Evaluating and predicting water consumption by irrigated agriculture in the semi-arid regions of Israel and the U.S.: inverse biophysical modeling utilizing spaceborne imagery

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Abstract

Agriculture is the world's largest fresh water-use sector and has a strong influence on the water cycle, especially in arid and semi-arid regions, through the diversion of surface water and extraction of underground water. The current project evaluates and predicts water consumption by irrigated agriculture in the semi-arid regions of the Middle East and the U.S. The project was driven by the fact that in many parts of the world, including the Middle East and the Southwest U.S., the effects of climate change and population growth on agricultural land-use, and consequently on amounts of required water, is significant.

The aims of the study were twofold. The first was to estimate the amount of water required for irrigation in crop production as influenced by crop type, climate, soil properties, and irrigation efficiencies. The second was to understand spatial and temporal land-use changes in agricultural lands by examining the human decision-making processes and physical environmental changes that ensue in response.

For fulfilling the first objective, a modeling approach, named SiB2, was used to quantify the minimum amount of water required for optimal irrigation in arid and semi-arid regions of Israel and Southwestern U.S. The algorithm is a satellite supported biophysical inverse modeling system developed at NASA and adapted to the study regions

For fulfilling the second objective, spatial land-use land cover models were implemented in Israel and Jordan. In Israel, the Spatially Explicit Agricultural Dynamics (SEAD), an agent-based model, was used to understand agricultural spatial and temporal land-use changes by examining the human decision-making process and the physical environment's changes that ensued in response. In Jordan, a change detection model consisting of a combination of the Change Vector Analysis (CVA) and the Tasseled Cap (TC) transform was used for detecting the temporal dynamics of major water resources reservoirs. In both countries, detection of agricultural lands was executed using intra- and inter-annual Landsat images.

Contribution of collaboration

The project was carried out by three groups: NASA (Dr. Bounoua and Dr. Imhoff), BGU-ARO (Prof. Karnieli and Dr. Ben-Gal), and USDA (Dr. French).

Dr. Bounoua and Dr. Imhoff led the irrigation model, named SiB2, part of the project. From a practical point of view, they developed and run this model with data from Israel and USA. In this regard, they also downloaded and processed the MODIS spacecraft data. Prof. Karnieli and Dr. Ben-Gal provided the field data (e.g., crop types, meteorological data, irrigation schedule, etc.) for calibration/validation of the model over the northwestern Negev and Dr. French over the southwestern USA. The latter groups were involved in interpretation and evaluation of the results.

The land-use land-cover change models part of project, over the Israeli and Jordanian drylands, was led by Prof. Karnieli with intensive involvement of the NASA partners.

Explain in lay terms the major achievements accomplished in the project to date

The project reached major achievements in two related areas.

The first is the development of a new model-based algorithm with satellite-derived data over agricultural irrigated lands in semi-arid regions for quantifying the amount of irrigation water needed for crops. Because of the method's linkage to satellite data, it is applicable to any arid and semi-arid regions where water and food security are of concern. The methodology has great potential for water management and agricultural application and can provide valuable information for improving agricultural productivity through optimization of water use. The model was successfully applied in agricultural fields located in the northwestern Negev in Israel and in southwestern US.

The second is concerning monitoring and predicting agricultural land-uses temporal dynamics using satellite imagery. It is important in light of global climate change phenomena with a decreasing average annual and seasonal rainfall and increasing frequency and amplitude of the heat waves, droughts, storms, and floods. The project introduced a sophisticated model to monitor and predict the agriculture land-use changes in the drylands of the Middle East (Israel and Jordan). To reveal major factors and tendencies of the agriculture land-use dynamics we applied remote sensing?. The research addressed human activities, e.g., transformation of one landscape to another, particularly pasture to agriculture. The land-use over the studied areas change fast in their extent and composition influencing adjacent forests, grasslands, wetlands and other landscapes. This, in turn, impacts the provision of ecosystem services, biodiversity conservation, and returns to landowners.

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Summary

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For fulfilling the second objective, spatial land-use land cover models were implemented in Israel and Jordan. In Israel, the Spatially Explicit Agricultural Dynamics (SEAD), an agent-based model, was used to understand agricultural spatial and temporal land-use changes by examining the human decision-making process and the physical-environmental changes that ensued in response. In Jordan, a change detection model consisting of a combination of the Change Vector Analysis (CVA) and the Tasseled Cap (TC) transform was used to detect the temporal dynamics of major water resources reservoirs. In both countries, detection of agricultural lands was executed using intra- and inter-annual Landsat images. This part of the project is summarized in Sections 5 and 6.

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1 At issue

One of the world's most vital needs is a stable supply of food and water. The Earth's population increases roughly by 75 million persons each year, and agricultural food production must increase to keep up with growing demand. Agriculture is the world's largest fresh water-use sector and has a strong influence on the water cycle, especially in arid and semi-arid regions, through the diversion of surface water and extraction of ground water. Variables including climate, soil salinity, crop type, yield, agricultural practices, technology, market price, and population growth are primary drivers for agriculture, and consequently the amount of water used for crop production.

In many parts of the world, including the Middle East and the Southwest U.S., the effects of climate change and population growth on agricultural land-use, and consequently on amounts of required water are significant. In these regions there is a need to focus on the efficient and sustainable use of all water sources (groundwater, surface water, rainfall, desalinized, recycled water, etc.) and on water allocation strategies that maximize the economic and social returns to limited water resources, while enhancing the water productivity of all sectors. For this reason, a major challenge for sustainable irrigated agriculture is learning how to establish effective and equitable agricultural water management practices. These practices require knowledge, expertise, and investment at institutional and technical levels. Understanding the relationships between agricultural production (land-use and water demand) and current and future local climate trends can significantly improve agricultural efficiency and optimize its production, thus slowing its impact on land cover and water resources, and providing essential information to farmers, food producers, water managers, and policy makers to develop sustainable solutions in terms of adaptability to a changing climate.

Water consumption by agriculture is a function of crop type and cover extent, phenological stage of growth, water availability, and climate. In irrigated agriculture, the amount of water applied must compensate crop-climate driven consumption and not compromise yields. This is the physiological water requirement. Additional water must be provided to compensate for losses due to inefficiency of delivery and application systems and evaporation. Field scale water application by farmers must also consider the salinity of soils and irrigation water. The presence of dissolved salts necessitates application of additional water quantities to leach salts and prevent their build up in the root zone (Ayers and Westcot. 1994). The amount of water to be applied for leaching is a function of water (or soil) salinity, crop sensitivity, climate, soil type and the grower's predetermined level of accepted loss of yield (Shani et al. 2007). Today, available water (physically and economically) for irrigation in water scarce regions is often of low quality (re: high salinity).

Detection of agricultural lands has been studied by researchers in the U.S. and elsewhere, but only a few focused on the rapidly changing arid and semi-arid regions.

Previous studies can be categorized roughly into three groups: (1) Remote sensing studies based on classification schemes (Hansen et al., 2000; Friedl et al., 2002; de Colstoun et al., 2006). These studies, through calibration of remotely sensed observations against cropland inventories, have provided important insight into the spatial distribution of agriculture at different scales; (2) The use of surface energy balance models for detection of agricultural land. Combining high resolution Landsat data with such models proved to be useful in detecting agricultural land and estimating the total evaporation based on Landsat thermal channels (Bastiaansen. 2000; Allen et al., 2005; Anderson et al., 2011). While the limitations of the first category were obvious in the sole use of remote sensing data, the second category proved to be useful in humid zones but systematically underestimated evapotranspiration in arid and semi-arid regions; (3) The third category introduced a mapping methodology that relies on remotely sensed multi-temporal data from MODIS and used climate and agricultural information in an advanced image classification algorithm. Applications from the third category of detection over the continental U.S. produced an objective map that exhibited expected and reasonable patterns. However, this methodology was not designed to quantify the amount of water used for irrigation (Ozdogan and Gutman. 2008). It should be noted that that Normalized Difference Vegetation Index (NDVI) classification is a non-unique crop classifier, and therefore provides no information on specific crop phenology.

To address the stated problems of current and future water supply measurement and management, we proposed to develop new and robust ways to quantify water used in irrigated agriculture. We combined remote sensing data from Landsat and MODIS with an inverse biophysical modeling methodology to detect irrigated agricultural lands in arid and semi-arid regions of Israel and the U.S. and to quantify the amount of water used for agricultural irrigation. We also developed and applied change scenarios based on climate, population, technology, agricultural demand, and water supply (quality and quantity) and examined the impact of these changes on agricultural land use and the adaptability to adapt to a changing climate.

2 Objectives

The aims of the study were twofold. The first was to estimate the amount of water required for irrigation in crop production as influenced by crop type, climate, soil properties, and irrigation efficiencies. The second was to understand spatial and temporal land-use changes in agricultural lands by examining human decision-making processes and physical-environmental changes that ensue in response.

3 Satellite supported biophysical modeling technique

3.1.1 Model description

The model used is an inverse approach using observations from MODIS and the Simple Biosphere model (SiB2, Bounoua *et al.*, 2010) to quantify the minimum physiological water requirement, defined as the 'minimum water required', for plants to sustain the satellite observed Leaf Area Index (LAI). The technique consists of simultaneously constraining the carbon and water cycles modeled under equilibrium (balance between vegetation and prevailing local climate) and non-equilibrium (water added through irrigation) conditions, based on the principle that the degree to which irrigated lands vary from local equilibrium climate conditions is related to the amount of irrigation water used. To estimate irrigation requirements, water is added to the prevailing climatology at each model time step to minimize the water stress function following the stream of procedures illustrated in Figure 3.1. In SiB2, water stress depends on the water content in the root zone, itself a function of the precipitation amount and soil physical and hydraulic properties. A stress value of 1 corresponds to no-stress while a value of 0 represents a maximum stress. When the soil water content in the root zone reaches a low threshold level, the water stress function inhibits plant photosynthesis, indicating disequilibrium between the satellite observed LAI and the amount of water in the root zone, and triggering the irrigation mechanism.

Along with the minimum physiological water requirement, several efficiency factors apply when computing the total water use in agriculture (Hsiao *et al.*, 2007). These are partially attributable to yield efficiency, itself depending on the carbon allocation efficiency (carbon allocated to leaves and stems or roots) and the delivery method, which in some cases consisted of spray irrigation during maximum insolation.

Since agricultural water use efficiencies are not available for all types of crops and practices it is needed to build an extensive database of irrigation efficiencies for major crops, soil types, agricultural practices (e.g., irrigation method, scheduling, soil cultivation, plant spacing, weed control practices), and prevailing climate for the target regions. Several common types of irrigation schemes, such as sprinkler, drip or flood irrigation, are considered and the efficiency of each scheme in each of the target regions are compared.

Both in Israel and the southwestern US., as well in other regions around the world, there is a serious need to assess the water use efficiency and sustainability of water resources, especially in agriculture as it is the most water consuming human activity. To do so and to optimize the water use in agriculture a baseline water requirement to which measurements can be compared must be established.

An important challenge in this endeavor was to obtain ground measurements to validate and calibrate the model. Worldwide, these measurements are rare and often incomplete. In some regions of the world where water is a subject of trans-boundary conflicts, this information is politically charged and protected.

Figure 3.1: Iterative process for the determination of irrigation water. Baseline in this case is the observed LAI from MODIS and local meteorology (obtained hourly from daily observations), which includes precipitation. Water is added to keep the water stress function greater (less negative water potential) than the permanent wilting point (PWP). Transpiration and transport efficiencies are shown as examples. Output is the amount of water required to maintain that balance.

3.2 Model results for the Southwest U.S.

A series of agricultural plots in Southern Arizona (Figure 3.2), where some accurate irrigation data are available, were used in this study to compare model results to actual amounts of water used to irrigate different crop types. Several of these farms were in close proximity to each other and therefore were subjected to the same meteorological forcing even if, in some cases, they grew different crops. The major crops recorded over the area were cereals (wheat and sorghum), alfalfa, and cotton. We have geolocated the farms within the $0.05^\circ \times 0.05^\circ$ (approximately 5x5 km) Climate-Modeling Grid (CMG)

of the SiB2 model and selected five farms to summarize results obtained from this first analysis (Figure 3.2). Information related to farm locations is reported in Table 3.1.

Figure 3.2: Selection of Farms and their location in the Climate-Modeling Grid (CMG) used to test the model. The CMGs are numbered (e.g.; AR3) to facilitate the location of the farms.

Table 3.1: Location and names of farms used to test the model

SiB2 CMG	Farm within SiB2 CMG	Crop type	Latitude (°)	Longitude (°)
AR3	C-28	Corn	32.76686	-111.5200
AR4	N-19	Alfalfa	32.79870	-111.5370
AR7	C-50	Wheat	32.72691	-111.5770
AR8	C-54	Cotton	32.69059	-111.5940
AR9	C-65	Sorghum	32.68253	-111.7020

Results presented are preliminary and more calibration calibration/validation of the model is underway. Aspects related to soil salinity and leaching will be added to the model.

