AMERICAN UNIVERSITY OF BEIRUT

AN INTEGRATED DECISION-MAKING FRAMEWORK TOWARDS IMPROVED WATER MANAGEMENT IN COASTAL AREAS OF MOUNTAINOUS WATERSHEDS

by
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ABSTRACT
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The coastal zone is vital to littoral countries, as its natural resources provide life support and economic development opportunities. Land conservation goals and the preservation of coastal assets is achieved through the sustainability of land use planning and ecological integrity of these zones. In the context of agricultural lands and landscape conservation, the management and planning is dictated by farmers' perception, response and decisions about adaptation facing the ongoing changes in the conditions of the watershed especially in the context of climate change. Understanding farmers' behaviour is therefore indispensable for land conservation and sustainability. Despite advances in farmer's behavior research, it remains challenging to understand, predict and manage. Given the complexity of farmers' behavioral processes, agricultural lands are in need of a tool that models farmers' perception, response and decisions with special consideration of the complexity of the systems incorporating socio-economic and ecological facets.

This research targets the Eastern Mediterranean coastal agricultural areas, highly vulnerable to climate change. It examines the main drivers of farmers' behavioral and decision making processes, assessing the impacts of local anthropogenic activities and projected global climate change. The research appraises the spatial and temporal dynamics of farmers' behavior integrating socio-psychological, economic and empirical modules, as the basis for understanding farmers' decision making in response to climate change. It develops spatio-temporal Agent Based Models covering the three modules for farmers' behaviour future predictions. This research further develops a hybrid Morkov Chain- Cellular Automata modelto evaluate the projected future landcover landuse, as well as a hydrologic model able to quantify the impacts of climate change on water resources availability in small mountanious mediterranean watersheds.

Results of the projected future water availability spatial distribution indicated a decrease in water availability with a mean of 24% between 2008 and 2032. The 2032 LCLU projection showed a significant increase in urban areas of reaching a 93% rate. Agricultural lands were also predicted to increase by an average of 11%. Agricultural and urban areas will be growing at the expense of forest and grasslands. Forests and grass lands will be reduced by 5 and 73%, respectively while barren lands will increase slightly (0.4%).

Results of the decisional models highlighted the significance of the integration of empirical, socio-psychological and economic modules with site-specific socio-cultural features on behavioral evaluation. Empirical-economic based ABM returned a 35% compatibility with the true response of farmers. The compatibility increased to 69% upon considering an exclusive socio-psychological model which when combined with socio-economic rules, conformity with the true response of the farmers reached 83%. By means of generating a stable representation of the drivers and logic lying behind farmers' decisions, the constructed framework acts as an effective decision support tool to aid decision makers in land conservation planning and management.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS 1

ABSTRACT 2

ILLUSTRATIONS 9

TABLES 11

ABBREVIATIONS 13

INTRODUCTION 15

1.1. Background 15

1.2. Research Objectives 23

1.3. Research Innovation 24

1.4. Research Framework 25

1.5. Dissertation Structure 26

Forecasting land cover land use at a watershed scale: Towards enhanced sustainable land management 28

Abstract 28

2.1. Introduction 29

2.2. Material and methods 31

2.2.1. Test area 31

2.2.2. Framework approach elements 32

2.2.3. Validation 42

2.3. Results and discussion 43

2.3.1. Cellular Automata Markov projection 43
2.3.2. Model Validation 50

2.4. Conclusion 51

2.5. Acknowledgements 52

2.6. References 52

CAN SWAT FORECAST WATER AVAILABILITY IN MOUNTAINOUS WATERSHEDS WITH SNOWMELT? 56

Abstract 56

3.1. Introduction 57

3.2. Methodology 65

3.2.1. Study Area 65
3.2.2. Model description and setup 66
3.2.3. SWAT Snow Melting Module 69
3.2.4. Source code modification 71
3.2.5. Model calibration and validation 77
3.2.6. Water availability predictions 81

3.3. Results and Discussion 83

3.3.1. Model setup 83
3.3.2. Model calibration 84
3.3.3. Water availability predictions 89

3.4. Conclusion 92

3.5. Acknowledgements 93

3.6. References 93

MENTAL AND PROBABILISTIC MODELING OF FARMERS' BEHAVIOR TOWARDS IMPROVED CLIMATE CHANGE ADAPTATION..99

Abstract..99

4.1. Introduction..100

4.2. Methodology...103

4.2.1. Test area..103
4.2.2. Data collection..104
4.2.3. Structured (Probabilistic) vs Unstructured (Mental) analysis...............105

4.3. Results and Discussion..109

4.3.1. Data collection..109
4.3.2. Probabilistic models..110
4.3.3. Mental models...113
4.3.4. Probabilistic vs mental analysis..119

4.4. Conclusion..121

4.5. Acknowledgements...121

4.6. References...122

AN INTEGRATED SOCIO-ECONOMIC AGENT-BASED MODELING FRAMEWORK TOWARDS ASSESSING DECISION MAKING UNDER CLIMATE CHANGE-INDUCED WATER SCARCITY 127

Abstract..127

5.1. Introduction..128

5.2. Methodology...131

5.2.1. Study area...131
5.2.2. Data collection..132

5.2.3. ABM framework development ... 134
5.2.4. Validation ... 144
5.2.5. Sensitivity-Scenario analysis ... 145

5.3. Results and discussion ... 150

5.3.1. Field survey ... 150
5.3.2. ABM framework predictions ... 151
5.3.3. ABM framework validation ... 154
5.3.4. Sensitivity analysis ... 156

5.4. Conclusion ... 162

5.5. Acknowledgements ... 163

5.6. References ... 164

CONCLUSION AND RECOMMENDATIONS ... 169

6.1. Summary and findings ... 169

6.2. Recommendations for future work ... 172

APPENDIX A- QUESTIONNAIRE ... 174

APPENDIX B- R CODE ... 179

APPENDIX C- CADASTRAL MAP OF DAMOUR COAST ... 181

APPENDIX D- NETLOGO CODE ... 182

APPENDIX E SUPPLEMENTARY MATERIAL CHAPTER 5 ... 246

BIBLIOGRAPHY ... 251

ILLUSTRATIONS

Figure

Study area watershed 31

Framework approach *LCLU: Land Use Land Cover* 34

Suitability maps 44

Conditional probabilities 46

Past and future LCLU changes 47

LCLU simulations 49

Study area 65

Overall Modeling Framework 72

Gauging stations within or near the study area watershed 80

Land use-land cover projection for 2032 81

Monthly predicted precipitation for 2032 82

Average daily temperature for 2032 83

SWAT synthesized input data *AGRR Agricultural land, BARR Barren land, FRST Forest, RNGE Range-Grasses, URBN Urban areas, UTRN Transportation, WATR Water 84

Calibration parameters sensitivity 85

Comparison of the observed and simulated flows with and without source code modification (Calibration) 87

Comparison of the observed and simulated flows with and without source code modification (Validation) 89

Water deficit of 2032 at Station 5 (Sea Mouth) 91

Study test area 104

Mental Model schemes 118

Study test area 132

Behavioral modules flowchart f Farm index, y Year index, k Decision index, D Number of decisions, F Number of farmers, Y Number of years, NE_f Neighboring effect of farm f, U Utility, D_f Decision of farm f 139

Predicted LULC changes based on the utility functions at the end of the simulation Grey area (i.e., resorts, urban, industrial); Other crops (vegetables, tropical fruits); Others (river and sandy beaches) 153

LULC based on the farmers' responses vs ABM predictions by the end of simulation period 156

Percent differences between farmers' responses and model predicted LULC Grey areas (i.e., resorts, urban, industrial); Other crops (vegetables, tropical fruits); Others (river and sandy beaches) 156

The probabilities of farmers' decisions as a function of varying the NE rate. Reported probabilities are for the end of the simulation (2032) 157

Probability of the different farmers' decisions in 2032 as the α_f/β_f ratio is varied . 159

Probability of the 2032 decisions as a function of varying water availability........ 162

TABLES

Table

Land cover classes suitability and weights 35

Agricultural and urban areas pairwise comparison matrix 39

Transition probability matrix 45

Observed vs expected areas of land cover types.. 50

Classification accuracy 51

Types of rainfall-runoff models 58

Comparison of commonly used hydrologic models 63

Rainfall Stations 69

Snow parameters 75

Calibration parameters 79

Range of model efficiency parameters for river flows 80

Projected temperature and precipitation 81

Calibrated values for the most sensitive model parameters.................................... 85

Model evaluation with and without source code modification............................... 87

Validation results 89

Differences between mental and probabilistic modelling..................................... 102

Farmers clusters by reaction to climate change 110

Best fitted probabilistic models 111

Summary of the mental models of the six groups 113

Determinants of the decision models.. 119

Utility functions of choice behavior alternatives 140

Relative water deficit and yield decrease 148

Sensitivity-Scenarios characteristics of the ABM framework.............................. 149

Distribution of the probability of farmers' decisions across utilities at the end of the simulation.. 153

ABBREVIATIONS

ABM	Agent-Based Model
ALPHA_BF	Baseline flow recession constant
CA	Cellular Automata
CANMX	Maximum amount of water intercepted by vegetation
CH_K2	Effective hydraulic conductivity of the channel
CH_N2	Manning coefficient for the main channel
DEM	Digital Elevation Model
ENS	Nash-Sutcliffe efficiency
EPCO	Factor of compensation of water consumption by plants
ESCO	Soil water evaporation compensation factor
GIS	geographic information system
GW	Groundwater
GW_DELAY	Time interval for recharge of the aquifer
GW_REVAP	Coefficient of water rise to saturation zone
GWQMN	Water limit level in the shallow aquifer for the occurrence of base flow
HEC-HMS	Hydrologic Engineering Centre Hydrologic Modeling System
HiRAM	High Resolution Atmospheric Model
HRU	hydrologic response unit
ICZM	Integrated Coastal Zone Management
IPM	Integrated Pest Management
K	Kappa Indicator
LAI	Leaf Area Index
LCLU	Landcover Landuse

LL	Lebanese Pound
NPMPLT	National Physical Master Plan of the Lebanese Territories
R^2	Coefficients of determination
RMSE	Root Mean Squared Error
RCP	Representative Concentration Pathways
REVAPMN	Water depth in the aquifer for the occurrence of water rise to the unsaturated zone
SCS CN	Soil Conservation Service Curve Number
SLSUBBSN	Average slope length
SOL_AWC	Soil water storage
SURLAG	Delay time of direct surface runoff
SW	Surface Water
SWAT	Soil and Water Assessment Tool
SWATCUP	Calibration Uncertainty Program for SWAT
SWE	Snow-Water Equivalent
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
USDA	United States Department of Agriculture
USLE	Universal Soil Loss Equation
UTM	Universal Transverse Mercator
WRF	Weather Research and Forecasting
$	US Dollar

CHAPTER 1

INTRODUCTION

1.1. Background

The coastal zone is vital to littoral countries, as its natural resources provide life support and economic development opportunities (Rochette et al., 2012; Clark, 1994). The ecological integrity of these zones is affected by the various stressors disturbing the balance of water use and water demand such as climate change and anthropogenic pressures. Global water demand is largely controlled by the increasing anthropogenic stresses caused by population growth and the amplification of human needs (Dia, 2013). The world's changing climate is expected to result in increased inconsistency in precipitation, with a concomitant decrease in the amount of fresh water available for human consumption (Strayer & Dudgeon, 2010; Pereira et al., 2009; Pimentel et al., 2004; Bouwer, 2002; Vörösmarty et al., 2000; Rosenzweig & Parry, 1994).

The Mediterranean Sea has historically experienced intense human activities associated with its location between the three continents of the Old World. Its littoral has thus been affected by high maritime traffic along with a wide range of anthropogenic stressors, including industrialization, urbanization, tourism, agriculture, fishing, and overexploitation of resources. These pressures have led to pollution, loss of species and habitats, as well as to the degradation and fragmentation of the ecosystems leading to the depletion of the coastal zones resources (Soliman et al., 2015; Zdruli, 2014; Akkemik et al., 2012; Ghani et al., 2012; Rochette et al., 2012; Lotze et al., 2011; Boudouresque et al., 2009; Shaban , 2008; Alphan, & Yilmaz, 2005; Marmer, & Langmann, 2005; Lakkis, & Novel-Lakkis, 2000). In the Mediterranean basin, climatic conditions are dictated by the combination of the various dominating circulation regimes (i.e. mid-latitude and sub-tropical) and the complex morphology of the lands, causing this region to be one of the most vulnerable to climate change (Daoud, & Dahech, 2017; IPCC, 2013). The impact of climate change in this region has been recently reflected through an increase in amplitude/duration of heat waves and a decrease in precipitation accompanied by severe variations in rainfall patterns (Cramer et al., 2018; Negev et al., 2015; Iglesias et al., 2007; Lionello, & Giorgi, 2007). The global reduction in rainfall, the increase in the frequency and intensity of rain and the shift in snow will be inducing higher runoff for shorter periods of time and therefore decreasing the availability of accessible surface and groundwaters. This fact is exacerbated by the increase of temperature provoking enhanced evapotranspiration and producing more green water and therefore less blue water will be available, which is the main source of water for irrigation (MedECC, 2019; Clifton et al., 2018; Kelley et al., 2015; Chenoweth et al., 2011; FAO, 2011; Plan Bleu, 2009; Allan, 2002). These changes have significant implications on landscape and ecosystem integrity which determines, to a large extent, the viability of coastal agriculture.

Reconciling the development priorities of the coastal zones with ecological considerations is crucial to guaranteeing their environmental protection. Natural resource management along the coast is a process that seeks to achieve the sustainability of land use planning to simultaneously satisfy land conservation goals and preserve coastal assets. Accordingly, the Protocol on Integrated Coastal Zone Management (ICZM) along the Mediterranean coast was proposed and signed in Madrid on January 21, 2008. The contracting parties are Albania, Algeria, Bosnia and Herzegovina, Croatia, Cyprus, Egypt, France, Israel, Italy, Lebanon, Libya, Malta, Monaco, Montenegro, Morocco, Slovenia, Spain, Syria, Tunisia, Turkey and the European Union. This protocol is one of the set of Protocols of the Convention for the Protection of the Marine Environment and the Coastal Region of the Mediterranean" (UNEP/MAP/PAP, 2008). It relies on the "principle of balance" which targets the preservation of natural landscapes, coastal ecosystems and geomorphology while still permitting urbanization and coastal activities under legitimate threshold (Rochette et al., 2012; UNEP/MAP/PAP, 2008).

In Lebanon, located at the Eastern shore of the Mediterranean, the National Physical Master Plan of the Lebanese Territories (NPMPLT) was proposed in 2005, by the Council for Development and Reconstruction in collaboration with the General Directorate of Urban Planning (CDR, 2005). This plan emphasized the importance of the preservation and management of coastal ecosystems and landscape. In this plan, coastal agriculture is considered to be one of the main ecological and economic assets of the country, as the comparative advantage offered by the mild Mediterranean climate positions Lebanon competitively on the international scene (CDR, 2005). The conservation and development of agriculture along the coast is presented as a compromise for landscape preservation and economic profitability. The Damour is one of the main rivers of Lebanon. It feeds a significant area of mountainous agricultural lands, in addition to the Damour coastal plain which is almost entirely dedicated to banana plantations. Recent (2010 and 2016) records indicate that the Damour is experiencing significant decrease in the annual volumes of flow at all gauging stations at elevated rates ranging between 31 and 58 %. The decrease in water availability in the river is significantly affecting the littoral agricultural areas of the watershed since the river is the major water source feeding the agriculture lands.

The evolution of land use and land cover along the coast and consequently the future of agriculture across the region is dictated by farmers' perception, response and decisions regarding adaptation to the ongoing changes in their extrinsic and intrinsic conditions. Extrinsic conditions occur as the result of external factors such as climate, planning, zoning and policies. Intrinsic conditions come from farmers' subjective drivers such as socio-demographic characteristics and agricultural practices (Vermaire et al., 2017; Darby, & Sear, 2008). In response to the intrinsic and extrinsic conditions, farmers make decisions in an effort to sustain their livelihood (Serrat, 2017; Adato, & Meinzen-Dick, 2002). These decisions affect land use planning and land cover along the coast (Teshome et al., 2016; Valbuena et al., 2010; Hassan, & Nhemachena, 2008). Developing a clear understanding of the dynamics of the evolution of the agricultural system is essential in order to mitigate the impact of climate change. The decision making process of farmers is in a continuous update and based on problem detection, problem analysis and choice. For this purpose, there is a need for a tool that allows, through modeling, to explore the perception, response and decisions of farmers with special consideration of the complexity of the decisional process incorporating socio-economic as well as ecological dimensions.

Farmers' decision-making processes are complex because of the many influencing determinants, involving economic, social and ecological aspects. Farmers tend to make economically viable decisions while still taking into account their past experience, their surrounding community, the weather constraint and the political background (Von Ketteler, 2018; Bradford Lori, 2009; Rehman et al., 2003).

Assessment of farmers' decisions is commonly based on normative theory which assumes that all farmers are profit maximizers. They adopt individual profit or utility optimization, subjected to practical constraints (Maes & Van Passel, 2017; Ding, 2014; Ng, 2010; Marques et al., 2009; Mjelde, 1986; Bellman, 1954). This type of model predicts people's behavior in the context of economic modeling. It works with the cognitive concerns of rational decision makers (Von Ketteler, 2018; Bradford Lori, 2009). The assumption that farmers are rational profit maximizers has been central to agricultural modeling for many years (Sengupta et al.2005; Wallace & Moss, 2002; Moxey et al., 1995; Bell, 1988; Norton & Scheifer, 1980).

More recent approaches indicate that farmers' decision-making processes appear to be motivated by multiple objectives which include socio-psychological dimensions. This is attributed to the fact that farmers assign great significance to farming lifestyle, family, community, work traditions and past experience (Von Ketteler, 2018; Bradford Lori, 2009; Tzima et al, 2006; Feuillette et al., 2003; Austin et al., 1996; Fairweather & Keating, 1994; Salamon, 1992; Coughenour & Swanson, 1988; Gillmore, 1986; Salamon & Davis-Brown, 1986; Casebow, 1981; Gasson, 1973). For instance, if all farmers made decisions based only on profit maximization, one might expect farmers living in the same area with the exact same soil type, water availability, weather and cost to be planting the same type of crops. Observations suggest that it is rare to find this kind of conformity. Therefore, the models that only account for the economic dimension of decision-making, are prone to give fallacious statements about farmers' decisions and may be considered unreliable descriptors/predictors of farmers' reality. To uncover the complexity of farmers' decision making, socio-psychologists have developed models that take into account attitude, intentions, beliefs and norms. These models use a social psychology theory, the Theory of Reasoned Action (TORA). This theory is based on the view that there are two central drivers of human behavior: (1)

attitude and (2) subjective norms, rather than financial profit alone (Kashif et al., 2018; Senger et al., 2017; Edwards-Jones, 2006; Austin et al., 2005; Rehman et al., 2003; Hassan, 2002; Zubair , 2002; Beedell & Rehman, 2000; Bursey & Craig, 2000; Willock et al., 1999; Wilson, 1997; Austin et al., 1996; Ajzen, 1991; Carr & Tait, 1991). The theory seeks to understand how humans in general and farmers in particular behave and why they behave differently, using explanatory data such as past experience and implicit knowledge (Senger et al., 2017; Rehman et al., 2007; Edwards-Jones, 2006; Beedell & Rehman, 2000; Lynne et al., 1995; Ajzen, 1991; Fishbein & Ajzen, 1975).

On the other hand, the results of model simulations without empirical-based information are considered hypothetical or semi-hypothetical. On that account, a third approach to understanding decision-making, known as the empirical or descriptive approach, was also developed. This method tends to explain human behavior focusing on people's goals, values, knowledge and ways of thinking through investigating patterns, and by relying mainly on surveys (Kashif et al., 2018, Castella & Verburg 2007; Castella et al., 2005; Bell, 1988; Greenblat, 1981). This approach is presented in mental or probabilistic models describing the appropriate choices, through a set of decision rules (Bergez et al., 2010; 2006; Boissau et al., 2004; Attonaty et al., 1999; Aubry et al., 1998). A mental model is a construct that explains the function of the system and predicts perception and behavior. It processes knowledge, skills, related values, beliefs and previous experience that dictate and guide the decisions people take (Tschakert, & Sagoe, 2009; Krauss et al., 2009; Eckert, & Bell, 2006; Franzel & Scherr, 2002; Seel, 2001). This method has been proved to be a useful tool and the closest to reality, that permits the observation and elicitation of real time farmers' actions, with an interactive discussion about the motivations underlying the taken actions (Sabzian et al., 2019; Douglas et al., 2016; Vuillot et al., 2016; Eckert, & Bell, 2006; 2005; Boissau et al., 2004; Greenblat, 1981; Ng et al.2011; Ng, 2010; Scheffran & BenDor, 2009; Sengupta et al. 2005). Probabilistic models are based on regression models. These are statistical tools relying on predictive modeling procedures. Their main purpose is to forecast the dependent variable and to identify significant independent variables and how they affect the response of decision makers to proposed conditions and changes in their environment in terms of amount and direction (Jeon, 2015). Lately, they have been applied for the purpose of examining the drivers and determinants behind decisions and to predict potential behavior especially in the context of farmers' decision making (Bragg, & Dalton, 2004; Foltz, 2004; Goetz, & Debertin, 2001; Boehlje, 1992; Bentley, & Saupe, 1990; Gale, 1990).

Another approach for decision making assessment is based on spatially explicit computerized means developed into agent based models (ABM) (Zhang et al., 2016; Turner et al., 2010; Mahajan et al., 1990). ABMs are algorithmic computer-based programs that simulate a set of action and interaction between a series of agents to predict their behavior in response to various alterations in the system (Diogo et al., 2015; Feola et al., 2015; Portoghese et al., 2013; Ng et al., 2011; Miller & Page, 2007; Tzima et al, 2006; Gunkel, 2005; Barreteau et al., 2004). Most ABM are composed of agents, environment and decision rules. These models have been recently used in the context of farmers' decision making (Maes & Van Passel, 2017; Feola et al., 2015; Daloglu, 2013; Oudendag, 2013; Ng et al., 2011; Sengupta et al, 2005; Polhill et al, 2001; Berger, 2001; Kerridge et al., 2001; Balmann, 1997). ABM have a wide range of decision-making rules that have the potential to account for various modules. These rules may be data driven or theoretically-based, therefore relying on empirical data or on heuristics and optimization approaches (Castella et al., 2005; Dia, 2002; Berger, 2001; Kerridge et al., 2001; Balmann, 1997). Data driven models have decision making rules that are defined on the basis of empirical data from surveys or controlled experiments (Castella et al., 2005; Dia, 2002). Usually survey-based rules consist of asking respondents about their behavior and reaction. As for the controlled experiments, they are based on an imitation of the reality (Castella et al., 2005; Dia, 2002). The results of model simulations with empirical information-based parameters and implications make the problem more practical and meaningful. Yet some biases can result from directly asking about the behavior and reaction, due to the fact that people don't usually reveal what they do, nor do what they state. Biases can also result from direct behavioral observation where individuals may take risks they don't usually take in real life. Theoretically-based models' rules are based on heuristics and optimization approaches (Berger, 2001; Kerridge et al., 2001; Balmann, 1997; Epstein & Axtell, 1996). Heuristic based rules are mostly survival rules and based on logical reasoning. They form decision patterns according to logic-based methods that usually assume limited human cognition. One limitation is that they fail to account for the social factors affecting the decision-making process and marginalizingthe maximization of economic profit. Optimization rules are essentially economic-based and lack of some social aspects (Berger, 2001; Kerridge et al., 2001; Balmann, 1997). This optimization-based approach may lead to several biases while assuming the maximization of a single objective, ignoring the social aspects and the heterogeneity of social behaviors (Sengupta et al.2005), especially that farmers' behavior is not driven only by profit optimization but results from complex processes affected by a range of socio-economic and psychological aspects (Tzima et al, 2006; Feuillette et al., 2003; Austin et al., 1996;

Fairweather & Keating, 1994; Coughenour & Swanson, 1988; Gillmore, 1986; Salamon & Davis-Brown, 1986; Casebow & Shears, 1981; Gasson, 1973). On that account, an integrated decision making process of farmers' behavior in response to the change in water resources systems is needed covering the socio-psychological, economic and empirical modules in a spatially explicit domain.

This research targets the assessment and understanding of farmers' behavior in response to changes in water ressources systems in the context of climate change and anthropogenic stressors in Mediterranean coastal agricultural lands within small mountanious watersheds. This process is based on an integrated framework coupling socio-psychological and econometric modeling into a spatially explicit agent based models. The reaserch generates a solid representation of the drivers, aims and logics of farmers' decision making. It develops a framework covering the future projections of ecological and economic features while examining the implications of all modules on farmers' behavior. The model is tested and validated in a pilot area representing a typical coastal agricultural Mediteranean area part of a small mountainous watershed.

1.2. Research Objectives

The overall objective of the research is to develop a platform that facilitates decision making towards the sustainability and conservation of coastal natural resources through the evaluation of the impacts of climate change and anthropogenic stresses on farmers' behavior. The sub-objectives towards the realization of such a platform consist of:

1. Appraise the evolution of decision makers' behavior prediction methods over time

2. Evaluate the efficiency of mental models and probabilistic models in modeling farmers' response to climate change

3. Generate a hybrid Morkov Chain- Cellular Automata model to predict future landuse/landcover change in a small mountainous mediterranean watershed

4. Generate a physically-based hydrological model able to quantify the impacts of climate change on water resources availability in small mountanious mediterranean watersheds

5. Generate a spatially explicit decision making model (ABM) integrating socio-psychological, economic and empirical features as the basis for understanding farmers' decision making in response to climate change

6. Evaluate the efficiency of the three modules of the ABM; (1) Economic based module, (2) Socio-psychological based module and (3) Socio-economic module

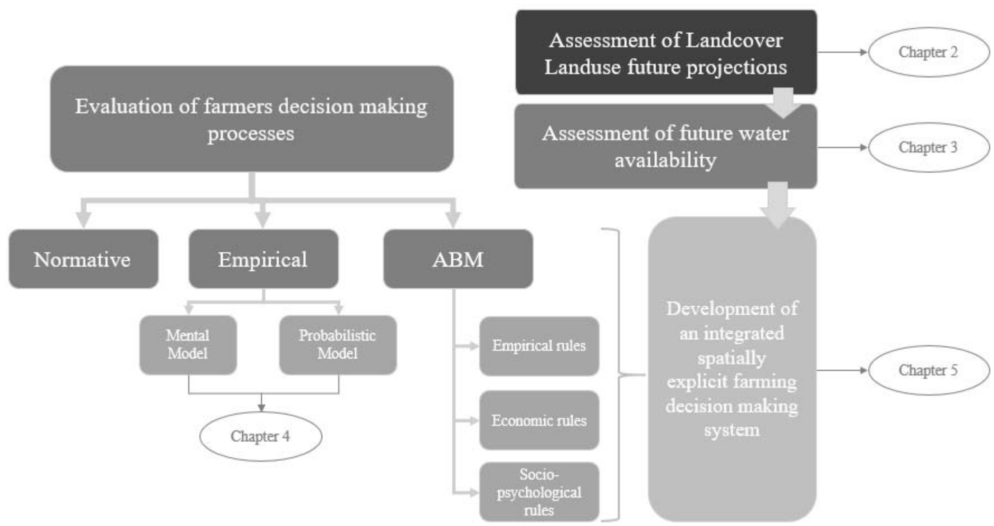
1.3. Research Innovation

It is widely accepted that farmers' decision making processes are influenced by economic and socio- psychological factors but limited insight is available on the holistic decision making process and its modeling features. Existing models in this context are usually purely economic or socio-psychological based and are presented at the general level of agro-ecological zones without spatial explicitness. Decision makers and affected communities such as farmers are therefore left incapable of effective action due to the limited research on behavioral modeling and predictions. The proposed research closes the gap between what both scientists and farmers know and need to know to plan their adaptation to water scarcity issues. It represents a compromise between the impartial scientific evaluation of the situation and the prejudiced response of farmers relying on the aims and logics of their mental processes. This research proved that an ABM covering empirical, social, economic aspects and site-specific socio-cultural modules can successfully represent the complexity and multifaced aspect of farmers' decision making.

