic to be lower than what would be expected from identifying pixels that are outside of the city limits.

Many bare land use pixels were also misclassified as built. This is apparent throughout the image and is shown in the low producer's accuracy. Many of the built land uses had low reflectivity and in identifying as built, many bare land use pixels that were spectrally similar were also assigned as built. Evidence of the overclassification of built pixels can be seen in Figure 4.31.

Figure 4.31: The unclassified image of Qiryat Ono is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

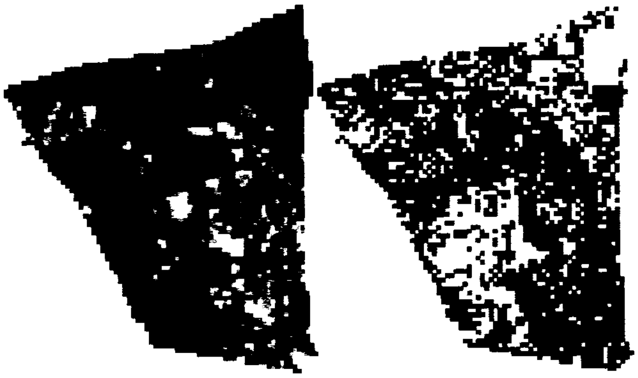


Table 4.66: Error matrix for Qiryat Ono.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	73	3	10	86
Built	12	85	31	128
Bare	4	7	17	28
Totals	89	95	58	242

Table 4.67: Accuracy statistics for Qiryat Ono.

Accuracy Statistics			
Overall Accuracy: 71.721%		**95% Confidence Interval (65.866% 77.577%)**	
Overall Kappa Statistic: 0.558%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	82.022% (73.483% 90.562%)	84.884% (76.732% 93.036%)	0.7620
Built	89.474% (82.776% 96.171%)	66.406% (57.833% 74.979%)	0.4499
Bare	29.310% (16.734% 41.887%)	60.714% (40.839% 80.590%)	0.4846

Ra'anana

The percent of built land in Ra'anana in 1999 was 42.97%. The median NDVI was 0.268. The error matrix and accuracy statistics are shown in Tables 4.68 and 4.69. The accuracy statistics show that the classification of the pixels was highly accurate. The misclassifications occurred where built and bare land use pixels were misassigned. This occurred in other cities too. Many of the bare land uses exhibited spectral similarity to built land uses and were classified as built (Figure 4.32).

Figure 4.32: The unclassified image of Ra'anana is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

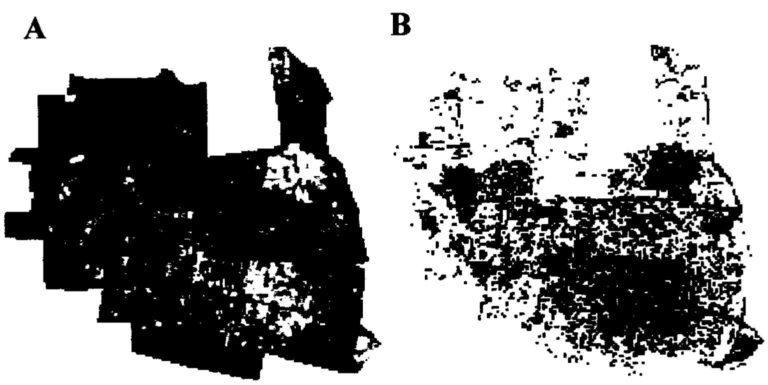


Table 4.68: Error matrix for Ra'anana.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	82	0	7	89
Built	0	39	17	56
Bare	7	14	81	102
Totals	89	53	105	247

Table 4.69: Accuracy statistics for Ra'anana.

Accuracy Statistics				
Overall Accuracy: 81.781%		**95% Confidence Interval (76.765% 86.798%)**		
Overall Kappa Statistic: 0.718%		**Overall Kappa Variance: 0.001%**		
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**	
No values	92.135% (85.980% 98.289%)	92.135% (85.980% 98.289%)	0.8770	
Built	73.585% (60.772% 86.398%)	69.643% (56.707% 82.579%)	0.6135	
Bare	77.143% (68.635% 85.651%)	79.412% (71.074% 87.749%)	0.6419	

Rahat

The percent of built land in Rahat in 1999 was 20.30%. The median NDVI was 0.107. The accuracy statistics were high (Table 4.71) with the exception of the producer's accuracy for the built pixels. Only a small number of pixels were sampled in the accuracy assessment and 14 of those were excluded from their correct class (Table 4.70). Five built land use pixels were identified as bare. This level of accuracy showed in the high user's accuracy for built land. The bare land user's and producer's accuracy statistics were high. The Kappa statistics for each land use class were high showing that the observed accuracy was high.

Figure 4.33 shows the classified and unclassified images for Rahat. There was great spectral separability for the land use pixels in Rahat. The bare pixels were unlikely to be assigned to the built land use class, which happened in other images. The built land was concentrated in one part of the city. This also led to high accuracy in the unsupervised classification.

Figure 4.33: The unclassified image of Rahat is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

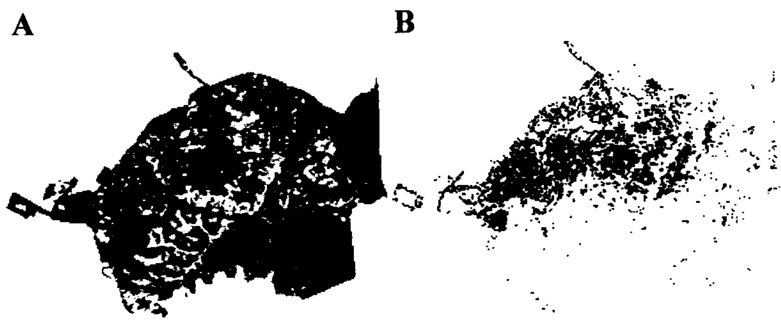


Table 4.70: Error matrix for Rahat.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	115	0	4	119
Built	0	16	5	21
Bare	5	14	91	110
Totals	120	30	100	250

Table 4.71: Accuracy statistics for Rahat.

Accuracy Statistics			
Overall Accuracy: 88.800%		**95% Confidence Interval (84.691% 92.909%)**	
Overall Kappa Statistic: 0.809%		**Overall Kappa Variance: 0.000%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	95.833% (91.841% 99.825%)	96.639% (92.980% 100.297%)	0.9354
Built	53.333% (33.814% 72.852%)	76.190% (55.593% 96.788%)	0.7294
Bare	91.000% (84.891% 97.109%)	82.727% (75.209% 90.246%)	0.7121

Ramat Gan

The percent of built land in 1999 in Ramat Gan was 66.04%. The median NDVI was 0.231. The error matrix and accuracy statistics (Tables 4.72 and 4.73) show high classification accuracy values and Kappa statistics. The accuracy statistics were high for

Ramat Gan with less confusion between the built and bare pixels than other cities in the study.

A high percentage of the land in Ramat Gan was built. The parts of the image that were bare or undeveloped were sometimes mistaken for built land. For example, the land was undeveloped in the southern tip of the city but contained a lot of erroneously classified built pixels due to the spectral similarity of the bare land uses to the built land uses (Figure 4.34). The accuracy assessment did not sample many pixels in this part of the image, and thus this inaccuracy was not reflected in the statistics.

Figure 4.34: The unclassified image of Ramat Gan is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

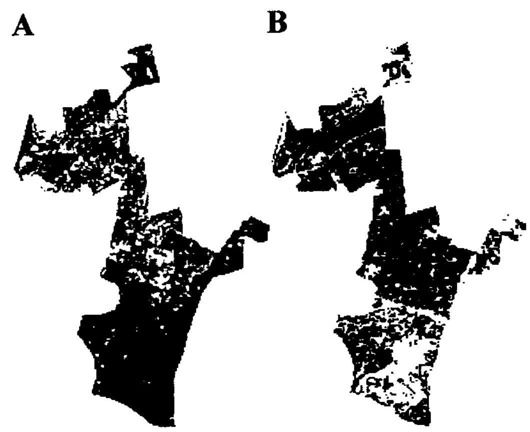


Table 4.72: Error matrix for Ramat Gan.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	164	6	0	170
Built	1	40	8	49
Bare	2	7	17	26
Totals	167	53	25	245

Table 4.73: Accuracy statistics for Ramat Gan.