The results for different farms are presented in the form of temporal plots showing the climate and physiological parameters as well as the amount and frequency of irrigation water as estimated from the model (Figure 3.3). The model is forced with hourly

observation of climate including precipitation, temperature, wind speed, specific humidity, shortwave and longwave direct and diffuse radiation. The model runs a coupled stomatal conductance-photosynthetic sub-model driven by satellite data and consistent with a radiative transfer and a hydrological model to estimate soil water in 3 soil layers. SiB2 vegetation takes up water from the root zone only (Bounoua et al. 2015) with water permitted to diffuse up and down between the different layers. The irrigation model takes full consideration of the precipitation (if any) and predicts, among other state variables, the amount of water in the root zone. For each crop and soil type, the model determines a critical value of the root zone water below which a plant is physiologically water-stressed. The stress value (limited between 0-1, with the value of 1 representing no stress) is modulated by the plant's density, LAI, and the salinity of the soil. It is indicative of the disequilibrium between satellite observed LAI and the amount of water in the root zone, and triggers the irrigation mechanism.

Figure 3.3 shows results from the modeling procedure for a corn field for the 2008 cropping season and for flood irrigation. This is farm C28 located in the model CMG AR3. During the beginning of the year rainfall was present and with low LAI there was enough water in root zone. However, towards the end of March, the satellite observations show a continuous and consistent increase in LAI with a rapid intensification of the water stress which triggered the irrigation mechanisms. Modeled irrigation was maintained during the entire growing season and consistent with reported irrigation. The flood irrigation maintained a low stress level of about 0.95 and provided an average irrigation amount of 7.0 mm of water per day. It first saturates the canopy interception store, fills the surface layer store and then infiltrates into the root zone. If the infiltration rate is in excess of the infiltration capacity of the soil, the excess water contributes to surface runoff. As water is added, however, the moisture content in the root zone increases and maintains values significantly higher thus reducing water stress. The monthly totals obtained from the model (Figure 3.3B) for this farm and this type of crop are close to those reported by other farms.

In SiB2 evapotranspiration is divided into canopy and soil components. The canopy components consist of interception loss (potential evaporation of precipitation or irrigation water intercepted by leaves on the canopy) and transpiration through stomata, i.e., the actual amount of water used for photosynthesis. Similarly, the soil component consists of ground interception loss and ground transpiration. Since the only component contributing to photosynthesis is transpiration, we develop an irrigation efficiency factor as the ratio of the amount of water going into transpiration to the total evapotranspiration during irrigation. We assumed a total transportation water loss of 15% including the transport from source to farm gate and from farm gate to the field. This percentage of water loss represents an average estimate over the entire region

After calibration over several nearby farms, the model was capable of reproducing the reported irrigation amount with a RMSE of about 61.41 m³/ha. Irrigation efficiency for this farm ranged between 70 and 85 % and is lowest towards the beginning and end of the growing season. This suggests that evaporative loss is greater when LAI is low and/or there is an excess irrigation in those periods. The model constitutes an ideal tool for continuous testing and monitoring, however, more farm information such as leaching, soil salinity and method of irrigation is need to improve the model performance.

Results obtained for the other 4 farms are similar to the ones obtained on farm C-28 in AR3. They are represented graphically in the following figures and tables.

Figure 3.5: Same as Figure 3.3. Results for farm C-50 in grid AR7.

Table 3.4 : Irrigation statistics for farm C-50 in grid AR7.

128.2	306.6	702.45026	645.7	429.03	12.434	0	0	0	0	0	0
147.4	352.6	807.8178	742.55	493.38	14.3	0	0	0	0	0	0
454.8	1577	1643.862	1914.8	191.28	0	0	0	0	0	0	0
90.8	211.7	453.79898	512.13	329.28	11.565	0	0	0	0	0	0
37.36	94.95	248.65128	133.56	99.746	0.8695	0	0	0	0	0	0
70.85	69.03	64.602294	79.315	76.751	93.007	0	0	0	0	0	0
1	2	3	4	5	6	7	8	9	10	11	12
Row 1 Model irrigation (m ³ /ha)											
Row 2 Model irrigation & transportation loss (m ³ /ha)											
Row 3 Reported irrigation (m ³ /ha)											
Row 4 Effective irrigation (m ³ /ha)											
Row 5 Water loss to evaporation (m ³ /ha)											
Row 6 Irrigation efficiency (%)											
Row 7 Month of the year

3.3.2 Results

For farms in the Northwestern Negev region, finding ground measurements to validate and calibrate the model was particularly challenging. There was some available data however, for potato and cotton crops in the area of Shikma for the year 2014 (Table 3.6). The few farms with available data were close to each other and therefore were subject to almost the same climate forcing. For this region, the climatological precipitation and temperature regimes are illustrated in Figure 3.8. It is clear from the climatology that most of the rainy season is confined between the month of November and March with an annual mean monthly temperature around 14°C making the rainy season optimum for most crops. 2014 however was drier than normal, as the maximum rainfall recorded for the month of January for the area was only 27.6 mm as compared to the climatological 47.8 mm.

Latitude	longitude	crop type	Dec.	Jan.	Feb.	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
31.373	34.692	Cotton					220.58	595.37	1128.39	2432.12	1988.27	419.71		
31.378	34.694	Potato Valor	615.18									633.27	1240.71	1179.81
31.459	34.765	Potato Rozna	24.54	313.9	370.06	194.25	177.36	21.74						

Table 3.6: Positions (latitude/longitude), crop type and reported irrigation amount (cubic meter per hectare) for some farms in Southern Israel.

Figure 3.8: Climatological total monthly precipitation and monthly mean temperature for the region of Mishmar Hanegev (Israel).

Similar to Arizona, results from the irrigation algorithms obtained for the Shikma Farm are encouraging and irrigation values estimated are close to those reported (Table 3.7). Figure 3.9 shows a clear growing season between December and April with rainfall being consistent starting in November and leaf area index reaching a peak in February and March. Except for the start of irrigation where the model delivers one daily value of 7.85 mm of water in about 3 hours, the following irrigation events are evenly spaced by about 24 hours and deliver between 0.45 mm and 2.03 mm depending on the meteorological conditions. Warmer days have higher water demand and evaporative loss (Figure 3.10). Most of the modeled irrigation happens in the early morning between 6 and 8 AM for most of the months; however as daily maximum temperatures get warmer in April and May, water stress gets stronger during mid-day hours and forces the model to irrigate between 10 and 12 AM.

Figure 3.9: Shikma Farm Same as Figure 3.3.

263.50	286.60	147.70	124.60	29.60							79.90
316.10	344.00	177.00	149.40	35.40							95.80
313.91	370.06	194.25	177.36	21.74							95.90
2.20	59.50	44.70	17.20	5.40							15.90
215.30	226.80	102.70	107.40	24.10							64.10
18.00	20.76	31.78	13.80	18.67							21.00
1	2	3	4	5	6	7	8	9	10	11	12
Row 1	Model irrigation (m ³ /ha)										
Row 2	Model irrigation & transportation loss (m ³ /ha)										
Row 3	Reported irrigation (m ³ /ha)										
Row 4	Effective irrigation (m ³ /ha)										
Row 5	Water loss to evaporation (m ³ /ha)										
Row 6	Irrigation efficiency (%)										
Row 7	Month of the year										

Table 3.7: Irrigation statistics for Shikma Farm cropping Potato Rozna

The results clearly indicate that at any time of the day, irrigation is more efficient at the start of the process, decreases during the next 20 minutes, then stabilizes. This is reasonable as the soil is relatively dry at the beginning of irrigation and most of the irrigation water is retained by the soil and used by plants. During and immediately after irrigation both the ground and canopy are wet and water loss to evaporation increases thus reducing the transpiration efficiency (Te; Figure 3.11). While the time evolution of the Te factor remains similar for different months of the growing season, its amplitude does not. Indeed the transpiration efficiency decreases as time progresses towards warmer months of the season, implying that more water is lost to evaporation rather than used by plants for photosynthesis.

Although these model results are preliminary, modeling outcomes appear to be consistent and to capture the essence of the physics involved in the process of irrigation.

Figure 3.10: Tri-daily irrigation events for the Shikma Farm.

Figure 3.11: Transpiration efficiency; ratio of water used by plant transpiration to total water used for evapotranspiration.

3.4 Conclusions

Water is the most vital commodity in the world and the Middle East and North Africa (MENA) and the Southwest U.S region are no exceptions. Quantifying the amount of water required for agriculture is of paramount importance to a sustainable economy. The objective of this section was to quantify the minimum amount of water required for optimal irrigation in arid and semi-arid regions of Israel and Southwestern U.S using a model. The algorithm was a satellite-supported biophysical inverse modeling system developed at NASA and adapted to these study regions.

This study has been completed as planned and lessons were learned. The research has shown that despite difficulties in finding accurate calibration and validation data, the modeling approach satisfactorily estimated the amount of water used in some major crops in both the U.S. and Israel. It also revealed that, under similar climate and soil conditions, different crops require different amount of water. Further, we found that the specification of the leaf area index from satellite also needed time rephrasing to correspond to actual growing season. Satellite data usually contain missing data due to clouds or other acquisition issues, which means that time interpolation can introduce undesirable time-shifts. This is usually well corrected by reported irrigation observations. The intensity of the leaf area index is also crop dependent. In general the model produced an irrigation amount in-phase with the reported values with an amount within an acceptable range of uncertainty. The overarching objective is to advise farmers on how much water is needed for their crops and therefore there is an underlying assumption that the amount used is overestimated. There is an overt perception that in traditional agriculture, farmers a) irrigate the soil rather than the crop and b) apply excess amounts of water in order to minimize field scale variability and purchase “insurance” against stress. All of these lead to potential substantial over irrigation. This issue justifies further research into farmer behavior and decision making.

Overall, we believe some important conclusions have been reached, the most important of which is that the model developed can provide guidance towards the minimum amount of water required for irrigation in the studied regions. It still needs further development that will be part of potential future research. Refinement of high-resolution satellite data can be of central importance to both the detection of irrigated agriculture and the automation of water management.

4 Remote sensing estimation of crop water use over Arizona farms

4.1 Introduction

To verify and support SiB2 model calibration activities for the Arizona, USA component of the project, satellite-based remote sensing data from observations made in 2008 were collected, processed and modeled for evapotranspiration (ET). These data included a core group of 19 Landsat 5, and 15 Landsat 7 scenes. These have been supplemented by 10 ASTER, 47 MODIS Terra, and 48 MODIS Aqua scenes to selectively provide higher spatial and temporal resolutions, and to reduce gaps due to cloud cover. Observations from these scenes were modeled in two ways to highlight bias and model sensitivity of ET estimates due to differing algorithms: (1) the empirical FAO-56 crop coefficient approach, with coefficients updated by remotely sensed vegetation indices; and (2) the Two-Source Energy Balance (TSEB) ET approach, and physically based land surface temperature model.

4.2 Study area

The Central Arizona Irrigation and Drainage District (CAIDD) is a 35,400 ha irrigation district in central Arizona, centered around the town of Eloy and is mid-way between Phoenix and Tucson (http://www.gcairoinc.com/central_arizona_irrigation.php) (Figure 4.1). Using 360 km of lined canals, delivering regulated groundwater and Colorado River water, provided by the Central Arizona Project, CAIDD has historically delivered up to 34,000 ha-m per year. Approximately 85% of the district uses flood irrigation, with the remaining fraction using overhead sprinkler and sub-surface drip irrigation systems. Due to increasingly tight and costly water supplies, the number of farms using pressurized systems is increasing. The region has nearly year-round growing conditions. In recent years predominant crops have been cotton, alfalfa, and wheat with lesser production for sorghum and corn.

A unique aspect of this study is the availability of water use data. Due to agreement between USDA and CAIDD, which stipulates confidentiality of growers, water delivery data organized by water turnouts have been made available to the U.S. PI. A map provided by CAIDD identifies turnout locations and enables correlation with USDA crop maps. To preserve confidentiality, individual farm names and their owners are not included. These turnout data provide water delivery dates and volumes and are deemed accurate. However, there are on occasion ambiguities caused by uncertainties for how much, where, and how each water delivery was applied to plots within the turnout service area. To overcome these problems, a subset was identified where such ambiguities did not significantly affect water use estimates. Where multiple crops and varying planting dates existed, satellite data were used to estimate delivery fractions based on cropping areas.

Figure 4.1: Central Arizona Irrigation and Drainage District (lower right) and environs, 2008. Colors denote crop classifications obtained from the USDA Cropland survey. Prominent crops were cotton (red), alfalfa (pink), wheat (brown).

4.3 Satellite-based ET estimation

To accomplish this time-series assessment, high spatial resolution (≤ 120 m) satellite visible, near infrared (VNIR) and thermal infrared (TIR) data were required. The core data sets consisted of 40 Landsat 5 and 7 observations every 8 days. VNIR data used were provided by the NASA Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS; landsat.usgs.gov/CDR_LSR.php) collections, consisting of surface reflectances obtained after correction for atmospheric effects. TIR data were corrected to land surface temperatures by modeling the atmospheric profiles with the Moderate resolution atmospheric transmission radiative transfer model (MODTRAN, www.modtran5.com). Profile data from the Earth System Research Laboratory radiosonde (esrl.noaa.gov/raobs/) Tucson collections were used. A nominal land surface emissivity of 0.97 was assumed for the Landsat Band 6 observations. Crop cover information was provided by the USDA National Agricultural Statistical Service (nassgeodata.gmu.edu/CropScape), a compilation providing an annual classification. The crop cover data are field checked and deemed accurate. Additional checking in this study was conducted based on remotely sensed phenology and known cropping

practices. Where the nominal crop type was inconsistent with satellite observations and typical practices, such sites were flagged as having an uncertain crop type.