Hydrologic modeling are usually used for the prediction of water availability and were succesfullly relied upon in water scarcity subjects. The Soil Water Assessment Tool (SWAT) model has been able to estimate hydrologic budget soil erosion, chemical processes, agricultural management measures and biomass changes over long time periods at a watershed scale. Yet in moutanious watershed where snowmelt is significant, the model would return erronous results for watersheds outside the designated location of the model (i.e. North America). The proposed research provides an edited version of the SWAT model tailored for mediterranean mountanious watersheds which aids in providing a more realistic environment conducive for decision makers on adaptation.

1.4. Research Framework

The conceptual framework of the proposed research is summarized in Figure 1-1. The scope of work adopts a multi-disiplinary research methodology integrating various modules of decision making. The construct represent a branch of the agri-intelligence concerning strategic decision making to meet today's farming challenges with knowledge and confidence. The aim is to provide farms with a solid ground to be able to adapt autonomously and in real-time to the changes towards the sustainability and conservation of coastal natural resources. Hence the proposed framework helps in the development of a decision support tool for guiding farmers through a proper adaptation to stressors and effective management of their ressources.



1.5. Dissertation Structure

Chapter 2 provides a framework for predicting landcover landuse in a small mountainous mediterranean watershed namely the Damour watershed in Lebanon. A hybrid Morkov Chain- Cellular Automata model was generated and validated based on historical available data of landcover.

Chapter 3 generates a model able to quantify the impacts of climate change on water resources availability in small mountanious mediterranean watersheds. For this purpose the physically-based hydrological model, The Soil and Water Assessment Tool (SWAT), was used. The snowmelt module was altered to suit this type of watersheds; SWAT source code was modifed for the snowmelt dates and factors to suit the targeted areas. Then a calibration was applied on available gauging stations on the river for measured monthly streamflow to optimize the most sensitive parameters. Three scenarios were then considered to predict the water availability in 2032 and to examine the impact of exterme changes in precipitation and temperature.

Chapter 4 presents a modeling framework covering the mental and probabilistic modules to evaluate farmers' behavior under projected climate change and various anthropogenic stresses. It examines and investigates farmers' decisions, the aims and logics lying behind and the drivers behind their response. This framework provides a comparative assessment between the corresponding modeling tools. The Damour plain of Lebanon was studied, as it represents the prevalent conditions of the Mediterranean coastline.

Chapter 5 proposes a model that integrates socio-psychological, economic and empirical features as the basis for understanding farmers' decision making in response to climate change. As a starting point, the model was solely based on economic rules. Then an exclusive socio-psychological module was generated, followed by a socio-economic module. The output from the three modules was finally compared to the true response of farmers to assess the validity and accuracy of the proposed framework.

Chapter 6 presents a synthesis of the research and concludes with challenges to address in future work.

Chapter 7 lists the bibliographic citations used throughout the dissertation.

CHAPTER 2

FORECASTING LAND COVER LAND USE AT A WATERSHED SCALE: TOWARDS ENHANCED SUSTAINABLE LAND MANAGEMENT

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Abstract

Human-induced environmental stressors represent a major source of recent global change that are reflected through alterations in the land cover land use (LCLU) due to urban growth associated with socio-economic development having a significant impact on LCLU. In this study, we develop a framework approach driven by developmental indicators under a GIS platform to predict future LCLU changes. For this purpose, Cellular Automata and Markov Chain analyses were coupled while relying on a multi-criteria decision evaluations and pairwise comparisons of social, economic, and environmental indices based on field surveys alongside transitional probabilistic rules based on historical LCLU data. The framework was validated using past land cover maps with a 71% similarity between simulated and observed results. Urbanization expansion (93% in 15 years) was the driving force behind the loss of forest (5%) and grasslands (73%). Agricultural and barren lands increased over the same period albeit at a lower magnitude of 11% and 0.4%, respectively. The proposed framework can serve as an effective tool for predicting LCLU change and improved policy planning and decision-making towards resilience in sustainable land development..

Keywords LCLU, Markov chain, Cellular automata, GIS

2.1. Introduction

Globally, changes in land cover land use (LCLU) are manifested by the replacement of natural soil cover by impervious surfaces or by a change in agricultural areas through crop type or cropped and arable lands. The land cover represents the biophysical characteristics of the land, namely the distribution of its physical features such as vegetation, water and soil whereas the land use is the way in which the land has been used or altered emphasizing its functional and economic role (Lu et al., 2019). The combined LCLU changes are driven by the combination of natural and socio-economic forces, and reflect the utilization of the land forming the basis for resource management and planning, and exerting a significant impact on ecosystem processes, biological cycles, and biodiversity. More importantly, LCLU changes present significant impacts on water availability that is further exacerbated in recent years with climate change and its potential impacts on ecosystems (Lu et al., 2019; Gharbia et al., 2016; Myint, & Wang, 2006; Reinau 2006).

The prediction of LCLU changes requires an understanding of the rate and direction of LCLU change over time as well as the main drivers behind these changes. In this context, a spatial dynamic analysis is invariably needed for accurate predictions of LCLU changes that are often clustered into two types: Conversion and Modification (Fu et al., 2018; Yagoub, & Al Bizreh, 2014; Adhikari, & Southworth, 2012; Myint, & Wang, 2006; Jianping et al., 2005). Conversions occur when the alteration of the land is so significant that it modifies its cover type, such as the transformations occurring when agriculture or forest or barren lands are converted to urban areas. In contrast, Modifications occur when the outcomes of changes do not impact the land cover category (Fu et al., 2018; Yagoub, & Al Bizreh, 2014; Adhikari, & Southworth, 2012; Myint, & Wang, 2006; Jianping et al., 2005). Both types have been examined through change detection-based approaches that are classified as pre- or post-classification methods, which are limited by their static diagnosis of land cover change (Yagoub, & Al Bizreh, 2014; Guan et al., 2011; Myint, & Wang, 2006). The latter is a dynamic process in space and time that focuses on the change outcome, the underlying driving factors, and the pace of the change state (Fu et al., 2018; Adhikari, & Southworth, 2012). In this context, the integration of Cellular Automata with Markov Chain (CA-MC) offers promising reliability by considering changes in the land cover as a stochastic process while treating the cells as entities depending on their direct previous temporal state and the state of their spatial neighbors (Fu et al., 2018; Yagoub, & Al Bizreh, 2014). Yet the convention on which the MC-CA relies still limits its ability to simulate the physical situation and requires relaxing the analysis to cover complexity more realistically by emphasizing the irregularity of the cell space, the convolution of transition rules, and the dynamicity of neighbors (Yagoub, & Al Bizreh, 2014; Myint, & Wang, 2006).

In this study, we propose a framework approach whereby a multi-criteria evaluation was expanded to integrate key socioeconomic, environmental and climatic indicators to assess LCLU changes using empirical data collected through field surveys. An overall CA-MC analysis was validated against past land cover maps to demonstrate the usefulness of the integrated approach for landscape changes with the objective to serve as a tool for effective watershed management as well as improved policy planning and decision-making for sustainable land development.

2.2. Material and methods

2.2.1. Test area

The Mediterranean region houses highly vulnerable coastal agriculture lands rich in important ecological and economic assets (Parry et al., 2007). The future of these lands is affected mostly by water availability and sustainability of water resources and therefore needs reasonably accurate LCLU projections (Head et al., 2017; Daoud, & Dahech, 2017; Casas et al., 2015; Kovats et al., 2014; Trujillo et al., 2012). The study area is located in this vulnerable region and encompasses the Damour watershed in Lebanon. It covers an area of 290 km2 (Figure 1) with a watershed spanning several mountain ranges, deep valleys, canyons and plains in addition to side streams and steep tributaries (Khair et al., 2016; Makhzoumi et al., 2012).

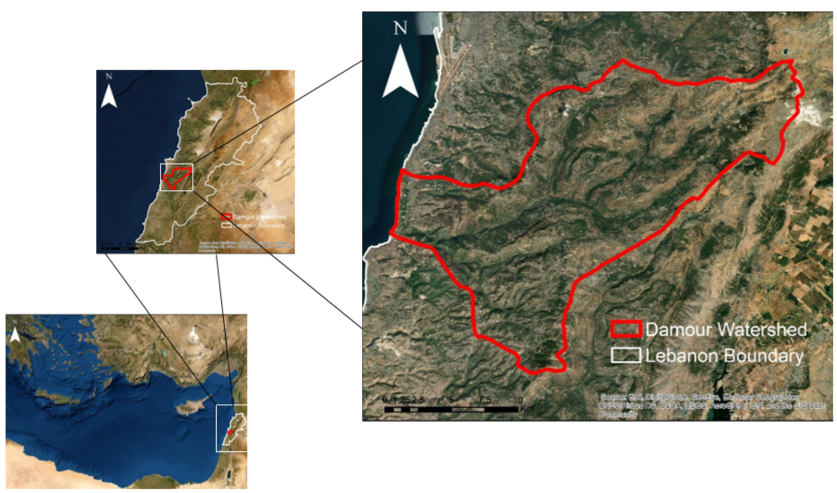


Figure 1 Study area watershed

The watershed comprises large rock exposures, clastic and carbonate geologic outcropping with a considerable number of springs distributed across the karstic limestone bedrock. It is characterized by a diverse vegetation cover with arable lands, forests, and agricultural areas constituting its main LCLU categories (Khair et al., 2016; Makhzoumi et al., 2012). Natural vegetation areas are dense both at the bottom of valleys and along mountain slopes but decrease upon reaching high altitudes (Khair et al., 2016; Kovats et al., 2014; Makhzoumi et al., 2012). Agricultural patterns in the basin have evolved since the late century, when the cultivation of mulberry dominated to accommodate the production of silk. The latter which declined dramatically after World War One with mulberry trees replaced with orange and citrus trees that lasted for two decades and then replaced with banana. The entire coastal region is currently threatened by touristic ventures and real-estate developments that are more profitable than agriculture. The development of industrial and urban areas has been subject to several changes causing significant impacts on water availability. Furthermore, past land use changes were forced by socio-anthropogenic factors including civil unrest and population displacement. While agriculture is considered as a main ecological and economic asset, its future will be dictated by urbanization pressure and water resources sustainability. In this context, a proper LCLU projection becomes imperative.

2.2.2. Framework approach elements

A framework approach was adopted consisting of several interrelated elements that allowed reasonable LCLU predictions. These elements included the coupling of Cellular Automata with Markov Chain analysis under which a linear combination of multi-criteria decision evaluations were tested through pairwise comparisons and an integration of social, economic, and environmental indices based on field surveys alongside transitional probabilistic rules based on historical LCLU data (Figure 2). The cellular automata (CA) analysis targets the prediction of the state of the cells relying on a set of rules based on the state of neighboring cells. This process requires the development of suitability maps that were built through multi-criteria analysis (MCA) requiring the integration of several rules to generate suitability indices. In the context of land cover change, the decisions involve land allocation and site selection for potential development (urban, industrial, touristic or agricultural) and can be reached by generating suitability maps, while considering the influencing factors such as socio-economic and environmental conditions represented by criteria and weights (Agyemang, & Silva, 2019; Fu et al., 2018; Palmate, 2017; Gharbia et al., 2016; Moghadam, & Helbich, 2013; Adhikari, & Southworth, 2012; Reinau 2006). Suitability maps were thus generated for each land cover type and corresponding ranks were assigned for each pixel to the considered land cover type on a scale from 0 to 200 (from the least to the most suitable for change to the corresponding LCLU) (Figure 2).

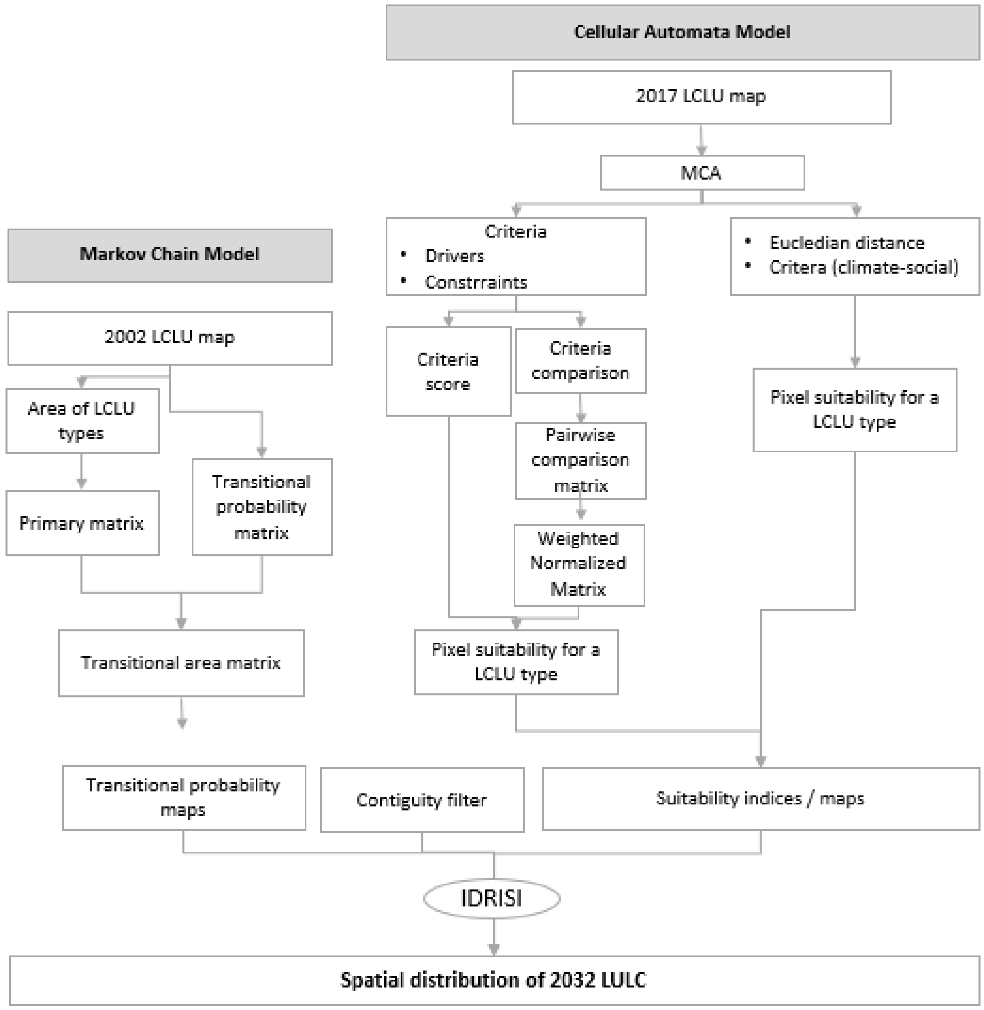


Figure 2 Framework approach
LCLU: Land Use Land Cover

Several controls were imposed on each LCLU class in the context of its ability to shift to another LCLU class. Namely, the available land cover classes were able to become subject to urban development (at different rates) except for water bodies. The rates represent suitability weights and were assigned using a fuzzy logic approach and based on expert judgment relying on field surveys and reported literature on the probability of transformation of a LCLU class to another class1 (Abisaab, 2020;

[1] An early master plan divided the study area into six zones: two mixed for commerce and housing, a residential zone, an agricultural plain, an industrial zone, and a tourist zone. The old town was assigned the highest ground exploitation

Ghosseini, 2017; Hani et al., 2017; Gharbia et al., 2016; Myint & Wang, 2006) (Table 1). Ten members of the study area municipality and all farmers along the coastal zone were asked about the tendency of a land type to transform into another type. Each land cover type represented a cluster and each cluster was assigned a rank. Accordingly, each cluster was given 33 values (which is the total number of farmers) and a center corresponding to the mean. The means were normalized to assign values between 0 and 200. Fuzzy models were used to provide a similarity to human ways of thinking to simulate information of qualitative information into numerical representation (Rodriguez et al., 2011; Berkes, & Berkes, 2009).

Table 1 Land cover classes suitability and weights

	Agriculture	Urban	Forest	Barren	Grass	Water
Agriculture	1		1	1	1	
Urban	1	1	1	1	1	
Forest			1			
Barren	1		1	1	1	
Grass	1		1		1	
Water						1
Suitability weights	100	200	100	50	50	200

*1 represents "Yes" in the Boolean operation
(Abisaab, 2020; Ghosseini, 2017; Hani et al., 2017; Gharbia et al., 2016)

The highest weight was assigned to the urban areas since they are not capable of change. Agricultural and forests are given the second highest ranks due to the restrictive regulations imposed by some municipalities in the study area for the protection of forests and agricultural lands especially coastal agriculture. As such, the LCLU classes

ratios to encourage construction therein and limit the urbanization of agricultural lands and natural areas. Social displacement induced by civil unrest, encouraged the promulgation of a law to encourage the return of the displaced by relaxing construction norms which pushed the authorities to impose restrictions on natural and agricultural areas to minimize illegal urbanization. Similarly, reforestation initiatives and land protection legislation were implemented in some mountainous regions of the watershed that protected the restoration of agricultural terraces (Abisaab, 2020; Ghosseini, 2017; Hani et al., 2017) although many rural villages could not be conserved and evolved as rural territory center with no turning back to forested lands (Hani et al., 2017) were reduced from 60 to the five main classes, namely: water bodies, urban, agricultural, forest, bare land and grassland. The corresponding initiation of the MCA process covered several constraints and drivers.

Constraints

Topographic Data Suitability. It represents the slope of each cell in each LCLU type. The slope gradient was derived using the 3D analyst package toolbox in ArcMap from a 50 m Digital Elevation Model (DEM). The slope values were divided into two categories: suitable and non-suitable whereby the suitability is assessed for both agricultural development and urban growth. Zero means the LCLU is not suitable for development and 1 is suitable. Lands with slopes > 20% are not suitable for urban development but are still acceptable for agricultural expansion due to the terracing option. Slopes < 20% correspond to areas suitable for both urban and agricultural development (Shahumyan et al., 2009). The slope map was converted into a raster and the divisions of 0 and 1 was created using the reclassify tool in the spatial analyst tools in ArcGIS (Houet, & Hubert-Moy, 2006).

Environmental Data suitability. These data cover the proximity to existing and planned wastewater treatment plants (WWTP), waste disposal sites, air polluting industries and water bodies. The locations were equally divided into two categories: suitable and non-suitable whereby the suitability is also assessed for agricultural development and urban growth. The appropriate distance to WWTPs and air polluting industries must exceed 3 km for urban and agricultural development to occur (El ARD, 2012). Whereas solid waste disposal requires a threshold of 2 km (Hilal et al., 2015). Urban development should not occur at the proximity of water bodies to limit water pollution (Kaloustian et al., 2016; Faour, & Mhawej, 2014). In this context, a threshold was used and defined with 0 suitability for distances < 1km and 1 for distances > 1 km (Robert, 2016; Vantarakis et al., 2016; Brender et al., 2011; Maantay et al., 2010).

Drivers

Transportation Network Data suitability. Transportation plays a major role in locating the areas prone to urban and agricultural development. Areas that are easily accessible are the ones with highest suitability for growth. Designers consider areas within 500m of a road to be most suitable for urban development (Myint & Wang, 2006) which was adopted in this study with areas beyond 50 m considered as having a continuously decreasing suitability although the decreasing trend does not touch 0. Therefore, we used the 50 m as the first control point corresponding to a maximum score of 100 and the 500m as the last control point corresponding to the lowest score (close to 0). Accordingly the distance between 0 and 50 has the highest suitability and distances greater than 500 has the lowest suitability. Road networks are not subject to frequent change in the study area therefore, the existing road map was used (Rietveld & Bruinsma 2012; Reilly et al., 2009).

Existing communities' suitability. This factor reflects the socioeconomic aspect of the region. Urban growth is highly affected by the proximity to socioeconomic centers and highly populated residential areas. A linear decay function, the Euclidean distance, was adopted with highest suitability corresponding to nearest locations to highly populated residential areas and health services relying on satellite imagery of 2017 (Li et al., 2013). Agricultural expansion is likely to develop at locations close to previously cultivated areas since there are no significant variations in soil type in the watershed (Hubert-Moy, 2006). Distances to these areas were rescaled using a linear function matching the 0 distance to a maximum score, and the maximum distance to a minimum score. All distances to each land type were standardized to the same continuous scale of suitability (0–100) using their minimum and maximum values with linear interpolation in between.

Climate projection. This factor includes the projected rainfall and maximum temperatures with corresponding distributions throughout the watershed. Future Climate data were obtained from a dynamical downscaling process based on WRF (Weather Research and Forecasting) simulations forced by HiRAM (High Resolution Atmospheric Model) for 2008 representing a typical hot and dry year (El Samra et al., 2017a; b). Between 2020 and 2032, the simulations predicted a decrease of 21 to 37% in rainfall along the mountain and coastal zones, respectively at a temperature change of 1.5oC. Based on past drought years, local farmers are particularly concerned with respect to rainfall change across the watershed that can cause a significant decrease in agricultural yield as well as reportedly forest density (Thiébault et al., 2016). These rates were determined from farmers' elicitation though a questionnaire administered to a sample of farmers along the coastal region of the study area. Based on these statements, the climate layer would penalize the suitability of locations for agriculture, forest and grasslands.

A weighted linear combination was used by assigning a weight to each criterion that reflects its importance relative to others. The corresponding summation provides a suitability map: S=Σwixi, where S is the suitability, wi is the weight of criterion i, and xi is the score of criterion i. Accordingly, the criteria were compared to each other in terms of their importance to the targeted LCLU type (for instance, the importance of the distance to water bodies and the distance to a WWTP for the spread of urban areas). This step requires the comparison of all possible pairing into a pairwise comparison matrix. The Saaty2 technique was used for this purpose. It relies on the principal eigenvector of a square reciprocal matrix of pairwise comparisons between the criteria. This comparison relies on available empirical and literature data of similar studies. The scores were provided on the 9 point continuous scale (for instance if proximity to WWTPs is significantly more important than the distance to water bodies in evaluating the change in urban areas, a value of 9 is entered and the statement inverse would be given the score inverse: 1/9). A pairwise comparison matrix is generated reflecting the relative weights for each criterion to the others. The final weight of each criterion is defined as the average of each column (Eastman, 2020).

The initial matrices generated were the pairwise matrices (Table 2). A normalized pairwise was then generated by dividing all elements of the matrix by their column total. The weighted matrices of the priority criteria were then generated by dividing the normalized pairwise by their ranks. The eigenvector for the pairwise comparison matrices were finally generated by multiplying the pairwise matrices and the weighted matrices of the priority criteria (Eastman, 2020).

Table 2 Agricultural and urban areas pairwise comparison matrix

		Road	River	WWTP	Industrial	Dumpsites	Climate	Slope
Road	A	1	7	1	0.5	0.2	2	5
	U	1	9	0.25	6	0.2	9	6
River	A	0.14	1	0.2	0.2	0.2	0.5	2
	U	0.11	1	0.11	2	0.11	5	0.25
WWTP	A	1	5	1	1	1	4	6
	U	4	9	1	9	1	9	5

[2] Saaty scale
1 Equally important 1/1 Equally important
2 Equally or slightly more important 1/2 Equally or slightly less important
3 Slightly more important 1/3 Slightly less important
4 Slightly to much more important 1/4 Slightly to way less important
5 Much more important 1/5 Way less important
6 Much to far more important 1/6 Way to far less important
7 Far more important 1/7 Far less important
8 Far more important to extremely more important 1/8 Far less important to extremely less important
9 Extremely more important 1/9 Extremely less important

Industrial	A	2	5	1	1	1	4	6
	U	0.16	0.5	0.11	1	0.14	0.33	0.14
Dumpsites	A	5	5	1	1	1	4	6
	U	5	9	1	7	1	9	8
Climate	A	0.5	2	0.25	0.25	0.25	1	6
	U	0.11	0.2	0.11	3	0.11	1	0.14
Slope	A	0.2	0.5	0.16	0.16	0.16	0.16	1
	U	0.16	4	0.2	7	0.12	7	1

A: Agriculture; U: Urban; WWTP: Wastewater Treatment Plant

Therefore, the principal eigenvector of the pairwise comparison matrices representing the criteria weights for the agricultural and urban areas are:

Agriculture: Road 1.12, River 0.30, WWTP 1.55, Industrial 1.70, Dumpsites 2.15, Climate 0.59, Slope 0.21

Urban: Road 9.13, River 1.93, WWTP 16.11, Industrial 1.22, Dumpsites 18.75, Climate 1.9, Slope 3.77

Water bodies were assumed to remain constant with no further development or reduction. The suitability maps of other classes (i.e. forests, bare lands and grass lands), were generated assuming that "the pixel closer to an existing land cover type has the higher suitability". As such, pixels within any land cover type considered, have highest scores with decreasing suitability with distance. Distances to these areas were resampled according to a linear function corresponding the minimum distance to the maximum score (100) and the maximum distance to a minimum score (0). Accordingly all distances to each land type were standardized to the same continuous scale of suitability (0–100) using their minimum and maximum values with linear interpolation.

The Markov chain analysis was then used relying on a transitional probability matrix for future projections (Figure 2). The matrix shows the probability that each land cover type will change into another type in the future, given the present state of the class (Agyemang, & Silva, 2019; Fu et al., 2018; Kumar et al., 2014; Moghadam, & Helbich, 2013; Kamusoko et al., 2009). It is obtained from a cross tabulation of two existing land cover maps and reflects the nature of the change while forming the basis for the projection to another time period (Kumar et al., 2014; Jianping et al., 2005). It includes the conversion from one state to another through transition probabilities and is represented by (Dongjie et al., 2008):

$$P_{ij} = \begin{matrix} P_{11} & \dots & P_{1n} \\ P_{i1} & \dots & P_{in} \\ P_{n1} & \dots & P_{nn} \end{matrix} \; ; \sum_{j=1}^{j=n} P_{ij} = 1 \text{ and } 0 \leq P_{ij} \leq 1.$$

Where Pij is the probability from state i to state j.

The transition area matrix is then generated by multiplying the transition probability matrix with the corresponding primary matrix (Fu et al., 2018; Adhikari, & Southworth, 2012; Jianping et al., 2005) which is the area matrix representing the area of each land cover class of the first year. In this study, we used the 2002 and 2017 LCLU coverages for the transition probability matrix to be projected for 2032. Therefore, for each LCLU class, a transitional probability map was generated where each pixel is associated with a score from 0 to 100 reflecting the probability of transformation to the designated LCLU type, from the less to the most probable.