Accuracy Statistics			
Overall Accuracy: 90.204%		**95% Confidence Interval (86.278% 94.130%)**	
Overall Kappa Statistic: 0.793%		**Overall Kappa Variance: 0.000%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	98.204% (95.890% 100.517%)	96.471% (93.403% 99.539%)	0.8891
Built	75.472% (62.945% 87.999%)	81.633% (69.770% 93.495%)	0.7656
Bare	68.000% (47.714% 88.286%)	65.385% (45.175% 85.595%)	0.6145

Ramat HaSharon

Ramat HaSharon was 32.48% built in 1999 with a median NDVI of 0.252. The error matrix and accuracy statistics are shown in Tables 4.74 and 4.75. They show a low producer's accuracy for built land uses and a low user's accuracy for bare land uses. The Kappas for the built and bare pixels were also low. In the accuracy assessment, many built and bare pixels were confused. However, there were no parts of the images (Figure 4.35) that consistently showed clusters of misclassified pixels. There were small areas that showed bare pixels designated as built, but this occurrence was lower than in other cities, in spite of the accuracy statistics.

Figure 4.35: The unclassified image of Ramat HaSharon is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

Table 4.74: Error matrix for Ramat HaSharon.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	120	0	1	121
Built	1	26	12	39
Bare	7	34	46	87
Totals	128	60	59	247

Table 4.75: Accuracy statistics for Ramat HaSharon.

Accuracy Statistics			
Overall Accuracy: 77.733%		**95% Confidence Interval (72.342% 83.124%)**	
Overall Kappa Statistic: 0.643%		**Overall Kappa Variance: 0.000%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	93.750% (89.166% 98.334%)	99.174% (97.147% 101.200%)	0.9828
Built	43.333% (29.961% 56.705%)	66.667% (50.590% 82.744%)	0.5597
Bare	77.966% (66.542% 89.390%)	52.874% (41.810% 63.938%)	0.3808

Ramla

Ramla was 39.19% built and had a median NDVI of 0.195 in 1999. Tables 4.76 and 4.77 show the error matrix and accuracy statistics. The producer's accuracy for built land and the user's accuracy for bare land were low. Almost half of the pixels in the two accuracy statistics were assigned omitted from the correct class or assigned to the wrong class causing these statistics to be low. The bare land use Kappa statistic is also low, but the classification is still greater than what is expected by chance.

The unclassified and classified images (Figure 4.36) show that areas with misclassified pixels were around roads, where the road was erroneously classified as bare and the surrounding undeveloped land was classified as built.

Figure 4.36: The unclassified image of Ramla is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

Table 4.76: Error matrix for Ramla.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	106	0	3	109
Built	1	42	8	51
Bare	6	37	45	88
Totals	113	79	56	248

Table 4.77: Accuracy statistics for Ramla.

Accuracy Statistics			
Overall Accuracy: 77.823%		**95% Confidence Interval (72.450% 83.195%)**	
Overall Kappa Statistic: 0.661%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	93.805% (88.918 % 98.692%)	97.248% (93.718% 100.778%)	0.9494
Built	53.165% (41.528% 64.801%)	82.353% (70.910% 93.796%)	0.7410
Bare	80.357% (69.058% 91.656%)	51.136% (40.124% 62.149%)	0.3688

Rehovot

The percent of built land in 1999 was 28.32% in Rehovot. The median NDVI was 0.232. The accuracy statistics for Rehovot were high (Table 4.79) with little misclassification of pixels (Table 4.78). As with other cities, there was some confusion between built and bare pixels, but the overall, producer's, and user's accuracies remained high, as did the Kappa coefficients.

The high image classification accuracy can be attributed to the spectral dissimilarity between the bare and built land uses (see Figure 4.37). The built land uses were concentrated in the image with the land outside of the developed area having sparse development. There was some misclassification by the unsupervised classification algorithm in the bare areas. Some of the misclassified areas were found by the photointerpreter to be incorrect and led to the decrease in accuracy statistics.

Figure 4.37: The unclassified image of Rehovot is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

Table 4.78: Error matrix for Rehovot.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	129	1	3	133
Built	1	27	7	35
Bare	1	12	64	77
Totals	131	40	74	245

Table 4.79: Accuracy statistics for Rehovot.

Accuracy Statistics			
Overall Accuracy: 89.069%		95% Confidence Interval (84.975% 93.163%)	
Overall Kappa Statistic: 0.817%		Overall Kappa Variance: -0.001%	
Class Name	Producer's Accuracy (95% Confidence Interval)	User's Accuracy (95% Confidence Interval)	Kappa Statistic
No values	98.473% (95.992% 100.955%)	96.992% (93.714% 100.271%)	0.9360
Built	67.500% (51.735% 83.265%)	77.143% (61.803% 92.483%)	0.7273
Bare	86.486% (78.022% 94.951%)	83.117% (74.100% 92.133%)	0.7590

Rishon Letzion

The percent of built land in Rishon Letzion was 17.64% and the median NDVI was 0.189 in 1999. The accuracy statistics were high (Table 4.81) with the exception of the high misclassification of built pixels into bare pixels. More than half of the built pixels were misclassified as bare pixels as shown in the error matrix (Table 4.80). There were many bare pixels that were misclassified as built pixels, but the accuracy assessment did not sample enough of these pixels to reflect this. Figure 4.38 shows this. The area in the west side of the image was mostly sand and was designated as bare and undeveloped land. The unsupervised classification algorithm clustered many of these pixels with other built pixels.

Figure 4.38: The unclassified image of Rishon Letzion is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

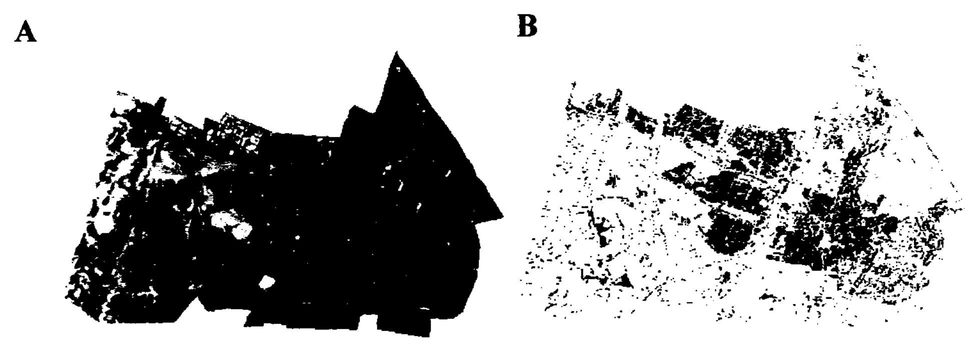


Table 4.80: Error matrix for Rishon Letzion.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	95	0	1	96
Built	1	18	9	28
Bare	1	19	106	126
Totals	97	37	116	250

Table 4.81: Accuracy statistics for Rishon Letzion.

Accuracy Statistics			
Overall Accuracy: 87.600%		**95% Confidence Interval (83.314% 91.886%)**	
Overall Kappa Statistic: 0.794%		**Overall Kappa Variance: 0.000%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	97.938% (94.595% 101.282%)	98.958% (96.407% 101.510%)	0.9830
Built	48.649% (31.192% 66.105%)	64.286% (44.752% 83.820%)	0.5808
Bare	91.379% (85.841% 96.918%)	84.127% (77.349% 90.905%)	0.7039

Rosh Ha'Ayin

The percent of built land in Rosh Ha'Ayin was 28.31% in 1999 with a median NDVI of 0.165. The overall accuracy statistics were as were the Kappa coefficients and user's and producer's accuracies for the no values and bare pixels. The Kappa coefficient and user's and producer's accuracies for the built pixels were lower than for the bare pixels (Table 4.83). Many of the built pixels were misclassified as bare. Thirteen were classified as built that were bare and 16 were classified as bare that were built (Table 4.82). These misclassifications were reflected in the lower accuracy and Kappa statistics.