Using the cropland map as a mask, farm-averaged time-series NDVI were obtained (Figure 4.2).

Figure 4.2: Time-series of vegetation indices by crop for selected CAIDD farms. An example crop coefficient function using the base FAO-56 algorithm is illustrated in A).

The FAO-56 ET approach (Allen 1998), in contrast to SiB2, is an empirical crop coefficient approach driven by weather data and standardized crop coefficient functions. Using the crop coefficient and estimates of potential ET, one can estimate unstressed, standardized hourly or daily ET provided a known crop type and representative weather data. Potential ET is based on the Penman-Monteith equation for a standard crop. For non-standard conditions the FAO-56 ET estimates can be improved by adjusting the nominal crop coefficients according to plant fractional cover and leaf area. This approach was adopted by following the methodology of Hunsaker et al., 2005.

The TSEB approach (Norman et al., 1995) to ET estimation is a physically based approach using a vegetation index, land cover, and land surface temperature to compute instantaneous evaporative fluxes. ET is computed by modeling this flux with an estimate of diurnal evaporative fraction. Unlike SiB2, TSEB does not model soil and plant moisture status. The seasonal composition of TSEB-based ET is illustrated in Figure 4.3.

Figure 4.3: Time-series input data for modeling ET with TSEB. Cumulative irrigation delivery (black) and corresponding ET estimates from TSEB are shown in A. Instantaneous latent heat flux peaks mid-summer exceeding 600 W/m² (B). Crop cover for cotton only for this area is shown as NDVI in C.

Based on monthly water use data, FAO-56, TSEB, and previously mentioned SiB2 modeled irrigations, time series estimates of ET are presented in Figure 4.4. Salient information from these comparisons show that the locally calibrated FAO-55 /NDVI approach was most accurate for cotton and alfalfa, SiB2 was most accurate for corn, while all models exhibited high or low bias for sorghum. Results from this comparison indicate that for crops other than corn, the SiB2 model will require further calibration to

address under-estimation bias. The methodology for this correction is currently being reviewed by all project scientists and will be published in a peer-reviewed journal in the near future.

Figure 4.4: Cumulative water used by crop type, CAIDD 2008.

4.4 Summary

Results from multiple model inter-comparisons for five different crops at CAIDD showed good to fair agreement between water use models and measured water volumes in 2008. Locally calibrated ET models were consistent with cumulative irrigation amounts and generally showed that the SiB2 approach accurately predicted early season crop water use for cotton, corn, and sorghum. Cumulative water use for the dominant crop, cotton, was very well modeled for almost the entire growing season, indicating minimal additional model calibration will be needed. Discrepancies for SiB2 estimates for wheat and alfalfa can be addressed by increasing the model's early season water use estimates. Additional model calibration is underway.

5 Spatially explicit modeling of agricultural dynamics in semi-arid environments

5.1 Introduction

One of the world's most vital needs is a stable supply of food and water. Agriculture is the world's largest freshwater user, thus impacting the water cycle, especially in arid and semi-arid regions, through the diversion of surface water and the extraction of groundwater. The effects of climate change and population growth on agricultural land-use and, consequently, on the amounts of water required are significant. Therefore, agricultural food production must keep up with the continuously growing demand. This is likely to be exacerbated by increases in the standard of living, and crop yield reductions resulting from land overuse and degradation (Nellemann, 2009). Climate, soil properties, crop type, water quality (e.g., salinity) and availability, yield, agricultural practices, social conventions, market price, technology, and population growth are drivers for agricultural land-use change, and the amount of water used for crop production (Bounoua et al., 2010).

In order to estimate future agricultural water needs and provide the agricultural sector with the appropriate amount of water that will guaranty its sustainability, it is important to understand the dynamics in agricultural land-use land-cover change (LULCC). To better understand the rules that govern change, it is necessary to investigate the past dynamics in agricultural lands, connect these changes to the drivers and extrapolate future change according to forecasted future reality, thus allowing the application of appropriate adaptation measures. Remote sensing (RS) is a first-choice tool for realizing these tasks.

Whereas, historically, agricultural output increases were achieved mainly by increasing the cultivated area, since the "green revolution" and markedly since the 1960s, agricultural yield intensification has propelled agricultural production per cultivated unit area, thus promoting world food production while curbing agricultural expansion (Lambin et al., 2003). However, there are ample examples for agricultural expansion in areas that were previously untouched natural habitats, such as forests, grasslands, and other natural vegetation areas (Brink and Eva, 2009, Lambin et al., 2003, Teferi et al., 2013). Using global agricultural statistics data can aid in revealing the intensification-land sparing causal chain. The overall results show that over the last four decades, there has been a global increase in agricultural cultivated areas, rather than land sparing (Rudel et al., 2009).

In order to examine the spatial and temporal dynamics of agricultural lands, one must first be able to differentiate between agricultural land and other land-use types. According to the amount of land that is used for agricultural production, it is possible to estimate crop yield and agricultural water demand. Using RS technology, one can look into the past and examine the LULCC dynamics of agricultural lands by overlaying

images from different periods on top of each other and applying a change detection technique on the detected agricultural land.

While detection of agricultural lands has been studied by several groups of researchers, only a few have focused on rapidly changing arid and semi-arid regions. In general, in semi-arid regions, the precipitation and temperature regimes are out of phase (Bounoua et al., 2009). Precipitation occurs during the winter and early spring when cold temperatures reduce vegetation growth, while vegetation growth is inhibited by the lack of precipitation during the late spring and summer. The phenology of dense, green agricultural lands during summertime creates a clear contrast with the precipitation and temperature signals and makes detection possible. However, abandoned agricultural fields in fallow that might be re-cultivated in future seasons cannot be easily discriminated from non-cultivated land using only phenological classification techniques (Prishchepov et al., 2012), and thus require a collection of multiple intra- and inter-annual images and the use of an advanced classification technique.

Modeling is a useful pathway allowing for the verification and better understanding of factors that determine agricultural LULCC, and the linkage between the human and biophysical dimensions. Many different modeling approaches to LULCC have been developed and implemented at all levels, from a single household to an entire country. LULCC models deal with spatially explicit outcomes (Bert et al., 2011, Irwin and Bockstael, 2002) and combine statistical approaches with dynamic considerations of the land-use changes (Brown et al., 2002). Land-use dynamics models combine cellular automata (CA) and agent-based (AB) approaches.

Whereas CA describes the physical environment, the AB modeling technique explicitly introduces humans and their decision-making processes, representing a real driver of land-use changes (Benenson and Torrens, 2004). Agents in AB models represent decision-makers: farmers, developers, institutions, townships, and non-governmental organizations (Magliocca et al., 2012, Parker et al., 2003). Agents follow their behavior rules and respond to inputs from other agents and from the environment and may change their behavior, through learning or evolution based on their experience. Typically, AB models include several layers representing the physical environment, e.g., land units, water bodies, and road links, whose dynamics is defined by both human and environmental factors, e.g., soil erosion and forest growth (Benenson and Torrens, 2004). It is therefore advantageous to combine CA and AB modeling techniques in order to depict land-use changes that are influenced by well-defined human behavior and changing environments.

AB and CA modeling approaches have been extensively used to describe LULC changes, with a major focus on the dynamics of human settlement patterns and urbanization processes (Batty, 1997, Benenson, 1998, Benenson et al., 2005, Benenson and Torrens, 2004, Clarke et al., 1997, Portugali et al., 1994, Sanders et al.,

1997, Torrens, 2003). Much less attention has been given to agricultural LULCC dynamics.

Schreinemachers and Berger (2011) introduced the MP-MAS model simulating an agricultural farm decision-making system, in order to examine how market dynamics, economic constraints, technology and environmental changes and policy interventions affect heterogeneous farm households. The model incorporates dynamic interactions between environmental and social components, focusing on microeconomics at the farm management level and diffusion of agricultural innovation. Similar work was done by Berger (2001) and Schreinemachers et al. (2009). Happe et al. (2006) constructed the AgriPoliS AB agricultural land-use model examining how policy changes cause and affect structural changes using empirical data on individual farms. Each farm is represented by an agent that is equipped with a behavioral model and interacts with its environment. The model cycle includes the investment-production-output stages and decisions (e.g., continuation of farming; agricultural practices changes) regarding the next cycle. The model of Bert et al. (2011) is similar to the AgriPoliS model and focuses on agricultural land tenure, interactions between big/small farms, and preferred crop type. Freeman et al. (2009) developed a model that looks at the single farm level, evaluating farmland ownership and lease auctions, farm size changes, and production and marketing choices, based on farmer risk and financial behavior. Our model has some similarities with the abovementioned agricultural land-use models: the cellular landscape (elemental cell representing LULC), parcel construction, and farmer agent cultivation decision-making processes. However, whereas the focus in the abovementioned models is on the individual farm level, the focus of this model is on the regional level, to examine and forecast macro-changes in the spatial spread of agricultural fields in semi-arid to arid regions. It uses RS technology combined with AB and CA modeling techniques, based on environmental, sociopolitical, demographical and market changes that similarly affect the family farm level and the agricultural cooperative level.

With global population growth and an increased standard of living in a continuously increasing urban consumer sector in developing countries, it is expected that the positive trend in demand for food production will persist in the near future. As several studies have shown, agricultural intensification cannot fully compensate for this growth in demand, and agricultural expansion into open pristine natural environments and marginal lands will remain the common practice (Brink and Eva, 2009, Cai et al., 2013, Lambin et al., 2003, Meyfroidt et al., 2013, Rudel et al., 2009, Teferi et al., 2013).

The aim of this work was to understand spatial and temporal land-use changes in agricultural lands by examining the human decision-making processes and the physical environment's changes that ensue in response. In particular, it examined whether changes in the amounts and distribution of water available for agricultural use and other

factors, such as climate, geographical, pedological, and topographical properties, population growth, policies, and infrastructure (the road system, irrigation piping), have affected the spread of agricultural lands into rural frontier areas within the semi-arid to arid region of the northwestern Negev Desert, Israel. Specific objectives included providing the following: (1) a land-use land-cover (LULC) map of the study area for the next 30 years in five-year time increments; (2) the future agricultural sector water demand; and (3) an agricultural yield prediction.

5.2 Study area

The current study is focused in the northwestern Negev Desert area, Israel, (Figure 5.1A,B), characterized by a semi-arid to arid climate where average annual precipitation gradually decreases from 350 mm in the north to 150 mm in the south (Evenari et al., 1982). The ratio of precipitation to potential evapotranspiration (P/PET) is about 0.2 (Figure 5.1C) (Safriel, 2014). This aridity index value, somehow following the 200-mm rainfall isohyet in the study area, is considered to be the border between possible rainfed (non-irrigated) and exclusive irrigated agriculture (Evenari et al., 1982, Gutterman, 2008). The study area stretches from the Zohar Reservoir in the north to the “Pitchat Shalom” area in the south that marks the current southern point of agricultural activity and irrigation infrastructure (Figure 5.1A). The western edge of the study area travels along the Gaza Strip border, and the eastern limit of the study area is the city limits of Be’er Sheva. The total size of the study area, including open space for agricultural expansion, is 2,126 square km (212,670 ha), out of which 64% is loess, 16% is sandy soil, 5% is brown-red silty sandstone soil, and 15% comprises other soil textures that are less suitable for agriculture.

Figure 5.1: The study area of the northwestern Negev (A), within the greater area of Israel (B), and the aridity index map of Israel (reproduced from Safriel (2014)) (C).

Israel has insufficient natural water resources to support its growing population, especially with the vast agricultural cultivation within its borders. Therefore, this lack of water has instigated creative thinking and policy changes for alternative water sources. The two main innovative techniques with which Israel is currently overcoming water shortages are wastewater reclamation systems and desalination facilities, with more than 70% of its wastewater being treated and reused mainly for agricultural purposes (Dreizin et al., 2008, Friedler, 2001, Ickson-Tal et al., 2003, Wintgens et al., 2008). There are two major water sources for the northwestern Negev: (1) the “Yarkon-Negev” freshwater pipeline that was inaugurated in 1956 and is used for agricultural and domestic water supply; and (2) Israel’s biggest reclamation system, called the Shafdan Project (wastewater carrier), delivering reclaimed domestic and industrial wastewater from the densely populated Tel Aviv metropolis south to the Negev with a special dedicated pipeline (Figure 5.2) for unrestricted agricultural usage (Ickson-Tal et al., 2003, Wintgens et al., 2008). The wastewater carrier, inaugurated in 1989, was added in order to supplement the “Yarkon-Negev” pipeline. Since the inauguration of the wastewater carrier, the amount of fresh water from the Yarkon-Negev pipeline to the northwestern Negev has dropped (Figure 5.2) and been rerouted to mitigate water shortages elsewhere in Israel. Therefore, overall, the agricultural water balance of the northwestern Negev has increased by 50-70 million cubic meters (MCM) within the period of 1990-2013.

Figure 5.1: Agricultural water delivered to the northwestern Negev from 1982-2013.

Climate change, population growth, and political consequences have also had significant effects on agricultural land-use and water demand in the northwestern Negev. Tremendous changes have occurred since the 1970s in Israel. Demand for food supplies have increased, leading to the vast expansion of agricultural land in the peripheral areas of the state, including the northwestern Negev. Furthermore, following the peace agreement with Egypt, the government relocated agricultural settlements from the Sinai Peninsula to the northwestern Negev in 1982. Another wave of relocating agricultural settlements within the northern Negev happened after the evacuation of Israeli settlements from the Gaza Strip in 2005. These two major events had a significant influence on the demography/agricultural situation of the study area.