In the last element of the framework the cellular automata suitability maps and the Markovian transitional probability maps were exported to IDRISI (version 17)3 (Figure 2). This combination adds the component of spatial contiguity and the awareness of the likely spatial distribution of the transitions to the Markov analysis and

[3] IDRISI is an image processing software developed by Clark Labs in the U.S. and able to undertake several operations such as image restoration, enhancement, classification and transformation. It has been used for prediction future LCLU maps under the image transformation category. It derives new images as a result of several mathematical treatment of available imageries (Mukhopadhaya, 2016; Li et al., 2015; Yuan et al., 2015; Subedi et al., 2013; Xu et al., 2013; Sang et al., 2011) . In this context, it targets mainly the coupling of 3.1. Cellular Automata Markov models. The software is used to generate suitability matrices for the proposed LCLU types and transitional probability matrices, and/or coupling the Cellular Automata and Markov results to generate LCLU projections.

then is used to predict the future LCLU. A contiguity filter is applied to the Cellular Automata results to create spatially weighting factors that alter the state of a cell according to its neighbors to take into account the effect of neighboring conditions. The use of the contiguity filter is interpreted by the pixel near to a certain class that is most likely to be changed into the aforementioned class (i.e. areas closer to a LCLU class are most likely to change to the aforementioned category than areas that are farther) (Fu et al., 2018; Ahmed, 2011). In this study, a 3×3 mean contiguity filter was applied to the five suitability maps to generate five reweighted suitability maps on a 0 to 100 scale. The reweighted maps were combined with the five probability maps that were also ranked on the 0 to 100 scale. This step generates a series of five other maps showing the preference of each pixel for a LCLU type. These weighted preferences can therefore be combined into one single map showing the projected LCLU of 2032 based on the maximum index choice (Fu et al., 2018; Ahmed, 2011).

2.2.3. Validation

Validation is a crucial step to test model performance by examining it against data that were not used in its construction. If the model was created using time t1 and t2, then the land cover of t3 was predicted from t2, the validation would be processed for ti and ti+1 (with i other than 1 or 2) (Fu et al., 2018; Adhikari, & Southworth, 2012). In this study the 2032 land cover was assessed based on the change between 2002 and 2017. The model was validated using the observed land cover maps of 2010 and 1995 since they were not used in building the model. The validating was evaluated using the kappa and the Chi-squared testing indicators at a pixel level (Liping et al., 2018; Kumar et al., 2014). The Kappa index was regained from Kappa = (P0 –PC)/(PP – PC); where

P0 is the proportion of correct simulation, PC is the expected proportion of correct simulation in random circumstances, and PP is the proportion of correct simulation in ideal circumstances. The index ranges between 0 and 1 from the lowest to the highest fit of two LCLU images (Yuan et al., 2015). Chi-squared was obtained from $\chi 2 = \sum(Oi – Ei)2/Ei$, where Oi is the observed value (actual value) and Ei is the expected value. A good fit between two images is represented by a low Chi-square value corresponding to a low p value (less than 0.05) (Liping et al., 2018; Kumar et al., 2014).

2.3. Results and discussion

2.3.1. Cellular Automata Markov projection

The cellular Automata model was applied to assess the suitability of each pixel for each LCLU type. The Markov Chain analysis was applied in order to assess the transitional probability of each pixel for each LCLU type. Then both were combined through IDRISI to generate the future projected LCLU map.

Under the Cellular Automata, a suitability map was generated for each LCLU type, where each pixel have a score from 0 to 100 (lest to most suitable) (Figure 3).

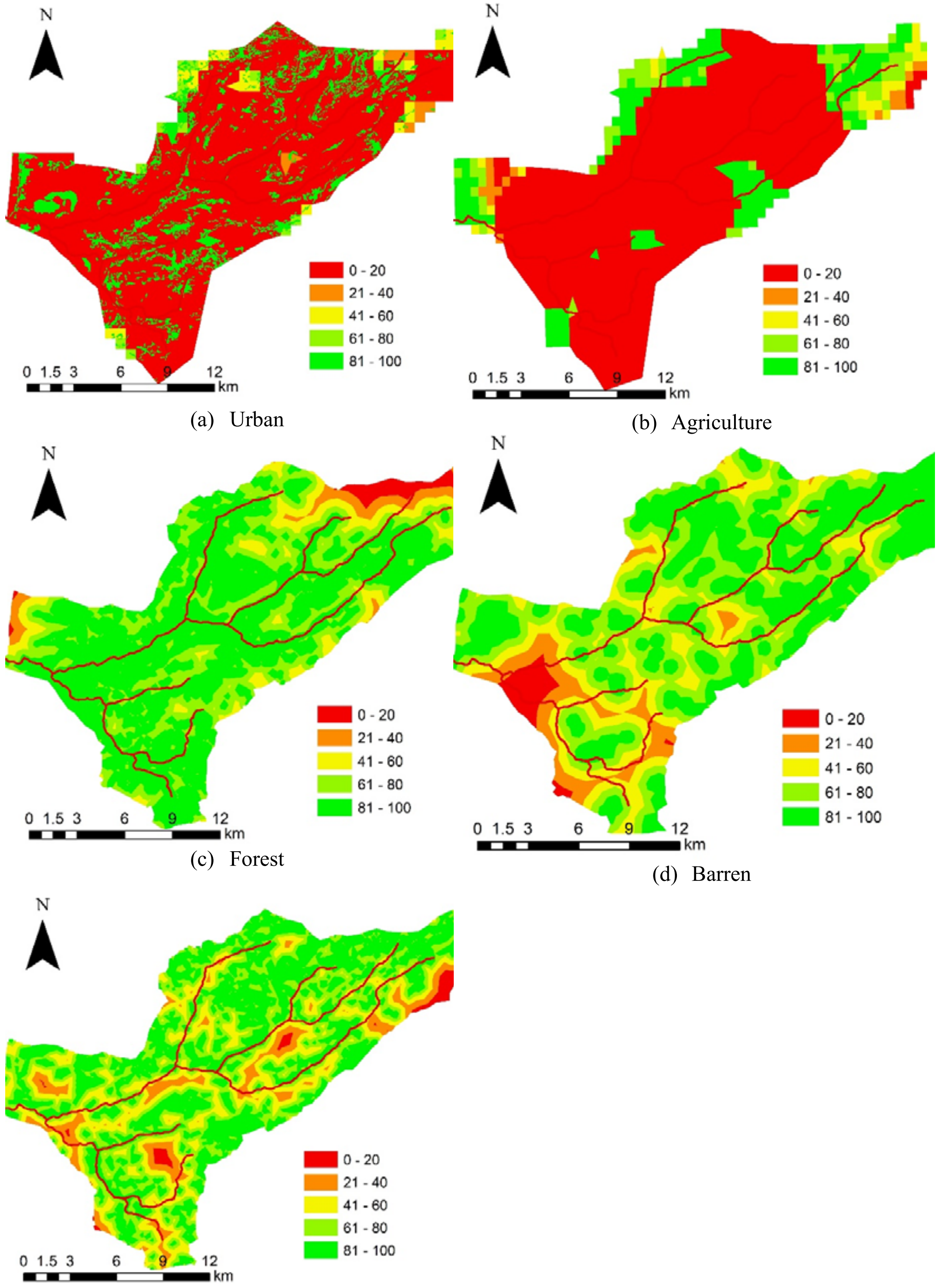
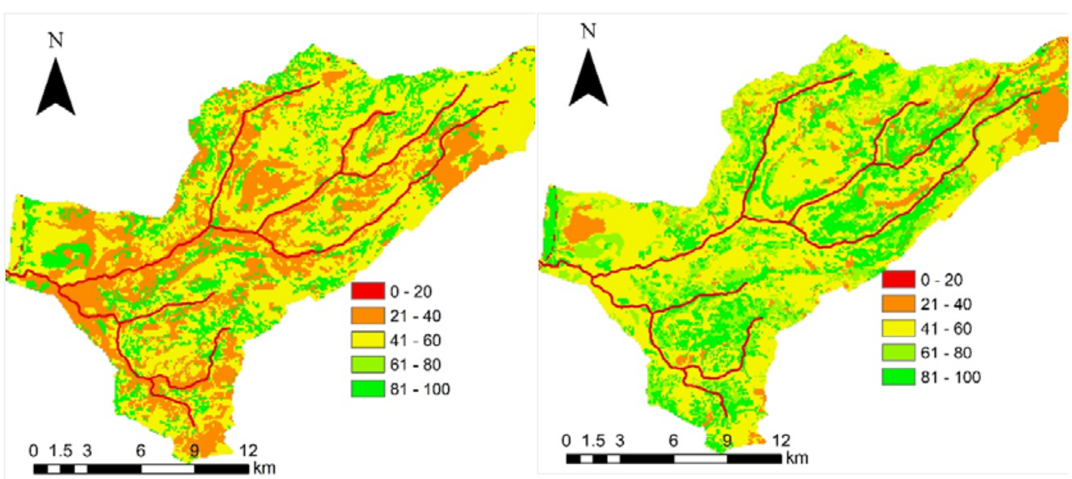


Figure 3 Suitability maps

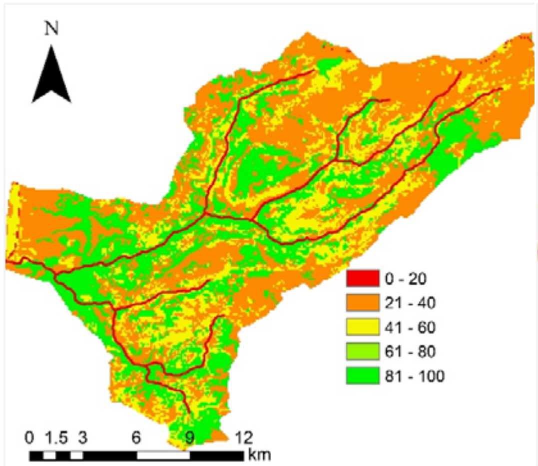
The Markov module was applied based on the available land covers of 2002 and 2017. The transition probability of the six land cover types between 2002 and 2017 is presented in Table 3. The corresponding conditional probability maps show the probability of each land cover at each pixel. These maps were generated on a land cover type basis since the model does not account for spatial distribution (Figure 4).

Table 3 Transition probability matrix

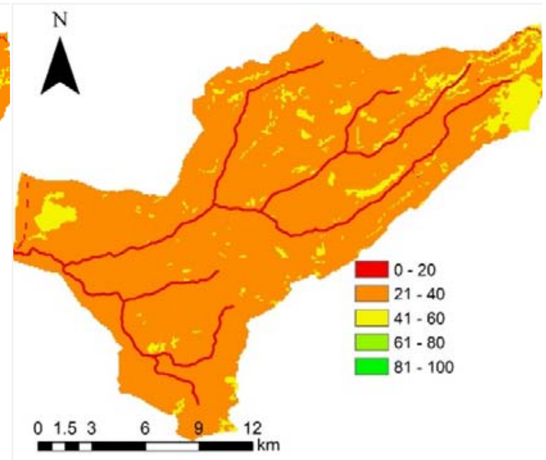
		LCLU 2017					
	Land type	agriculture	barren	forest	grass	urban	water
LCLU 2002	agriculture	0.32	0.06	0.22	0.19	0.21	0.00
	barren	0.18	0.24	0.09	0.30	0.20	0.00
	forest	0.25	0.05	0.33	0.20	0.18	0.00
	grass	0.24	0.10	0.18	0.25	0.23	0.00
	urban	0.27	0.04	0.18	0.21	0.30	0.00
	water	0.00	0.00	0.00	0.00	0.00	1.00



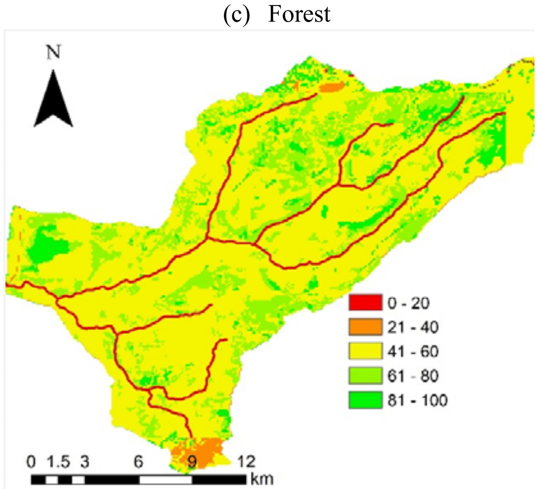
(a) Urban (b) Agriculture



(c) Forest



(d) Barren



(e) Grass

Figure 4 Conditional probabilities

The conditional probability maps from the Markov model for all land covers were used with the suitability maps for the 2032 projection. The 2032 projected areas were compared with the land cover coverages of 2002 and 2017. Urban areas in 2032 are expected to increase 93% compared to the 2017 built-up areas while agricultural lands are predicted to increase by 11% over the entire period. Agricultural and urban areas will be growing at the expense of forest and grasslands which will decrease by 5 and 73%, respectively while barren lands will increase slightly (0.4%) between 2017 and 2032 (Figure 5).

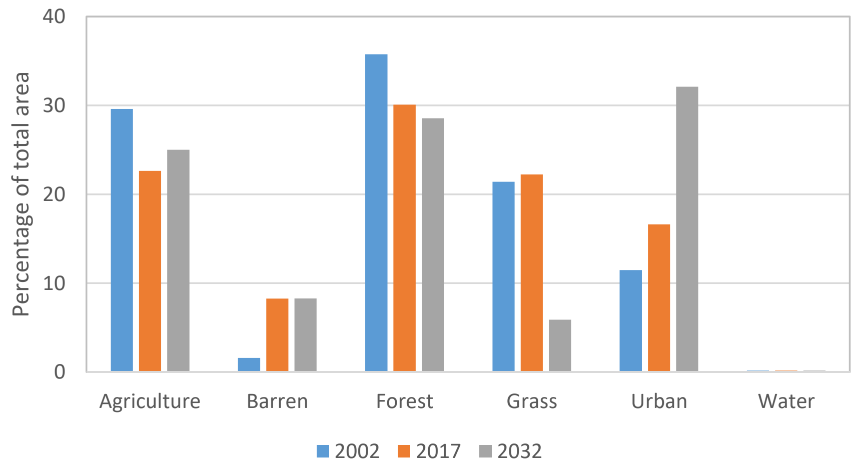


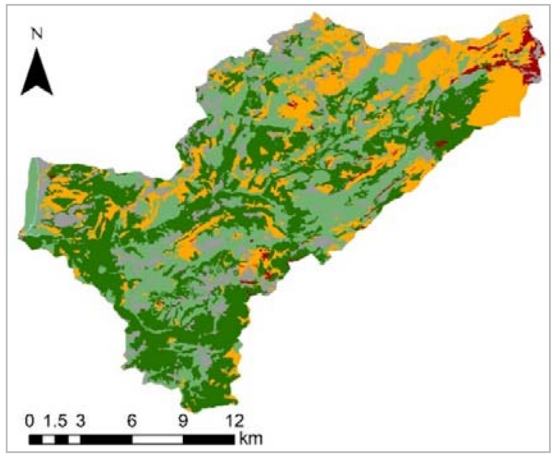
Figure 5 Past and future LCLU changes

The previous LCLU changes (till 2002) were mainly dictated by socio-political challenges during and after civil unrest that changed the demographic state of the watershed and the social state of residents. Starting in 1975 the study area was subject to a significant wave of population displacement whereby residents were forced to leave their houses and by early 2000, and in order to motivate their return to their lands, the government issued a decree permitting them to build on properties not meeting legal conditions for construction. This policy reflected the increase in urbanization between 2002 and 2017, affecting the projected 2032 increase in urban areas at the expense of forest and grasslands.

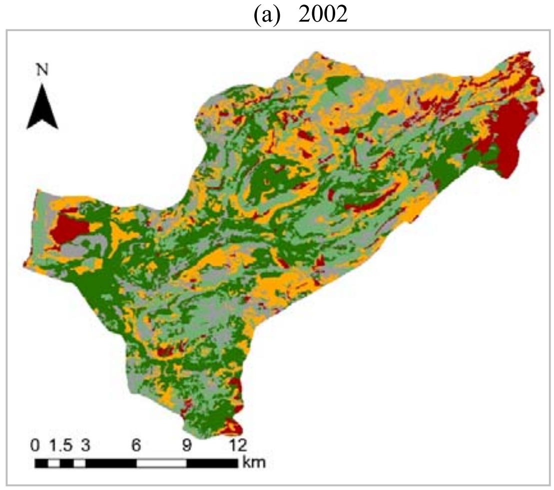
After the civil unrest phase, agriculture exhibited a significant decrease mainly because of land selling or the abandonment of agricultural lands by their owners. These lands were sold for economic and development purposes or left barren inducing rapid changes that increased urban areas and barren lands at the expense of forests and agricultural areas amidst the emergence of sectarian fears about social change. As a result, laws on the conservation and protection of agricultural areas from urban sprawl were imposed explaining the projected increase in these areas by 2032 compared to the decrease witnessed between 2002 and 2017.

The impact of the civil unrest and displacement was also shown in the significant increase in barren lands till 2017. This increase is mainly the result of the loss in agricultural areas after the displacement of inhabitants, abandoning large areas that were initially intended for agriculture. The increase in barren lands was restricted after 2017 reflecting the impact of the 2000 decree. The laws and regulations that were imposed to ameliorate agriculture and facilitate the coming back of displaced inhabitants started showing their impact on agriculture after 2017 and therefore stopped the increase of barren lands beyond 2017. Under normal conditions, most studies on the prediction of LCLU changes reflect an increase in urban areas at the expense of woodlands and forests (Liping et al., 2018; Kumar et al., 2014) due to human activities influenced by population growth and increase of individual needs.

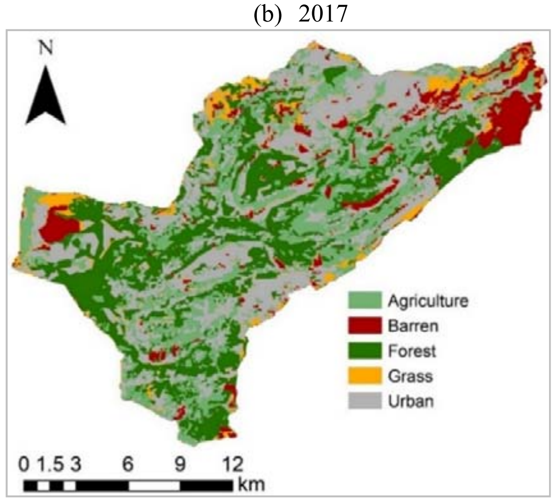
The spatial distribution of the 2032 land cover in the watershed was concluded from the combination of the weighted suitability maps and the conditional probability maps. It showed an increase of agricultural lands along the coastal region at the Western part of the basin and in the high mountainous region at the Eastern part of the basin. Agricultural lands and built-up areas spread also at the Northern part of the basin. Built-up areas were often found to be spreading near existing urban areas (Figure 6). The 2032 projected increase in built-up areas started showing in 2020 especially at the Northern parts of the watershed alongside pockets at the center and Eastern limit boundaries.



(a) 2002



(b) 2017



(c) 2032

Figure 6 LCLU simulations

2.3.2. Model Validation

The land cover model was validated by comparing the predicted coverage for 2010 (using the 1995 coverage) with the actual 2020. The results were statistically tested using a Chi-squared test to verify the suitability of the model. The test results returned a $\chi 2$ of 38 corresponding to a very low p-value (3.6 e-7) (Table 4). These outcomes confirm that no significant difference is present between simulated and actual values. Thus, the proposed model can be used in land cover forecast in the study area.

Table 4 Observed vs expected areas of land cover types

	Expected values E	Observed values O	O - E	$(O - E)^2$	$(O - E)^2/E$
Agriculture	71.53	85.65	14.12	199.37	2.79
Barren	57.86	15.35	-42.51	1807.10	31.23
Forest	76.07	92.1	16.03	256.96	3.38
Grass	62.56	64.47	1.91	3.65	0.06
Urban	65	73.52	8.52	72.60	1.12
Water	0.13	0.31	0.18	0.03	0.25

The Kappa index of agreement was assessed for a more accurate validation of the model because the consistency obtained by the Chi-square test does not necessarily reflect an agreement on the spatial distribution of the observed and simulated 2010 LCLU. This statistic evaluates the model according to the scale: less than 0 is a less than chance agreement, between 0.01 and 0.40 is a poor agreement, between 0.41 and 0.60 is a moderate agreement, between 0.61 and 0.80 is substantial agreement, and between 0.81 and 1.00 is an almost perfect agreement. The kappa index was generated through the classification accuracy of the observed and simulated LCLU maps of 2010. This was done by overlapping the output classes and the reference classes. The average kappa value was found to be 0.71 indicating that the LULC categories of the actual and simulated image were more than 71% similar (Table 5).

Table 5 Classification accuracy

Land type	Agriculture	Barren	Forest	Grass	Urban	Water	Average
Agriculture	66	0	0	5	0	0	0.21
Barren	5	15	13	5	20	0	0.17
Forest	2	0	70	0	4	0	0.23
Grass	5	0	2	55	0	0	0.19
Urban	7	0	8	0	50	0.1	0.20
Water	0	0	0	0	0	0.2	0.00
Average	0.26	0.05	0.28	0.20	0.22	0.00	

Kappa: 0.71; 95% c.i.: 0.06

The main limitation of the model is that under the Markov chain analysis the assumption that the factors of change in the past remain the same in the future. This limitation can be covered by improving the Multicriteria analysis of the cellular automata by introducing indicators covering all possible realms affecting land cover change ranging from environmental to socio-economic to climatic. By covering this features the results of this study reflected the usefulness of the proposed framework approach in predicting the future of LCLU. The combination of the Cellular Automata and Markov Chain Models was found reasonably accurate for projecting LCLU with the 71% overall accuracy. This framework can be applied for any LCLU projection with refinement of criteria corresponding to the proposed study area. It represents a basis for the analysis of urban sprawl, landscape and natural resource conservation.

2.4. Conclusion

Worldwide, LCLU is experiencing significant changes due to population growth and anthropogenic interventions to meet increased demand on resources. This study presented a simulation of the future LCLU using the combined Cellular Automata Markov model with developmental indicators that consider social, economic and environmental characteristics. Land cover maps of 2002 and 2017 were used as input to predict the 2032 LCLU. The study demonstrated the usefulness of the proposed framework approach producing an overall accuracy of 71% when comparing simulated maps to the past LCLU maps. Future simulations indicated an increase of 93% and 11% in urban and agricultural areas, respectively from 2017 till 2032, at the expense of forest and grasslands that decreased by 5 and 73%, respectively while barren lands changed slightly (0.4%). These changes are dictated mostly by socio-political factors following a long civil unrest period causing an abrupt increase in urban areas thereafter with agricultural lands continuously challenged by land selling or abandonment. The simulations equally confirmed that the natural equilibrium of the watershed is highly affected by population growth and associated pressures, social beliefs and experience. The spatial-temporal model provides decision makers with a quantitative description of the LCLU dynamic changes with corresponding direction and magnitude.

2.5. Acknowledgements

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CHAPTER 3

CAN SWAT FORECAST WATER AVAILABILITY IN MOUNTAINOUS WATERSHEDS WITH SNOWMELT?

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Abstract

The assessment of the hydrological response to projected changes in climatic variables is imperative for water resources management, especially in watersheds where snowmelt represents a significant source of runoff and is an important water reservoir. In this study, we modify the source code of the snow accumulation and melting algorithm of the Soil and Water Assessment Tool (SWAT) model with the objective to improve runoff simulations at a river basin scale, dominated by snow dynamics. A sinusoidal snowmelt function under the degree-day factor snow-melt method was adopted with its parameters calibrated based on historical data. Historical river flow simulations generated by the modified SWAT model were compared to those generated from the unmodified model. The results showed that the implemented modifications improved the runoff simulations significantly by better capturing the flow dynamics as represented by the daily flows and the daily variability in the flows during the snowmelt period. The modified model increased the Nash-Sutcliffe efficiency coefficient at three gauging stations from 64 to 79%, from 60 to 80% and from 70 to 75%. The correlation coefficient R2 also improved from 48 to 67%, from 48 to 69% and from 58 to 75% after the source code modification. Model differences in the future predictions (year 2032) of river flows under the RCP 4.5 scenario were also assessed. The results showed that while the two models predicted that the overall water availability will likely decrease in

the basin, future simulations with the modified snowmelt algorithm predicted that the drop in the water availability as compared to the baseline year (year 2008) will be less dramatic (24%) as compared to the predictions from the unmodified SWAT (31%). We argue that the proposed source code modifications to the snowmelt algorithm of SWAT provide better insights about future water availability in snow-dominated watersheds that are increasingly under stress due to population growth and climate change.

Keywords Snowmelt; SWAT; Climate Change; Eastern Mediterranean

3.1. Introduction

Most rivers have their headwater located at high elevations with snowmelt runoff invariably relied upon to meet water supply needs. In fact, mountains tend to receive a relatively large amount of precipitation, rain and snow, with snowmelt contributing significantly to annual runoff (Liu et al., 2020a; b; Pepin et al., 2015; Barnett et al., 2005). As such, the quantification of the hydrologic response to climate variations in mountainous catchments is critical towards improved water resources management, particularly in areas experiencing chronic water shortages associated with population growth and exacerbated with climate change impacts. In this context, several types of rainfall–runoff models with different characteristics are commonly used to assess water flow and storage at the watershed scale (Bouslihim, 2020; Pandey et al., 2020; Abbas et al., 2019; Singh, 2018; Beven et al., 1995). These models can also shed light on the impacts of anthropogenic activities and climatic changes on water resources and thus can assist in the planning and management of river basins (Pandey et al., 2017; Kalcic et al., 2015; Ravazzani et al., 2015; Tundisi & Tundisi, 2010). Several rainfall-runoff models have been tested to examine the impacts of climate variations on water availability (Brouziyne et al., 2017; Qiu et al., 2012)4. These models are most commonly classified according to their type, namely, lumped, semi-distributed, distributed, conceptual, empirical, and physical (Brouziyne et al., 2017) (Table 1).

Table 1 Types of rainfall-runoff models

Model type	***Description***	***Reference***
Lumped	Lumped models simulate the watershed as a single unit with no consideration to the spatial variability of geometric system characteristics; therefore outputs would be generated with limited reproduction of the reality and may result in increased model complexity and simulation time when applied to sub-watersheds	Singh, 2018; Carpenter, & Georgakakos, 2006
Semi-distributed	Semi-distributed models offer a compromise by combining the advantages of spatial representation with fewer data and lower computational effort	Bouslihim, 2020; Orellana et al., 2008;
Distributed	Distributed models divide the watershed into smaller entities and change the parameters spatially requiring finer resolution data and greater computational effort	Carpenter, & Georgakakos, 2006
Conceptual	Conceptual models are the compromise between empirical and physically based models. They consider the physical laws of the hydrologic cycle but in a simpler form and include semi-empirical equations	Bouslihim, 2020; Singh, 2018
Empirical	Empirical models rely on experiments and observed input-output relationships. They assume that the original conditions of the system do not change along the simulation	Devia et al., 2015; Aghakouchak, & Habib, 2010; Yang, & Wang, 2010
Physical	Physically based models are mechanistic and based on the spatial distribution of parameters describing the watershed. They rely on the hydrologic cycle with a logical structure resembling the real world.	Devia et al., 2015; Singh, 2018; Yang, & Wang, 2010

[4] Soil and Water Assessment Tool (SWAT), the Hydrologic Engineering Centre Hydrologic Modeling System (HEC-HMS), the Kinematic Runoff and Erosion Model (KINEROS), the Areal Non-point Source Watershed Environment Response Simulation (ANSWERS), the Physically Based Runoff Production Model (TOPMODEL), the Agricultural Non-Point Source model (AnnAGNPS), MIKE SHE, and the Stanford Watershed Model (SWM)/Hydrologic Simulation Package-Fortran IV (HSPF)

The choice of a hydrological model is often based on evaluating several suitability criteria, such as data availability, spatial resolution, computational needs, simulation time step, and output requirements (Pandey et al., 2017; Kalcic et al., 2015; Ravazzani et al., 2015). In the context of watersheds with snow, snowmelt is a significant contributor to peak runoffs; yet few models support snowmelt simulations (Table SM1). Some models with snowmelt simulation capabilities (e.g. HSPF, HEC HMS, & MIKE SHE) do not consider the impacts of the frozen ground on snowmelt, which is key towards improving the accuracy of runoff simulations. Other models (e.g. SWAT, HSPF) have preset snowmelt parameters representing specific geographic regions. In all cases, the hydrological models that do simulate snowmelt rely on two basic approaches namely, 1) the energy balance approach that is based on energy fluxes within the snowpack, which requires intensive data rarely available at mountainous regions; and 2) the degree day or the temperature index approach that has limited data requirements. The degree-day factor method assumes that temperature is a major driving force in snowmelt processes, whereas the energy balance assumes that temperature alone cannot adequately explain the processes of snowmelt (Yang et al. 2015; Debele et al., 2010). Whereas the former approach is simpler and easier to use, the latter is data intensive and sometimes un-easy to be applied due to inadequacy of the data. Several studies have compared the degree day factor method and energy balance approach under the snowmelting module (Qi et al., 2017; Meng et al., 2015). Qi et al., (2017) reported a significant improvement in the accuracy of snowmelt prediction when switching from the degree day factor method (NSE 0.44) to the energy balance approach (NSE 0.74). While Meng et al., (2015) found that the relative error increased from 0.13 to 0.17 when switching from the degree day method to the energy balance approach. Several studied have shown that the degree day approach can be as effective and accurate as the energy balance approach for small-scale watersheds (less than 300 km2) (Haddeland et al., 2011; Guðmundsson et al., 2009).