Some of the misclassifications are readily apparent in the images for Rosh Ha'Ayin. Figure 4.39 shows unclassified and classified images for the city. There were large parts of bare land that were spectrally similar to the built land and were clustered with the built land uses in the unsupervised classification. This is also seen in the developed land. There are many bare pixels interspersed with the built pixels that should have been clustered with the built pixels.

Figure 4.39: The unclassified image of Rosh Ha'Ayin is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

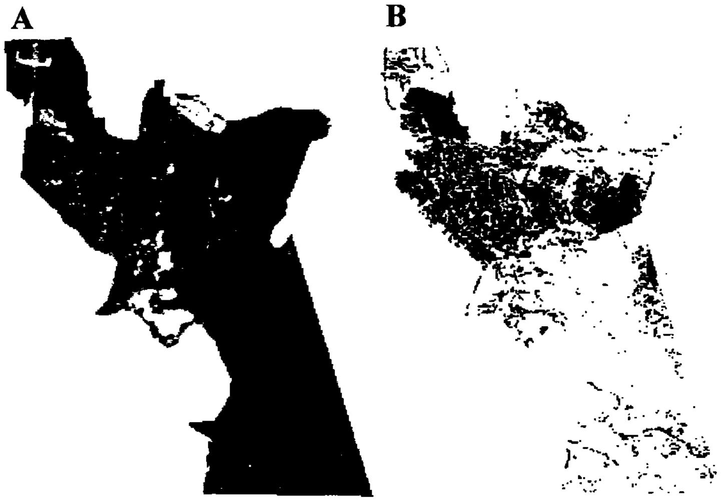


Table 4.82: Error matrix for Rosh Ha'Ayin.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	132	0	3	135
Built	0	16	13	29
Bare	3	16	67	86
Totals	135	32	83	250

Table 4.83: Accuracy statistics for Rosh Ha'Ayin.

Accuracy Statistics			
Overall Accuracy: 86.000%		95% Confidence Interval (81.499% 90.501%)	
Overall Kappa Statistic: 0.758%		Overall Kappa Variance: -0.002%	
Class Name	Producer's Accuracy (95% Confidence Interval)	User's Accuracy (95% Confidence Interval)	Kappa Statistic
No values	97.778% (94.921% 100.635%)	97.778% (94.921% 100.635%)	0.9517
Built	50.000% (31.113% 68.887%)	55.172% (35.348% 74.997%)	0.4859
Bare	80.723% (71.634% 89.812%)	77.907% (68.557% 87.257%)	0.6693

Sderot

The percent of built land in Sderot was 63.08% and the median NDVI was 0.170 in 1999. The accuracy statistics (Table 4.85) for the built and no values pixels were high. The accuracy statistics for the bare pixels were lower because many pixels were omitted from the bare land use class or were committed to the bare class that belonged in another land use class (Table 4.84).

Figure 4.40 shows the imagery for Sderot. Many bare pixels were assigned to the built class, due to the spectral similarity between the two land use classes in this city. This led to an overclassification of built land in Sderot.

Figure 4.40: The unclassified image of Sderot is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

A B

Table 4.84: Error matrix for Sderot.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	106	4	2	112
Built	4	74	21	99
Bare	3	10	23	36
Totals	113	88	46	247

Table 4.85: Accuracy statistics for Sderot.

Accuracy Statistics			
Overall Accuracy: 82.186%		**95% Confidence Interval (77.212% 87.160%)**	
Overall Kappa Statistic: 0.714%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	93.805% (88.918% 98.692%)	94.643% (90.026% 99.259%)	0.9013
Built	84.091% (75.881% 92.301%)	74.747% (65.684% 83.811%)	0.6077
Bare	50.000% (34.464% 65.536%)	63.889% (46.809% 80.968%)	0.5562

Taiyiba

The percent of built land in Taiyiba in 1999 was 23.85%. The median NDVI was 0.202. The accuracy statistics for the no values and bare pixels were high. They were lower for the built pixels because many built pixels were omitted from the built class or were assigned to the built class but were not built (Tables 4.86 and 4.87).

The images for Taiyiba (Figure 4.41) show that the built land was clustered in the center of the image with the surrounding built areas being mostly roads and sparse development. Many bare pixels outside of the central built cluster were assigned to the built land class because of those pixels' spectral similarity to the built pixels. The bare pixels that were correctly classified had higher NDVI values than the pixels that were misclassified.

Figure 4.41: The unclassified image of Taiyiba is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

Table 4.86: Error matrix for Taiyiba.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	76	0	3	79
Built	0	23	15	38
Bare	9	12	107	128
Totals	85	35	125	245

Table 4.87: Accuracy statistics for Taiyiba.

Accuracy Statistics			
Overall Accuracy: 83.065%		**95% Confidence Interval (78.195% 87.934%)**	
Overall Kappa Statistic: 0.722%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	89.412% (82.282% 96.541%)	96.203% (91.355% 101.050%)	0.9422
Built	65.714% (48.560% 82.869%)	60.526% (43.669% 77.384%)	0.5404
Bare	85.600% (79.045% 92.155%)	83.594% (76.787% 90.400%)	0.6692

Tel Aviv

The percent of built land in Tel Aviv was 67.13% and the median NDVI was 0.202 in 1999. Tables 4.88 and 4.89 show the error matrix and the accuracy statistics. The accuracy statistics were high for the built and no values pixels. The producer's accuracy for the bare pixels were low because many bare pixels were classified as built. Because the percent of built land was high, there were fewer bare pixels from which to sample in the accuracy assessment. This could have artificially lowered the accuracy statistics for the bare and undeveloped land use pixels.

Figure 4.42 shows the unclassified and classified images for Tel Aviv. Along the sandy coastal region in the northwest corner of the city, many bare pixels were misclassified as built. Sand has a high reflectance that is similar to the reflectance of some developed land uses. This spectral similarity caused the unsupervised classification algorithm to cluster the pixels together.

Figure 4.42: The unclassified image of Tel Aviv is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

A B

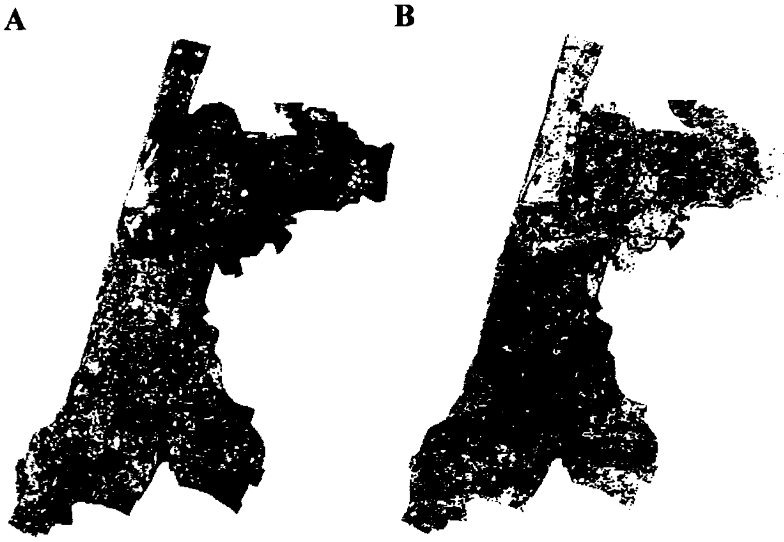


Table 4.88: Error matrix for Tel Aviv.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	152	1	0	153
Built	5	54	15	74
Bare	1	7	14	22
Totals	158	62	29	249

Table 4.89: Accuracy statistics for Tel Aviv.