5.3 Methods

Looking at the historical agricultural spatial dynamics, along with water availability data, yielded insights regarding the pattern of agricultural spread, and irrigation and road infrastructure spread. These data, along with the agricultural experts' input of farmers' decision-making processes, were then translated into rules that dictate agricultural expansion, and inserted into a high-resolution spatially explicit model using AB and CA techniques that enabled the future LULCC of agricultural areas to be predicted, given different scenarios of prevailing conditions, thus also shedding light on future agricultural water demands and crop yields. The flowchart presented in Figure 5.3 illustrates the main constituent processes of this research, and the way that these

processes are connected to and feed each other. In this section, a detailed description of the concept and design of these processes is presented.

Figure 5.2: Research process sequence flowchart.

5.3.1 Landsat images

Intra- and inter-annual images of the study area from four different periods were analyzed. The differences in land-cover were detected, with emphasis on vegetation cover. Landsat 1 MSS, Landsat 5 TM, and Landsat 7 ETM+ images, courtesy of the

U.S. Geological Survey, were used for this comparison. The years that were chosen for comparison are: 1972-3 (8 images), 1984-5 (4 images), 1999-2002 (10 images), and 2012-13 (24 images), path 174, row 038, according to Landsat's World Reference System-2 (WRS-2). These periods were chosen according to major technical and local events that had pivotal impacts on the northwestern Negev landscape: 1972: the launch of the first Landsat satellite (used here as a temporal baseline); 1981: relocation of the Israeli settlements from the Sinai Peninsula; 1989: inauguration of the recycled wastewater carrier pipeline; 2005: relocation of the Israeli settlements from the Gaza Strip. All in all, 46 high-quality noiseless images, with low cloud cover (less than 10%), were analyzed. The analyzed images were radiometrically and atmospherically corrected using Atcor2 and Atcor3 tools (ERDAS, 2011). A relevant digital elevation model (DEM) image at a 28.5-m horizontal resolution for the study area was obtained courtesy of the U.S. Geological Survey and used as an input for the Atcor3.

5.3.2 Applying NDVImax for agricultural land classification

The corrected images were analyzed in order to extract vegetation cover using the normalized difference vegetation index (NDVI). Healthy vegetation's reflectance (ρ) in the near infrared (NIR) spectral band is high, and low in the red (R) spectral band. NDVI measures the normalized difference between the NIR and the R spectral bands (Eq. 5.1):

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} \quad (5.1)$$

NDVI ranges between -1 and 1, with higher positive values indicating healthier vegetation. The NDVI images of every period were integrated into one image that represents the period's cultivated agricultural land. A maximum NDVI (MaxNDVI) image was created; for every pixel, the maximum value was used as the representative of the given period (Maxwell and Sylvester, 2012). This procedure is similar to the maximum value composite method used for the same purpose for the NDVI computed from the NOAA-AVHRR images (Holben, 1986). The resulting image contains the maximum NDVI index for every pixel from the analyzed images for a given period. Pixels with positive NDVI values were classified as containing agricultural vegetation. MaxNDVI is presented in Eq. 5.2.

$$\begin{aligned} \text{MaxNDVI} = & \text{for (every pixel } i \text{ within the image frame)} \\ & \text{pixel } i = \max(\text{InputImage}_1\text{pixel}_i, \text{InputImage}_2\text{pixel}_i, \dots, \text{InputImage}_n\text{pixel}_i) \end{aligned} \quad (5.2)$$

5.3.3 Change detection of historical agricultural spread

Once the aggregated NDVI images for each period were generated, it was possible to find the differences in agricultural vegetation between two adjacent periods and to

achieve vegetation change detection. The aggregated images were subtracted from each other, in order to acquire a new image, which represented the difference in NDVI (ΔNDVI), displaying the difference between the two periods. This operation is presented in Eq. 5.3.

$$\Delta\text{NDVI} = \text{NDVI}_2 - \text{NDVI}_1 \quad (5.3)$$

The ΔNDVI product image has floating values between -1 and 1, for which the zero value represents no change, and positive/negative values represent increases/decreases in vegetation respectively: the higher the values, the greater the change in NDVI. In order to better analyze the differences between different periods, thresholds were created representing different classes of changes and accounting for natural inter-period variation, so that changes within ± 2 standard deviations (STDs) were negligible. Reclassify, a spatial analysis tool within ArcMap 10.1, and the Knowledge Engineering tool within Erdas Imagine were used to create these classes based on STDs from the mean NDVI difference (Karnieli et al., 2008, Karnieli et al., 2014, Volcani et al., 2005). Accordingly, five classes were created to characterize changes (Table 5.1). A high increase in vegetation vigor ($\Delta\text{NDVI} \geq 2\text{STD}$) between two periods was considered as an agricultural addition. Since the study area is predominantly arid, we considered a sharp increase in the NDVI value in a certain location to be exclusively attributed to agricultural activity, rather than to change in natural vegetation.

Table 5.1: Change detection class definitions

Change Type	STD Threshold
High Decrease	$\Delta\text{NDVI} \leq -2\text{STD}$
Small Decrease	$-2\text{STD} \leq \Delta\text{NDVI} \leq -1\text{STD}$
No Change	$-1\text{STD} \leq \Delta\text{NDVI} \leq 1\text{STD}$
Small Increase	$1\text{STD} \leq \Delta\text{NDVI} \leq 2\text{STD}$
High Increase	$\Delta\text{NDVI} \geq 2\text{STD}$

5.3.4 Classification validation

As suggested by Rozenstein and Karnieli (2011), in order to validate the RS classification product, comparisons with three different reference maps were conducted:

- A LULC map from the Israeli Central Bureau of Statistics (ICBS) from 2004.
- A LULC map from the Survey of Israel (SIS) from 2003.
- A LULC map from the Israeli Ministry of Agriculture (MOAG) from 2008.

These vector maps contain agricultural fields as one of the categorized land uses. Agricultural areas within the reference maps were highlighted and clipped from the original maps using the Clip (Analysis) tool with ArcMap 10.1. These vectors were then rasterized into pixels sized 30*30 m, to be compared to the remotely sensed data. The comparison between the classification and the reference data took into consideration the entire study region, with total sampling of all 1.5 million pixels (of size 30*30 m) of the original Landsat image. A confusion matrix, including the overall accuracy and a Kappa coefficient (Congalton, 1991, Foody, 2002) was used to provide the best possible accuracy metrics. Since the fourth period of RS classified data is from 2012-2013, the references are not up-to-date and lack some of the agricultural spread data. Therefore, this period (2012-13) was classified separately updating the confusion matrix accordingly. It is important to mention that this type of comparison—not relying on sampling but using the entire 100% of the data for comparison—is very robust and provides full certainty in the obtained overall accuracy values. The MOAG reference map suffers from an underestimation of agricultural fields since it is based on farmers' data, and not all farmers complied; thus not all fields are present. On the other hand, the SIS reference map suffers from an overestimation of agricultural fields. Therefore, it was decided to combine both the SIS and MOAG reference maps together into one map and compare it with the classified data.

5.3.5 Model description

The model was implemented using the Repast Simulation Toolkit (Collier, 2003, North et al., 2013). In the next section, the model is described according to the overview, design concepts, and details (ODD) protocol (Grimm et al., 2006, Grimm et al., 2010).

5.3.5.1 Purpose

The purpose of the model is to understand agricultural land-use change dynamics using RS techniques and spatially explicit high-resolution modeling of the rules that govern change. In particular, the expansion of agricultural land in frontier rural areas is of special interest. The model can handle both traditional and modern agricultural practices, and thus is generic in nature and can be applied to a variety of agricultural realities encompassing both developing and developed countries.

5.3.5.2 Entities, state variables, and scales

The farmer is the main agent of this model. A farmer agent represents a family farm or an agricultural cooperative (a group of farmers that share the same agricultural practices or an agricultural private enterprise). State variables of the farmers include the location of their plots, the number of plots, and the total cultivated area, as well as current and past cultivated crops. Farmers choose which crop to cultivate according to crop rotation rules and crop characteristics, determined by the crop's input (amount of

water, soil type, fertilizers and pesticides, days from seeding to harvesting) and output (yield per hectare, market price).

The physical environment includes the following entities:

- Settlement: a settlement includes areas that are both suitable and unsuitable for agriculture and are divided into agricultural parcels. A settlement is characterized by its location, age, number of agricultural plots, total arable area, number of farmers, and population growth rate.
- Agricultural parcel: characterized by its location, size, soil type, fertility status, current amount of organic matter, amount of annual rain (rainfed potential), irrigation availability and irrigation scheme, owner, settlement, cultivation status, and past, current and future cropping.
- Road: a dynamic network of roads representing connectivity.
- Irrigation pipeline: a network of dynamic irrigation piping infrastructure used for water distribution and accounting for nearby parcels. Water quantity availability is dynamic and can be adjusted on a yearly basis, thus affecting farmers' water quota and pricing. Both fresh water and reclaimed water piping infrastructures can be simultaneously presented.

The model space is represented by 30*30 m cells, and can be adjusted according to the spatial resolution of the remotely sensed data.

5.3.5.3 Process overview and scheduling

At the beginning of every cultivation year, the irrigation water quota surplus is tested: if the water surplus reaches a certain amount (adjustable) that can support a new agricultural settlement, a new settlement is created and allocated the water quota surplus. In case there is no irrigation infrastructure in the vicinity of the new settlement, a new irrigation (and road) infrastructure will be added to the new settlement.

The model works in annual time steps. Every year farmers decide for each of their fields whether to cultivate or not and which crop to plant. Farmers' decisions are based on crop rotation rules (Figure 5.4), water availability and land fertility, and these decisions reflect their specific situations. At each time step, the following variables are updated: number and age of settlements, settlements' number of farmers, settlements' number of agricultural plots and total arable area, soil fertility (organic matter), agricultural parcels' cultivation status, irrigation availability and next cropping, water quantity, quality and availability, farmers' number of plots, total cultivated area, and water quota, and the spread of road and irrigation networks. While updating some of the variables is trivial and done automatically (e.g., settlements' and farmers' numbers and ages, number of plots, total arable area), other variables require some more detailed calculations. Soil fertility is calculated by the amount of organic matter in the

soil in each and every plot. The current amount of organic matter in the soil is calculated according to the last grown crop (every crop has different specific demands of organic matter) and the amount of fertilizers applied by the farmer. Irrigation availability for a given parcel is calculated according to its proximity to the irrigation infrastructure that is updated and checked every cycle. Water quality is determined by the type of water (fresh or reclaimed) that is used for irrigation. Once the irrigation source is set (or changed), water quality is updated. Each agricultural parcel's cultivation status and next cropping is decided according to soil fertility and crop rotation rules. The following variables are considered to be constants once they are set: agricultural parcels' location, size and soil type, amount of annual rain, owner and settlement. The model is terminated either when no more spread is possible or after a predetermined number of years.

Figure 5.3: An example of non-irrigated (A) and irrigated (B) crop rotation cycles.

5.3.5.4 Design concepts

5.3.5.4.1 Emergence

Spatial, temporal, and physical rules for agricultural dynamics (creation of new settlements and agricultural land expansion)

The creation of new agriculturally oriented settlements is an emergent outcome of several combined variables. The variables that govern the spread of settlements and agricultural plots are:

- Population growth and an increase in demand for agricultural produce.

- Availability and price of water.
- Availability of irrigation infrastructure.
- Availability of suitable land for agriculture.

According to spaceborne imagery's temporal classification of agricultural fields, the newest additional agricultural fields are located in the southwestern corner of the study area (Figure 5.8 in 5.4.1.1.1), and belong to three agricultural settlements that were founded in 2008, relocated after the evacuation of Israeli settlements from the Gaza Strip in 2005. These settlements form a cluster that possesses 1500 ha of agriculturally cultivated land. This cluster, in particular, is interesting to examine, since it is a source of information regarding contemporary agricultural expansion trends within the study area. Learning the agricultural spread patterns from the map, along with interviews with agricultural experts, enabled the formation of agricultural spread rules for the model. The below-mentioned rules for the creation of a new settlement are specific rules that apply to the Negev study area, and can be adjusted when applying the model to other locations:

- A new settlement can be created only in proximity (up to a 1.5-km distance) to road and irrigation infrastructure.
- A new settlement needs 500 ha of arable land, spread within a radius of 1.5 km from the settlement's center.
- There should be a minimum distance of 3 km between neighboring settlements.
- Every hectare needs, on average, 5000 m³ of irrigation water per growing season; therefore a settlement requires 2.5 MCM of irrigation water per year, assuming one growing season.
- No rainfed agriculture can be sustained with less than 200 mm of annual precipitation.
- A settlement will be created, preferably, on sandy or loess soils.
- No agricultural fields will be created in areas with a slope greater than 10 percent.

At model initialization, all open space that is suitable for agricultural activity is registered. Agricultural settlements can be potentially established within these areas. Every year, irrigation water surplus availability is tested. In case there is enough water to support a new settlement, the abovementioned rules are tested for every pixel representing potential arable area. The weight given to every variable is adjustable and dependent on the scenario and the socioeconomic and physical environment. The exact location for a settlement is then determined after a sweep over the modeled area, guaranteeing that all rules are met and that the pixel with the best agreement with the abovementioned rules is found.