The applications of SWAT in snow-dominated watersheds outside of the US have shown low to poor model skill (Liu et al., 2020a; b). This is primarily due to the fact that the snow module is based on empirical values for North America (Liu et al., 2020a; Pandey et al., 2017). Few studies have attempted to improve the snowmelt simulations of SWAT through modifying the snow module or other input in the models. Namely, Qi et al., (2016) proposed a new physically-based soil-temperature module within SWAT to address the intermediary role of snow cover. They introduced three new parameters to the original empirical soil-temperature module. While the integration was reported to improve the accuracy of snowmelt simulations, it did not modify the snowmelt processes themselves (Qi et al., 2016). Qi et al., (2017) then tried to modify the snowmelt module through the modification of the energy balance snowmelt equations in an effort to improve the ability of the model to predict snowmelt in maritime regions. They reported that their modified model improved the accuracy of predicting snowmelt as compared with the non-modified degree day factor process that is default in SWAT (NSE from 0.71 to 0.8, and R2 from 0.75 to 0.84). Other studies have also attempted to explicitly modify SWAT's snowmelt module. Lui et al. (2020) and Duan et al. (2018) targeted the improvement of the snowmelt module relying on the degree day factor method. They reported that their modifications slightly increased the accuracy of the snowmelt simulations (NSE from 0.69 to 0.7 and from 0.71 to 0.75, R2 from 0.76 to 0.78 and constant to 0.78 respectively).

SWAT has been reported to be applied in Mediterranean watersheds with limited snowmelt simulations. As such it has been used to estimate soil erosion (Bouslihim et al., 2020), to assess the model performance in predicting water availability (Saade et al., 2021; Martínez-Salvador, & Conesa-García, 2020; Bouslihim et al., 2019). The studies indicated satisfactory precision in fitting observed and simulated flow. Saade et al. (2021) reported good model performance in Nahr El Kalb watershed in Lebanon for monthly flows with NSE values of 0.57 and 0.78, and PBIAS of 0.06% and -8.35%. Martínez-Salvador, & Conesa-García, (2020) reported also good results applied on Upper Argos River, in southeast Spain, for monthly and yearly discharge and sediment load with NSE of 0.62 and 0.52, PBIAS of -20.6% and 10.65%). Bouslihim et al. (2019) returned also satisfactory results when applying SWAT inn Morocco for Mazer and El Himer with an NSE value for discharge calibration of 0.65. All have addressed the prediction of discharges with limited snowmelt considerations but with satisfactory results. In short, the choice of the simulation refinement process of the snowmelt module in SWAT depends highly on the study area characteristics. In this context, many mountainous Mediterranean watersheds receive large amounts of snow and can benefit from a better estimation of runoff predictions by improving the snowmelt module in SWAT, which is the objective of this study. Accordingly, we modified the snowmelt module using the degree day factor method by changing the sinusoidal function of the snowmelt equation and implementing a recalibration process based on a long-term historical data on snow. We then conducted a parametric sensitivity analysis on the revised model and tested SWAT with and without source code modification at a mountain watershed scale along the

Eastern Mediterranean. The model was then used to predict future water availability and potential water deficit in the watershed as a function of future climate change.

Table 2 Comparison of commonly used hydrologic models

Model Indicators		***HSPF***	***TOPMODEL***	***HEC-HMS***	***SWAT***	***AnnAGNPS***	***MIKE SHE***	***KINEROS***	***ANSWERS***
Model type	Lumped	X							
	Semi-Distributed		X	X	X				
	Distributed					X	X	X	X
	Conceptual	X	X						
	Empirical	X				X			
	Physical			X	X		X	X	X
GIS interface		X		X	X	X	X	X	
Open source		X	X		X	X		X	X
Intensive Data & Computational need							X	X	X
Flow computation	Manning equation	X					X		X
	Curve number		X		X	X			
	Green Ampt				X				
	Penman-Monteith					X	X		
	Priestley-Taylor						X		
	St. Venant equations						X		
	kinematic wave							X	
Management option		X		X	X		X		
Snow modelling		X		X	X		X		

Snowmelt approach	Energy balance	X		X	X		X		
	Degree day	X		X	X		X		
Reference		Johanson et al., 1980; Bicknell et al., 1997	Beven et al., 1995	Feldman, 2000	Parsons et al., 2004; Arnold et al., 1998	Bingner et al., 2018	DHI, 2017	Smith et al., 1995	Bouraoui & Dillaha, 2000

3.2. Methodology

3.2.1. Study Area

The study was conducted using data collected from a 290 km2 mountainous watershed along the Eastern Mediterranean (Damour, Lebanon) (Figure 1). The watershed's elevation ranges from 0 m at sea level (river mouth), to 1,980 m above sea level at the peak of the mountain (Massoud, 2012). The watershed encompasses several mountain ranges and plains lying within a river basin in addition to side streams, small and large tributaries with steep slopes, canyons, cliffs, and deep valleys reaching 700 m in some locations, along with high reliefs in many others (Khair et al., 2016). Nearly 50% of the watershed falls above 900 m elevation and ~25% above 1100 m, making these locations susceptible to snow and subsequent snowmelt. Snowmelt in the watershed contributes significantly to Spring flows (Koeniger et al., 2017; UNDP, 2014).

Figure 1 Study area

The area is characterized by a Mediterranean climate, with moderately warm and dry summers and moderately cold, windy, and wet winters with almost 80 to 90% of total precipitation occurring between November and March with scattered rainfall events beginning in October and ending in May (Khair et al., 2016). Temperatures decrease with elevation causing a shift from rain to snow mostly at elevations above 1000 m. Snow fall extends from November to April. The study area is dominated by a snow hydrologic regime influenced by accumulation and melting processes. Snowmelt occurring between March and May constitutes a significant source of fresh water for the coastal region with a Snow-Water Equivalent (SWE5) that is moderately constant (~ 32 cm) in the winter and reaching its highest levels (~ 114 cm) between mid-February (lower elevation 1600–1980 m) and mid-March (regions above 1980 m). Elevations lower than 1600 m encounter rain on snow events leading to quicker snowmelt (Fayad, 2017). Forest, green natural lands and agricultural areas cover more than 90% of the watershed (forest: 43%, green natural lands: 23%, agricultural areas: 26%), with agriculture consisting mainly of banana, citrus fruit trees, field crops, vineyards and protected produce. Soils consist of loamy sands and sandy loams, with non-calcareous gleysol/clay anthrosols/arenosol and aridic and shallow leptosol (Darwish, 2012).

3.2.2. Model description and setup

The SWAT model was used to simulate long-term hydrological processes in the study area. SWAT is a hydrologic model developed by the United States Department of Agriculture (USDA). It is physically based and a semi-distributed agro-hydrological model (Arnold et al., 2011). SWAT is able to concurrently simulate hydrological processes, soil erosion, chemical processes, agricultural management measures and biomass changes. It is able to catch the long-term impacts of climate change and can

[5] $SWE = HS\rho_s/\rho_w$; HS is the snow height in cm; ρ_s is the density of snow g/cm^3; ρ_w is the density of water 1 g/cm^3

simulate land-use management measures on water, sediment, and agrochemical production (Liu et al., 2020a; Pandey et al., 2020; Varga et al., 2016; Gassman et al., 2014; 2010; Arnold et al., 2012; Arnold et al., 2011; Neitsch et al., 2011; Refsgaard et al., 2010). Simulations are done continuously over an extended period of time in large and complex basins as well as small catchment areas (Arnold et al., 2011; Neitsch et al., 2011). Its wide-scale adoption has been promoted by the fact that (1) it has an integrated geographic information system (GIS) interface; (2) its code is open-source, (3) it includes a snowmelt module that can be based either on the energy balance or the degree day method, while accounting for the presence of frozen ground modules, and (7) detailed documentation and user-support are readily available (Chiphang et al., 2020; Liu et al., 2020a; b ; Pandey et al., 2020; Abbas et al., 2019; Andrade et al., 2019; Pandey et al., 2017; Monteiro et al., 2015; Kalcic et al., 2015; Ravazzani et al., 2015). In its latest version, SWAT can simulate the long-term impacts of climate change on water and land use. Its GIS interface allows the delineation of the basin as well as the definition of stream flows and hydrological units (HRU). Its main spatial inputs include a digital elevation model (DEM), land-use/land-cover (LULC), soil and meteorological data (Winchell et al., 2009; Jayakrishnan et al., 2005). Based on topography, land use and soil type, a river basin is divided into sub-basins, which are further divided and grouped into smaller HRUs with similar land use, slope and soil type (Arnold et al., 2011; Neitsch et al., 2011). The main output in the context of this study was the water yield6.

[6] Water yield = Surface runoff generated in the watershed + Lateral flow contributing to streamflow in the watershed + Amount of lateral flow and ground water flow contributing to main channel from HRU – Transmission losses – Pond abstraction

The basis of the hydrologic calculations in SWAT is the water balance expressed in Equation 1 (Arnold et al., 2012; Neitsch et al., 2011).

$$SW_t = SWo + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}) \quad (1)$$

Where SWt is the final soil water content in mm H2O, SW0 is the initial soil water content in mm H2O, t is the time in days, Rday is the precipitation on day i in mm H2O, Qsurf surface runoff on day i in mm H2O, Ea is the evapotranspiration on day i in mm H2O, wseep is the amount of water entering the vadose zone from the soil profile on day i in mm H2O, and Qgw is the return flow on day i in mm H2O.

In this study, a 50 m x 50 m resolution DEM, spatially referenced to the WGS 1984 UTM-Zone 36N was used. The DEM was processed to generate several sub-basin properties such as channel slope, length and width. The DEM was also used to define flow direction and accumulation, create the stream network, choose the watershed outlets, delineate the watershed, and calculate sub-basin parameters (area, elevation, location, and slope). The country's 2017 LULC was used (CNRS 2017 LULC map) with reclassification to ensure that the LULCs types in the study area corresponded to those defined in SWAT. Similarly, the country's 2012 soil map (Darwish, 2012) was used in the GIS layers representing the soil properties of the study area. The LULC and soil data were then analyzed with slope information to generate HRUs (Arnold et al., 2011; Neitsch et al., 2011; Winchell et al., 2009). Monthly precipitation data were obtained from rainfall stations located in the watershed or within its proximity (Table 3). Daily average, maximum and minimum temperatures were gathered from the nearby Beirut Airport and a 6.5oC decrease in temperature was used for every 1000 m change in elevation.

Table 3 Rainfall Stations

ID	Name	Latitude	Longitude	Elevation (m)	Period of Available Record	Location
A	Jezzine	33º:32.639 N	35º:34.263 E	1070	2001-2010	In the WS
B	Barouk	33º:42.320 N	35º:40.709 E	1114	2000-2009	Near the WS
C	Deir El Qamar	33º:41.853 N	35º 33.875 E	850	2000-2010	In the WS
D	Jbaa El Chouf	33º:37 N	35º:38 E	1130	1991-2009	Near the WS
E	Meshref	33º:42.821´ N	35º:29.065´ E	395	2002-2010	In the WS
F	Dahr El Baydar	33º:48.565´ N	35º:46.073´ E	1516	1999-2010	Near the WS

*WS Watershed

In the study area, terraces are common in agricultural lands with slopes exceeding 4%. Terracing was simulated in the model by adjusting the erosion and runoff parameters represented by the Universal Soil Loss Equation (USLE) parameters on land management practices, the curve number, and the slope length (Haan et al., 1994). The curve number corresponding to the combination of vegetation and soil type was chosen according to the runoff curve number of agricultural areas. The maximum distance between terraces was set at 10m according to satellite images verified by field visits and HRUs were edited according to their topography, land use, and soil properties to account for terracing.

3.2.3. SWAT Snow Melting Module

The SWAT snowmelt module is separated into two parts, namely snowpack and snowmelt. Snowpack activation is based on the critical parameters that define the mean air temperature threshold that dictated the occurrence of snow. SFTMP represents the mean air temperature at which precipitation is equally likely to fall as rain or as snow/freezing rain. The precipitation would therefore be classified as snow when the mean daily air temperature is less than the snowfall temperature. Under such events, the liquid water equivalent of the snow precipitation would be added to the snowpack. This module relies on the snowpack mass balance:

$$SNO_i = SNO_{i-1} + R_{sfi} – E_{subi} - SNO_{mlt_i} \qquad (2)$$

Where SNOi is the snow equivalents at day i, SNOi-1 is the snow equivalents at day i-1, Rsfi is the snowfall equivalent of day i, Esubi is the evaporated snow equivalent of day i, and SNOmlti is the melted snow equivalent of day i.

The snowmelt module is activated when the snow cover conditions and the snowmelt temperature threshold is exceeded. In this study, the snowmelt module was based on the degree-day factor method. Under this method, a sinusoidal equation is used for snowmelting (Neitsch et al., 2011). This approach assumes that the potential snowmelt rate varies between a maximum and a minimum following a sinusoidal function based on the day of a year. The snowmelt runoff is derived from the snow cover condition and the temperature threshold of the snowmelt. A snowmelting temperature threshold is usually set. When the temperature rises by 1 ◦C, the melted snow water equivalent is a fixed value. When the snow is completely melted, the resulting water forms the vertical depth of the water layer. The formula for snow melting calculation is presented in Equation 5 (Neitsch et al., 2011).

$$T_{snow_i} = T_{snow_{i-1}} (1 – T_{IMP}) + T_{av_i} T_{IMP} \qquad (3)$$

$$SNO_{mlt_i} = b_{mlt_i}\, sno_{cov_i} ((T_{snow_i} + T_{max_i})/2 – SM_{TMP}) \qquad (4)$$

$$b_{mlt_i} = \frac{SMF_{MX} + SMF_{MN}}{2} + \frac{SMF_{MX} - SMF_{MN}}{2} \text{ x} \sin\left(2\pi \frac{i-81}{365}\right) \quad (5)$$

Where Tsnowi is the temperature of the snowpack at day i, TIMP is the snow temperature lag factor, and Tavi is the mean air temperature at day i. SNOmlti is the amount of snowmelt at day i, bmlti is the melt factor for day i, snocovi is the fraction of the HRU area covered by snow, SMFMX is the snow melt factor for 21 June (mm H2O °C−1 d−1), SMFMN is the snow melt factor for 21 December (mm H2O °C−1 d−1), Tmaxi is the maximum air temperature at day i and SMTMP is the snow melt base temperature (Arnold et al., 2012; Arnold et al., 2011; Neitsch et al., 2011).

The SWE (Snow-Water Equivalent) is estimated using a linear function with the snowmelt factor method based on the mass balance for snow (Equation 6) (Neitsch et al., 2011).

$$SWE_i = SWE_{i-1} + R_{day_i} - E_{sub_i} - SNO_{mlt_i} \quad (6)$$

Where SWEi is the snow water equivalent at day i in mm H2O, Rdayi is the amount of snowfall in day i in mm H2O, Esubi is the snow sublimation at day i in mm H2O and SNOmlti is the amount of snowmelt in day i in mm H2O (Arnold et al., 2012; Arnold et al., 2011; Neitsch et al., 2011).

3.2.4. Source code modification

The SWAT model was used for calibration and future prediction of water availability with and without modification of its source code to account for snowmelt and its impact on runoff simulations within the context of the study area. In the initial simulation, the default of the SWAT snowmelt module code was adopted with changes only made to the default values to better represent the test area. The second simulation focused on modifying the snowmelt algorithm (Equation 5) and its corresponding parameters7 (Figure 2).

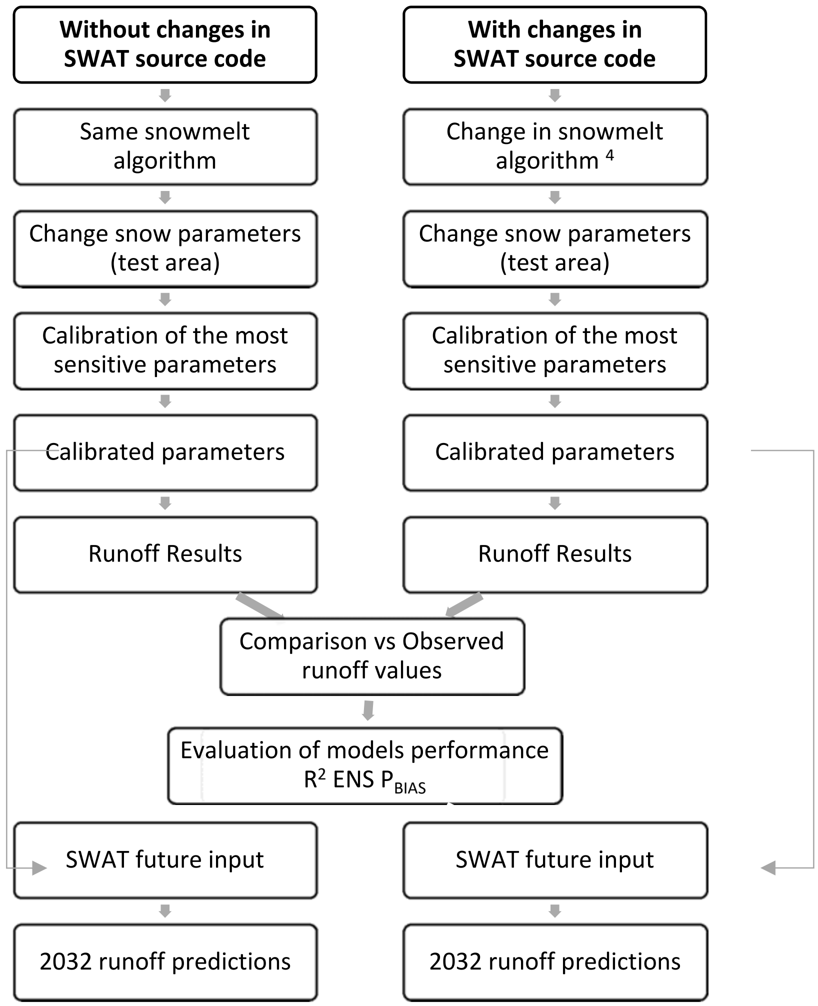

Figure 2 Overall Modeling Framework

A. *Snow parameters*

The snow density is usually calculated from the snow-water equivalent and the depth of snow (i.e. snow density = SWE/depth). In this study, the snow density ranged between 450 and 520 kg/m3 (Fayad, 2017; DAHNT/NOVEC, 2016). The snowfall

[7] Snowfall temperature, snowmelt base temperature, maximum melt factor, minimum melt factor, snowpack lag temperature (i.e. influence of the snowpack temperature of the previous and current day), and the minimum snow water content.

temperature of the area is usually around 2 oC and the snowmelt temperature is around 0.5 oC (Fayad, 2017; DAHNT/NOVEC, 2016) (Table 4). The snowpack lag temperature corresponds to 100% snow cover and represents the threshold of snow water content above which 100% of the surface is covered by snow. The fraction of the snow volume corresponding to 50% snow cover is usually represented by an exponential increase as a function of the snow water equivalent index (i.e. SWE/SWEi, where SWEi is the snow water equivalent with 100% of the area covered with snow). According to the available snow data in the study area the best fit is for the 50% area coverage corresponding to a 0.3 ratio of snow depth at 100% coverage. Accordingly the percentage of snow cover area is defined:

$$\mathrm{SNO_{covi}} = \frac{SNO_i}{\mathrm{SNOCOVMX}} \left[\frac{SNO_i}{\mathrm{SNOCOVMX}} + \exp\left(cov_1 - cov_2 \frac{SNO_i}{\mathrm{SNOCOVMX}} \right)\right]^{-1} \quad (7)$$

Where SNOcovi is the percentage of snow cover area at day i, SNOCOVMX is the equivalent to the minimum snow content when snow coverage is 100% and cov1 and cov2 are the shape coefficients of the curve. The mean air temperature of the previous day affects the snowmelt compared to the current day. High elevations are accompanied by low atmospheric pressure and therefore high relative humidity that may cause a warmer feeling and therefore the previous day will affect the snow-melting of the current day. The influence of consecutive days (i and i-1) on the snowpack temperature is controlled by the lagging factor (Equation 3).

The regions of the study area covered with snow, returned a snow depth higher than 30 cm most of the time. When snow depth is higher than 30cm (deep snow) the snow temperature is highly affected by air temperature. Due to the lack of temperature data for snow melt, an approximation of some available data showed that every 1 degree difference between the snow temperature at day i and its temperature at day i-1 corresponds to a 1.4 degree difference between the temperature of snow and air at day i. This assumption returned a 0.7 lag factor, higher than 0.5, and representing the pronounced impact of air temperature on the snow temperature compared to the impact of snow temperature of the previous day (Fayad, 2017; DAHNT/NOVEC, 2016; Arnold et al., 2011; Alexander, & Gong, 2011; Decker et al., 2003) (Table 4). The minimum snow water content that corresponds to 100% snow cover (SNOCOVMX) was acquired from the combination of the historical snow data and satellite imagery. Satellite images were extracted from Landsat 7 for the period between 2015 and 2016 corresponding to the period of historical snow data availability. The Normalized Difference Snow Index (NDSI)8 was calculated from the Landsat images based on bands 2 and 5 in Landsat 7 to identify the snow cover while ignoring cloud cover. NDSI = (Green - SWIR) / (Green + SWIR) where Green refers to pixel values from the green band and SWIR refers to pixel values from the shortwave infrared band with the NDSI range for snow between 0.4 and 1 (Riggs et al., 1994). Additionally, data from snow courses established by the government and that represent permanent stations to measure snow parameters were used. These stations included the Cedars (1800 - 2900m asl), Mzar (1350 - 2350m asl), and Laqlouq (1350-2350m asl) stations, with a total of 649 snow course measurements. Each snow course was associated with snow depth, density and snow water content at each measurement date for each water year. For the dates with the lowest snow depth, Landsat TM images (Landsat 7) were analyzed to determine the date with 100% of the area covered with snow combined with a minimum snow depth. The dates with 100% of area covered with snow were accordingly delineated and the minimum corresponding

[8] The NDSI employs Landsat Thematic Mapper (TM) visible (0.56 /spl mu/m) and near-infrared (1.65 /spl mu/m) data. The snow algorithm uses the NDSI in combination with near-infrared reflectance to identify snow cover and discriminate snow from clouds.

snow water equivalent was chosen from the available snow data of the available snow data sets. Therefore, the SNOCOVMX was found to be 10.2 cm (Table 4).

Table 4 Snow parameters

Snow parameters	Value
Snow density, kg/m^3	450 - 520
Snowfall temperature, °C	2
Snowpack lag temperature, °C	0.7
Snowmelt temperature, °C	0.5 °c
Minimum snow content when 100% snow coverage	10.2

B. Snowmelt equation

In SWAT, the maximum and minimum melt factors are set according to the North American values and considered to be occurring on the 21st of June and 21st of December respectively. As such, the source code was modified9 to account for the snow in terms of the snow melting. The snowmelt period was extended from early March to early June, with the minimum of snowmelt occurring at the beginning and end of the period and the maximum occurring around the middle of the period (April-May) (Fayad, 2017; DAHNT/NOVEC, 2016). Accordingly, the pre-imposed dates in the model were changed. The values of the degree-day factor (mm◦C−1 d−1) were estimated based on the snow water equivalent and the air temperature (Equation 9).

$$\mathrm{DDF} = \frac{\mathrm{SWE}}{\sum_1^N (T_B - T_t)} \qquad (9)$$

Where SWE is the snow water equivalent in mm, TB is the average daily air measured temperature in oC and Tt is the average daily temperature threshold for snowmelt in oC. N is the number of days for all the snow to melt The SWE was

[9] The source code of SWAT 2012 revision 664 was accessed from http://swat.tamu.edu/ and modified in Fortran 2013.

acquired from a data set at three nearby locations10 for the years 2015-2016. The data represent typical snow data for surrounding mountains with unexisting measurements (Fayad, 2017).

While a small decline in rainfall between 1967 and 2009 has been reported at a nearby catchment11, a significant decrease in the snow residence time from 110 days to 85 days (DAHNT/NOVEC, 2016) has been reported in Lebanon, an evidence that climatic changes have resulted in higher melting rates. Snowmelt is not only driven by air temperature but mostly by the solar radiation that affects significantly the ablation of ice for its upper and lower parts and the lateral melting. In this context, the melting of snow occurs when the air temperature is above 0oC and the longwave outgoing radiation falls above 316 W/m2 (Hock, 2005; 2003). Coupled with the average of snow parameters measurements (snow depth, density and snow water content) from the three surrounding locations, the snow-melting period extended from January 23 to April 26 with the maximum around April 4 (Fayad, 2017) with an SWE of 79.2 and 96.9 cm, respectively. By applying the DDF formula (Equation 9) applied on the corresponding SWE and temperatures across all snowmelt periods, the minimum and maximum snow-melting factors were 2.2 and 2.8. The modification of the snowpack module in SWAT targets mainly the amount of snowmelt at day i formula (Equations 5).