Accuracy Statistics			
Overall Accuracy: 88.000%		**95% Confidence Interval (83.772% 92.228%)**	
Overall Kappa Statistic: 0.773%		**Overall Kappa Variance: -0.035%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	96.203% (92.906% 99.499%)	99.346% (97.743% 100.950%)	0.9822
Built	87.097% (77.946% 96.248%)	72.973% (62.179% 83.767%)	0.6406
Bare	48.276% (28.364% 68.187%)	63.636% (41.262% 86.011%)	0.5886

Tira

The percent of built land in Tira in 1999 was 38.32%. The median NDVI was 0.230. Tables 4.90 and 4.91 show the error matrix and the accuracy statistics. The accuracy and Kappa statistics were high for the no values and bare pixels. The producer's accuracy and Kappa coefficient were low for the built land class. More than half of the built pixels that were classified as built were bare (see Table 4.90). This error in misclassification is apparent in the imagery for Tira. Figure 4.43 shows the unclassified and classified images. The east side of the city was largely undeveloped but contained an erroneously high number of built pixels.

Figure 4.43: The unclassified image of Tira is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

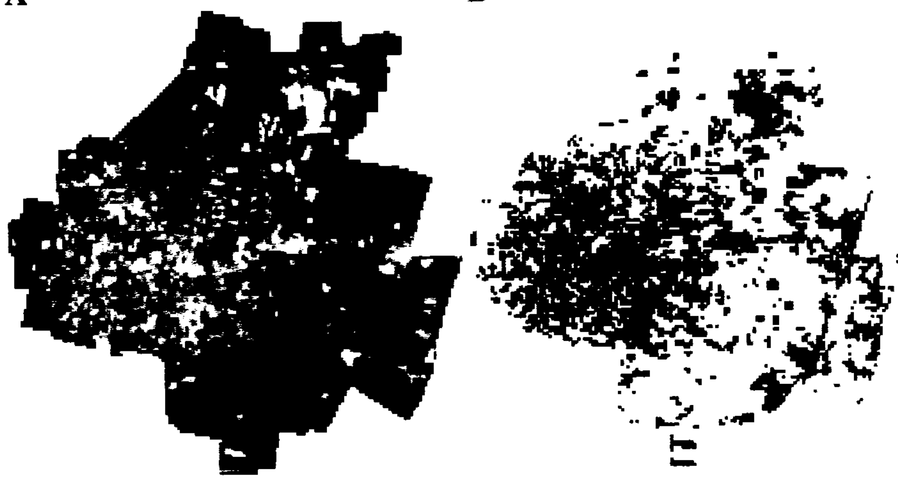


Table 4.90: Error matrix for Tira.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	97	0	6	103
Built	1	25	31	57
Bare	1	12	74	87
Totals	99	37	11	247

Table 4.91: Accuracy statistics for Tira.

Accuracy Statistics			
Overall Accuracy: 79.352%		**95% Confidence Interval (74.102% 84.603%)**	
Overall Kappa Statistic: 0.677%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	97.980% (94.703% 101.256%)	94.175% (89.166% 99.184%)	0.9028
Built	67.568% (51.132% 84.003%)	43.860% (30.100% 57.619%)	0.3397
Bare	66.667% (57.446% 75.887%)	85.057% (76.991% 93.124%)	0.7286

Yavne

The percent of built land in 1999 in Yavne was 29.99%. The median NDVI was 0.202. The error matrix (Table 4.92) and accuracy statistics (Table 4.93) show a high classification accuracy in the accuracy assessment. In the accuracy assessment, the bare pixels had higher accuracy and Kappa values than the built land uses. However, in the west side of the city (Figure 4.44), the bare pixels often incorrectly clustered with the built pixels (and are seen in red). There were built areas within the image that had high NDVI values. Many bare pixels with high NDVI values were also clustered with the built pixels that had the high NDVI values.

Figure 4.44: The unclassified image of Yavne is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

A B

Table 4.92: Error matrix for Yavne.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	119	0	2	121
Built	0	25	13	38
Bare	2	15	71	88
Totals	121	40	86	247

Table 4.93: Accuracy statistics for Yavne.

Accuracy Statistics			
Overall Accuracy: 86.694%		**95% Confidence Interval (82.265% 91.122%)**	
Overall Kappa Statistic: 0.783%		**Overall Kappa Variance: 0.000%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	98.347% (95.662% 101.032%)	98.347% (95.662% 101.032%)	0.9677
Built	62.500% (46.247% 78.753%)	65.789% (49.389% 82.189%)	0.5921
Bare	82.558% (73.957% 91.160%)	80.682% (71.865% 89.499%)	0.7043

Yehud-Newe Efrayim

The percent of built land in Yehud-Newe Efrayim in 1999 was 59.98%. The median NDVI was 0.250. The error matrix and accuracy statistics are in Tables 4.94 and 4.95. The accuracy statistics for the no values and built pixels showed a high degree of accuracy. They accuracy statistics show confusion in distinguishing between the bare and built land use types. More bare pixels were classified incorrectly as built or as having no value than were classified correctly as bare.

Figure 4.45 shows the unclassified and classified images for Yehud-Newe Efrayim. The most discernable location of pixel misclassification is in the southern part of the city. The land was bare there, but many pixels were clustered as built by the unsupervised classification algorithm. There was variation in NDVI values among the built land uses, so high NDVI values that would typically be classified as bare were classified as built. Other bare areas were also erroneously classified as built due to spectral similarities with built pixels.

Figure 4.45: The unclassified image of Yehud-Newe Efrayim is in panel A. The classified image is in panel B. The red pixels represent built land uses, beige represent bare and undeveloped land uses, and the gray represent areas outside of the city borders.

Table 4.94: Error matrix for Yehud-Newe Efrayim.

Error Matrix				
	Reference data			
Classified data	No values	Built	Bare	***Totals***
No values	93	2	3	98
Built	1	71	23	95
Bare	7	20	22	49
Totals	101	93	48	242

Table 4.95: Accuracy statistics for Yehud-Newe Efrayim.

Accuracy Statistics			
Overall Accuracy: 75.918%		**95% Confidence Interval (70.360% 81.477%)**	
Overall Kappa Statistic: 0.629%		**Overall Kappa Variance: 0.001%**	
Class Name	**Producer's Accuracy (95% Confidence Interval)**	**User's Accuracy (95% Confidence Interval)**	**Kappa Statistic**
No values	92.079% (86.317% 97.841%)	94.898% (90.031% 99.765%)	0.9132
Built	76.344% (67.169% 85.519%)	74.737% (65.473% 84.001%)	0.5928
Bare	45.833% (30.696% 60.971%)	44.898% (29.951% 59.845%)	0.3147

CHAPTER 5: DISCUSSION

SUMMARY OF RESULTS

This research used remote sensing data to quantify the percent of built land and NDVI in 45 cities in Israel. A principal components analysis was performed using the percentages of built land in each city, NDVI, conflict events, and socioeconomic variables to explore the relationships among the variables. The study found that NDVI clustered with all of the socioeconomic variables, and conflict clustered with population and percent built land. These results are important because they provide a way to relate conflict to remote sensing information and I found a link between environmental quality and socioeconomic variables.

This chapter includes a comparison of the results of the remote sensing to other studies and a discussion of the levels of accuracy of the unsupervised classification and urbanization in Israel as measured using remote sensing. In addition, the significance of the relationships between NDVI and the socioeconomic variables, conflict and population, and conflict and the percent of built land are discussed.