Spread of irrigation system infrastructure

The spread of irrigation infrastructure depends on the availability of water for agricultural purposes and the availability of arable land. Once a location for a new settlement is determined, the irrigation infrastructure will be laid out from the closest existing pipe to the new settlement. The distance from the irrigation infrastructure to the new settlement is measured taking into consideration the whole stretch of pipe and not just the edges—new junctions within the existing irrigation infrastructure can be created based on need.

Movement from rainfed agriculture to irrigated agriculture

Since in most cases, irrigated agriculture yields more profit to the farmer than rainfed agriculture, the farmer will aspire to irrigate as much land as possible. The farmer's decision whether to install an irrigation system in an agricultural parcel depends on the availability of irrigation piping infrastructure in the vicinity of the plot and the water quota availability. If the water quota increases compared to the previous year and non-irrigated plots are within a certain threshold (adjustable) distance from the existing infrastructure, then the farmer will irrigate these plots.

Irrigation water allocation

According to agricultural experts, an average water consumption of 1 ha of cropped vegetable in semi-arid to arid land is 5000 m³ of irrigation water (not including annual precipitation within a range of 150-300 mm) per growing season. Therefore, the total agricultural area's annual water consumption (assuming 70% of the fields have one annual crop, and 30% have two annual crops, and that 100% of the land is utilized annually) is 578 MCM/yr (based on 89,000 ha of cultivated land in 2013, the model's starting year; see subsection 5.4.1.1.1). However, only parts of the fields are irrigated; some sections are solely used for rainfed agriculture, and some are kept in fallow. The starting annual water supply to the study area (including both fresh water and reclaimed water) is roughly 250 MCM/yr (Figure 5.2). As the current water supply for the study area is growing at the rate of 2 MCM/yr (Figure 5.2), more water is available for irrigating more land, thus both expanding the total agricultural areas and irrigating previously rainfed lands.

The water amount availability is dynamic and can be adjusted on a yearly basis, thus affecting the farmers' water quota and pricing. Farmers can decide what percentage of their arable land they will irrigate, given that irrigation infrastructure exists in their vicinity. An agricultural parcel's irrigation potential depends on the distance from the irrigation infrastructure; once the irrigation infrastructure has reached within 1500 m of the parcel (distance adjustable), this parcel can be potentially irrigated, depending on the irrigation water quota, as described by the decision flow chart presented in Figure 5.5. In general, an increase in the overall water supply will primarily go to irrigating new

agricultural lands on newly established settlements, rather than to existing rainfed or non-irrigated parcels. Farmers strive to use their entire water quota to irrigate as many plots as possible. In this version of the model, we assume equal average crop water consumption. If there is not enough water to irrigate all the farmer's lands, a random selection mechanism that decides which plots should be irrigated is applied, leaving the rest of the plots non-irrigated. The farmers' water quota is decided according to the amount of annual average precipitation their lands receive:

- Settlements that receive 350 mm of rain (or more) will receive water to irrigate 60% of arable lands.
- Settlements with 250-350 mm of rain will receive water to irrigate 75% of arable lands.
- Settlements with less than 250 mm of rain will receive water to irrigate 90% of arable lands.

Every year, the order in which water is distributed to existing settlements is set randomly, thus allowing for a stochastic pattern of lands left in fallow.

Figure 5.4: Farmer's crop decision-making process according to water availability.

5.3.5.4.2 Stochasticity

Irrigation water allocation is stochastically distributed; therefore, farmers need to decide each year, according to the amount of water they receive, which fields to keep in fallow. The initial number of farmers per settlement is also stochastic, determining the amount of the settlement's arable area to be initially cultivated.

5.3.5.4.3 Observation

The model's progress appears in a graphical display (spread of agricultural lands, settlements, roads, and irrigation infrastructure) and can be saved for future reference

as snapshots. It is possible to create graphs that are updated during the model's run and show the change in different variables, such as: number of settlements; number of farmers (and their status); amount of current arable land: per farmer, per settlement, and for the whole study area; amount of irrigation water used: per farmer, per settlement and for the whole study area, etc. These data can be saved to dedicated output files.

5.3.5.5 Initialization

The model begins by loading the RS product of agricultural areas within the northwestern Negev. The spatial input maps (layers) and important attributes contain (Figure 5.6):

- Settlements (point shapefile layer). Attributes: agricultural area, total area, number of farmers and parcels, and age.
- Agricultural parcels (polygonal shapefile layer). Attributes: soil type, soil organic matter, area, potential irrigation, rain amount, membership to settlement and farmer.
- Restricted areas for agriculture (a polygonal shapefile layer containing: army bases, riverbeds, forests, natural reserves, urban areas, inappropriate soil for agriculture, etc). Attributes: type of restricted area, area.
- Soil type (polygonal shapefile layer).
- Annual rain amount (polygonal shapefile layer).
- Road system (polyline shapefile layer). Attributes: road number, length.
- Irrigation piping infrastructure (polyline shapefile layer). Attributes: pipe ID, type of water (fresh water/reclaimed), online year.

The area is divided into grid cells. Each cell is described by its land use. The possible land uses are: road, settlement, suitable and not suitable for agriculture. For every cell, the potential (positive/negative) for rainfed and irrigated agriculture is delineated according to the annual rain amount and proximity to irrigation infrastructure. This potential can be changed according to the spread of irrigation infrastructure. After map initialization, the model traverses every existing settlement and allocates agricultural parcels either according to a preset size (which is modifiable) or according to the existing agricultural fields that are fed into the model (Figure 5.6B). Figure 5.7 presents an example of a simulation run in which three new settlements (indicated by arrows) are created in open space, on the edge of existing settlements. The allocation of new agricultural fields is done from the center of the settlement outwards. For every settlement, an initial number of farmers is determined (either from field data sources or from a ratio of its overall agricultural fields, randomly generated from a preset range).

Figure 5.5: Model initialization map of the full research area, showing land-cover categories, road and irrigation piping infrastructure, and settlements, for the year 2013 (A), and close up of the southern part of the research area with existing agricultural parcels as classified by spaceborne images (B).

Figure 5.6: Close up of three simulated new settlements (indicated by arrows) within the research area's southern fringe of open land.

5.3.5.6 Input

Input maps are mentioned in the initialization section. Currently the model does not use input data that represent time-varying processes.

5.3.5.7 Scenarios

5.3.5.7.1 Basic "business as usual" scenarios for new settlement creation

The model was run using two different scenarios for the new settlement creation algorithm. The first scenario gives maximum importance (weight) to the minimum distance from the existing irrigation piping infrastructure and shall be referred to as the IrrigationFirst scenario. The second scenario gives maximum weight to the minimum distance from the existing road system (dubbed the RoadFirst scenario). The IrrigationFirst scenario will search for a location that is potentially suitable for a new settlement and is the closest to the existing irrigation infrastructure. The RoadFirst will do the same but will search for a potential spot that is the closest to the existing road system infrastructure. Fine tuning of these two scenarios was examined, while different prioritization combinations of the two parameters were also checked: giving equal weight to the proximity to the road and piping infrastructure; and a varying prioritization ratio of 20-80% to road-irrigation, respectively, and vice versa.

5.3.5.7.2 Climate change scenarios

The problems of water scarcity are forecasted to be most severe in the arid and semi-arid regions that are affected by droughts and wide climate variability (Arnell, 2004, Bounoua et al., 2010, Chenoweth et al., 2011, Givati and Rosenfeld, 2004, Jin et al., 2010, Nohara et al., 2006, Perkins, 2011). The study area, located in the northwestern Negev, contains both semi-arid and arid areas (Figure 5.1); therefore, it is forecasted to face both decreases in precipitation and increases in evapotranspiration rates. Studies examining the reduction of spring outflow, feeding the sources of the Jordan River, have linked this phenomenon to a decreasing trend in orographic precipitation, caused by anthropogenic submicron air pollution particles; they have estimated a precipitation loss of 15-25% within the area beyond the topographical barrier downwind from the Israeli coastal area (Givati and Rosenfeld, 2007, Givati and Rosenfeld, 2004). Other studies estimate an annual reduction of up to 0.8% in precipitation within the Jordan River Basin, and an annual increase of up to 0.33% in agricultural demand for the years 2015-2060 (Chen and Weisbrod, Rimmer et al., 2011).

According to the abovementioned findings, the climate change trend scenario has the following characteristics: (1) an annual decrease of 0.8% in precipitation; and (2) an annual increase of 0.33% in agricultural crop water demand. Furthermore, whereas in the "business as usual" scenario, the annual water supply for the study area grows at the rate of 2 MCM/yr (Figure 5.2), two different options were examined in the climate

change scenario: (i) the water supply growth rate decreases by 2% annually (simulating a decrease in the fresh water allocation for agricultural purposes and domestic water saving); and (ii) the water supply growth rate increases by 1% annually (simulating an increase in the treated wastewater supply for agricultural use due to a planned increase in the number of desalination plants in Israel, and population growth).

Furthermore, the abovementioned three variables were tested in two different ways: (1) active for the whole duration of the model run; and (2) active only for the first 30 years of the model run, simulating an overall accumulated reduction of 21.5% in precipitation, a 10.4% increase in crop water demand, and either a 45.5% decrease or a 34.8% increase in the annual water supply growing rate (from the original 2 MCM/yr).

5.3.5.8 Model validation

In order to better estimate the model's prediction accuracy, it is necessary to compare the model's simulated change to the actual change. For this purpose, the model was loaded with the LULC map of 2002 (according to the remotely sensed data for this period), and was run for the period of 2002-2013. Then, the model's simulated results were compared to the actual LULC map of 2013. Simulated changes were compared to actual changes for this period. The distances from both the road and from the irrigation infrastructure were taken into consideration, and were given equal weight; maximum weight for a new agricultural settlement was given to the potential location that has the minimum sum of distances to irrigation and road infrastructures.

5.4 Results and discussion

5.4.1 Northwestern Negev agricultural land RS classification products and validation for the years 1972-2013

5.4.1.1 Classification

As can be seen in Figure 5.8, the RS classification products revealed that agricultural fields have spread south over the years, following the wastewater carrier pipeline that carries treated wastewater from the central part of Israel into areas with loess and sandy soils. The total cultivated agricultural area as of 2013 (including all classified agricultural fields from 1972-2013, assuming there is no agricultural land abandonment) is 89,000 ha, which is more than double the amount of cultivated land during the period from 1972-1973 (33,000 ha). Over the years, there were additional cultivated lands of 19,000, 26,000, and 11,000 ha during the periods from 1973-1985, 1985-2002 and 2002-2013, respectively. It is interesting to see the trend in the southern expansion of agriculture into open unused land, especially during the last period from 2002-2013: forming a "front" of cultivated land along the southern line of existing cultivated land, pushing into pristine land. Another notable pattern of expansion can be seen in the

difference between the expansion patterns of 1973-1985 and 1985-2002. During the period from 1973-1985, additional cultivated landfills gaps and "holes" within the already cultivated area, whereas the bulk of the additional cultivated land from 1985-2002 is concentrated where the wastewater carrier pipeline was laid (mostly in the southeastern corner of the existing cultivated area for that time period).

Even though political circumstances have instigated the construction of new agricultural settlements in the study area (as mentioned in the introduction), other factors, such as the availability of irrigation water and irrigation infrastructure, water costs, climate, the demand for food supplies, agriculturally suitable soil types, etc., have also played crucial roles in the decision-making processes of identifying and determining where these new settlements should be located. The political circumstances created the need to relocate existing settlements. But without the availability of irrigation water or the increase in the demand for food supply, it is probable that the relocated population would have migrated to non-agricultural settlements. Furthermore, the exact locations of these new settlements were determined according to physical criteria, namely the availability of irrigation water and irrigation infrastructure, climate, soil type, etc.

Figure 5.7: Northwestern Negev agricultural field expansion from 1972-2013 in three time steps according to remotely sensed data, overlaid on a lithology map.

5.4.1.2 Classification validation

When comparing the classified map with the ICBS, SIS, and MOAG reference maps, total accuracies of $71\% \pm 0$, $77\% \pm 0$, and $74\% \pm 0$ and Kappa coefficients of 0.45, 0.55, and 0.47 were achieved, respectively. The combined SIS and MOAG reference map yielded an overall accuracy of $86\% \pm 0$ (a 0 error margin was obtained since there was no sampling of points. All of the ~1.5 million pixels within the study area were sampled) with a Kappa coefficient of 0.73, which is a high agreement rate for RS classified data (Anderson et al., 1976), especially when taking all classified pixels into consideration for the comparison (Table 5.2). As can be seen from the validation map (Figure 5.9), the red and yellow colored areas that represent commission and omission errors (respectively) are limited and do not form a pattern that implies any systematic classification error.

Table 5.2: Confusion matrix validating RS classification data for agricultural fields in the northwestern Negev from 1972-2013 with Survey of Israel (SIS) and Ministry of Agriculture (MOAG) reference land-use land-cover maps

RS classified data		Reference data		Sum
		Agricultural pixels	Nonagricultural pixels	
Agricultural pixels 1972-2002		571346	44579 (commission error)	615925
Agricultural pixels 2002-2013		49890	13001	62891
Nonagricultural pixels		175757 (omission error)	723582	899339
Sum		796993	781162	1578155
	Producer's accuracy	User's accuracy	Kappa	Overall accuracy
Agricultural	0.779	0.933	0.731	0.860 ± 0
Nonagricultural	0.942	0.804

Figure 5.8: Validation of spaceborne image classification of agricultural fields in the northwestern Negev Survey of Israel (SIS) and Ministry of Agriculture (MOAG) reference LULC maps.