In this method, the potential snowmelt rate varies between the minimum and the maximum occurring in January 23 and April 4 following a sinusoidal function based on the day of the year. The change of time in the predefined formula of the melt factor is

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[10] Permanent sites established by the government to measure snow parameters (https://doi.org/10.5281/zenodo.583733): Cedars (1800 - 2900m asl), Mzar (1350 - 2350m asl), and Laqlouq (1350-2350m asl) at about 40 to 120 kms North of the study area with a total of 649 snow course measurements (30 different snow courses during snow season 2015 and 2016 with an average revisit time of 11.4 days)

[11] Nahr Ibrahim about 50 kms north of the study area

81 (Equation 5), which corresponds to 81 days and calculated based on the minimum and maximum occurring in North America. In our study area, the minimum corresponds to the 23rd day of the year and the maximum to the 95th day. According to the principle that the snowmelt factor should be the maximum value of 1 on the 95th day, the sinusoidal function was modified to generate the maximum snowmelt at the 95th day and the minimum at the 23rd day (Equation 5 modified to Equation 10) and the source code was modified accordingly and re-compiled.

$$\frac{SMF_{MX}+SMF_{MN}}{2}+\frac{SMF_{MX}-SMF_{MN}}{2}\ \mathrm{x}\ \sin\left(5\pi\ \frac{131-i}{365}\right) \tag{10}$$

3.2.5. Model calibration and validation

Calibration aims at reducing simulation uncertainties and can be conducted manually or through automated programs such as the SWATCUP (SWAT Calibration and Uncertainty Program) with several optimization algorithms and calibration procedures including GLUE (Generalized Likelihood Uncertainty Estimation), ParaSol (Parameter Solution), and SUFI (Sequential Uncertainty Fitting) (Abbaspour et al., 2018; Abbaspour et al., 2007; Van Griensven & Bauwens, 2003; Van Liew et al., 2007). In both manual and automated calibration, the model outputs are compared to observed data and parameters are varied until the best fit between the two sets of data is reached. The next step is model validation to ascertain that it is capable of performing acceptably accurate simulations. During this process, the model runs with the calibrated parameters for different times and same spatial frame or same time and different spatial frame, while comparing the predicted and observed data. Note that the calibration and validation should include observed data of dry and wet years (Kamamia et al., 2019;

Ahmadisharaf et al., 2019; Abbaspour et al., 2018; Almeida et al., 2018; Arnold et al., 2012; Abbaspour et al., 2007).

In this study, the SUFI2 module of SWAT-CUP version 5.1.6 was used to examine the sensitivity, calibration, and validation of the model. This sequence starts with identifying the most sensitive parameters upon which to base the calibration. The sensitivity analysis defines the rate of change in the output for a specific variation in certain parameters. This procedure can be carried out globally (allows all parameter values to change simultaneously) or locally (corresponds to one parameter change at a time) (Almeida et al., 2018; Arnold et al., 2012; Abbaspour et al., 2007). Therefore, global sensitivity considers the effect of change of one parameter on the others but requires a large number of simulations with 15 parameters used for the initial configuration (Table 4) and held within realistic ranges. These parameters were chosen according to their occurrence among the main reported calibration parameters for variable flow rate (Ahmadisharaf et al., 2019; Abbaspour et al., 2018; Almeida et al., 2018; Blainski et al., 2017; Durães et al., 2011; Muleta & Nicklow, 2005). A sensitivity ranking was then performed based on the t-stat or the ratio of the parameter coefficient by the standard error and the p-value that reflects the rejection of the hypothesis that an increase in the parameter value provides a significant increase in the variable response. Therefore, the most sensitive parameters were ranked according to the highest t-stat and lowest p-value.

Table 5 Calibration parameters

Parameter	Meaning	Range	Reference
ALPHA_BF	Baseline flow recession constant (days)	0-1	Pandey et al., 2020; Arnold et al., 2012
CANMX	Maximum amount of water intercepted by vegetation (mm)	0-100	
CH_K2	Effective hydraulic conductivity of the channel (mm h-1)	-500	
EPCO	Factor of compensation of water consumption by plants (dimensionless)	0-1	
ESCO	Soil water evaporation compensation factor (dimensionless)	0-1	
GW_DELAY	Time interval for recharge of the aquifer (days)	0-500	
GW_REVAP	Coefficient of water rise to saturation zone (dimensionless)	0.02-0.2	
GWQMN	Water limit level in the shallow aquifer for the occurrence of base flow (mm)	0-5000	
REVAPMN	Aquifer water depth for the occurrence of water rise to the unsaturated zone (mm)	0-500	
SOL_AWC	Soil water storage (mm/mm)	0-1	
HRU_SLP	Average slope steepness (m/m)	0-1	Abbaspour et al., 2018; Arcement, & Schneider, 1989; Chow, 1959
SLSUBBSN	Average slope length (m)	10-150	
CH_N2	Manning coefficient for the main channel (s m-0.33)	-0.31	Kamamia et al., 2019; Arcement, & Schneider, 1989; Chow, 1959
OV_N	Manning’s value for overland flow	0.01-30	Arcement, & Schneider, 1989; Chow, 1959
SURLAG	Delay time of direct surface runoff (days)	1-12	Abbaspour et al., 2018; Almeida et al., 2018

The initial calibration and simulation used default values of SWAT snow parameters. The modified version of the source code was then run after changing the snow parameters. Both simulations were compared with field-flow measurements at three gauging stations with available monthly discharge measurements along the river[12] (Figure 3). Monthly discharge data between 2006 and 2009 were used for the initial calibration that consisted of 500 simulations until the objective function was reached (Nash-Sutcliffe efficiency coefficient > 0.6 for satisfactory results). The coefficients of determination (R2) and Nash-Sutcliffe (ENS) efficiency and the Percent Bias (PBIAS) were used to evaluate the model (Table 5) (Arnold et al., 2012). The parameters were then tested with available data that were not used for the calibration process, namely the years 2004 and 2005, to complete the validation process (Arnold et al., 2012).

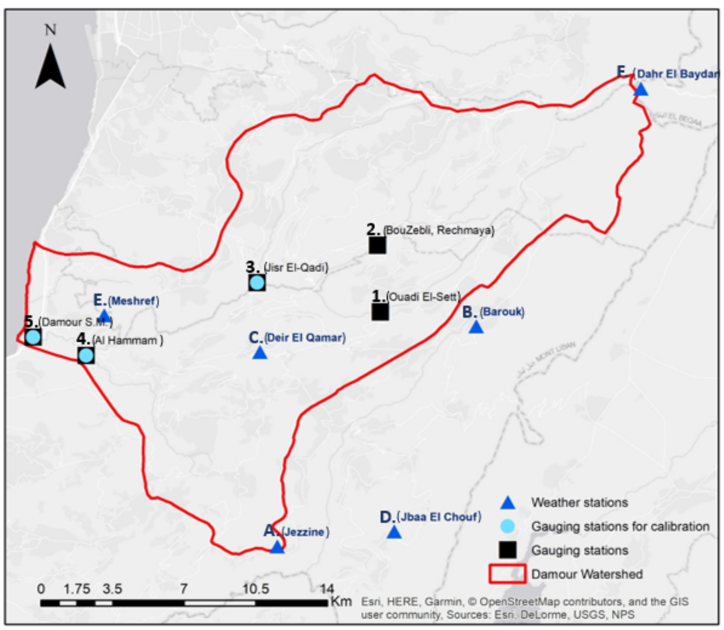


Figure 3 Gauging stations within or near the study area watershed

Table 6 Range of model efficiency parameters for river flows

NSE	PBIAS	R^2	Classification
$0.75 < NSE \leq 1.00$	$P_{BIAS} \leq \pm 10$	$0.75 < R^2 \leq 1.00$	Very good
$0.60 < NSE \leq 0.75$	$\pm 10 < P_{BIAS} \leq \pm 15$	$0.60 < R^2 \leq 0.75$	Good
$0.36 < NSE \leq 0.60$	$\pm 15 < P_{BIAS} \leq \pm 25$	$0.50 < R^2 \leq 0.60$	Satisfactory

[12] 3. Jisr El-Qadi, 4. Al Hammam, 5. Damour Sea Mouth

$0.00 < NSE \leq 0.36$	$\pm 25 < P_{BIAS} \leq \pm 50$	$0.25 < R^2 \leq 0.50$	Bad
$NSE \leq 0.00$	$\pm 50 \leq P_{BIAS}$	$R2 \leq 0.25$	Inappropriate

NSE Nash-Sutcliffe; P_{BIAS} Percentage bias; R^2 Correlation coefficient; Moriasi et al. (2007) and Van Liew et al. (2003)

3.2.6. Water availability predictions

Future LULC data were obtained from an integrated Markov chain analysis with cellular automata approach using a GIS platform that was used for 2002 and 2017 to predict the linear trend of the watershed land cover change in 2032 (Figure 4).

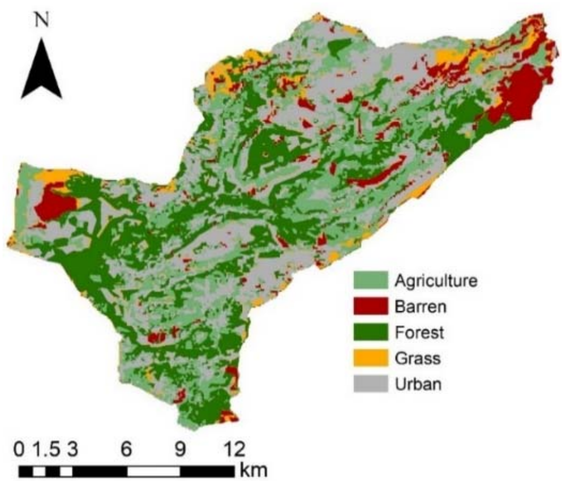


Figure 4 Land use-land cover projection for 2032

Future Climate data were obtained from regional high resolution dynamical downscaling targeting extreme conditions of hottest and driest years (El Samra et al., 2017a; b) for the study region. Average predicted temperature and precipitation (i.e. rain and snow) for the coast and mountain areas are presented in Table 6.

Table 7 Projected temperature and precipitation

Year	2008	2020	2029	2040	2050
Temperature (°C)					
Coast	18.70	17.84	18.25	17.97	17.69

Mountains (> 900 m)	12.78	11.99	12.34	12.32	11.70
Precipitation (mm)					
Coast	686	830	563	490	478
Mountain (> 900 m)	1046	1153	938	792	795

Six weather stations13 were used in the calibration process (Figure 2). The 2032 precipitation was extracted from the regression applied on the projected data (Table 6) corresponded to 520 and 900 mm on the coast and mountain, respectively. The temporal distribution of precipitation was extracted from years with similar total precipitation (Figure 5). The projected daily average, maximum and minimum temperature were gathered from the future prediction in coastal area while applying the 6.5oC decrease in temperature every 1000m (Figure 6).

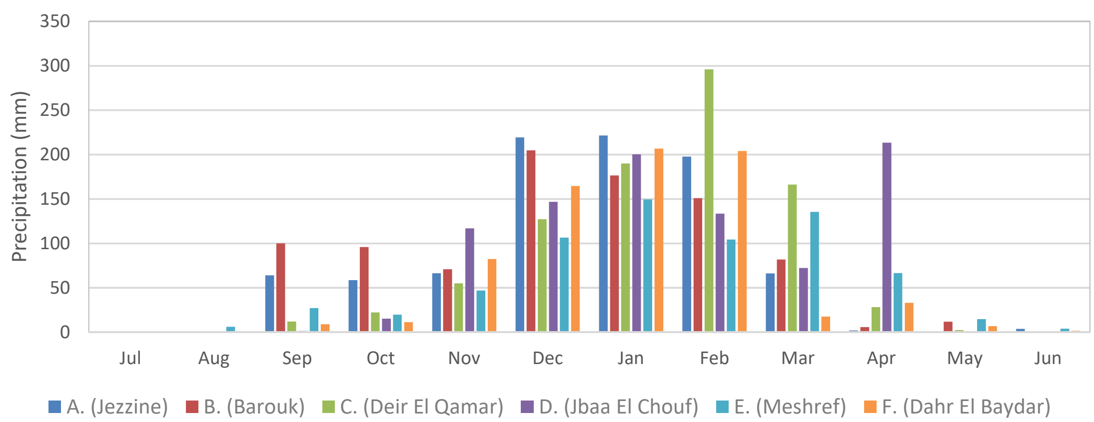


Figure 5 Monthly predicted precipitation for 2032

[13] One coastal (**E.** Meshref) & five mountainous (**A.** Jezzine, **B.** Barouk, **C.** Deir El Qamar, **D.** Jbaa El Chouf, and **F.** Dahr El Baydar)

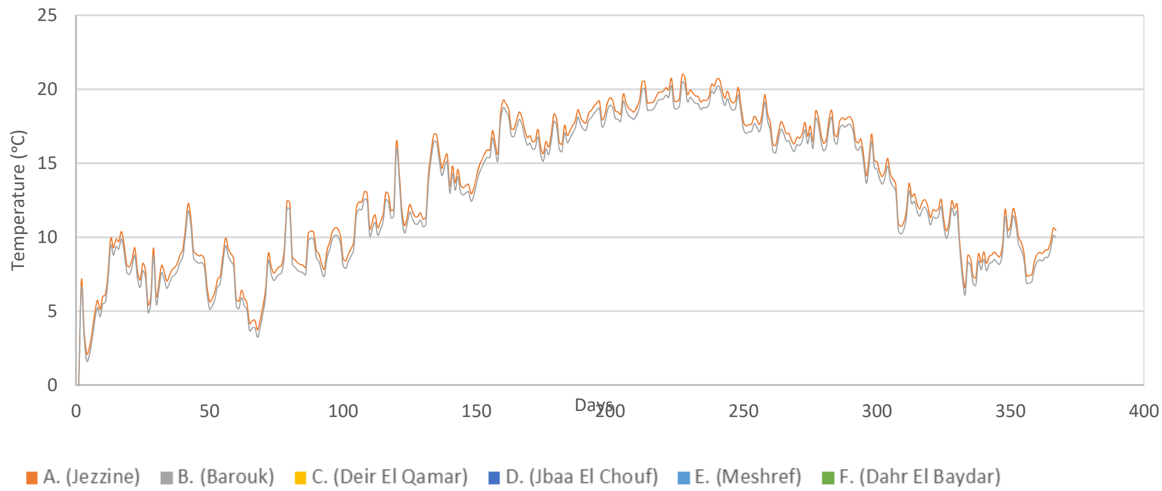
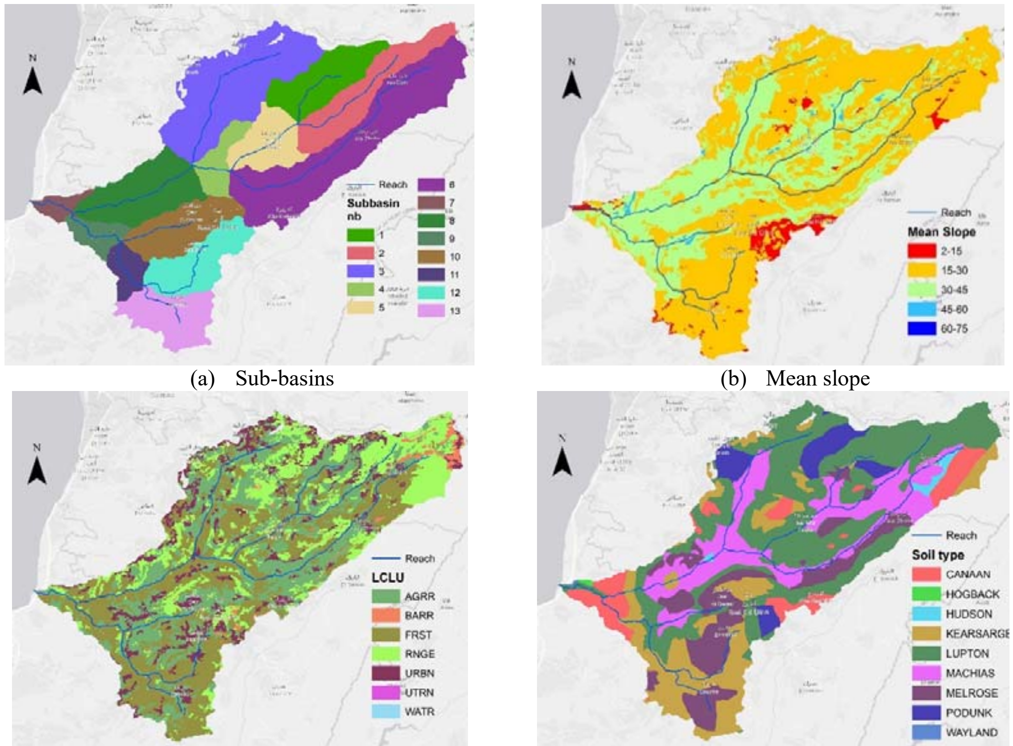


Figure 6 Average daily temperature for 2032

3.3. Results and Discussion

3.3.1. Model setup

Figure 6 presents the SWAT synthesized input parameters showing 13 sub-basins generating 270 HRUs that are clustered similarly between agricultural lands, forest, range grasses, and urban areas. The slope ranged between 2.3 and 73% with only one HRU associated with an extremely high mean slope (i.e. 73%) and is assigned to be barren in the LCLU of 2017. Most agricultural areas have slopes above 4%, and hence they are terraced. Agricultural areas were mostly located near watercourses with soil types dominated with non-calcareous arenosol or clay anthrosols or gleysol corresponding to the Machias, Melrose and Lupton user soils in SWAT. Five sub-basins (1, 2, 3, 4, 6) have elevations above 900m with a high likelihood to receive snowfall during the winter season.



(a) Sub-basins (b) Mean slope
(c) LCLU (d) Soil

Figure 7 SWAT synthesized input data

*AGRR Agricultural land, BARR Barren land, FRST Forest, RNGE Range-Grasses, URBN Urban areas, UTRN Transportation, WATR Water

3.3.2. Model calibration

The sensitivity of the model to parameters was ranked according to the p-value and t-stat. As shown in Figure 8, the most sensitive parameters were CH_K2, GWQMN, ALPHA_BF, SURLAG, REVAPMN, and GW_DELAY and chosen for p-values less than 0.3 and t-stats higher than 1.5 absolute. These parameters are related to the flow in the channel (CH_K2), water in the soil (GWQMN and REVAPMN) and the groundwater flow (ALPHA_BF and GW_DELAY) (Figure 7). The calibration of those parameters resulted in the values shown in Table 7.

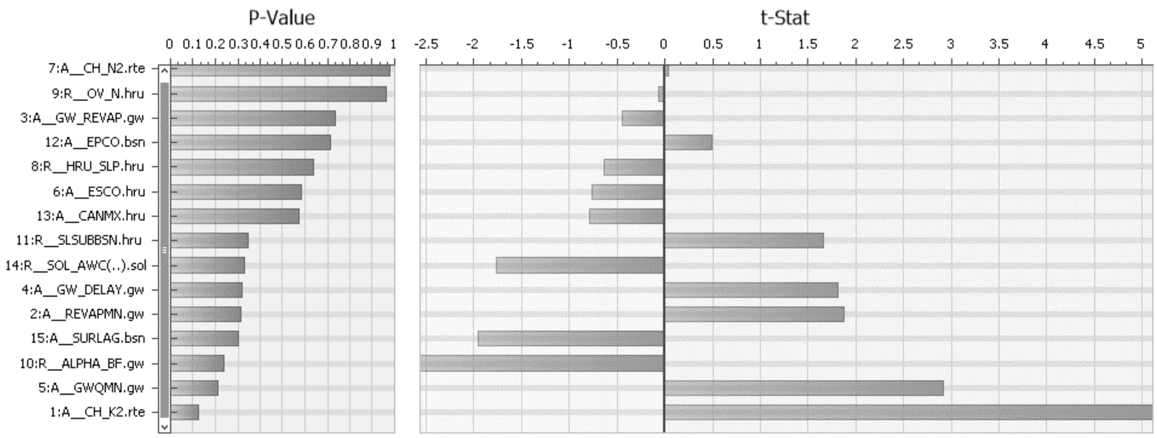


Figure 8 Calibration parameters sensitivity

ALPHA_BF: Baseline flow recession constant (days);
CANMX: Maximum amount of water intercepted by vegetation (mm);
CH_K2 Effective hydraulic conductivity of the channel (mm h-1);
EPCO: Factor of compensation of water consumption by plants (dimensionless);
ESCO: Soil water evaporation compensation factor (dimensionless);
GW_DELAY: Time interval for recharge of the aquifer (days);
GW_REVAP: Coefficient of water rise to saturation zone (dimensionless);
GWQMN: Water limit level in the shallow aquifer for the occurrence of base flow (mm);
REVAPMN: Aquifer water depth for the occurrence of water rise to the unsaturated zone (mm);
SOL_AWC: Soil water storage (mm mm^{-1});
HRU_SLP: Average slope steepness (m/m);
SLSUBBSN: Average slope length (m);
CH_N2: Manning coefficient for the main channel (s m-0.33);
OV_N: Manning's value for overland flow;
SURLAG Delay time of direct surface runoff (days)

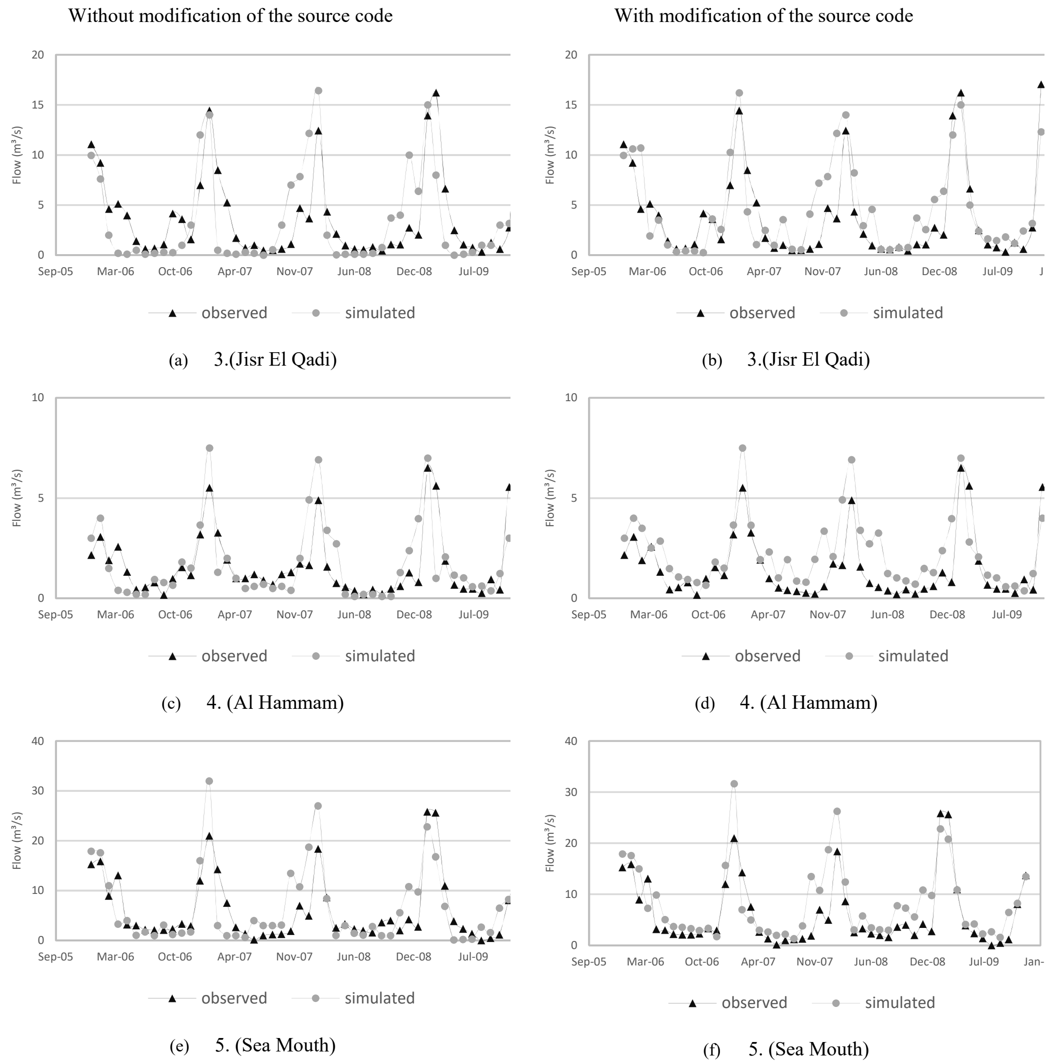
Table 8 Calibrated values for the most sensitive model parameters

Parameter	Method	Minimum value	Maximum value	Calibrated value
ALPHA_BF	Relative	0	0.048	0.045
CH_K2	Absolute	0	25	16.07
GW_DELAY	Absolute	10	120	80.71
GWQMN	Absolute	-500	1000	214.28
REVAPMN	Absolute	-50	100	89.29
SURLAG	Absolute	0.5	10	1.18

ALPHA_BF: Baseline flow recession constant (days); CH_K2 Effective hydraulic conductivity of the channel (mm h-1); GW_DELAY: Time interval for recharge of the aquifer (days); GWQMN: Water limit level in the shallow aquifer for the occurrence of base flow (mm); REVAPMN: Aquifer water depth for the occurrence of water rise to the unsaturated zone (mm); SURLAG: Delay time of direct surface runoff (days)

The model was then run with the calibrated parameter values, with and without the snowmelt modification. The runoff simulation results were close to the observed flow data at the 3 gauging stations; yet the model systematically overestimated river flows (Figure 9). At station number 3 (Jisr El Qadi), the efficiency coefficient of Nash-Sutcliffe (NSE) was 0.64 and 0.79 for the unmodified and modified SWAT model, which are considered good. The correlation coefficient (R2) of the non-modified snowmelt module had a low value of 0.48, which increased significantly when modifying the source code reaching a good value of 0.67. The model bias (PBIAS) was 10 and -19, which indicates that the model without the code modification tended to underestimate the flows by 10%, and after the code modification, it overestimated the flows by 19%. At station number 4 (Al Hammam), the efficiency coefficient of Nash-Sutcliffe (NSE) was 0.6 and 0.77 (without and with source code modification respectively). The correlation coefficient (R2) of the non-modified model had a value of 0.48, which increased when modifying the source code. It reached a value of 0.69. The percentage of BIAS was -2.9% and -29%. At station number 5 (sea mouth), the results were the most satisfactory. The ENS increased from 0.7 to 0.75 when modifying the source code. Similarly, the correlation coefficient (R2) increased from 0.58 to 0.7. Meanwhile, the PBIAS indicated an overestimation of flows by 12 and 35% (Figure 9; Table 7).

While the simulation results before and after modifying the snowmelt module indicated a good fit, when the modified code was used, the overall accuracy increased compared to the original model. Additionally, some of the overall periodicity and peaks were captured adequately. The largest discrepancies between the two SWAT models (with and without source code modification) were during the period between March and June, which is mostly affected by snowmelt. The original model predicted lower runoff during the snowmelt period. Moreover, the peak value of the modified simulated flows also increased with further improvement in corresponding periods and an increase in simulated flows of the snowmelt period, indicating that the modification is effective (Figure 9; Table 8).