COMPARISON OF REMOTE SENSING CLASSIFICATION RESULTS TO OTHER STUDIES

Reese et al. (2002) performed a classification of Wisconsin land uses using Landsat TM data. The authors measured land cover using Anderson's Levels I, II, and III land use classes (Anderson et al., 1976). The Anderson et al. (1976) land use scheme classifies land use by levels. Level I is the most general, Level II classifies its land uses as subunits of Level I, and Level III classifies its land uses as subunits of Level II. Their accuracy rates were 94% for Level I, 77% for Level II/III upland classes, 84% for Level II/III wetland classes, and 70 – 84% for the overall forest classification. They also used the user's accuracy statistic to describe their data. Their user's accuracies for their Level I data ranged between 62.79% for shrub land to 100% for urban land. For their classification, they used a mix of supervised and unsupervised classifications called guided clustering. They used training data based on field observations, ran an ISODATA unsupervised classification, and then a maximum likelihood classification based on principal components data. They also performed postprocessing smoothing on the data.

Reese et al. (2002) used a more in depth classification system than the K-means unsupervised classification used in this project. The percent urban user's accuracies for my project ranged between 33 – 92%. The results for my project differed from the results of Reese et al. (2002) because of the different methods that they used to collect and analyze their data. They used field methods to gather training data, while this project used ground truth data from maps. This project did not use a hybrid classification system and used a more straightforward classification system, the K-mean unsupervised classification, which is commonly used. Other classification systems yield more accurate results but preliminary trials for this study using the other classification systems did not yield higher results. A supervised classification was not possible for this study due to signature inseparability when selecting the training sites. Signature inseparability occurs when two or more land uses have similar reflectances in the electromagnetic spectrum and cannot be distinguished due to their similarities. Better and more accurate ground truth data could have improved the results for this study, but those data were not available.

The user's accuracy for the percent of urban land was still high in many cities. In other cities where the user's accuracy was lower contained a high degree of pixel misclassification and confusion between built and bare land uses.

Oetter et al. (2000) used Landsat TM to classify agricultural land. They performed a Tasseled Cap transformation and an unsupervised classification on the Tasseled Cap data. They stratified urban and forested land. They stratified the urban land into three classes: high-density built, medium-density built, and water. They had a fourth class, "confused urban," that they later reclassified. They also classified forested land types using training plots from an aerial photo. They performed an unsupervised classification on the training data and then a supervised classification on the pixels from the unsupervised classification that were labeled "closed-forest." They then classified the pixels that were not urban and forest. They found that according to their classifications, the overall accuracies ranged from 40% for park land to 100% for flooded/marsh land. Only five park land and four flooded/marsh pixels were sampled in the accuracy analyses. Of their urban land covers, they classified 81.8% of high-density, 66.7% of medium-density, and 54.5% of low-density built land correctly. The low numbers of pixels sampled could have caused an inflation or deflation in the accuracy statistics.

A preliminary study for this project was performed using a Tasseled Cap transformation. The Tasseled Cap transformation of the data did not improve classification and was not used for the final project. The study by Oetter et al. (2000) used a combination of an unsupervised classification and a supervised classification to classify their data. While this allowed them to classify their data into more specific land cover types, their accuracy statistics were still low for some of the land covers. The data of Israel for this project used an unsupervised classification and did not characterize built data as high, medium, or low density but different cities showed varying levels of accuracy in classification and computing the accuracy statistics. Some of the variability in the accuracy statistics could be due to the built pixels being low, medium, or high density. I did not analyze my data according to detailed land use types because these analyses were irrelevant to the hypotheses and the level of ground truth data necessary for more land use classes were not available.

San Miguel-Ayanz and Biging (1997) performed supervised and unsupervised classifications of Landsat TM and SPOT data. Their unsupervised classification was an ISODATA unsupervised classification. Their unsupervised classification yielded an overall accuracy of 45.63% for the Landsat TM data and 43.70% for the SPOT data. Various supervised classification methods were used and their accuracies ranged from 45.63% and 65.56% for the Landsat TM data and 43.70% and 61.24% for the SPOT data. They did not find a statistically significant difference between the Landsat and the SPOT data.

A supervised classification was attempted for this project, but it was unsuccessful due to the signature inseparability between land use classes. San Miguel-Ayanz and Biging (1997) used several different approaches to maximize accuracy, whereas the preliminary research for this project did not. San Miguel-Ayanz and Biging (1997) also identified more land cover types, which could have led to better results and signature separability than a supervised classification would yield for this project. However, the supervised classification only slightly outperformed the unsupervised classification in the research of San Miguel-Ayanz and Biging (1997). The unsupervised classifications performed for this project varied in overall accuracies—the overall accuracies ranged from 71.721% to 97.177%—but were much higher than the 45.63% found in the research of San Miguel-Ayanz and Biging (1997). This project on Israel used the K-means unsupervised classification. In a preliminary study on the Landsat image, the K-means unsupervised classification outperformed the ISODATA classification, which San Miguel-Ayanz and Biging (1997) used. The higher overall accuracies for the unsupervised classification in this project could be attributed to goal of identifying fewer land use classes. More land use classes would have improved the producer's and user's accuracies but more detailed ground truth data were not available.

Cihlar, Ly, and Xiao (1996) classified AVHRR data and used Landsat TM data as the reference image in performing the ground truth verification. Their purpose was to determine which band or band combination was most effective in land use classification in an AVHRR image. They used the NDVI and other band combinations. They used the ISOCLASS algorithm in performing their unsupervised classification. They found that the NDVI yielded the highest level of accuracy.

In this project on Israel, NDVI was not used in the classification analysis. I did not use band combinations and instead included all of the bands in the unsupervised classification. NDVI was used as a separate variable that would be studied in the principal components analysis. This resulted in varying levels of accuracy as shown in the accuracy statistics. Reducing the number of bands used in the analysis, either through use of NDVI or through principal components analysis, might have improved the accuracy in this study.

Haack et al. (1987) used Landsat TM and MSS imagery to differentiate between urban and near urban land uses. They used an unsupervised and supervised classifications. For the unsupervised classification, they used four subscenes from the image to represent four land use classes. The land uses were water, nonforested wetland, agriculture, and residential-commercial. They used a transformed divergence to determine statistical distance between land use classes to determine if there is separability between the classes and a correct land use classification. They used the transformed divergence instead of performing accuracy analyses on their classifications using the traditional overall, user's, and producer's accuracies and Kappa statistic. They found that the higher resolution Landsat TM data outperformed the MSS imagery.

A transformed divergence could have been used in this project on Israel to determine the signature distance between the land use classes. It could have also been used to determine which bands would be most suitable for a supervised classification to maximize signature separability. The Bhattacharyya distance (Jimenez and Landgrebe, 1997) is often used to examine signature separability in a supervised classification. The transformed divergence, as used by Haack et al. (1987), could be an alternative. Signature separability was a problem with this research on Israel and precluded the use of a supervised classification. The unsupervised classification was deemed most useful because the computer algorithm clustered the land uses without human input from training data. This sought to take the human error out of the initial land use clustering.

Yang et al. (2006) compared unsupervised classifications of QuickBird and airborne imagery to compare the accuracy of the two high resolution image types and to determine the efficacy of using an ISODATA unsupervised classification in identifying grain yield. They found that the QuickBird and airborne imagery were significantly related to grain yield and that the correlations between both types of imagery with grain yield were similar to each other. The unsupervised classification also differentiated between grain yield levels.

The unsupervised classification for this project on Israel did not use correlational analyses to examine the relationship between the satellite imagery and land use type. It used an accuracy assessment to determine the accuracy in identifying the land uses. The accuracy statistics for the analyses of the cities in Israel varied. The variability may have been based on the use of the medium resolution satellite, Landsat, or the use of thematic imagery for the reference data. Many pixels in Landsat were mixed with different land covers. Because QuickBird and airborne imagery were a higher resolution, the presence of mixed pixels is lower. The results by Yang et al. (2006) are significant because they show that a simple unsupervised classification can be used to accurately classify land use data. Their results also suggest that for a simple unsupervised classification to be successful, high resolution imagery should be used.

The accuracy statistics for the research on land use in Israel varied, but studies by other researchers yielded similar levels of accuracy, even if they used a more complex method than a simple unsupervised classification. The one study that used an unsupervised classification that yielded high accuracy (Yang et al., 2006) used high resolution imagery for the analysis. Because other researchers yielded similar levels of accuracy, the results from the urban land quantification were used as a variable for the principal components analysis portion of the research.