5.4.2 Model results

5.4.2.1 Model validation

As can be seen in Figure 5.10, the simulated agricultural change is very similar to the actual agricultural spread pattern. From 2002 till 2013, three new settlements were created in the southwestern corner of existing agricultural fields, in 2009, 2010, and 2011. These settlements' agricultural fields have expanded (and are still expanding) over the years, as new residents (farmers) join the newly formed settlements. The model accurately depicts these changes: the first additional settlement is created in 2009 (Figure 5.10B), followed by two more settlements in 2010 and 2011 (Figure 5.10C-D), as in the actual agricultural spread. A fourth settlement is created in 2013, within the total area of the actual settlements' cluster. All in all, the actual cluster's allotted agricultural area is 2,600 hectares, whereas the simulated total agricultural area of the four new settlements is 2,550 hectares. Given the high similarity between the simulated and the actual agricultural LULCC, it is therefore presumed that the model's predictions are accurate according to the prevalent present conditions.

Figure 5.9: Model validation images. (A) Actual agricultural spread in 2002; (B-E) modeled agricultural spread in: 2009, 2010, 2011, and 2013, respectively, compared to actual agricultural spread in 2013 (F). The red oval shape denotes simulated (E) and actual (F) change in agricultural spread between 2002 and 2013.

5.4.2.2 Basic "business as usual" scenarios for new settlement creation

Both the RoadFirst and IrrigationFirst scenarios begin with the same starting point (Figure 5.6) of the number of existing settlements (87), agricultural parcel (63,800 ha) spread, total potentially irrigated area (52,200 ha), irrigation water demand (261 MCM/yr, but actual supply is lower since some percentage of the parcels are in fallow every year), road and irrigation infrastructure grid, etc. The total irrigation water supply is 225 MCM/yr, and it is growing at a rate of 2 MCM/yr (Figure 5.2). Within five years, the water supply exceeds water demand, and a new settlement can be created and allocated with the excess amount of water.

Figures 5.11-5.12 portray the progress of settlement creation in the RoadFirst and IrrigationFirst scenarios, respectively. As can be seen in Figure 5.11, the settlement expansion is concentrated along the main road that goes from northwest to southeast along the open land within the study area (Figure 5.11B-C). When space is taken along the road, new roads are created, branching away from the main road, with new road infrastructure connecting the main road to the new settlements (Figure 5.11D-F). Irrigation infrastructure is also laid to accommodate new settlements. Only after space is exhausted along the vicinity of the main road do new settlements crop up south of existing settlements on the western edge of the study area (Figure 5.11G-I), with new infrastructure connecting them to existing road and irrigation systems. From this point onwards, there is "competition" between these two clusters, where new settlements are created and connected to new recently laid road and agriculture infrastructure (Figure

5.11J-M). Towards the end of the model run, new settlements are also created east of the main road that breaks the study area into two zones (Figure 5.11N-P). The reason for the eastern areas' delayed colonization is due to the soil type in this zone, which is mostly unsuitable for agricultural usage (and marked in gray).

In Figure 5.12, new settlements are first created within the fringe of existing settlements, just south of the existing settlements within the western part of the study area, close to the existing irrigation infrastructure (Figure 5.12B-D). When the area immediately south of existing settlements is full, and space is exhausted, a new path progressing south into open land is created with new settlements and with new road and irrigation infrastructure to support them (Figure 5.12E-G). This path spreads both east and west in space. Simultaneously, another two clusters are developed (along the main road that crosses the study area and within the center part of the open space area), further expanding to the south and sending branches west and east, with new road and irrigation infrastructure (Figure 5.12H-N).

Figure 5.10: RoadFirst scenario progress run for 74 years (each step is a year). Labels mark years: A = year 0 (2013); B = +5; C = +10; D = +15; E = +20; F = +25; G = +30; H = +35; I = +40; J = +45; K = +50; L = +55; M = +60; N = +65; O = +70; P = +74.

Figure 5.11: IrrigationFirst scenario progress run for 76 years (each step is a year). Labels mark years: A = year 0 (2013); B = +5; C = +10; D = +15; E = +20; F = +25; G = +30; H = +35; I = +40; J = +45; K = +50; L = +55; M = +60; N = +65; O = +70; P = +76.

The reason for the difference in spread is due to the different weights given to prioritize settlement creation; in the RoadFirst scenario, one can see that new settlements will be created along the existing roads first, whereas in the IrrigationFirst scenario, new settlements will be created close to existing settlements, where irrigation infrastructure exists. Both scenarios end after 74-76 years (Table 5.3), when agricultural land is no longer available. Whereas the spread patterns of newly founded agricultural settlements are different in stages A-H, the differences are minimal in stages I-P, when all available agricultural land is taken.

In both scenarios, the model starts with 8% of the total agricultural land in fallow, 70% irrigated and 22% rainfed (Figure 5.13). The model finishes with 8% fallow, 76-78% irrigated, and 14-16% rainfed (Figure 5.13). The differences in the rainfed agricultural fields' ratios stem from the fact that all new settlements are located on irrigated-only lands. At the end of the model run, there are 57-59 new settlements that consume 148-152 MCM/yr of irrigation water (Table 5.3). More detailed information appears in Table 5.3. Ninety percent of agricultural fields are annually cultivated with the remaining 10% of alternating agricultural fields in fallow. An agricultural average annual yield forecast can be estimated according to the amount of cultivated area. A very simplified

estimation, based on 90% of the fields being annually cultivated, can be deduced given yield per hectare data obtained from local farming experts (e.g., 35-60 t for potatoes; 85-120 t for carrots; etc.).

Figure 5.12: Total agricultural area by use.

Table 5.3: RoadFirst and IrrigationFirst scenarios' main results

Scenario name	Initial # of settlements	Initial area of agricultural land (hectares)	Initial water quota (MCM/yr)	Number of years for model run	Number of new settlements	Final additional agricultural land (hectares)	Final additional water quota (MCM/yr)
RoadFirst	87	63,825	225	74	57	30,704	148
IrrigationFirst				76	59	31,897	152

Even though both scenarios ended with very similar amounts of additional agricultural settlements, and therefore with similar amounts of supplemental agricultural areas and water demand, there are spatial differences between the two scenarios that affect both infrastructure spread (irrigation and road system) and the surrounding environment. The RoadFirst scenario, which gives more weight to the proximity to existing roads, requires paving less than half the length of the roads in the first 20-25 years of the model run, when constructing up to 15-20 new settlements, as compared to the IrrigationFirst scenario (Figure 5.14A). In the RoadFirst scenario, the first additional settlements are located very close to existing roads, where irrigation is not necessarily present, therefore requiring additional irrigation infrastructure and minimal road additions. As the model progresses and space in proximity to existing roads is

exhausted, new settlements will be created in previously open space that is in proximity to formerly new settlements (that already have infrastructure). In this case, both additional irrigation and road infrastructures for the new settlement will be similar (and will frequently share the same route). On the other hand, in the IrrigationFirst scenario, which gives more weight to the proximity to existing irrigation, 25-40% less irrigation piping infrastructure will need to be laid in the first 20-25 years of the model (Figure 5.14B).

The differences in infrastructure between Figure 5.14A and Figure 5.14B stem from the fact that all existing piping infrastructure is already surrounded by previously existing agriculture. On the other hand, not all existing roads are surrounded by agriculture. Therefore, whereas one can set up a new settlement in direct proximity to an existing road, one cannot establish a new settlement in direct proximity to existing irrigation infrastructure, thus requiring the construction of both types of infrastructure. In terms of costs, it is cheaper to construct irrigation pipeline than to pave a road. Therefore, when planning the span of irrigation and road infrastructure, one would want to minimize the road system's additional mileage; therefore, the RoadFirst scenario is better in this case.

Figure 5.13: Total (A) road and (B) irrigation infrastructure added in the RoadFirst and IrrigationFirst scenarios.

The IrrigationFirst scenario creates more fragmentation of open space (Table 5.4). The IrrigationFirst settlements' locations are more spread out, sending "tentacles" into the open space. The direction of settlement spread is towards the heart of the open space zone, whereas in the RoadFirst scenario, there is a tight cluster around the existing

main road, which is already an environmentally disturbed area (Figures 5.11-5.12, stages B-H). Therefore, it takes less time (and energy) to commute from one newly founded settlement to another in the RoadFirst scenario. Since new settlements are forecasted to be populated with 500-1000 residents and will need regional commercial, educational and cultural centers, the advantages of clustering in this case are obvious: minimal distances to these regional centers are beneficial, while at the same time, they have lower harmful effects on the natural environment. Furthermore, road structure in the RoadFirst scenario is based on the existing main road (Figure 5.11) that can function as a highway: being faster (higher speed limit), more economical (lower gas consumption) and safer than small separate winding roads between different settlements, as can be seen in the IrrigationFirst scenario.

Table 5.4: Number of fragmented areas for the RoadFirst and IrrigationFirst scenarios.

Model year	No. of fragmented areas	
	RoadFirst	IrrigationFirst
0	2	2
5	2	2
10	2	2
15	2	2
20	2	3
30	2	5
40	4	7
50	7	10
60	11	13
70	13	15

Tweaking the weights given to the parameters representing proximities to road and irrigation infrastructure yielded sub-scenarios in which it was possible to fine tune the weight given to each parameter. Three such sub-scenarios were checked: (1) 80% weight given to proximity to road and 20% to proximity to irrigation infrastructure (Road80Irrigation20); (2) equal weight given to proximity to road and irrigation infrastructure (Road50Irrigation50); and (3) 20% weight given to proximity to road and 80% to proximity to irrigation infrastructure (Road20Irrigation80). The results obtained from these sub-scenarios are on the continuum between the two main scenarios that represent the two extremes: giving maximum weight to either one of the parameters, and only considering the other parameter in cases in which the main parameter is the same value when comparing two candidate locations for a new settlement. For example, minimal added road infrastructure was obtained in the RoadFirst scenario (Figure 5.14A), since this scenario strives to keep road additions to a minimum. Next in line is the Road80Irrigation20, which gives more weight to proximity to road

infrastructure than to irrigation infrastructure. Third is Road50Irrigation50, which gives equal weight to both parameters. Fourth is Road20Irrigation80 and last is IrrigationFirst, which gives maximum weight to proximity to irrigation infrastructure and neglects the proximity to road infrastructure. This continuum proves the model's flexibility and allows for versatility and adjustability in the scenario creation and fine tuning, according to infrastructure requirements.

5.4.2.3 Climate change scenarios

The main difference between the climate change scenarios and the basic scenarios is that there are much fewer new agricultural settlements in the climate change scenarios. The reason is because there is less water available for agricultural expansion: crop water demand is higher, while the precipitation rate is lower, creating a situation in which the existing agricultural lands require more irrigation water, and most of the surplus in the agricultural water quota is directed to satisfy these growing demands.

In looking at the two main climate change scenarios, when there is a decrease of 2% in the water allocation growth rate (Figure 5.15B), no new settlements are created during the entire model run. The overall cultivated area is stable for the first 27 years, and then it continuously drops, whereas the non-cultivated area amount increases; the reason for this is because the decrease in precipitation pushes the drought line (the line with less than 200 mm of annual precipitation) further north. Thus previously rainfed cultivated fields are no longer arable, since they are not connected to the irrigation infrastructure and cannot be potentially irrigated, and the annual precipitation in their area is no longer above the minimum 200 mm; therefore, these fields become fallow. These drought line shifts occur in year 28 and 51 (Figure 5.15). In case in which there is a 1% increase in the water allocation growth rate (Figure 5.15A), it takes 16 years before the first new settlement is formed (compared with five years in the basic scenarios, Figures 5.11-5.12). All in all, 30 new settlements are created within 60 years of the model run.

When the climate change scenario variables are active only for the first 30 years of the model run, with a 2% decrease in the water allocation growth rate (Figure 5.15D), new settlements start to appear after 36 years, and a new settlement is established every other year (compared to a new settlement established almost every year in the basic scenarios). All in all, 11 new settlements are created. With a 1% increase in the water allocation growth rate (Figure 5.15C), when the variables cease to be active, a new settlement is created every year, with 38 new settlements within 60 years. In both scenarios, the area of rainfed agricultural fields slightly diminishes when the drought line is pushed north in year 28, and then remains stable for the rest of the run.

Figure 5.14: Climate change scenario: increase of 1% (A,C), and decrease of 2% (B,D) in the water allocation growth rate. Parameters are active for the entire duration of the model run (A,B), and for the first 30 years of the model run (C,D).

5.5 Conclusion

Detection of agricultural fields has proved to be a difficult task for RS experts. The classification technique applied in this research successfully yields an accurate classification of agricultural fields in fragmented small-scale semi-arid to arid agricultural areas. It mainly relies on the fact that during the summer time, there is a clear contrast between irrigated agricultural fields and other nonagricultural open areas, since there is no precipitation in this period. Furthermore, the idea of overlaying multiple images from different periods and extracting the maximum NDVI value indicating agricultural activity has proved to be adequate for this task. The overall accuracy of the RS classification of agricultural lands is $86\% \pm 0$, which is above the minimum threshold, stated by Anderson et al. (1976) as sufficient for the classification of LULC categories from RS data. The entire pixel domain (~1.5 million pixels) was compared to the reference maps in the validation process (rather than random sampling), thus enhancing the strength of the accuracy.