(a) 3.(Jisr El Qadi)

(b) 3.(Jisr El Qadi)

(c) 4. (Al Hammam)

(d) 4. (Al Hammam)

(e) 5. (Sea Mouth)

(f) 5. (Sea Mouth)

Figure 9 Comparison of the observed and simulated flows with and without source code modification (Calibration)

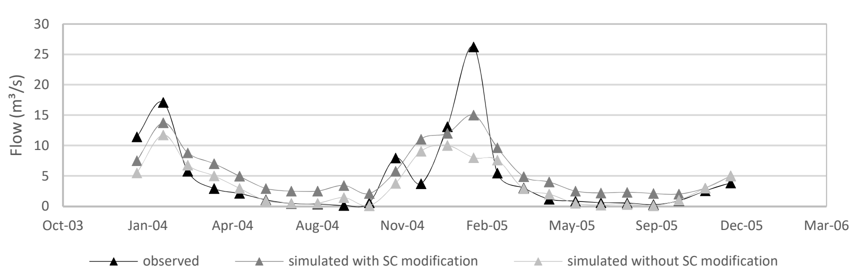
Table 9 Model evaluation with and without source code modification

	Without source code modification			With source code modification		
Station	3.(Jisr El Qadi)	4. (Al Hammam)	5. (Sea Mouth)	3.(Jisr El Qadi)	4. (Al Hammam)	5. (Sea Mouth)
R^2	0.48	0.48	0.58	0.67	0.69	0.70
NSE	0.64	0.60	0.70	0.79	0.80	0.75

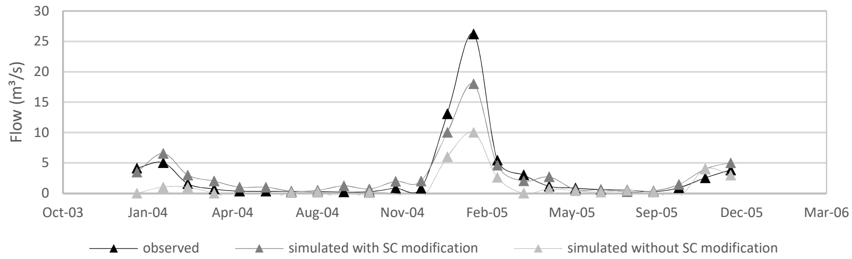
PBIAS	10.0	-2.9	-12.0	-19.0	-29.0	-35.0

* R^2: Correlation coefficient; NSE: Nash-Sutcliffe; PBIAS: Percentage of trend

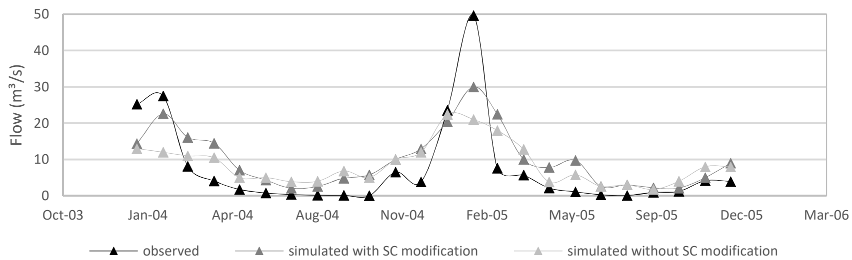
The model was validated for the three stations for 2004 and 2005. The validation presented acceptable results for all stations in terms of efficiency coefficient of Nash-Sutcliffe (ENS), correlation coefficient (R2) and the percentage of trend (PBIAS) (Table 9). The modified predictions were better than those generated by the original model, although the accuracy improvement was not large. The modified version of the model underestimated the flows at station 3 (Jisr El Qadi) by 22%, station 4 (Al Hammam) by 2% and station 5 (Sea mouth) by 44%. Without source code modification, station 3 (Jisr El Qadi) and stations 4 (Al Hammam) underestimated the flows by 20 and 45%, while station 5 (Sea mouth) overestimated the flows by 22%. Note that both model formulations were unable to capture the extremely high discharge during February 2005, which saw one of the strongest storms recorded in the basin. The differences between both models are mainly highlighted for the snowmelt period between March and June. The results after the source code modification showed a significant increase in the flows during the validation of the model. These differences decreased from station 3 (Jisr El Qadi) to station 4 (Al Hammam) to station 5 (Sea mouth) from 119, to 48 to 36% (Figure 10).



(a) 3.(Jisr El Qadi)



(b) 4. (Al Hammam)



(c) 5. (Sea Mouth)

Figure 10 Comparison of the observed and simulated flows with and without source code modification (Validation)

Table 10 Validation results

	Without source code modification			With source code modification		
Station	R^2	PBIAS	NSE	R^2	PBIAS	NSE
3.(Jisr El Qadi)	57% (satisfactory)	20 (very good)	0.80 (very good)	75% (good)	-22 (satisfactory)	0.86 (very good)
4. (Al Hammam)	72% (good)	45 (bad)	0.73 (good)	95% (very good)	-2 (very good)	0.91 (very good)
5. (Sea Mouth)	62% (good)	-22 (satisfactory)	0.6 (good)	70% (good)	-44 (bad)	0.68 (good)

* R^2: Correlation coefficient; NSE: Nash-Sutcliffe; PBIAS: Percentage of trend

3.3.3. Water availability predictions

Future stream flows were simulated using the projected weather and LULC data. Considering 2008 as a reference of a typical dry and hot year, the predicted 2032 precipitation decreased by 20% and 30% in the coastal and mountainous regions, respectively. Similarly, the 2032 maximum temperature increased by 2% along the coast and by 8% in the mountainous regions of the basin.

Agricultural and residential water demands, the main water users in the basin, were estimated based on field surveys and international indicators. On average, agricultural land requires ~30mm/m2/month14 while the residential demand reaches 4.4mm/m2/month for 2032 assuming a yearly population growth of 0.15%15 at an overall consumption rate of 300 l/c/d16 including distribution losses.

The water yield represents the net amount of water contributing to stream flows including the surface runoff, lateral flow, and groundwater. The projected weather conditions of 2032 and LCLU with the use non-modified source code revealed a decrease in water availability for every month. A significant shortage of water all over the basin between March and October is expected. After modifying the source code and with the projected weather conditions of 2032 and its LCLU, the results showed lower decreases in water availability for every month but with the same water shortage duration between March and October. The mean monthly water yield decreased by 24% compared to the baseline (i.e. 2008). The largest change still occurred in January reaching an average of 84% decrease in inflow in all sub-basins (Figure 9). These results reflect the impact of the source code modification targeting the snow module, reflecting higher runoff and accordingly less water shortages.

[14] In the test area, 1000 m^2 (I dunam) include 140 banana trees. Based on the soil type and the weather conditions, each tree needs an average of 3.3 mm of water per day. Each tree occupies ~7.14 m^2 reflecting a total water need of 1 mm/m^2/day.

[15] 0.15% / year (average between 2017 and 2020) and an expected 2032 population of 140,991 based on a density of 409 and 485/km^2 in 2002 and 2032, respectively (Worldometer, 2021; World Bank, 2021).

[16] The net national average for domestic water demand varies between 120 and 150 l/c/d with losses at 50 to 60% resulting in 42,273 m^3/d for the total domestic need.

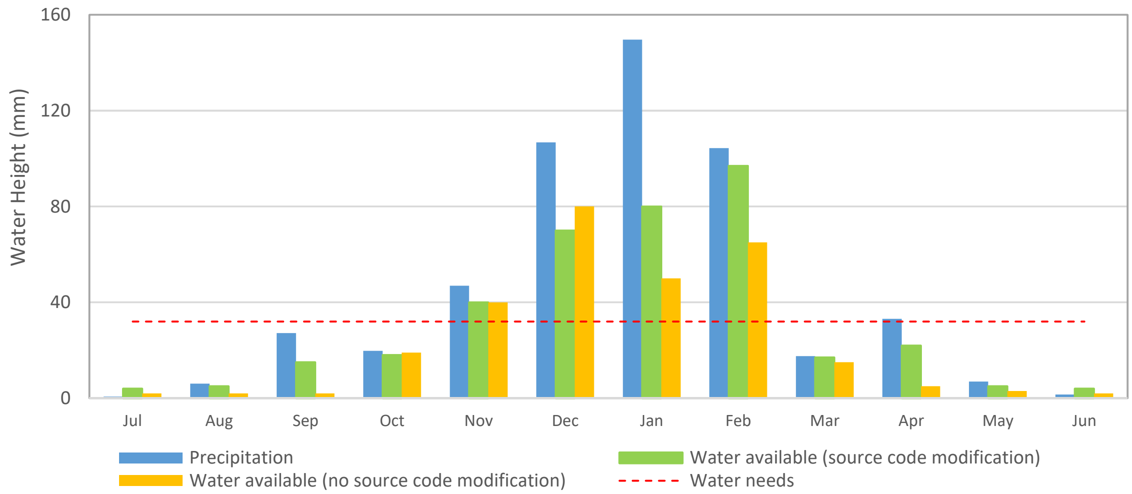


Figure 11 Water deficit of 2032 at Station 5 (Sea Mouth)

The results of the 2032 projection without change in the snow module showed a decrease in the water availability in the first part of the year compared to the modified model. A significant change was also observed in the last month of the year where the water availability returned a higher value compared to the modified model. The future mean monthly water yield decreased by 31% compared to the baseline (i.e. 2008). These results highlight the differences with and without source code modification in the snowmelt module in SWAT. Accordingly, the snow melting between January and May was not taken into account causing lower flows (runoff). A two-tailed t-test assessed between the two series of projected water yields (with and without source code modification) returned a p-value of 0.09. Accordingly, the difference between the modified source code model and the initial model is at a 10% level. Therefore, an underestimation of runoff projections and water availability is expected without a source code modification in the context of snow simulations. This development highlights the importance of snowmelt simulations in mountainous catchments and the need to improve the simulation of such processes. SWAT can simulate hydrological processes including snow-generated runoff based on the snowpack and snowmelt modules. The snowpack module can be adjusted manually through the user interface, while the snowmelt module (usually applied based on site-specific empirical data) needs to be adjusted for better representation and improved simulation by targeting the refinement of the snow melting factor (bmlti) that resulted in greater runoff from snowmelt.

3.4.Conclusion

In mountainous watersheds snowmelt is often a significant source of runoff with a need for better hydrological characterization. In this study, the physically based hydrological model, SWAT was used with and without code modification of its snow module to improve runoff simulations. Proposed modifications were introduced because the model relies on empirical values for North America thus invariably requiring refinement to represent regions outside that region to improve runoff simulations. As such, the snowmelt algorithm was modified by targeting the improvement of the degree day factor method then SWAT was tested with and without this source code modification at a mountain watershed along the Eastern Mediterranean. The runoff simulation results were compared to field observed measurements then water availability and potential deficit were predicted. The source code modification improved runoff simulations with simulated rived flows closer to observed measurements as reflected in an NSE increase from 7 to 28% and an R2 from 21 to 44%. In addition, the modified snowmelt algorithm indicated an improvement in predicting future water availability whereby its corresponding decrease is expected to reach 24% in comparison to the 31% predicted without the source code modification. The proposed source code modifications to the snowmelt algorithm of SWAT appears to provide better insights about future water availability in snow-dominated watersheds that are increasingly under stress due to population growth and climate change.

3.5. Acknowledgements

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CHAPTER 4

MENTAL AND PROBABILISTIC MODELING OF FARMERS' BEHAVIOR TOWARDS IMPROVED CLIMATE CHANGE ADAPTATION

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Abstract

In this study, we examine farmers' decision-making and logic through quantitative and qualitative processes (probabilistic and mental) with the aim of better understanding the main drivers behind their responses and their mind maps regarding the external environment. We then present a comparative assessment between the two types of behavioral modeling with regards to their ability to capture the perceptions of farmers and their adaptation to climate change. While both models shared some common determinants, they differed in selecting other significant determinants and/or in assigning their relative importance weight. Probabilistic models were able to map mechanistically the ways of the mind, whereas mental processes were anchored to the motives and experiences that shape farmers' vision of their surroundings and thus are not bounded by immediate materialistic considerations. Based on our results, we propose that stakeholders and decisions makers should concomitantly use both probabilistic and mental models to generate a better understanding and a more realistic representation of how farmers may respond to climatic change impacts.

Keywords Farmers' perception & behavior; Mental & probabilistic models; Climate change adaptation

4.1. Introduction

The future of agriculture is invariably dictated by farmers' perceptions, responses, and decisions regarding the needed adaptation to counterbalance ongoing changes in their extrinsic and intrinsic conditions. Extrinsic conditions are a result of the combined effect of external factors such as climate, planning, zoning and policies. Intrinsic conditions come from farmers' subjective drivers such as socio-demographic characteristics and agricultural practices (Vermaire et al., 2017; Darby, & Sear, 2008). In response to these conditions, farmers make decisions in an effort to sustain their livelihood (Serrat, 2017; Adato, & Meinzen-Dick, 2002). These decisions in turn affect land use and land cover (LULC) planning (Cramer et al., 2018; Teshome et al., 2016; Valbuena et al., 2010; Hassan, & Nhemachena, 2008).

Usually, the system through which information is processed towards decision making can be explained through the quantitative and qualitative analyses of survey results. Such analysis can be done using various tools, of which probabilistic and mental models are most common. Both types of models focus on the most likely decision to be adopted by the respondent, while providing a corresponding explanation (Sabzian et al., 2019; Callo-Concha, 2018; Vuillot et al., 2016; Baynes et al., 2011, Hisali et al., 2011; Deressa et al., 2009; Bragg, & Dalton, 2004; Foltz, 2004).

Probabilistic models are largely based on regression analysis, which are statistical tools relying on predictive modeling. Their main purpose is to forecast the dependent variable and identify the significant independent variables and to understand how they affect the response of decision makers to potential changes in their environment (Jeon, 2015). They are used extensively in various fields (engineering, transportation, environment, sociology, economy, psychology, etc.) and equally applied in examining the determinants behind farmers' decision-making and in predicting their behavior (Suvedi et al., 2017; Poppenborg, & Koellner, 2013; Fosu-Mensah et al., 2012; Ellis-Iversen et al., 2010; Sarker et al., 2009; Bragg & Dalton, 2004; Foltz, 2004).

On the other hand, mental models are constructed to explain and regulate human perception about their social and physical world (Sabzian et al., 2019; Vuillot et al., 2016; Baynes et al., 2011; Jones et al., 2011; Otto-Banaszak et al., 2011) by processing knowledge, skills, values, beliefs and previous experiences that dictate and guide decisions (Bardenhagen et al., 2020; Suit-B et al., 2020; Tschakert and Sagoe, 2009; Krauss et al., 2009; Eckert and Bell, 2006; Franzel and Scherr, 2002; Seel, 2001). Their main functions include the description of the system and its purpose, the explanation of the function of the system, and the prediction of perception and behavior (Krauss et al., 2009; Rouse, 2007). In recent applications, mental models have been gaining popularity (Palmunen et al., 2021; Uitdewilligen et al., 2021; Bardenhagen et al., 2020; Suit-B et al., 2020; Nath and van Laerhoven, 2020; Sabzian et al., 2019; Vuillot et al., 2016; Otto-Banaszak et al., 2011; Eckert and Bell, 2006; 2005; Franzel and Scherr, 2002) because they help in the understanding of the determinants affecting the decision making process (Douglas et al., 2016).

While both probabilistic and mental models have been applied to understand and assist decision makers and support development, they fundamentally differ in their techniques to gain insights into the decision-making process. For instance, probabilistic models rely on structured questionnaires followed by regression analysis; whereas mental models rely on unstructured open-ended questions followed by descriptive analysis. Probabilistic regression-based models help identify the drivers behind decision making and their significance; whereas mental models help in understanding the dynamics behind farmers' decision making (Vuillot et al., 2016; Eckert & Bell, 2006; Bragg & Dalton, 2004; Foltz, 2004). Accordingly, probabilistic regression-based models focus on the parameters of interest and their effect on the response without capturing all the dynamics that may hide behind those parameters. On the other hand, mental models may at times produce biases in the response variable since people do not usually fully verbalize their thought process.

In short, both models have limitations (Table 1) and applying them concomitantly in future studies may allow them to complement each other. In this study, we present a comparative assessment of probabilistic, mental, and combined models for predicting farmers' response to climate change and its impact on resource allocation. We examine specifically whether an increase in temperature and a reduction in water availability, both of which are expected to accompany climatic changes, would drive farmers to change their agronomic practices, or even abandon agriculture altogether and sell their land thereby paving the way to more urbanized and less "green" forms of land uses, often further disrupting fragile ecological balances.

Table 1 Differences between mental and probabilistic modelling

Characteristic	Probabilistic Model	Mental Model
Forecast perception and behavior	✓	✓
Statistical tools	✓	
Unstructured questionnaires		✓
Structured questionnaires	✓	
Drivers of decision making		
Significance [a]	✓	✓
Weight [b]	✓	
Sign [c]	✓	✓
Dynamics of decision making		✓

[a]: Significance is the presence of a correlation between independent and dependent variables
[b]: Weight is the relative effect of independent variables on dependent variables
[c]: Sign indicates whether the correlation between independent and dependent variables is positive or negative

4.2. Methodology

4.2.1. Test area

A coastal plain (Damour, Lebanon) along the Eastern Mediterranean was used as a test area. The plain (2.5 km2) stretches from the Mediterranean Sea to an altitude of 40 m above sea level. The area presents the western section of the Damour river watershed (290 km2) that is typical of many Mediterranean rivers with regards to its short run to the sea and large seasonal flow fluctuations (Figure 1). The land use in the plain is mostly agriculture (> 80%), of which 65% is banana and 9% is protected agriculture (plastic tunnels). The plain, with its deep alluvial soils, has proven to be ideal for this type of cultivation. On the shoreline, touristic resorts have spread during the past two decades, occupying around 8% of the total area. Industrial and urban areas make up 1% and 0.55% of the total area, respectively. The plain is characterized by a Mediterranean climate with moderately warm and dry summers and moderately cold, windy, and wet winters with almost 80 to 90% of total precipitation occurring between November and March (Khair et al., 2016). Scattered rainfall events begin in October and end in May. Climate simulations regained from a dynamic downscaling process using WRF (Weather Research and Forecasting) forced by HiRAM (HIgh Resolution Atmospheric Model) reported a decrease in precipitation (20%) and an increase in temperature (1.5 oC) by 2030, reflecting a decline in water availability (El-Samra et al., 2017).

Figure 1 Study test area

4.2.2. Data collection

Data was collected through a field survey using a questionnaire (with a set of structured and unstructured questions) administered to farmers in the test area (owners or tenants of the land). The farmers (interviewees/respondents) were identified through an agricultural census conducted by the municipality. Experts and stakeholders'17 opinions were solicited to help in the preparation of the questionnaire and anticipate determinants of farmers' decisions to external changes in the socio-ecological system that constitutes farming in the plain. The survey questionnaire was pretested and revised to ensure that the questions are meaningful to the farmers' respondents. The field survey covered 23 farmers and 68 farms. While the sample may be perceived as small, it

[17] Selected based on their experience (>20 years each): A professor, two famers from the test area, and one municipality representative responsible for agricultural and social development in the test area.

actually covers 100% of the farmers and farms in the study area and falls within the sample size range of reported literature on mental models (i.e. 7 to 40 respondents) (Hansson and Kokko, 2018; Salliou and barnaud, 2017; Jabbour et al., 2014; Otto-Banaszak et al., 2010; Schoell and Binder, 2009; Tschakert and Sagoe, 2009; Bell, 2007; Eckert and Bell, 2005). While many studies are bounded by a small sample size due to the population size or limited resources, when the population is small usually a finite population correction may be used for increasing the power of statistical tests. This process is based on the sampling fraction $f = n/N$, where n is the sample size and N is the population size. If $f=1$, then there is a census, and therefore no sampling error is present (McNeish, 2017). In this study, we are observing the entire population and therefore, we are dealing with a census not a sample.

Meetings were held by appointment with individual farmers and the survey was administered face-to-face, either on the farm site or at the residence of the farmer. Upon introduction of the project, the interviewer always obtained oral consent from farmers, who were assured that they have the option to keep their answers confidential as an attempt to reduce potential bias. Interviews lasted between 60 to 120 minutes.

4.2.3. Structured (Probabilistic) vs Unstructured (Mental) analysis

The structured part of the questionnaire was developed into three sections of 68 questions that tried to find the main determinants that may explain farmers' decisions or influencing their adaptive response to climate change impacts. The sections included (1) a section on the socio-demographic characteristics (age, education level, religion, farming experience, daily working hours), (2) the second section focused on the agricultural features and practices on the farm (land tenure, degree of reliance on agriculture, number of workers, farming traditions, type of produce, type of practice, yields, water source, type of irrigation, land price, produce sold, presence of well, water quality, water price, water availability, cost), and the last section (3) focused on the behavioral response to changes in the system induced by climate change (past experience, the influence of neighbors' actions, influencer agents, the feasibility of each decisions, attitude towards every decision, subjective norms towards every decision, Civil Unrest). Responses to structured questions were coded and served as the raw data for the multinomial logistic regression analysis that forms the mathematical basis of the probabilistic model. The regression analysis was conducted using the MASS (Venables and Ripley, 2002), foreign (R Core Team, 2021), nnet (Venables and Ripley, 2002), ggplot2 (Wickham, 2016) and reshape2 (Wickham, 2007) packages in R (R Core Team, 2021).

The response variables considered were the adaptive responses of each farmer given the context of a changing climate over the next 10 years in terms precipitation and temperature (i.e. 1.5oC increase in mean summer temperature, 20% decrease in annual precipitation). Explanatory variables were coded from the structured questionnaire. The Akaike Information Criterion (AIC) and residual deviance of the model were calculated along with the p-value of each explanatory variable. Non-significant variables with the highest p-values were eliminated one at a time, while still examining the changes in the AIC score and residual deviance. The best-fitted model was chosen according to the best compromise of a reduced AIC, a reduced residual deviance, and significant explanatory variables.

Similarly, unstructured questions focused particularly on the farmers' willingness to change agricultural practices or to quit agriculture under climate change predictions (mean summer temperature increase +1.5oC and mean annual precipitation decrease 20% between 2008 and 2030 across the country). Farmers were asked about how they would adapt to these changes and what course of action(s) would they adopt. Such questions took the form of an open conversation to examine farmers' perceptions and build the mental models based on their responses to the effects of climate change. Interviewees expressed their views openly about their actions in case the temperature increased and water availability was reduced. They articulated their past experience in farming and their present circumstances and cited their perceptions of knowledge types about agricultural practices and how they developed this knowledge over time. The interviews tried to probe for the aim and logic behind their stated perceptions and decisions. These interviews facilitated charting the corresponding mental models based on their responses. The construction of these models followed a three step procedure. First we identified the concepts, which may be a single word or a group of words associated with relationships. Concepts identification was based on textual content analysis. This process assumes that mental models can be sufficiently represented by monitoring the presence/ absence and occurrence of specific concepts used in the text (Pillutla, & Giabbanelli, 2019; Carley, 1997). It focuses on counting what words, vocabulary or general concepts are most used by respondents. For this purpose WordStat 9.0 was used (Talib et al., 2016; Davi et al., 2005). Numerical analysis were built on the textual data by identifying words that appear to be representative of a group with their probability of occurrence (Alzate et al., 2020; Cotoranu, & Chen, 2020; Carley, 1997). A preliminary choice of words was applied according to the review of each context. A frequency table of words was generated showing a descending order of frequencies. A word vector was then be identified, where each element represents the probability of occurrence of each word in the text. We then determined the type of relationships between the identified concepts. Relationships are defined as the ties that link concepts (Pillutla and Giabbanelli, 2019; Carley, 1997). Relationships were identified by their significance and sign. The significance of the relationship indicates the presence, degree, or valence of the relationship between two concepts. Meanwhile, the sign of a relationship indicates if there is a positive or a negative relation between concepts. Both significance and sign were identified based on a qualitative analysis of the text resulting from the interviews (Pillutla and Giabbanelli, 2019; Tsai and Brusilovsky, 2019). Original text data are stored and processed in WordStat. Variable filtering was then applied manually in order to quantify and group the text data under predefined topics with their corresponding keywords and their occurrence in terms of frequency and coherence used to define the relationships (significance and sign). Finally, the coded mental models were displayed graphically by introducing the concepts and relationships into the Mental Modeler online tool for environmental planning and research. Concepts were separated into two categories: the decisions and the determinants (Papageorgiou et al., 2020; Gray et al., 2014). The Modeler online tool was developed to parameterize the qualitative relationships between concepts as perceived by the respondents (Gray et al., 2014; 2013). The tool ultimately generates concept maps and structural matrices for each mental model. These outputs were then converted into more user-friendly schemes by adopting a simpler representation of the mental models (Papageorgiou et al., 2020; Gray et al., 2014; 2013; Papageorgiou, 2013).

Determinants that were found to be significant in the probabilistic models were compared to the corresponding ones in the mental models in terms of their significance, positive or negative effect, and the magnitude of their effects on the response variable.

4.3. Results and Discussion

4.3.1. Data collection

The survey results revealed that farmers came from different educational backgrounds with most having attained high school (66%), whereas some have university degrees (34%) and have previously occupied various employment positions. Some farmers are retired employees with others relying on other part-time jobs, while the majority (~70%) are full-time farmers relying 100% on their agricultural income. The age of farmers ranged between 49 and 88 years with an average of 67 and their farming experience ranged between 6 and 75 years with an average of 36. Agriculture is mostly traditional with 74% of farmers having inherited their parents' practices. First generation farmers are usually people who were displaced during the civil unrest of 1975 and came back after the 1990s due to governmental economic incentives. Farmers were either owners (22%) or tenants (52%) of the lands or both (26%) at the same time. Cultivated land areas ranged between 2 and 250 dunam18 rented or owned by one farmer. Respondents mostly planted bananas due to the relatively warm climate in the area and the soil type, with 43% of farmers planting strictly bananas. The rest planted vegetables as well, mainly as protected agriculture, even though this practice needs more water, which is usually at the expense of bananas, according to farmers. Recently some have started planting tropical crops such as avocado, mangoes, and annona. All

[18] 1 dunam = 1000 m^2

farmers use the nearby river water, which is distributed by the municipality through a network of canals. During dry years when water is not available in adequate quantities, the municipality supplements their water from several groundwater wells that are experiencing saltwater intrusion due to overexploitation (Khadra, & Stuyfzand, 2018; 2014; Masciopinto, 2013). Nearly 43% of farmers have personal wells installed within their farms, with 20% equally suffering from high salinity.

In synthesizing the collected data for probabilistic and metal analysis, the farmers were divided into six categories (Table2) according to their envisaged reaction to future predictions of temperature increase and decline in the water supply that are associated to climate change. These reactions can affect changes in the state of the landscape as recognized in several assessment studies on climate change impacts (Kanianska, 2016; Morse, 2014; Kiersch and Tognetti, 2002).

Table 2 Farmers clusters by reaction to climate change

Response	Designation	Number of Farmers
No change	NC	1
Sell the land	S	2
Quit farming and leave the land bare	Q	4
Change crop	CC	7
Seek additional water	SW	7
Change crop & seek additional water	CCSW	2

4.3.2. Probabilistic models

The multinomial logistic regression revealed a best fitted model with an AIC of 80 and residual deviance of 0.0001 and a high pseudo R2 (~90%) indicating a good fit. The selling option was defined as the reference decision since it is the least desired in terms of land conservation and the sustainability of the landscape. The regression results of the farmers' decisions returned seven significant determinants ($p < 0.002$). The best fitted probabilistic model is summarized in Table 3.