URBAN LAND IN ISRAEL

Discrepancies in quantification of urban land

Israel has one of the highest population densities in the western world (Shoshany & Goldshleger, 2002), but the results from this study show that some cities are not as dense as one should believe based on Shoshany and Goldshleger (2002). For example, Orenstein (2004) said that built land in Rishon Letzion increased from 39% to 70% between 1961 and 2001. The results for this dissertation show that Rishon Letzion was almost 18% built in 1999. The difference between 70% and 18% is large, but Orenstein did not say how he quantified built land. He did not discuss what boundaries he used and he did not say what he used to classify built land. For my research, the CBS provided the border delineations from its website (http://gis.cbs.gov.il/website/landuse_2002/viewer.htm). The city borders that the CBS provided were far outside the built and developed part of many cities, including that of Rishon Letzion. There was a high amount of bare and agricultural land located within the city boundaries that the CBS provided. These factors led to a lower quantification of built land than how Orenstein (2004) classified built land.

A question that needs to be addressed is whether the liberal city boundaries invalidate the PCA. Because this research adhered to the borders as they were drawn by the CBS, the use of these city borders for the PCA is justifiable. Adhering to the edges of the built areas of the city would betray the legal borders and underestimate the areas that were not built.

There are other problems in analyzing urban land. The problems include heterogeneous land cover, such as trees, grass, soil, different building materials, and concrete (Zhang et al., 2002). Some urban land covers are spectrally similar to non-urban land covers (Zhang et al., 2002) or contain similar land covers to non-urban land covers such as irrigated vegetation, grass, trees, and soils. To ameliorate the problems associated with studying urban land, Zhang et al. (2002) studied urban land use through road density. Areas with greater road density are likely more urban. Bare areas that are spectrally similar to built areas tend to have fewer roads. Zhang et al. (2002) found that urban analyses using road cover improved urban classification. Extensive road data were not available for my study. Some of the roads could be digitized from the satellite and thematic imagery, but there was no verification to determine if the areas identified as roads were correct or extensive enough.

The relationship between NDVI and urban land in Israel

If the borders were delineated along the edge of the built parts of the city, the relationship between NDVI and the percent urban would be a negative relationship, instead of the weak positive relationship that actually occurred. Lo and Faber (1997) found that the NDVI has a negative correlation with percent of urban use, which contradicts the relationship between NDVI and percent of urban land that was found in this project on Israel. However, like this project on Israel, Lo and Faber (1997) found that the percent of urban and NDVI were unrelated and clustered in separate components in the PCA.

There are a couple of explanations for the weak positive relationship between the NDVI and the percent of urban land. There could be irrigated land uses within urban areas and open space in an area with rainfall.

Other studies have shown that irrigated land uses within a city have an effect on NDVI. Fung and Siu (2000) found that in their study location that urban areas that had a higher NDVI experienced urban renewal. Those cities experienced landscaping and environmental improvement, such as tree planting. These green spaces within the city contributed to the higher NDVI. Cities with a decrease in NDVI experienced urban sprawl.

Cities in Israel with a low NDVI that had a lot of open space, like Dimona, were located in parts of the country that received low rainfall and had a higher climate. Dimona had areas of land that were irrigated, but the bare undeveloped areas that were not park space were not irrigated and this caused a lower NDVI. Cities with a more temperate climate or that were on the coast and experienced more precipitation than the desert cities had a higher NDVI, like Tel Aviv. Fung and Siu (2000) found that arable areas with a low NDVI contained land that was abandoned.

The areas classified as bare in the dry regions also differed from the areas classified as bare in the coastal regions. Many cities in the coastal region had some agricultural land. Agricultural land was classified as bare, in addition to bare undeveloped land and rock in dry areas. In some built areas, park land was designated as built if the ground truth images designated that area of land as built.

NDVI AND ITS RELATIONSHIP TO SOCIOECONOMIC VARIABLES

Built land clustered with the socioeconomic variables in the PCA. This relates to the research of Lo and Faber (1997) who used urbanization and NDVI as derived from remote sensing. They used principal components analysis to determine who quality of life data related to temperature and the remote sensing data. The quality of life data that Lo and Faber (1997) used were population density, per capita income, median home value, and percent of college graduates. They found that population density, percentage of urban use, and surface temperature clustered together. Per capita income, median home value, percentage of college graduates, and NDVI clustered in a separate cluster.

The socioeconomic data used for this research on Israel were average income per capita, percent of new motor vehicles, percent of families with four or more children, median age, percent of students between 20 – 29 years old, and population. The type of socioeconomic data that Lo and Faber used was unavailable but comparable variables were used. The NDVI and percent of urban land were derived from the remote sensing data, and the conflict data were taken from the ICT in Herzliyya, Israel. Conflict events, population, and the percent urban grouped into one component. Average income per capita, percent of new motor vehicles, percent of families with four or more children, median age, percent of students between 20 – 29 years old, and NDVI grouped into another component.

There are various reasons why the relationship between NDVI and socioeconomic variables group together. Lo and Faber (1997) used their socioeconomic variables to represent quality of life variables. Quality of life can represent health (Juniper et al., 1997), environmental quality, climate, number of hours worked, urban condition (central city status, violent crime rate, and teacher-pupil ratio), and population growth (Blomquist et al., 1988). The various quality of life studies show that quality of life can represent many things outside of the variables that Lo and Faber (1997) studied. The socioeconomic variables studied for this remote sensing of Israel project can be considered quality of life variables too. Through PCA, Lo and Faber (1997) found that NDVI and quality of life are related.

NDVI is a representation of the amount of green cover in a location. Why would green cover relate to socioeconomic variables? Locations with more green cover (i.e. grass, trees, agriculture, and other green vegetation) may represent a climate with enough rainfall to support an economy that can cultivate its own food. Areas with more ideal and temperate climates are often located along the coast of a region. In this case, many of the cities in Israel with higher NDVI values were located along the coast. The cities with the lower NDVI values were inland. In many countries, coastal locations are more desirable places to live and cost more to live. Examples of this in the United States are coastal cities such as Los Angeles and New York City. These are two of the most expensive cities in the U.S., according to CNN (2005).

Fung and Siu (2000) found that NDVI is related to crowding. Cities with more green cover have more open space and may have a lower population density or fewer areas with high population densities. Kearney (2006) reports that people who have views of nature from their homes and who have nearby shared nature spaces that they access report greater satisifaction than those who do not have these things.

THE RELATIONSHIP BETWEEN POPULATION AND THE PERCENT OF BUILT LAND

The population and percent of built land had a weak statistically insignificant positive correlation (r = 0.193). Population and the percent of built land loaded together in the second principal component. The weak positive relationship between population and the percent of built land may have been due to the way the city borders were drawn according to how the Israel CBS delineated the city borders far outside the built parts of the city.

One would assume that population and the percent of built land would have a stronger significant correlation, but the study by Lo and Faber (1997) found a similar relationship between population density and the percent of built land ($r = 0.196$). Population density and the percent of urban land also loaded on the same component in their research.

One issue arose in the results from the PCA was the weak loading of the percent of built land on both components. However, the variable loaded more strongly on the second component, which contained the population and conflict variables. Since Lo and Faber (1997) found that population density and the percent urban loaded on the same principal component, this supports the location of percent urban on the second component in this research. Lo and Faber (1997) said that all of the physical variables loaded together in their research, with the exception of NDVI which loaded with the socioeconomic variables. These physical variables were population density, percent of urban land, and climate. This supports the loading of population and the percent of urban land on the same component in this research.

THE RELATIONSHIP BETWEEN CONFLICT, POPULATION, AND THE PERCENT OF BUILT LAND

Much of the prior research shows that if there is a relationship between conflict and population, there is a land use component that contributes to the relationship. Thus, the relationship between conflict, population, and urbanization are discussed together in this section, rather than as entities that impact each other separately.