The model shows that in the "business as usual scenarios," agriculture will continue to spread in the southern part of the northwestern Negev, into pristine open lands, showing once again that human and climate drivers are leading to profound, large-scale changes in land-use patterns. This spread, which can be termed as "agricultural sprawl," is possible due to the fact that water availability from alternative sources, such as reclaimed water and desalinated water, is on the rise. With the increase in population and the decline of agricultural areas in Israel's coastal and central areas, which have transformed into highly urbanized areas delivering sufficient amounts of reclaimed water, the increase in agricultural lands in the southern region is inevitable. The rate at which this process will occur depends on the amounts of water available, which in turn, depends on population growth and the standard of living: the two major factors that directly affect the domestic water demand. Loss of arable land due to urban encroachment and/or future agricultural populations' relocation (due to political reasons) is also forecasted to enhance this trend of agricultural expansion in the northwestern Negev.

It has also been shown that in the case of climate change trends, agricultural spread will be affected. No new settlements can be created in a severe climate change situation, and more fields will become non-arable due to lack of irrigation water, thus lowering the amount of total cultivated areas. The extent to which fields become non-arable depends on the severity of climate change.

The model's findings show that different scenarios can have different impacts on future land-cover in the northwestern Negev. It is vital to obtain water for irrigation and support of agriculture in this semi-arid to arid region. The irrigation piping infrastructure layout pattern and the existing road system infrastructure and pattern of spread play fundamental roles in shaping the spread of agricultural areas. It has been shown that

the RoadFirst scenario is a more beneficial scenario on all compared counts; therefore, the most attention should be given to the existing road system infrastructure, when beginning to plan the potential locations of future agricultural settlements. The current location of the existing irrigation infrastructure has less weight. The decision whether to extend the irrigation infrastructure depends on water availability, which depends, in turn, on natural climatic variables, on water consumption and on water management. The decision regarding in which direction to extend the infrastructure depends on the region's soil type inventory and positioning and on other existing infrastructure, such as: road systems, urban areas (both for reclaimed water availability and the agricultural workforce), existing water reservoirs, etc., as well as the need to keep newly founded settlements highly clustered, striving to locate these clusters on already naturally disturbed areas in order to minimally impact the natural environment. It is noted that for the Northwestern Negev area, it is possible to have a substantial increase in agricultural activities while maintaining and preserving the natural landscape. Our recommendation is to adopt the RoadFirst scenario for the first 30 years of the model's run (up until stage G in Figure 5.11) and to allow more research to assess the effects of agricultural activities and domestic presence on the nearby open space.

These variables affect irrigated agricultural dynamics everywhere. Therefore, the application of this model is not restricted to the Negev region alone. The weight given to each variable can be easily adjusted, thus allowing the model to be easily applied in other environments. It is also possible to add additional features to the model and customize it to fit different needs. These may include, for example: adding a crop-type influence on agricultural parcels' water demand; adding crop market price and demand; adding land and water quota trading to the farmer's decision-making process. This model is a powerful tool that can provide decision-makers and planners with essential information regarding future agricultural expansion, agricultural crop yields and agricultural water demand, allowing the design of adaptation measures for different scenarios.

6 Change detection of water resources in the Jordanian desert.

6.1 Introduction

Azraq Oasis, in Jordan, owes its name to the particularly light blue color of its water. The presence of pools of freshwater made Azraq a highly relevant spot in the Jordan eastern desert: the first settlements in the area date back to the Middle Paleolithic era and are testified by the presence of an ancient Castle, a thirteenth-century Ayyubid dynasty fortress built on some Roman ruins (Ramsar Convention, 1998, Cordova et al. 2013). Besides the human colonization, Azraq represents a strategically important area for local fauna and migratory birds, stopping on their way from East Asia, Africa and Europe.

The existence of this historically important site is now at high risk, since in the 1990s the Oasis went through a drastic drying up of the natural springs that were then releasing up to 16 million cubic meters (MCM) of water a year (Dottridge and Abu Jaber 1999, ESCWA and BGR 2013).

The main reason for the depletion of the water level in the Oasis is connected with human abstraction from the groundwater basin for domestic and rural use, especially after the so-called green revolution carried out by the Jordanian Government in the 1980s (National Research Council 1999, Demilecamps 2010, IUCN 2010). The springs that supported the Oasis in fact were the natural discharge of the Azraq–Dhuleil Basin, which today is one of the biggest sources of potable water for the capital Amman (25 %, in a country where groundwater resources make up 57 % of total supply) Mesnil and Habjoka (2012). The easily reachable water bed, in some points just a few meters under the soil level, allowed the exploitation of water resources by farmers that found in Azraq an easy and fast way of moneymaking, especially since at first the digging was not regulated or monitored. Subsequently and still currently, the illegal digging is flourishing and not completely under control. Besides the rural use, which accounts for up to two-thirds of the total abstraction, the drawing of water for domestic purpose by the Water Authority of Jordan (WAJ) constitutes the second source of water exploitation (Demilecamps 2010). Figure 6.1 shows how the estimated yearly abstraction grew from few MCM in the 1980s up to the current 60 MCM (IUCN 2010), from a basin for which the calculated safe yield is between 20 and 25 MCM (Ramsar Convention 1987, Al-Kharabsheh 2000).

Figure 6.1: Springs flow and water abstraction from the Azraq-Duhleil Basin since 1950, adapted from Dottridge (1999) and implemented. Source: based on data from the WAJ and Bajjali (2006), El Naqa (2007), IUCN (2011), GIZ (2012).

Besides the lowering of the water table, the groundwater conditions are also experiencing a general deterioration, mainly alteration in groundwater salinity as shown by recent studies (El-Naqa et al. 2007, Goode et al. 2013). The persistence of the present conditions will unlikely allow reversing the direction of the change, with a big loss in terms of desert biodiversity and cultural and esthetic values (Dottridge and Abu Jaber 1999, National Research Council 1999).

The situation at Azraq Oasis is a good example of how human behavior can pose a huge threat to the existence of an oasis, adding to the naturally imposed hazard of desertification. Oases' characteristics in fact make them particularly vulnerable to desertification, a process defined as land degradation in arid, semiarid and dry sub-humid areas resulting from various factors, including climatic variations and human activities' (UNCCD 1994). Understanding the evolution of desertification processes has a huge relevance in a country like Jordan, with a water supply of $145 \text{ m}^3/\text{person}/\text{year}$ putting it high in the list of worldwide water scarcity countries (Edwards et al. 1999; Al Eisawi 2005; WAJ 2007; Al-Bakri et al. 2013; UNICEF 2014; WHO 2015) and poses a question on the sustainability of a society in a growing demand regime. The amount of water available per capita is in fact predicted to diminish down to $90 \text{ m}^3/\text{person}/\text{year}$ in 2025 (personal communication), and this prediction will probably worsen if the number of refugees arriving from neighboring Arab countries keeps increasing (UNHCR 2015).

Several attempts have been proposed to choose valuable indicators of desertification: including soil erosion and sedimentation, perennial plant cover and biomass (Dawelbait and Morari 2011). In particular on a long-term temporal scale,

remote sensing is a proper tool to monitor such type of change, using land-use–land-cover change (LULCC) detection techniques, an effective device also for the investigation of desert environments (Mouat et al. 1997, Palmer and van Rooyen 1998, Lin et al. 2011). The changes to Azraq Oasis in recent history make it an exceptional case to test techniques for monitoring the desertification in drylands: by knowing a priori the change to terrestrial surface between two dates, it is possible to look for indicators proving it, and thus check whether the technique is able to detect the change and to which extent. The technique chosen in this study is Change Vector Analysis (CVA) applied to the output of a Tasseled Cap (TC) transform, usually fit to perform LULCC detection in vegetated areas (Malila and Lafayette 1980). CVA gives as an output the direction of change between two dates for each pixel of an image, having the advantage, differently from canonical supervised or unsupervised classifications, of not needing a land-cover classification to be performed in advance. The use of this technique in desert areas bears some doubts, since the TC transform is intrinsically intended to be used in vegetated areas; the aim of this paper is therefore to resolve this issue, using for this purpose a new set of parameters for the TC transform, calculated for Landsat 8 OLI system specifically for desert conditions.

6.2 Case study

Azraq Oasis is located in Jordan, 80 km east of the capital Amman approximately at coordinates 32°N and 37°S. It lays at the bottom of a relatively shallow natural depression at around 500 m of altitude, which constitutes the northern part of Wadi Sirhan depression, a huge hydrological system covering great part of central northern Saudi Arabia desert (Ramsar Convention 1990a; ESCWA and BGR 2013).

The groundwater system is rather complex and is part of a greater aquifer system that extends from southwestern Syria to Saudi Arabia, consisting mainly of three aquifers, one on top of the other. The upper one, called Basalt Aquifer, has been the most exploited one and is also the aquifer from which the Oasis' springs originated. The superficial catchment area of this aquifer is a huge basin called the Azraq–Dhuleil Basin, that extends almost longitudinally, from the southeastern side of Jebel Al-Arab (or Jebel Al-Druze, 1800 m high) mountain in Syria to the northeastern desert of Jordan (Dottridge and Abu Jaber 1999, El-Naqa et al. 2007, Cordova et al. 2013). The Basin area is considered predominantly arid, with annual precipitation ranging from less than 50 mm in the southeastern depression to more

than 300 mm in the northern part, in proximity of the most elevated point of the Basin (Al-Kharabsheh 2000, ESCWA and BGR 2013).

Before drying up in the 1990s, the Oasis was made up of two main groups of springs surrounded by marshes: the Aura and Moustadhema springs surrounded by the Druze Marsh in the northern part, and the Souda and Qaisiyah Springs surrounded by the Shishan Marsh in the south (Ramsar Convention 1990a). The springs and the marshes created a seasonal cycle with the nearby *Qa'or Sebkhah*, the Arabic terms to refer to a *mudflat*, also called *salt flat* or *playa lake*) (Alvarez Cobelas et al. 2005). The mudflat consists of a depressed area that is flooded during the winter season by the drainages from incoming streams) *wadies* (and then dries up due to the dry climate, creating temporary salty water ponds and swamps until the water evaporates (Cordova et al. 2013).

Figure 2 shows the position of Azraq in Jordan with the Azraq–Dhuleil Basin border and a Landsat look-like image of February 25, 2015, centered in the study area (in yellow), where the mudflat area and the RSCN Reserve are also shown.

Figure 6.2: Location of Azraq in the Middle East region and of Azraq–Dhuleil Basin in Jordan, with zoom on the study area) yellow border (showing the RSCN Reserve and the mudflat area (February 25, 2015, Landsat 8 look-like image).

The object of several study campaigns in the 1960s, mainly by ornithologists and desert researchers, Azraq Oasis starts to gain attention far before the complete drying up of the sources in the 1990s. A first draft of the Natural Reserve was drawn as early as 1965. Later, in 1977, Jordan designated the Azraq wetland for the List of Wetlands of International Importance under the Ramsar Convention, an international agreement. The Member States of the Convention committed to protect and preserve the wetlands enlisted in the agreement (the 'Ramsar Sites' across the world are more than 2000 for 160 Contracting Parties). Also thanks to the Ramsar Recommendations, which are periodically provided during the Ramsar Meetings, the Natural Reserve was finally instituted in 1978, under the jurisdiction of Royal Society for Conservation of Nature (RSCN) which got the mandate from the Ministry of Agriculture.

In 1980, a special cabinet committee created to establish a plan of action, assessed the safe yield at 20 MCM; in the meantime, the Amman Water and Sewage Authority (AWSA) set up a governmental wellfield for domestic use abstraction, and during the 1980s the pumping from the Oasis kept on growing, despite the calls from Ramsar Recommendations to reduce it at least by 50% (Ramsar Convention 1987; Ramsar Convention 1990b). Eventually, the sources dried up completely in 1992 and this led to a Global Environment Facility (GEF) funding of a three-year project aimed to restore and manage Azraq Wetlands Reserve. This resulted in a variety of management activities during 1994–1999, including the opening of a Visitors Center (active from 2000) and a guided natural trail through the Reserve, together with the return of a supply of water to the Shishan Marshes from June 1994, following lack of water for 2 years. In 1998, the artificial water supply started to be pumped bypassing the former springs (Souda and Quasiya), where a large amount of water was being lost through infiltration, and transported directly to the central marsh (Ramsar Convention 1999).

6.3 Materials and methods

6.3.1 Landsat data

For the present research, five images centered on Azraq Oasis were chosen, namely from path/row 173/38 of the Landsat database available at <http://glovis.usgs.gov/>. Cloudless images taken in summer season dates were chosen, this in order to avoid the climatic seasonal fluctuation and to have the most similar conditions on the terrestrial surface. Given the desert and arid conditions, we can assume that no big climatic variation occurs in summer in the analyzed area

and that the atmospheric correction is negligible. The earliest available image respecting the above-described criterion, and considering also the availability of TC transform for that type of sensor, is from the summer of 1984. Images taken around the 30th of August have been chosen over a span of 30 years, in order to detect the long-term change but also the shorter-scale variation. Tables 6.1 and 6.2 give the list of selected dates for the analysis and the characteristics of the involved Landsat satellites. Later in this article, the images will be denoted just by the year (i.e., 1984 for August 30, 1984.)