Table 3 Best fitted probabilistic models

Decision	Model
Sell - S	*Reference decision*
No Change - NC	$\ln(\frac{P(NC)}{P(S)})$ = -758.1 + 140.7 A – 488.9 LT – 123.5 YF – 788.4 TC – 1635.3 RA + 301.1 GW - 2389.9 WQ
Quit - Q	$\ln(\frac{P(Q)}{P(S)})$ = -2828.6 + 127 A + 2190.5 LT – 103.9 YF – 4563.6 TC + 178.7 RA + 1177.4 GW + 539.5 WQ
Change Crop - CC	$\ln(\frac{P(CC)}{P(S)})$ = 1799 + 131.4 A – 4642.5 LT - 242.8 YF + 1287.6 TC + 427.9 RA + 3556.7 GW -84.1 WQ
Seek more water - SW	$\ln(\frac{P(SW)}{P(S)})$ = -1355.7 + 136.9 A + 916.8 LT – 155.3 YF - 136 TC + 2544 RA – 1662.2 GW – 1689.3 WQ
Change crop and seek more water - CCSW	$\ln(\frac{P(CCSW)}{P(S)})$ = 250.1 + 122.4 A – 2921.9 LT - 174 YF + 146 TC + 1999.8 RA + 982.5 GW – 2288.3 WQ

A Age (continuous in years)
LT Land Tenure (1 when owner or part owner and 0 when tenant)
YF Years in Farming (continuous in years)
TC Type of Crop grown (1 when vegetables and 0 when cultivating only banana)
RA Reliance on Agriculture, (1 when fully relying on agriculture and 0 when partly relying on agriculture)
GW Groundwater (1 when available and 0 when not available
WQ Satisfaction with Water Quality (1 when satisfied and 0 when not satisfied)

Evidently, there are substantial differences between the different farmers' decision categories. These variations are dictated by the weight of the significant determinants. Older people (i.e. > 70) prefer not to change their practices under climate stress and are the least likely to sell. When confronted with the threat of reduced precipitation, landowners prefer to quit (without selling) with a least desired option to change their crop. In contrast, tenants are more flexible in changing practices and seeking new crops and sources of water. Having a long experience in farming increases the probability of selling the land or of quitting farming without selling. Less experienced farmers are more willing to adapt (i.e. crops and/or water source) probably because they still have the energy and vigor to adapt and continue farming, especially if it is their only source of livelihood. In fact, farmers who rely mostly on agriculture as a livelihood are more likely to adapt to changing conditions brought about by climate change, through shifting to other crops or seeking new sources of water. The availability of groundwater at the farm makes farmers less likely to seek new water sources unless they are dissatisfied with its quality. When that happens, they tend to seek new sources or to change their crops before they consider quitting or selling.

These results are consistent with previous studies showing that farmers' decisions are significantly affected by demographic characteristics, social and family bonds, past experience and profit (Agidew and Singh, 2018; Talukder et al., 2017; Tey et al., 2014; Arumugam et al., 2011; Dewi and Istriningsih, 2010). Agidew and Singh (2018) examined the factors that mostly affected farmers' decisions in participating in watershed management programs and reported that land redistribution and farm size, farmers' gender and agricultural labor force all had significant impacts. Talukder et al. (2017) examined the influence of socio-economic and demographic factors on the adoption of an Integrated Pest Management (IPM) and showed a high impact of farmers' age, education level, farming experience and training on their decision. Tey et al. (2014) studied the importance of multidimensional factors in the Malaysian vegetable production sector on farmers' decisions about the adoption of sustainable agricultural practices and reported a high impact of the farm's workforce size, financial capital and farmers' ethnicity and perceived advantages of the practices. On the other hand, Dewi and Istriningsih (2010) examined the factors influencing farmers' decision-making on the adoption of high yielding varieties of rice and argued that farmers' decisions were mostly affected by their income and the size of the cultivated land. Lastly, Arumugam et al. (2011) identified the socio-economic characteristics that affected the decision of farmers' participation in contract farming with land tenure and size, farmers' education and perceived benefits of the program identified as the most influencing factors.

4.3.3. Mental models

The farmers’ stories surrounding the future of their farms with the projected increase in temperature and decline in precipitation were synthesized and analyzed to provide insight on their interpretation of the external environment and to understand individual and group decision-making. The textual content analysis uncovered six common determinants with varying importance depending on farmers’ decision categories. They were extracted from the word vectors that were based on the farmers’ responses to the unstructured questions. These included water source, age, livelihood, land tenure, memories of civil unrest and displacement, and attachment to farming traditions. Table 3 summarizes the mental model results of farmers’ decisions clustered according to the six response categories.

Table 4 Summary of the mental models of the six groups

Decision	**NC**	**S**	**Q**	**CC**	**SW**	**CCSW**
Interviewees	1	2	4	7	7	2
Determinants						
Age	Over 80	Under 50 Over 70	Over 70	Under 70	Over 70	Under 50 Over 70
Livelihood	Retired	Part reliance Full reliance	Full reliance	Full reliance	Retired Full reliance	Full reliance
Farming traditions	Attached	Detached Attached	Attached	Detached	Detached Attached	Detached
Civil unrest	Displaced Strong effect	Displaced as youngster Displaced short period	Displaced Strong effect	Displaced Strong effect	Displaced Strong effect	Not relevant
Land tenure	Owner	Owner	Owner	Owner	Owner	Tenant
Water source	SW; GW	SW SW; GW	SW; Saline	SW	SW	SW

GW

NC No change, S Sell, Q Quit, CC Change crop, SW Seek additional water, CCSW Change crop and seek additional water;

The interviewee who is not willing to change (NC) practices is a retired landowner over 80 and has been farming for a long time. He was previously working in the agricultural sector in the study area when civil unrest displaced many farmers away from their land. Today, he prefers to continue with similar practices irrespective of the impacts of climatic changes with the main goal of farming to maintain a presence and refuses to be uprooted again by nature preferring to keep the land within the family and to transmit it to the next generation. Under this category, farming symbolizes the fusion of people with the land regardless of the economic profit and as such, they oppose selling the land to avoid the "dubious" infiltration of outsiders into the local society. While they do not object to touristic or industrial development in the plain, they have concerns about urbanization changing the demographic composition of the area. They are equally attached to their farming traditions and are not willing to change their crop because banana cultivation is a tradition. Their farms are equipped with wells with no willingness/need to seek other sources for irrigation (Figure 3a).

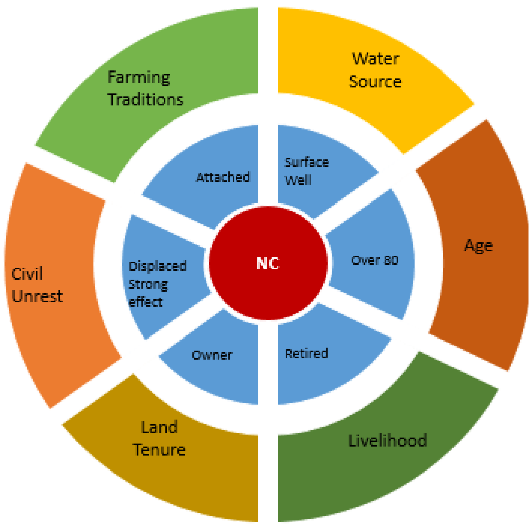
Farmers who are willing to sell (S) are below 50 or above 70. The one under 50 is a landowner and relies partly on agriculture as a source of livelihood. He was previously not working in the agricultural sector or the study area when the civil unrest took place. He was displaced as a youngster and has built a new life outside the study area therefore would probably accept selling the land for economic profit. The land was inherited and started being farmed after the civil unrest era. Naturally, he would have little emotional attachment to the land and would not be concerned with preserving agriculture in the area. Similarly, he does not object to touristic, industrial, or urban development in the plain because the logic is driven by rapid economic profitability, and seeking to maximize short-term return on minimal investment. Therefore, this respondent relies exclusively on surface water for agriculture and is not willing to change crops or seek other water sources for irrigation under climatic stress. The farmer above 70 in this category is also a landowner who relies fully on agriculture and was displaced during the civil unrest but returned earlier than others because of emotional attachment to the land. He is equally attached to farming traditions and considers that the cultivation of bananas should preferably not be changed but he is willing to sell when exterior constraints are exerted because of a perception that successors are not interested in preserving the land. He is already relying on surface and groundwater for irrigation and does not intend to seek other irrigation sources (Figure 3b).

The farmers who prefer to quit farming without selling (Q) the lands show similarities with the one unwilling to change. They are over 70, semi-retired landowners who have already granted the land to their heirs. They previously worked outside the agricultural sector and the study area, when civil unrest forced them to leave their lands. Under external stress, they would quit farming without selling probably because the past displacement increased their attachment to the land. For them, the principal goal of farming is to preserve the land regardless of the economic profit. They are equally attached to local traditions, symbolized by banana cultivation and as such, they are not willing to change their crop type. They have access to groundwater and surface water and hence not interested in seeking new sources. They are also encouraged by their children and family to retire (Figure 3c).

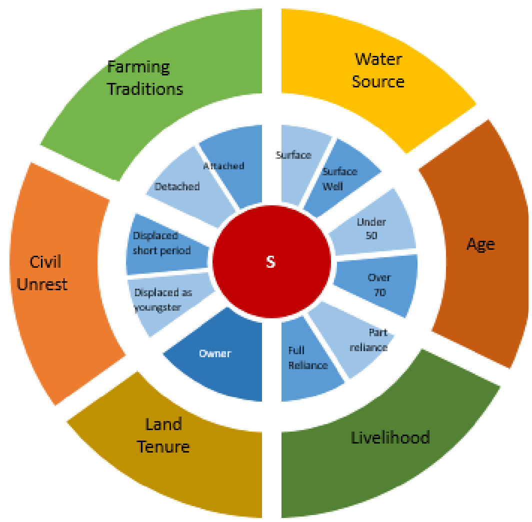
Farmers who are willing to change the cropping type (CC) are owners under 70 years of age who have been practicing agriculture for over 20 years. These farmers are also part of a generation that was displaced during the civil unrest and today, they feel the need to anchor themselves in their land. They indicated that they would carry on farming under any circumstance and they will adapt by changing their crops. Agriculture is their only source of livelihood with no attachment to farming traditions. Instead, they are adaptable and entrepreneurial with a willingness to seek viable alternatives to bananas hence their choice to change their crop type. The main drivers of their decision include a full reliance on agriculture as a source of income and the displacement memory. For them, the principal goal is to provide a source of livelihood and preserve the land with a strong desire to pass it-on to future generations, which explains their refusal to sell the land (Figure 3d).

Farmers who tend to seek additional water sources (SW) are over 70 and are landowners who were forcibly displaced from the land during the civil unrest. They prefer to continue farming under any circumstance and adapt to external stressors by seeking additional water. They were once displaced and show a strong attachment to the land, and wish to prevent it from “falling into the hands of outsiders”. They include full time farmers who rely on agriculture as a unique source of livelihood and part-time farmers for whom farming is important as a post-retirement leisure activity. Full time farmers are attached to banana farming as a symbol of the area. Part-time farmers, who retired after a life of employment in the city, enjoy the supplementary income afforded to them by banana, as well as its low labor requirement. As they currently only have access to surface water, they are willing to invest into a supplementary source of irrigation water (Figure 3e).

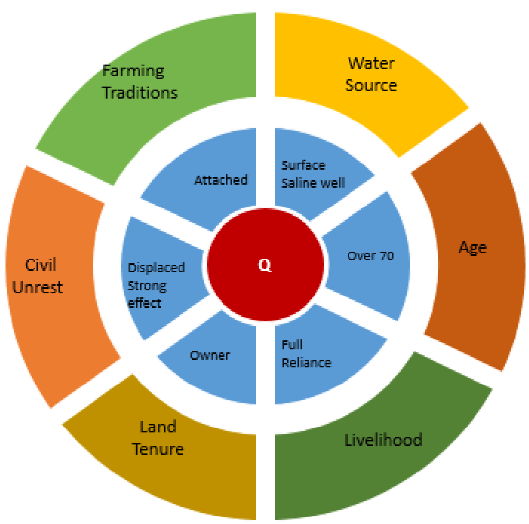
Farmers who are willing to change their crop type and seek additional water sources (CCSW) are tenants rather than landowners. They are full-time farmers to whom farming is a commercial venture aiming at maximizing net returns regardless of other emotional or cultural considerations. As tenants, the issue of protecting the land from “outsiders” is not relevant. They are willing to consider adaptive measures including changing crops and seeking additional water sources (Figure 3f).



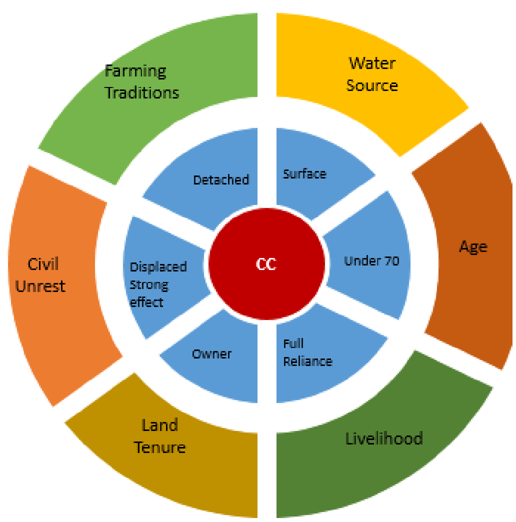
(a) No change



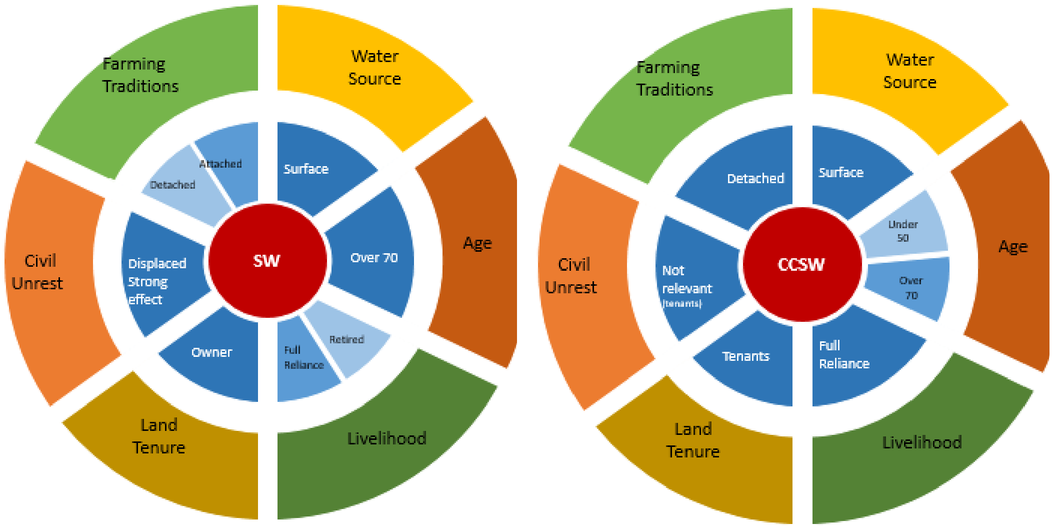
(b) Sell



(c) Quit



(d) Change crop



(e) Seek additional source of water (f) Change crop and seek additional source of water

Figure 2 Mental Model schemes

Previous studies of farmers' mental models showed the importance of social and economic modules (Jabbour et al., 2014; Otto-Banaszak et al., 2010; Tschakert and Sagoe, 2009; Eckert and Bell, 2006). The mental models of Jabbour et al. (2014) about organic farmers' weed management decisions highlighted the impact of farming experience and economic profit focusing on cost and yield. In their study on the choice of adaptation responses to climate change, Otto-Banaszak et al. (2010) reported several models corresponding to five basic stakeholder groups with similar objectives and logic with governing determinants focused on economic incentives, attachment to traditions, social values, farmers' cooperation, legislation and community awareness. Tschakert and Sagoe (2009) mental models showed high impact of respondents' social modules such as community awareness, attachment to religious conviction and their experience on climate change perception. Eckert and Bell (2006) examined the determinants of farmers' mental models about farming practices and emphasized the influence of prior values and knowledge as unique to each farmer.

These results are consistent with the mental models of this study in terms of the importance of social attributes including values, traditions and experience on decisions, with no special focus on economic implications. Yet, some physical characteristics found significant in this study were not reported previously such as land tenure and water source. The proposed mental models aim at analyzing qualitatively processes of the mind focusing on the links and concepts between determinants and decisions. They lack the statistical capabilities to determine the significance of different determinants (Baynes et al., 2011; Jones et al., 2011; Krauss et al., 2009).

4.3.4. Probabilistic vs mental analysis

In the probabilistic models, seven determinants were found to be most significant: age, land tenure, degree of reliance on agriculture, years in farming, type of crop grown, availability of groundwater, and satisfaction with water quality. Most of these determinants were also found to be reflected in the mental models, such as age, land tenure, presence of a well, and degree of reliance on agriculture/farming experience that can be combined under the livelihood rubric of the mental models. Two out of the seven significant determinants in the probabilistic models were not reflected in the mental models, namely the type of produce and being satisfied with the water quality. Two out of the five determinants in the mental models did not appear in the probabilistic models, either due to their non-significance in the model or their absence in the structured questionnaire. These are attachment to farming traditions and memories of displacement associated with civil unrest (Table 5).

Table 5 Determinants of the decision models

Determinant	**Exclusive to PM**	**Exclusive to MM**	**Similar in MM & PM**
Age			X

Attachment to Farming Traditions		X	
Satisfaction with Water Quality	X		
Years in Farming			X
Land Tenure			X
Memories of Civil Unrest		X	
Availability of Underground Water			X
Degree of Reliance on Agriculture			X
Type of Crop Grown			X

MM: mental model, PP: probabilistic model

Determinants that were found common between the probabilistic and mental models were consistent in their impacts in both models. The difference between the models can be attributed to the implementation methods underlying both models when using structured and unstructured questions. The structured questionnaire used to obtain the data for the probabilistic model, relies on a predefined number of determinants identified during the preliminary model construction phase. Thus, they may miss some determinants that would ultimately be mentioned by respondents in the unstructured questions, which was the case during the rapid ethnographic survey conducted for defining the mental model. This limitation has previously been highlighted with the existence of socio-demographic factors that researchers failed to take into account in constructing probabilistic models of decision-making (Agidew, & Singh, 2018; Talukder et al., 2017; Azizi, & Zamani, 2009). Similarly, mental models have their own limitations as they provide the direction or sign of the relationship between determinants and decisions without specifying the weight or rate of change. These limitations underscore the qualitative aspect of mental models (Jones et al., 2011) and can be alleviated through the concurrent use of probabilistic models.

4.4. Conclusion

The sustainability of agriculture is increasingly challenged particularly along coastal zones where it can lead to an unbalance in food security and landscape conservation if not well protected. The reversibility of these outcomes relies firstly on the understanding of farmers' decision making processes and the drivers lying behind their way of thinking. In this study we examined farmers' behaviors under climate change impacts using a combined quantitative (probabilistic) and qualitative (mental) approach. It represents the basis for land conservation planning and allows the prediction of the state of the landscape under extrinsic stressors.

The probabilistic and mental models did not agree with regards to all their determinants. Probabilistic models may miss some determinants that would invariably be mentioned by respondents to unstructured questions. Whereas mental models provide the direction of the relationship between determinants and decisions without specifying the rate of change. Therefore, using both models concomitantly may help in covering the largest trench of explanatory variables and provide a tracking of the weight and direction of their effect on the response in both qualitative and quantitative estimation.

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CHAPTER 5

AN INTEGRATED SOCIO-ECONOMIC AGENT-BASED MODELING FRAMEWORK TOWARDS ASSESSING DECISION MAKING UNDER CLIMATE CHANGE-INDUCED WATER SCARCITY

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Abstract

In this study, we develop an integrated spatio-temporal Agent Based Modeling (ABM) framework to probabilistically predict farmers' decisions concerning their future farming practices when faced with potential water scarcity induced by future climate change. The proposed framework encompasses three different utility functions (an economic profit optimization utility, a social reasoned-action utility, and a joint socio-economic utility) to forecast farmers' behavior. The ABM framework was tested and validated in an agriculturally dominated plain along the Eastern Mediterranean coastline. The results highlighted the importance of representing the farmers' combined socio-economic attributes, when assessing their future decisions on land tenure. Predictions that were based solely on optimizing the economic utility only captured 35% of the farmers' responses that were collected from a field-based survey. Meanwhile, social-based predictions concurred with 69% of field collected data. Predictions based on a combined socio-economic utility captured 83% of the farmers' responses. When faced with the negative impacts of climate change on water availability, farmers were predicted to seek adaptive measures, such as the opting to change their crops and/or seek new water sources, under a future with low water shortages (12% drop in available water). Yet, they were predicted to cease farming and

allow their lands to urbanize or go fallow, when the future was predicted to have high water shortages (> 24% drop in available water). Allowing farmers to be affected by their neighbors' decisions made them less willing to adapt to the negative impacts of climate change and doubled their propensity to sell or quit their land. In summary, the proposed framework represents an innovative modeling approach for assessing farmers' behavior and decision-making by integrating empirical and socio-economic attributes. The nonspecific structure of the framework allows its application at any agriculturally dominated setting.

Keywords Farmers' decision-making; Agent-Based modeling; Climate change

5.1. Introduction

Coastal agriculture is vital to littoral countries as its natural resources supply substantial economic development, maintain food security balance, and provide cultural ecosystem and landscape beauty (Rochette et al., 2012; Clark, 1994). The ecological integrity of these zones is affected by various stressors that disturb the balance of water use and demand such as climate change and anthropogenic pressures. Future climate change is expected to increase the amplitude/duration of heat waves and lead to spatio-temporal variations in rainfall patterns that in turn can represent a serious threat to coastal agriculture and crop yield. Worldwide, water scarcity is identified as one of the major threats to coastal agriculture, since fluctuations in rainfall, soil evaporation, and plant transpiration are likely to reduce the availability of water for crops, consequently reducing yields both in terms of quality and quantity (Kantamaneni et al., 2020; Cramer et al., 2020; Harmanny, & Malek, 2019; Gopalakrishnan et al., 2019; Cramer et al., 2018; Zampieri et al., 2017; Zhao et al., 2017; Mavromatis 2015; Negev et al., 2015;

Challinor et al., 2014; Kang et al., 2009; Lobell, & Field, 2007; Peng et al., 2004). It is thus expected that future climate change will have significant implications on the landscape and will threaten the sustainability of global food security, economic viability, and farmers' livelihood. As such, it is imperative to shed light on farmers' decision-making processes under water scarcity associated with projected climate change. In this context, current assessments of farmers' decisions are mostly based on the application of the normative theory, which assumes that farmers are profit optimizers (Von Ketteler, 2018; Maes & Van Passel, 2017; Ding, 2014; Ng, 2010; Marques et al., 2009; Bradford Lori, 2009). This theory has been central in agricultural modelling (Sengupta et al.2005; Wallace & Moss, 2002; Bell et al., 1988). Yet, evidence shows that experienced farmers tend to make economically viable decisions, while still considering their surrounding community, the weather, and their political background (Von Ketteler, 2018; Bradford Lori, 2009; Rehman et al., 2003). Farmers are also known to assign great value to their farming lifestyle, family, community, work traditions, and experience (Von Ketteler, 2018; Bradford Lori, 2009; Tzima et al, 2006; Feuillette et al., 2003; Austin et al., 1996; Fairweather & Keating, 1994; Coughenour & Swanson, 1988; Gillmore, 1986; Salamon & Davis-Brown, 1986). As a result, the use of normative models can misrepresent farmers' decisions and are often unreliable descriptors of the farmers' reality. Social models on the other hand have been developed to account for farmers' attitudes, intentions, beliefs, and norms so as to uncover the complexity of their decision-making process. These models rely on the social-psychology theory that is based on the view that there are two central drivers of human behavior, namely attitude and subjective norms, that affect decisions beyond profit optimization (Kashif et al., 2018; Senger et al., 2017; Edwards-Jones, 2006; Austin et al., 2005; Rehman et al., 2003; Zubair, 2002; Beedell & Rehman, 2000; Bursey & Craig, 2000; Wilson, 1997; Ajzen, 1991; Carr & Tait, 1991). This theory seeks to understand how humans in general, and farmers in particular, behave and why they behave differently than what is predicted by the normative models (Sok et al., 2021; Gatto et al., 2019; Senger et al., 2017; Rehman et al., 2007; Beedell & Rehman, 2000). Another modelling approach towards understanding farmers' decision-making is the empirical or descriptive approach that attempts to explain human behavior by emphasizing people's goals, values, knowledge, and their way of thinking through examining patterns and relying mainly on field surveys (Kashif et al., 2018, Castella & Verburg 2007; Castella et al., 2005).

Agent-Based Models (ABM) are powerful tools that have evolved toward assessing decision-making, while explicitly accounting for spatial dependencies (Mehryar et al., 2019; Huber et al., 2018; Zhang et al., 2016; Elsawah et al., 2015; Mialhe et al., 2012; Schmit, & Rounsevell, 2006; Evans, & Kelley, 2004). They are able to simulate actions and interactions between a series of agents and their environment (Elsawah et al., 2015; Feola et al., 2015; Ng et al., 2011; Barreteau et al., 2004) and to map mechanistically or probabilistically the ways of the mind (Mehryar et al., 2019; Zhang et al., 2016). ABMs can equally account for a wide range of decision-making rules that can be data-driven and/or theoretically based (Mehryar et al., 2019; Castella et al., 2005; Kerridge et al., 2001). They have been successfully used to predict farmers' decisions under different scenarios (Huber et al., 2018; Maes & Van Passel, 2017; Feola et al., 2015; Daloglu, 2013; Oudendag, 2013; Ng et al., 2011; Schmit, & Rounsevell, 2006; Sengupta et al, 2005).

In this study, we develop an integrated ABM framework, using economic and social economic utility functions, to capture farmers' behaviors and to understand their decision-making processes under potential water scarcity resulting from future climate change. We validate the ABM framework with empirical field-based surveys administered to farmers and conduct a parametric sensitivity analysis to identify key influencing parameters and assess the elasticity of farmers' behavior to changes in these parameters. While the framework was tested and validated at an agriculturally dominated field along the Eastern Mediterranean coastline, we maintain a generalized and nonspecific structure to allow its application in any agricultural setting.

5.2. Methodology

5.2.1. Study area

Located along the Eastern Mediterranean, the study test area consists of a 2.5 km2 coastal agricultural plain (Damour, Lebanon) at an altitude from 0 to 40 m above sea level forming the western edge of a river watershed (290 km2) (Figure 1). The land use is mostly agriculture (> 80%) of which 65% is banana and 9% is protected agriculture (plastic tunnels). The plain, with its deep alluvial soils, has proven to be ideal for this type of cultivation. Along the shoreline, touristic resorts have spread during the past two decades occupying around 8% of the plain area today. Industrial and urban areas make up 1% and 0.55% of the total area, respectively. The plain is characterized by a Mediterranean climate with warm and dry summers and moderately cold, windy, and wet winters with almost 80 to 90% of precipitation occurring between October and May (Khair et al., 2016). Climate simulations regained from a dynamic downscaling process using WRF (Weather Research and Forecasting) forced by

HiRAM (HIgh Resolution Atmospheric Model) reported a decrease in precipitation (20%) and an increase in temperature (1.5 oC) by 2030 reflecting a decline in water availability (El-Samra et al., 2017a; b).

Figure 1 Study test area

5.2.2. Data collection

Data were collected through a field survey using a questionnaire with a set of structured and unstructured questions. Experts and stakeholders'[19] opinions were solicited to help in the preparation of the questionnaire and to anticipate the determinants of farmers' decisions to external changes in the socio-ecological system that constitutes farming in the plain. The questionnaire was piloted and revised to ensure that the questions are meaningful to the farmers. The questionnaire was then administered to all farmers in the study area, including owners and tenants of the land (See Supplementary Material). The farmers (interviewees/respondents) were identified

[19] Selected based on their experience (>20 years each): A professor, two famers from the test area, and one municipality representative responsible for agricultural and social development in the test area.

through an agricultural census conducted by the municipality. In total, 23 farmers and 68 farms were covered. While the sample size may appear small, it actually covers 100% of the farmers and farms in the study area. Given that we observed the entire population (census), a correction term that accounts for the small sampling size is not warranted (McNeish, 2017).

Meetings were held by appointment with individual farmers and the survey was administered face-to-face, either on the farm site or at the residence of the farmer. After introducing the aims of the project, the interviewer obtained oral consent from farmers to proceed with the questionnaire. Farmers were assured that they would remain anonymous and their answers confidential in an attempt to reduce bias. Interviews lasted between 60 to 120 minutes. The questionnaire was divided into three sections and comprised 68 questions designed to capture determinants explaining farmers' decisions or those that can influence their adaptive responses to climate change impacts.