Many researchers studied the relationship between conflict, population, and land cover. Brunborg and Urdal (2005) said that the conventional wisdom is that population pressure can lead to conflict over arable land and freshwater scarcity. Tir and Diehl (1998) said that population growth increases the likelihood that a state will become involved in conflict. Hauge and Ellingsen (1998) found that population density in combination with land degradation, deforestation, and freshwater scarcity increase the risk of conflict. Urdal (2005) found that countries that have high population growth do not have a higher risk for conflict than do countries with lower population pressure. He also said that countries that undergo high population growth coupled with scarce productive land may face a greater risk of conflict. However, he is not confident in either of these relationships based on the lack of robustness of his findings.

In this research, conflict grouped with population and the percent of built land onto the second principal component. There are various reasons why conflict, population, and the percent of built land are associated. These reasons include the possibility that terrorists target areas with high populations or high population centers, are accessible by public or other transportation, are on transportation routes where the land is built, and have more roads in areas where there are more people. The terrorist attacks often occurred in city centers, transportation routes, or other built areas that were accessible or had a large population. Such locations were likely selected as the location for the terrorist attack to maximize impact and damage. This section discusses these terrorist attacks and their connections to population and land use.

The majority of the terrorist attacks that occurred in Israel between August 7, 1996 and August 7, 2002 were in cities, developed and built areas, crowded areas, buses, and transportation routes. The attacks occurred in areas where it appeared that the assailant wanted to maximize casualties. These areas were cities with high populations, development, or had transportation routes. Attacks that did not occur in populous or developed areas included drive-by shootings, killings of random civilians, an assassination of the tourism minister, and shootings at military bases or of military personnel performing their jobs off-base.

As mentioned above, Hauge and Ellingsen (1998) found that population density, in combination with land degradation, deforestation, and freshwater scarcity, increases the risk of conflict. This research on Israel partially supports their claim. Freshwater availability was not measured in this research because it was not available on the city level. Deforestation was not directly quantified either, but the NDVI could serve as a proxy for deforestation, since NDVI measures green cover. There was a weak statistically insignificant positive correlation ($r = 0.010$; $p = 0.990$) between NDVI and conflict, but conflict and NDVI did not group together in the same principal component. This suggests that the NDVI and conflict are not associated. Thus, if NDVI is used as a substitute for deforestation, this relationship does not hold true for the cities in Israel that were examined in this project.

The other variable that Hauge and Ellingsen (1998) used, land degradation, could be a substitute for the variables that were used for this project, NDVI and the percent of built land. In this case, NDVI is not appropriate because the change in NDVI was not measured and it is not known if degradation occurred. The percent of built land can be used as a proxy for land degradation, because the process of paving and developing land removes the cultivable and productive value from the land and it interrupts the natural habitat and ecosystem. The results from this research on the presence of a relationship between built and conflict supports the findings from Hauge and Ellingsen (1998).

Resource sharing

The West Bank sits over an aquifer that provides freshwater to Israel. Israel is allowed greater access to the groundwater than Palestinians are allowed. Israel overpumps groundwater to meet its water demand and damages the quality of the groundwater that is left behind (Klare, 2001). Jewish residents receive more water than the Palestinians receive (Isaac, 1995). Israel does not give permits to the Palestinians to drill water nor does it help create the proper wells, so the Palestinians build illegal wells which hurt the quality of the groundwater (Isaac & Ghanyem, 2003-2004).

Klare (2001) believes that the pressures over water and the needs of a growing population could lead to violent conflict in the future. Areas that are urbanizing and areas that support agriculture require large amounts of water to sustain the population and the development. Israel allows greater access to water to Israeli residents than to the Palestinians. Access to water allows for development and this inequality in access could contribute to conflict, especially if it prevents one side from developing and urbanizing while the other side thrives.

CONCLUSIONS

Determining the relationship between the environment, conflict, and other socioeconomic variables can impact the way that planners and government officials plan land uses and prioritize funding of social and educational programs. The way that land is developed impacts the attitudes of its residents and of neighboring residents who do not gain the same benefits. In Israel, this is a particular problem because many residents of Israel and the Palestinian territories do not have equal benefits in resource usage and land development. This research attempted to determine if there is a quantifiable relationship between land use, conflict, and various socioeconomic variables. These conclusions can be drawn from this research:

(a) Remote sensing can be used in the study of the relationship between environmental problems and conflict. There has been a lot of research in the environmental conflict arena but none has used remote sensing as an environmental measure and then related it to conflict. Most researchers perform qualitative research on environmental conflict or use other measures to quantify environmental problems.

(b) Medium resolution imagery like Landsat is not ideal in correctly classifying land cover but is more cost effective than higher resolution imagery. Different methods and better ground truth information could improve the level of accuracy when using medium or low resolution imagery.

(c) Additional information would be valuable, such as types of urban and vegetative ground covers. These types of information can help determine if more specific land uses relate to conflict.

These results demonstrate a relationship between QOL and the environment in Israel. The land use data derived from Landsat, which allows for a direct method to relate remote sensing data to socioeconomic data. It also allows for a statistical method to quantitatively relate conflict to the environment, which has not been done before in the environmental conflict literature. PCA finds relationships among the variables and found that the QOL of life variables loaded onto the same principal component with the percent of built land. This shows a relationship between QOL and built land. NDVI loaded most strongly onto the second principal component, while other QOL variables loaded less strongly onto the second component than onto the first component, their loadings were still strong enough to believe that there is also a relationship between QOL and NDVI.

A limitation of this study was the size of the area. The study included 45 cities in Israel. The small location in a country that faces unique challenges from terrorism makes it difficult to determine if the results are generalizable to other locations. Still, the results show that it is possible to relate QOL to the environment using remote sensing and PCA. Lo and Faber (1997) obtained similar findings. Previous literature shows relationships between socioeconomic and environmental variables (Fung and Siu, 2000; Millette et al., 1995). My literature offers further evidence of this relationship. This research should be further studied in other locations in Europe, North America, and the Middle East. Other Middle Eastern countries where QOL, conflict, and environmental issues are pertinent are Iraq, Syria, Jordan, and the Palestinian territories. Performing the study in the Palestinian territories would offer insight on the difference between QOL and the environment between the Arabs and the Jews who live there. Even though both Arabs and Jews live in the Palestinian territories, their lives and experiences are different due to their different histories and current realities. A study relating QOL, conflict, and the environment would elucidate the differences that they experience.

CHAPTER 6: LIMITATIONS AND CONTRIBUTIONS OF STUDY

LIMITATIONS IN REMOTE SENSING

Data needed for remote sensing

Studies using remote sensing need extensive ground truth data. Often, the researchers gather the ground truth data themselves by surveying the land during the timeframe of the study. If this is not possible, they use aerial photos of the land to verify the land uses. Aerial photos can also be used in conjunction with personally gathered land survey data.

These types of verification methods were not available in this research. The satellite image used in this study was from August 7, 1999, so it was impossible to collect ground truth data of a study area from a past date. Cities from different locations in the satellite image were studied and to collect ground truth data would have been laborious and expensive if the satellite image date had been selected contemporaneously.

Aerial images of Israel were difficult to find. In aerial imagery of the United States, there are several ways to obtain aerial imagery. They are available on the internet, from libraries, or from governmental agencies which make them accessible to the public. In Israel, these ways of obtaining data do not exist or are difficult. First, the research was conducted in the United States, so there were no means to travel to Israel in the hopes of finding the images in a library or an archive. Second, extensive aerial imagery is not available on the internet. It is available on a limited basis, often provided by private people and not by public or governmental agencies. Private people who own aerial photos often do not have a collection extensive enough for research purposes. An example of a private group that owns and sells aerial photos of Israel is israelimages.com. This group has aerial images of different cities around the country but these images are not dated and are not georeferenced, so it is impossible to know where exactly the image was taken in the city.