Table 6.1: Selected dates for Landsat 5 and Landsat 8 satellites for the multitemporal change detection.

Landsat 5	30 Aug. 1984; 31 Aug. 1990; 21 Aug. 1998; 19 Aug. 2003
Landsat 8	30 Aug. 2013

Table 6.2: Technical data of selected spectral bands used in the TC transform for the Landsat 5 satellite TM (Thematic Mapper) and Landsat 8 satellite OLI (Operational Land Imager) sensors, with resolution of 30 m.

Denomination	Landsat 5		Landsat 8	
	Band n.	Range (μm)	Band n.	Range (μm)
Coastal aerosol			1	0.43–0.45
Blue	1	0.45–0.51	2	0.45–0.52
Green	2	0.52–0.60	3	0.53–0.59
Red	3	0.63–0.69	4	0.64–0.67
Near infrared (NIR)	4	0.76–0.90	5	0.85–0.88
Shortwave infrared (SWIR1)	5	1.55–1.75	6	1.57–1.65
Shortwave infrared (SWIR2)	7	2.08–2.35	7	2.11–2.29

6.3.2 Tasseled Cap (TC) transform

The Tasseled Cap (TC) transform was introduced by a work of Kauth and Thomas (sometimes it is also called KT transform) in 1976 (Kauth and Thomas 1976) and consists of a linear transformation of the pixels' values of a satellite image of terrestrial surface, in order to convert the originally highly correlated bands (in the infrared and visible region, see Table 6.2 to a new set of uncorrelated axes. The new axes, also called TC features, bear a physical meaning in terms of the characteristics of the surface: brightness, greenness and wetness. As a linear transform, the TC consists of a set of parameters (frequently referred to as *coefficients* (that weigh the original spectral bands' values and sum up to give as an output a new value for that pixel in the new set of axes, therefore literally transforming the coordinates reference system passing from the satellite bands space to a new TC features space. Unlike other transformations, principal component analysis (PCA) as one example, TC transform is not image dependent; therefore, once a set of parameters for the transformation is given, it can be used to convert any image with the same characteristics (type of satellite, data and region) (Ivits et al. 2008, Yarbrough et al. 2012, Zanchetta et al. 2015). In particular, when dealing with desert conditions, special attention should be paid when applying the existing coefficients, noticing whether the original studies were carried out specifically for vegetated areas.

The coefficients present in the literature for Landsat 8 were calculated for vegetated conditions (Baig et al. 2014, Liu et al. 2015), therefore, a new set of parameters have been calculated for desert conditions, using top of atmosphere reflectance (TOAR) images (Table 6.3). The method chosen to calculate the coefficients uses the Gram–Schmidt orthogonalization as the original study by Kauth and Thomas and in other sources (Chang ;1989 Ivits et al.)

The first method was chosen following the considerations made by Zanchetta et al. (2015), from which the coefficients used in the present study for Landsat 5 images were also taken. The Gram–Schmidt orthogonalization was performed on selected pixels that belong to three categories of surface cover (indicative of soil, vegetated and wet surfaces) and on a range of images from different seasons and selected geographic locations in the Middle East (Jordan and Egypt), in order to overcome the dependency of the TC calculation on temporal conditions and location. These criteria allow the use of the new Landsat 8 coefficients to perform a LULCC detection against products of older Landsat systems.

Table 6.3: TC coefficients for Landsat 8 TOAR data for desert conditions.

	Band 1	Band 2	Band 3	Band 4
Brightness	0.185	0.206	0.316	0.403
Greenness	0.075	0.08	0.02	0.180–
Wetness	0.25	0.264	0.4	0.529

6.3.3 Change Vector Analysis (CVA)

Change Vector Analysis (CVA) was first implemented by Malila and Lafayette (1980) for detecting forest changes and then widely adopted for LULCC detection by several authors also for desert areas (Lorena et al. 2002, Bayarjargal et al. 2006), sometimes further developed and varied (Lambin and Strahlers 1994, Chen et al. 2003, Flores and Yool 2007, Dawelbait and Morari 2011, Dubovyk et al. 2013, Singh and Talwar 2014). The technique uses two (or more) spectral variables, like spectral bands or surface features or spectral indices, to produce in output a map of the *magnitude* and a map of the *direction* of the change between two dates. For each date, the pixel's values in the two bands are plotted on the bands space, generating a vector of the change in time. The vector's length and angle give, respectively, the magnitude and direction of the change. Once a threshold is chosen, the significant change is given as those pixels that exceed that value in the map of the *direction*.

As spectral variables, some biophysical indicators connected with surface characteristics are chosen. In this way, the combined variation can have a meaning in terms of surface change. In general (considering the two bands space), an indicator of the soil reflectance and an indicator of the vegetation vigor are used, like Albedo and NDVI (normalized difference vegetation index) (Karnieli et al. 2014) or the Tasseled Cap features brightness and greenness (Malila and Lafayette 1980).

6.3.4 CVA interpretation

The determination of the threshold and the interpretation of the direction of the change are critical points when applying the CVA technique and have been faced in several ways by different authors. The threshold in particular can be set with the use of empirical values, or through interactive trial-and-error procedures, or semi-automated approaches (He et al. 2013). For this work, the threshold given by the average plus the standard deviation of the *magnitude* values was chosen; therefore,

it is not a fixed value and it changes for each pair of images taken into consideration. This choice respects a statistical requirement and does not require human supervision, but in the same time, it bears some uncertainty connected with different statistical distributions of the values of *magnitude* when used for multitemporal analysis, meaning when, like in our case, the change is investigated in more than one time interval. To address this issue, the CVA was carried out on a vast area surrounding the Oasis (891 km²), and not only the actual area of interest around the Shishan marsh (see Figure 6.2 ,yellow border).

Once the angle of the change vector is mathematically determined, the meaning of the CVA *direction* is not straightforward. Generally, a simplified interpretation of the quadrants of the bands space is given: the first quadrant in fact represents a positive change for both variables, the third quadrant a negative change for both, and so on. In line with the interpretation given by other authors for desert conditions (Lorena et al. 2002, Karnieli et al. 2014), we defined the four change *directions* as follows. The first quadrant, which is characterized by an increase in both greenness and brightness, indicates moisture reduction and drying up of salty surfaces (Karnieli et al. 2014) the second quadrant, with increase in brightness, is indicative of chlorophyll increase and of regrowth and regeneration of vegetated features in general; the third quadrant, where both spectral features have a decrease, indicates burning or water and in general a change toward higher moisture land; the fourth quadrant, with increasing brightness, is strongly related to great losses of vegetation biomass and to bare soil expansion (Figure 6.3).

Figure 6.3: CVA explanation and physical meaning of the quadrants.

6.4 Results and Discussion

Before performing CVA on the selected dates, a visual interpretation of images was carried out in order to visualize the expected change between the pre-drying up conditions and the present conditions. As a reference for the pre-event situation, a map from 1979 was digitized and georeferenced (Figure 6.4). The map is available from the 1990s RAMSAR Report, and it contains also some updates from an expedition organized by the RAMSAR committee in March 1990 (Ramsar Convention 1990a). The annotations describe a general deterioration of the Oasis: stressed or tainted vegetation in the central area of the marsh (on dunes and water) and low water level in the pools, with the Ingleside pool almost dry and the ditches totally dry. As a reference for the present conditions, missing ground truth data, a comparison with updated base maps available online (OpenStreetMap, Google) was taken in consideration (Figure 6.5). Further help in interpreting the intermediate dates comes from aerial pictures available from the APAAME online catalog (Aerial Photographic Archive for Archaeology in the Middle East) that dates from 1998 to present.

Figure 6.4: Major habitats/vegetation communities in Azraq Wetland Reserve, digitization of a 1979 map. (Source Ramsar Convention 1990a).

Figure 6.5: Google Earth image of the Azraq Reserve in 2015, RSCN Reserve border (in red) and the 1979 Ramsar fence (in black) are shown.

The visual comparison over the entire time span shows indeed a deterioration of the general status of the Oasis area, while rural areas on the northeast part of the plateau seem to flourish. These impressions were confirmed during a field visit in June 2014.

The CVA image resulting from the comparison between 1984 and 2013 is given in Figure 6.6 where Landsat look-like images are also shown. The highest change occurs in the 'bare soil expansion' category, which accounts for more than 80% of the total changed pixels (see Table 4). A bare soil expansion was detected in and around the Reserve area, while 'generation/increase in chlorophyll' and 'moisture increase' were detected in the eastern side and around the mudflat area, with clear identification of agricultural fields (Figure 6.6).

Figure 6.6: Landsat look-like image for 30/08/1984 and 30/08/2013 (above) and CVA between the two images for the study area (below), RSCN Reserve border (in red) and the 1979 RAMSAR fence (in black) are shown.

Table 6.4: CVA results for the studied time periods in km² and % on the total study area (for the meaning of the categories refer to Figure 6.3).

Categories	1984–2013		1984–1990		1990–1998		1998–2003		2003–2013	
	(km ²)	(%)	(km ²)	(%)	(km ²)	(%)	(km ²)	(%)	(km ²)	(%)
Moisture reduction	0.2	0.02	26.34	2.96	26.65	2.99	26.54	2.98	0.02	0
Chlorophyll increase	10.2	1.14	28.43	3.19	29	3.25	34.67	3.89	4.58	0.51
Moisture increase	3.1	0.35	11.76	1.32	19.46	2.18	13.67	1.53	1.93	0.22
Bare soil expansion	76.8	8.62	30.81	3.46	21.83	2.45	11.21	1.26	83.71	9.39
No-change	801	89.9	793.7	89.1	794.1	89.1	804.9	90.3	800.8	89.9
Area changed	90.3	10.1	97.33	10.9	96.93	10.9	86.09	9.66	90.23	10.1

The long-term trend is replicated in the shorter-term periods, where the highest change occurs in the ‘bare soil expansion’ category with a maximum in the 2003–2013 period (9.39 %). The intermediate periods show in general a more varied picture, with change occurring homogeneously in all the categories. The whole area study includes also the northeast side of the image, where a high rural activity developed in the period taken into account; therefore, a closer view on the Oasis area, centered on the RSCN Reserve, for shorter temporal scales is also analyzed (Figure 6.7).

The centered CVA image for 1984–2013 (Figure 6.7j) detects a high change toward ‘bare soil expansion’ in the Reserve area, and this is affirmed by the base maps. The CVA image for 1984–1990 (Figure 6.7f) detects ‘bare soil expansion’ and ‘moisture reduction’ all along the Reserve area and the mudflat. This trend continues in the 1990–1998 CVA image (Figure 6.7g), where the drying up of the major pools adjacent to the mudflat is evident. This trend is partly halted in the following CVA image for 1998–2003 (Figure 6.7h) likely as a result of the restoration project completed in 1998 through the GEF fund, and in fact a replenishment of green areas is detected in the central part of the marsh. The following CVA image for 2003–2013 (Figure 6.7i) shows again a change toward ‘bare soil expansion,’ and this is attributable to the fire that broke out in October 2010, after which the Reserve was temporarily closed and could open again just in April 2011: the fire’s consequences on the vegetation were still evident during the field visit in June 2014.

Figure 6.7: Look-like Landsat images (a. 1984, b. 1990, c. 1998, d. 2003, e. 2013) and CVA results images (f. 1984-1990, g. 1990-1998, h. 1998-2003, i. 2003-2013, j. 1984-2013) for the Reserve area from 1984 to 2013 (for the dates specification see Table 6.1).

A closer analysis of the CVA results on the area of the pools surrounding the former Shishan springs was also considered (not shown here). The results show a main change toward drier conditions between 1990 and 1998, as expected, and a partial recovery between 1998 and 2003. Finally, between 2003 and 2013, the Oasis achieves its present conditions, with the former springs' pools left empty and a partial recovery of the marsh and of the stream that flows toward the former Burgees pool (Figure 6.5).

6.5 Conclusion

An analysis was performed of the capability of the Tasseled Cap (TC) transform combined with Change Vector Analysis (CVA) to detect surface changes in arid areas, using as a case study the wetland of the Azraq Oasis, Jordan. The analysis was carried out on a 30-year interval (1984–2013) on Landsat satellite images. For the purpose of the research, a new set of TC coefficients was calculated, using several Landsat 8 images of selected dryland locations in the Middle East, and is here presented for the first time.

CVA gives as an output a map of the magnitude and a map of the direction of the change between two dates, having the advantage of not needing a previous land-use/land-cover classification. There are two difficulties though that are intrinsic to the use of the CVA technique: the first is deciding what the meaningful change is, namely choosing a threshold for the change detection, and the second is the absence of an objective validation method. The first issue was addressed using a statistical criterion for the selection of the threshold (average of the magnitude values plus the standard deviation), allowing for an automatic selection of the value for each couple of dates. The second one was faced with the support of data and material collected in a field visit in June 2014, together with several sources available in the literature.

The results show that the CVA applied to desert-adapted TC transform features is able to detect the expected changes in the studied area and can therefore be considered a valuable technique for change detection studies in areas subject to desertification and deterioration processes in drylands.

7. References

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