The reference data used in this research were taken from the Israel Central Bureau of Statistics Land Use Viewer, Google Earth, Walla maps, and the Ministry of the Environment. The Land Use Viewer, Google Earth, and Walla maps used images or thematic maps from 2002, which were three years after the satellite image. The aerial photos from the Ministry of the Environment were not dated. The imagery from Google Earth was a slight improvement in detail over the Landsat image because each Google Earth pixel for the scene in Israel was 15 meters by 15 meters, compared to the Landsat image's pixel size of 30 meters by 30 meters.

Method used for this study

The unsupervised classification was used in this study. In this type of classification, the software algorithm clusters the pixels according to spectral similarities, and then the user determines which land uses these clusters represent. There are other types of classifications that are improvements over the unsupervised classification. These methods are the supervised classification and spectral mixture analysis.

The supervised classification is used when the user has extensive ground truth or reference data of the actual land uses. The user uses the ground truth data to classify land uses in a satellite image. The first step in the supervised classification is the training stage. In the training stage, the photointerpreter identifies the land use types in the satellite image. The algorithm identifies the adjacent pixels that are spectrally similar. In the classification stage, the software algorithm clusters all pixels in the image into the classes which they resemble based on the training stage (Lillesand & Kiefer, 2000). This supervised classification was attempted for this research but yielded poor results due to problems with signature separability. Many built and bare land uses that the photointerpreter had spectral signatures that were inseparable and yielded low statistical accuracy. Ward, Phinn, and Murray (2000) also initially used a supervised classification for their urban remote sensing research, but failed because could not distinguish between classes due to signature separability issues. They used an unsupervised classification.

Spectral mixture analysis (SMA) is used to unmix mixed pixels with multiple land uses. Each Landsat pixel's area is 30 meters by 30 meters and may contain multiple land uses. Traditional land use classification methods involve assigning one land use per pixel, SMA identifies the land uses in each pixels. To perform SMA, the user needs a spectral library of the spectral values of the pure land uses (also called endmembers) present in the image or extensive ground truth data to identify the endmembers that the algorithm generates. SMA has been used to identify spider mites in cotton (Fitzgerald et al., 2004) and vegetation change (Elmore et al, 2000). SMA was not used in this research because there was no available spectral library, it was not possible to identify pure endmembers or pixels with one land use from the satellite image, and there was not enough ground truth data available to identify what the software generated endmembers represented.

A method called imaging spectroscopy (IS) was used to study urban features in Tel Aviv, Israel (Ben-Dor et al., 2001). IS distinguished between spectral fingerprints and could map similar objects. The data must be high in spatial and spectral quality for it be useful. The IS method could not be used with medium resolution satellite from Landsat.

The unsupervised classification became the best and most trustworthy method of analysis because it did not need training input from the user and did not need the extensive ground truth knowledge required in SMA.

Signature inseparability

Many of the land uses covered by the built and bare pixels were spectrally similar and led to confusion in the land use analysis. This was especially true in the coastal cities and cities in the northern part of the Landsat image. Many pixels were misclassified due to this issue. Cities where spectral inseparability was less of a problem were located in the desert. Dimona is an example of a desert city where there was great spectral separability between the built and bare use covers. The desert land surrounding the developed land in the town did not resemble the built land and there was little misclassification.

Zhang et al. (2002) proposed a method to distinguish between built-up and non built-up land uses. Their method detailed using road density combined with spectral bands. Road density data were unavailable for Israel. Digitizing roads from the Landsat and thematic imagery was not possible without an extensive network of road data. If the road data were available, they could have been used to distinguish between the built and bare areas in areas with inseparable signatures.

City data

Forty-five cities were selected from the Landsat image for further study. More cities would have been selected but there was cloud cover the northwest part of the city. The cities from that area were eliminated from further analysis because of the high error that would have occurred in the remote sensing analyses. The Landsat image did not cover all of Israel. Three Landsat images would have been required to cover all of Israel. The Landsat image that covered northern Israel was contaminated with cloud cover and was excluded from analyses. The Landsat image from southern Israel was mostly desert and had little developed and populated area.

The small number of cities in the image impacted the principal components analysis. There are various rules for the minimum number of cases that can be included in principal components analysis. One rule states that the minimum number should be 50. Forty-five cities were available for analysis in this study.

Accuracy Assessment

There were problems with performing the accuracy assessment. These problems ranged from the small number of land uses analyzed, how the pixel was selected, and whether there was adequate pixel sampling if certain land use was low.

The accuracy statistics were lower when there was a low percentage of a certain land use because not enough pixels were sampled for the land use that had less cover in the image. There was higher statistical accuracy when the pixels were evenly sampled. Sampling the pixels evenly occurred when the land uses covered the image more equally.

The pixels were selected in the accuracy assessment by placing a marker on the corner of a pixel rather than inside the pixel. This led to confusion in determine for which pixel the marker was intended, since the marker could have been intended for four pixels. To counter this and to identify the pixel for which the marker was intended, the Identification tool identified the NDVI value under marker. The land use of the pixel with that NDVI was used in the accuracy assessment. This method of identifying which pixel was intended for the accuracy assessment was not always accurate, and this led to pixels that were identified incorrectly and lower accuracy statistics.

In cities that had a high cover of built land or a high cover of bare or undeveloped land, the accuracy statistics were lower. This occurred because the accuracy assessment sampled more in the land use that had greater cover in the image.

LIMITATIONS WITH THE CONFLICT DATA

The conflict data were collected in the year preceding and proceeding the Landsat image because there was very little conflict during that timeframe. During the years before the date of the satellite image, there was little conflict in Israel. In late 2000, the Second Intifada commenced and there were conflict events on a regular basis. The image from 1999 was selected because it was not during an intifada. There were no external triggers to the conflict, such as incitement from Arab leadership or failed peace negotiations. The disadvantage to using conflict from that timeframe was that there were few conflict events.

LIMITATIONS WITH THE SOCIOECONOMIC DATA

The socioeconomic data were provided by the Israel Central Bureau of Statistics (2003). The amount of data available on the city level was limited. There was more data available on the census tract, region, and sub-region levels. Since limited data from Israel were available, the socioeconomic data differed from the data used in another study by Lo and Faber (1997) that used remote sensing to look at the relationship between the physical environment and quality of life. Lo and Faber (1997) used data by census block group. They used population density, per capita income, median home value, percentage of college graduates, NDVI, percentage of urban use, and surface temperature. In spite of the different type of data that Lo and Faber used, similar findings were found in this research on Israel. The socioeconomic data grouped on the same principal component as the NDVI data, and the percent of built land (percent urban use in Lo and Faber, 1997) grouped with population density.

Population density was not used in this study even though Lo and Faber (1997) used it. Lo and Faber used population density per census block group, which gave a true measure of the population and population density in a given unit of land. The data used for this study were on the city level. In many cities, the city boundaries in Israel were drawn far outside of the built areas of the city, which would underrepresent the population density in the built areas of the city.

This study did not use census block group data because a multi-city study of Israel was desired to determine the relationship between conflict and land use. Census block group data would not have filled this purpose. Imagery reference data were also not available on the census block group level.

CONTRIBUTIONS OF THE STUDY

In spite of the limitations of the study, the study contributes to the literature by offering statistical evidence of a relationship between the environment and conflict and between the environment and other QOL variables. Prior research (Homer-Dixon, 1999) has shown a qualitative relationship between the environment and conflict. My study is unique in that uses techniques previously not used to study the relationship between environment and conflict: PCA and remote sensing. PCA was previously used to examine the relationship between environment and QOL. The correlations that I performed in my research did not adequately elucidate a relationship between environment, conflict, and other QOL variables. PCA showed how they were related. These relationships were not apparent from the correlation coefficients. PCA offers a different way to examine environment and conflict beyond the already established way of examining the relationship between environment and QOL.

Remote sensing is used in environmental and urban research, but it is not used in research examining the relationship between the environment and conflict. Establishing remote sensing and PCA as methods to relate environmental analysis to conflict and QOL in Israel allows for further research in other regions that experience conflict. PCA can also be used to study how conflict is related to other variables outside the scope of QOL and the environment.

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