Socio-demographic characteristics section collected information on the farmers' age, education level, farming experience, and daily working hours.

Agricultural features and practices section focused on information about land tenure, degree of reliance on agriculture, number of workers, farming traditions, type of produce and practice, yields, selling price of produce, water source, type of irrigation, land price, produce sold, the presence of a water well on-site, water quality issues, water price, water availability, and costs of production. Costs of production included costs related to machinery, maintenance and fueling, labor, water, seeds, fertilizers, pesticides and herbicides, municipality fees, land fees, and rental fees. Future costs/fees were predicted over the simulated timeframe (until 2032) by assuming a 2.7% average annual inflation rate (IMF, 2019) (Supplementary Material Table SM1).

Behavioral responses section solicited the responses of farmers to hypothetical situations where their agricultural system was impacted either by climate or as a result of other external changes (past experience, the influence of neighbors' actions, influencer agents, the feasibility of decisions, attitude towards decisions, subjective norms towards decisions, and civil unrest)20.

The questionnaire also included a set of unstructured questions that focused on the farmers' willingness to change agricultural practices or to quit agriculture as a result of future climate change (mean summer temperatures increase of +1.5oC and mean annual precipitation decreases by 20% between 2008 and 2030). Farmers were asked how they would adapt to such changes and what course of action(s) would they adopt. We consider this section as a true reflection of the respondents' decisions in face of these changes. The decision options that farmers had to select from included: (1): I would do nothing (No change NC), (2) I would sell the land (Sell S), (3) I would quit farming and leave the land bare (Quit Q), (4) I would seek to adapt by changing the crop to suit the new environment (Change crop CC), (5) I would seek to adapt by finding new sources of irrigation water (Seek additional water SW), and (6) I would seek to adapt by both changing my crop and finding new sources of water (Change crop and seek additional water CCSW).

5.2.3. ABM framework development

An ABM framework was built to examine the impacts of water scarcity and anthropogenic pressures on farmers' decisions based on three decision-making utilities.

[20] The attitude was measured via the response to "In your opinion how good or bad would it be to adopt one of the proposed behaviors?" The subjective norm was measured by asking "Would people who you respect in the farming industry be supportive if you adopted one of the proposed behaviors?" The weights on the subjective norm were determined by asking "how much would you be affected by the opinion of people who you respect in the farming industry?"

The framework was developed following the ODD (Overview, Design concepts, Details) protocol (Grimm et al., 2010; 2006), which is structured into seven elements (purpose, state variable, scheduling, design concept, initialization, input, and modules) that describe the framework completely. These elements allow for the potential occurrence of emergence, adaptation, sensing, interaction, and stochasticity in decision-making. Emergence was tracked by looking for spatial patterns in the overall Land Use Land Cover (LCLU) of the study area that may have emerged from the individual decisions of farmers. Adaptation was incorporated by allowing farmers to adjust and update their decisions under varying intrinsic and extrinsic conditions on a yearly basis. They adapt according to their prospective aims, logic, characteristics, and agri-environment circumstances. Meanwhile, sensing was incorporated by ensuring that farmers were aware of their previous years' yield, weather, market conditions, and decision. The Interaction between farmers was introduced through spatial networking that allowed farmers to communicate and share their decisions with their neighbors. Finally, all decisions were assumed to be stochastic. While it is common for decision-makers to assume that the agent are rational and will always select the choice with the highest utility, the proposed ABM framework assumed that agents were not perfectly rational and thus their decisions were probabilistic and based on the probability that a certain decision will be taken as compared to the remaining decision space. Stochasticity in the framework was also incorporated by the definition of statistical distributions for several parameters that affect farmers' expectations. These included the impact that the spatial network has on the farmers' decisions, the severity of water scarcity, and the ratio of the weight of economic versus social characteristics on farmers' decisions. Assigning distributions on parameters allows for randomly drawing different realizations from the defined distributions for each farm, thus permitting the generation of a spatially heterogeneous surface and accounting for parameter uncertainties in the final results.

The ABM framework was developed and run in Netlogo, an ABM tool that relies on a powerful programming language intended to simulate agents' behavior in a well-defined environment, with a built-in graphical user interface (Thiele, 2014; Mialhe et al., 2012). Farmers' decisions were simulated annually for a period of 15 years (2017 and 2032). The developed ABM framework is explained below in the context of three elements, namely the agents, the environment, and the behavioral rules.

Agents are entities with defined characteristics and goals. They behave as a unit and can interact with other entities and may be affected by external factors. They have specified locations in the environment and behave according to predefined rules of behavior (Dubbelboer et al., 2017). Under the developed ABM framework, agents are the farms. They are defined by their geographic locations in the plain. The framework also looked at farmers as agents, with each farmer linked to one or several farms. The farmers were also spatially defined by their fixed geographic location. Farmers were defined to be traditional or non-traditional, depending on their years of experience. Traditional farmers are those that have been in the farming industry for more than 15 years or those who took over farming from their parents. Farmers were allowed to interact with their spatial neighbors. As such, the ABM framework assumed that farmers maintained their spatial and social network connections21 throughout the simulated timeframe. Both farms and farmers had several state variables that helped differentiate between them. State variables included the social characteristics, land

[21] The spatial network corresponds to the neighbors and spatial surroundings of the farm. The social network is the association of people that may influence the decision of the farmer (such as family members, mentors etc.)

properties, crop yields, surrounding conditions, past experience, and future expectations. Parameters pertaining to the farmers' characteristics, agricultural activity, and land arrangements were assigned based on the data collected from the field surveys. Agents were expected to make decisions on a yearly basis given the defined utility function. A given farmer had to choose between one of six predefined decisions, namely: (1) No change (NC), (2) Sell (S), (3) Quit (Q), (4) Change crop (CC), (5) Seek additional water (SW), or (6) Change crop and seek additional water (CCSW). The agent decisions were then used to update the spatial distribution of the landscape on a yearly basis up till the end of the simulation.

An environment is defined as the space where agents exist and behave. It can be an abstract setting or a real geographic system that is described by a series of GIS layers. The environment can be static or dynamic, discrete or continuous. In this study, the environment is two-dimensional and divided into a grid of patches with each patch representing a parcel of land over which an agent exists (Dubbelboer et al., 2017). The environment was considered to be continuous in its representation of the study area. A shapefile of type polygon was used to define the extent of the NetLogo environment. This file represented the spatial boundaries of the study area. We assumed that water availability across the plain would decrease on average by 24% by the end of 2032 based on results from a hydrologic Soil and Water Assessment Tool (SWAT) analysis conducted on the study area (Harik, 2021). Water availability was assumed to decrease by 1%, 1.6% and 2.2% annually during the first, second and third 5-years periods. The drop in water availability is expected to decrease crop yields and deteriorate the quality of the produce, causing a decrease in the gross income of the farmers (Medyouni et al., 2021; FAO, 2019; 2018; Ripoll et al., 2014).

Behavioral rules define the actions that an agent can take at every point in time during the simulation. As such, all farmers have to make decisions concerning their farm(s) on a yearly basis. The decisions taken by farmers were simulated based on three utilities that targeted optimizing exclusively economic, social reasoned-action, or a combination of both (socio-economic). The decisions were thus based on multiple objectives that included the profitability of the business, the influence of spatial and social networks, as well as the current and past socio-demographic, environmental, and economic conditions. Behavioral rules were implemented according to a scheduling process. First, the utility of each potential decision was calculated for each agent for a given time step. Then, these decisions were updated based on the decisions taken at neighboring farms according to a defined neighboring impact function. Once all agents have taken their decisions, the decisions are executed and the simulation marches forward by one time step. Note that data on the agents' age and experience, the log of their previous decisions, and the changes they intend to implement on their plots are updated annually. This allows farmers to update their decisions over time, while considering the influence of personal factors, neighbors' decisions, and decision output from previous years (Figure 2).

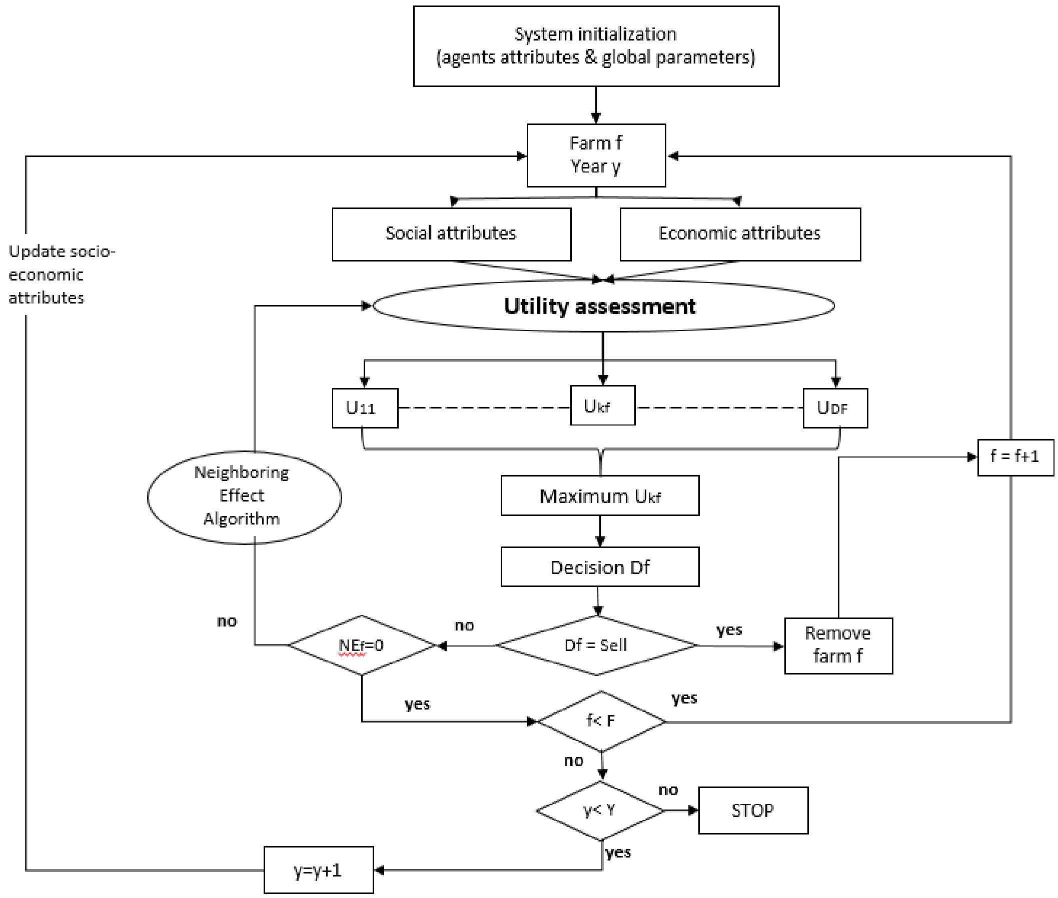


Figure 2 Behavioral modules flowchart
f Farm index, y Year index, k Decision index, D Number of decisions, F Number of farmers, Y Number of years, NE_f Neighboring effect of farm f, U Utility, D_f Decision of farm f

5.2.3.1. <u>Economic optimization utility</u>

The ABM framework was first run assuming that farmers' decisions were based exclusively on optimizing their agro-business budget. It is based on the gross profit associated with a choice. Thus, the total utility is the net revenue that can be obtained from each choice. It is represented by the annual gross income that is computed by multiplying the estimated crop price with the total yield for each crop type. The optimized general utility function is expressed in Equation 1 with the attributes affecting the various decisions summarized in Table 1.

$$EU_{kf} = \mu_1 \sum_1^n (GI_i - PC_i) + \mu_2 \sum_1^m A_j U_j + \mu_3 WC \qquad (1)$$

Where EUkf is the economic utility function, f is the farm index, k is the index of the choice behavior alternative, μ_1 is a weighing coefficient (= 1 when the farm is still being exploited by the farmer and 0 otherwise), GIi is the gross income from crop i and PCi is the production cost for crop i, n is the total number of crop types planted, μ_2 is a weighing coefficient (=1 when the farm is intended to be sold and 0 otherwise), Aj is the area of land j, Uj is the unit price of land j, m is the total number of lands of farm f, μ_3 is a weighing coefficient (= -1 when drilling a well and 0 otherwise), WC is the cost for drilling and permitting a well as well as the associated water pumping costs. All costs are standardized and reported in $/(m2 year). Note that if a farmer owns multiple plots, then he/she will assess the utility of each farm alone.

Table 1 Utility functions of choice behavior alternatives

Choice behavior	Attributes	Utility function
NC	Yield, market price, machine cost, maintenance and fuel, human resources, water, seeds, fertilizers costs, land rental	$\sum_1^n (GI_i - PC_i)$
Q	-	0
S	Land Price	$\sum_1^m A_j U_j$
CC	Yield, market price, machine cost, maintenance and fuel, human resources, water, seeds, fertilizers costs, land rental	$\sum_1^n (GI_i - PC_i)$
SW	Yield, market price, machine cost, maintenance and fuel, human resources, water, seeds, fertilizers costs, land rental, well cost	$\sum_1^n (GI_i - PC_i)$ + WC
CCSW	Yield, market price, machine cost, maintenance and fuel, human resources, water, seeds, fertilizers costs, land rental, well cost	$\sum_1^n (GI_i - PC_i)$ + WC

NC No change, S Sell the land, Q Quit farming and leave the land bare, CC adapt by changing the crop to suit the new environment, SW adapt by finding new sources of irrigation water, CCSW adapt by both changing crop and finding new sources of water, GI_i crop i gross income, P_i crop i production cost, n number of type of crops, A_j area of land j, U_j unit price of land j, m total number of lands corresponding to farmer f, WC cost of digging a well and water pumping

Once the utility of each decision is determined, the probability of that decision being taken is calculated assuming $P_{kf} = e^{EUkf}/\Sigma e^{EUkf}$.

5.2.3.2. Social reasoned-action utility

The social evaluation of farmers' decisions towards their farms accounted for the role of attitude, social network, spatial network, the effect of traditions, and the impact of human disturbances such as civil unrest. The attitude and social network effects were based on the Theory of Reasoned Action (TRA) (Equation 2).

$$SU_{kf} = \gamma_1 A_{kf} + \gamma_2 SN_{kf} \quad (2)$$

Where SUk,f is defined as the social utility for a given choice behavior alternative k for farm f. A is the attitude that a person holds towards performing a certain behavior. Meanwhile, SN is the subjective norm, which captures the person's perception of the social pressures placed to exhibit (or not) a certain behavior. Attitudes and subjective norms were both calculated based on data gathered from the farmers' field survey. The attitude represents the underlying intention, personal knowledge, and perception of the behavior. It was based on the farmers' response to "In your opinion how good or bad would it be to behave in a certain way?" The subjective norm or social network accounts for the impact of the social links between the agents, namely between the farmer and his family and friends. It was obtained from the response to "Would people who you respect in the farming industry be supportive if you adopt the intended behavior?" For each farm, the values of A and SN were calculated for each of the six choice behaviors. The parameters γ_1 and γ_2 were empirically derived weights that were based on questions about how much each respondent would rate the relative importance of his/her personal attitude as compared to the attitude of his/her social network towards a certain behavior. In an effort to include the potential effects of civil unrest and mass displacement that the region experienced between 1976 and the early 1990s as well as the impacts that farming traditions might have on the social utility, we expanded the conventional TRA (Equation 2) to include these two additional terms. Respondents were thus asked to evaluate the relative weight of four parameters (attitude, social network, impact of civil war, and farming traditions) on their social utility. Accordingly, the social utility was expressed in Equation 3.

$$SU_{kf} = \gamma_{1f} A_{kf} + \gamma_{2f} SN_{kf} + \gamma_{3f} W_{kf} + \gamma_{4f} FT_{kf} \quad (3)$$

Where γ_{if} are empirically derived relative weights ("how much does your attitude/opinion of people in your close circle/ civil unrest/ farming traditions affect your decision?"; $\Sigma\, \gamma_{.f} = 1$), A_{kf} were the attitudes corresponding to farm f with regards to decision k. SN_{kf} are the subjective norms or social networking of farm f and decision k. W_{kf} are the impact of civil unrest on farm f and decision k. FT_{kf} is the effect of farming traditions on-farm f and decision k.

Lastly, the social utility for each farm was modified to include the impacts of the spatial networking on the final utility. For each farm, the neighboring farms were identified according to its Moore neighborhood22. The social utility of farm f with regards to decision k was thus updated based on the social utility associated with that decision in the farms located in the defined neighborhood. The impact that the neighboring decisions had on the decision of farm 'f' was based on the Neighboring Effect coefficient (NEf) that varied between 0 and 1, with 0 indicating no effect and 1 associated with full effect. The NEf for each farm was obtained from the field surveys,

[22] The eight cells surrounding a central cell

whereby each farmer was asked about how much they were affected by the decisions of their neighbors. Therefore, the social utility SUkf of farm f corresponding to choice k was adjusted as shown in Equation 4.

$$SU_{kf} = SU_{kf}\,(1 + \eta_{kf}\,NE_f\,) \tag{4}$$

Where ηk,f is the number of neighbors within the defined Moore neighborhood of farm f who had their highest utility associated with decision k. This formulation rescales the social utility for each decision based on its prevalence within the Moore neighborhood of farm f. The probability that a decision k is taken in farm f can thus be calculated as $P_{kf} = \frac{e^{SU_{k,f}}}{\sum e^{SU_{k,f}}}$.

5.2.3.3. Socio-economic utility

The overall objective of the socio-economic utility model was to combine profitability and social utility together. Weighing factors for the economic and social utilities were obtained for each farmer based on two questions: "how much do you rate the importance of the economic benefit on your decision?" and "how much do you rate the importance of your intentions and beliefs on your decision?" Therefore, decisions under the socio-economic module were calculated and ranked according to Equation 5.

$$SES_{k,f} = \alpha_f ES_{k,f} + \beta_f SS_{k,f} \tag{5}$$

Where SESk,f is the standardized socio-economic utility of decision k for farm f, αf is the relative weight of the economic utility for farm f, and βf is the relative weight of the social utility for farm f (βf = 1−αf). ESk,f is the standardized economic utility of decision k for farm f, while SSk,f 6 is the standardized social utility of decision k for farm f. Note that the economic and social utility for each decision was standardized23 to allow mapping the utilities to a scale between 0 and 1. In the socio-economic module, the probability of each decision were calculated as $P_{k,f} = \frac{e^{SES_{k,f}}}{\sum e^{SES_{k,f}}}$.

5.2.4. Validation

The purpose of the proposed ABM is the assessment of the agents' actions under certain circumstances. Thus, validating the proposed model is imperative to assess the accuracy of the representation of real-world behavior. The validation of an ABM is the process through which the extent of modeling reality is assessed. Several techniques (See, 2012; Piorr & Müller, 2009; Windrum et al., 2007; Happe et al., 2006) exist and those can be clustered into three main types: (1) Replicative, where modeled results are compared to the real-world data, which is considered as an empirical validation, (2) Predictive, where modeled results are compared to behaviors that have not been observed yet (i.e. results from other theoretical models), (3) Structural, when the model is intended to reproduce the real-world data and the true process in which the system operates. In the context of empirical validation of ecological socio-economics, validation data / information is acquired mostly through surveys, interviews, and participatory processes (Heckbert et al., 2010). Accordingly, in this study a replicative validation was applied where the ABM results were compared to the stated preference survey responses. The purpose of the validation was to assess the predictive capacity of the model by comparing the collected responses to the simulated behaviors. A small

[23] For a farm f and a decision k, the standardized economic (ES) social (SS) utilities were calculated as $ES_{k,f} = (EU_{k,f} - minEU_f) / (maxEU_f - minEU_f)$ and as $SS_{k,f} = (SU_{k,f} - minSU_f) / (maxSU_f - minSU_f)$, where $maxEU_f$ and $maxSU_f$ are the maximum utilities for farm f across the k decisions and $minEU_f$ and $minSU_f$ are the smallest utilities for farm *f* across the *k* decisions

discrepancy would mean a good accuracy of the model, and a large gap would indicate less usability. This is evaluated by assessing the discrepancy between the actual responses of farmers and the simulated decisions through the Chi-Square Goodness of Fit Test.

5.2.5. Sensitivity-Scenario analysis

The sensitivity of the framework to variations in certain parameters was examining the impact of three main scenarios to better understand farmers' decisions: (1) the neighboring effect, (2) the relative weight of the economic versus social utility, and (3) the rate at which water availability would decrease over time (i.e. climate change).

5.2.5.1. Neighboring effect (NE)

This scenario targets the quantification of the impacts that the spatial network has on farmers' decisions and the future state of the landscape. The strength of the NE was thus varied between 0 and 100%. For each selected value, 40 runs were conducted generating 40 future 2032 LCLU states. For each run, farmers were assigned a random value to represent their NE. Values were drawn from Beta distributions with varying means and standard deviations (Table 3). Note that under this scenario, the ratio of the economic weight versus the social weight (SE) was set to one across all farms (Equation 5 with $\alpha f/\beta f = 1$). Moreover, the projected decrease in water availability was set at 24% over the study period. Water deficits in a given year was also considered to be spatially invariant. During the first 5 years, water availability was assumed to decrease by

1%/year, then by 1.6%/year between year 5 and 10, and finally by 2.2%/year in the last 5 years24.

5.2.5.2. Effect of varying the socio-economic weight (SE)

This scenario examined how changes in the relative contribution of the social utility as compared to the economic-based utility can affect the decision-making of farmers' and accordingly the future state of the landscape. Similar to Scenario 1, several setups were simulated with different relative weights assigned for the economic versus the social utility. For each setup, 40 runs were initiated and tracked over time. For each setup and for each run, farmers were assigned a random value for their αf/βf ratio that was drawn from exponential distributions with varying means ($1/\lambda = 0.001, 0.01, 0.1, 1$ and 2). All other parameters were kept constant during the simulations. Namely, the effect of the spatial network was set to zero for all farms and the water availability was still assumed to decrease by 24% over the entire simulation period.

5.2.5.3. Effects of changes in water availability

This scenario examines how changes in future climate may affect farmers' decisions by reducing water availability creating a deficit that affects crop growth and yields according to the growth phase (i.e., vegetative, flowering, and yield formation). In this scenario, we assumed that the water deficit will equally affect the three phases of crop growth with a uniform impact across the entire cropped area. The relationship between the decrease in crop yields ($1 - Ya/Ym$) and water deficit ($1 - Ea/Em$) over the entire growing period was represented by Equation 6 (FAO, 2011).

[24] Annual water deficits were estimated using simulated flows at the sea mouth of the river.

$$\left(1-\frac{Y_a}{Y_m}\right)=\left(1-\frac{E_a}{E_m}\right)K_y \tag{6}$$

Where Ea is the actual evapotranspiration in mm/day, Em is the maximum evapotranspiration in mm/day, Ya is the actual yield in t/ha, and Ym is the maximum yield in t/ha (i.e., the yield corresponding to the most suitable water availability and temperature conditions given the information collected from the study area). Finally, Ky is the rate between the relative yield decrease and the relative evapotranspiration deficit; it ranges between 1.2 and 1.35. (FAO, 2011; Surendar et al., 2013). We opted to use a Ky value of 1.2. The maximum evapotranspiration (Em) was assumed to range between 5 and 6 mm/day (FAO, 2011; Panigrahi et al., 2021; Surendar et al., 2013).

Water scarcity affects agricultural productivity and accordingly farmers' profits. Yet, there is relatively little literature that links water scarcity to the gross profit of farmers convincingly. Therefore, in this scenario, the change in agricultural profit was considered only with regards to its impact on decreasing crop yields. Several rates of water deficiency were considered (Table 2). We assumed that water availability would decrease on average by 24% by the end of the simulation based on hydrologic SWAT analysis (Harik, 2021). Two other changes in the water availability were tested, namely half and double (i.e., a 12% and 48% decrease) the rate predicted by the SWAT simulations. For the scenario with the 24% deficit in water availability, we assumed that the decrease would happen incrementally. The drop was assumed to progress from 1% to 1.6% and then to 2.2% annually during the first, second and third 5 years periods. For the scenario of the 12% total deficit, we assumed that during the first 5 years the water availability would decrease by 0.5% annually, then by 0.8% annually between years 5 and 10, and finally by 1.1% per year in the last 5 years. Finally, for the 48% decrease in water availability, we assumed that the annual drop would be 2%, 3.2% and 4.4% during the first, second and third 5 years.

The simulated water deficits (12%, 24%, 48%) correspond to a drop in banana yield of 14, 29, and 58%, respectively (Equation 6). For each setup, 40 runs were conducted and for each run, farmers were assigned a random value of their yield drop chosen from beta distributions (Table 3). All other parameters were kept constant during the simulations with the socio-economic weight ratio αf/βf ratio set to one across all runs and the effect of the spatial network set at zero for all farms. Note that the possibility that banana prices might drop as a result of a drop in quality resulting from water deficits was not consider in this scenario.

Table 2 Relative water deficit and yield decrease

Relative water deficit (%)	Ea/Em	Ya/Ym	Yield decrease (%)
80	0.2	0.04	96
70	0.3	0.16	84
60	0.4	0.28	72
50	0.5	0.4	60
40	0.6	0.52	48
30	0.7	0.64	36
20	0.8	0.76	24
10	0.9	0.88	12

Ea actual evapotranspiration in mm/day
Em maximum evapotranspiration in mm/day
Ya actual yield in t/ha, Ym maximum yield in t/ha

Table 3 Sensitivity-Scenarios characteristics of the ABM framework

						Distribution statistics					
Scenario	**Description**	**Hypothesis**	**Parameter**	**Range**	**Distribution**	**Mode**	**α[1]**	**β[1]**	**λ[2]**	**Mean**	**SD[3]**
(1) Neighboring effect	This scenario examines the impacts that the spatial network has on the farmers' decisions and the future state of the landscape	The spatial network has a significant effect on the future of the landscape in terms of urbanization and banana farming	NE	0, 1	Beta	0.001	1	1.29		0.44	0.274
						0.5	1.5	1.5		0.5	0.248
						0.99	34.17	1.34		0.96	0.032
(2) Ratio of the weight of economic versus social characteristics (SE)	This scenario examined how changes in the relative contribution of the social as compared to the economic-based decision-making affects farmers' decisions and the future state of the landscape	Changes in the socio-economic weights will alter significantly the landscape in terms of urbanization and banana farming	α_f/β_f	$0, +\infty$	Exponential				1000	0.001	0.001
									100	0.01	0.01
									10	0.1	0.1
									1	1	1
									0.5	2	2
(3) Relative water deficit	This scenario examines how changes in future climate affect farmers' decisions and the future state of the landscape. Variations in water availability/ Relative Evapotranspiration deficit for irrigation on LULC were assessed	Increased water shortages will cause an expansion of urbanization and a drop in banana production	ΔWA[4]	0,1	Beta	12%	1.5	9		14%	10%
						24%	2	5		29%	16$
						48%	1.95	1.69		53%	23%

[1]: α β shape parameters of the Beta distribution; [2]: λ rate parameter; [3]: SD Standard Deviation; [4]: ΔWA percent decrease in water availability

5.3. Results and discussion

5.3.1. Field survey

The interviewed farmers were all locals with different educational background. While 34% were university graduates and have previously occupied various employment positions, the majority (66%) had high-school education only. The farmers can be categorized in three groups: 1) retired employees living partly from agriculture and partly from their retirement stipend (15%), 2) farmers whose income originates partly from agriculture and in part from off-farm employment (15%), and 3) full-time farmers (70%). Their age ranged between 49 and 88 years, with an average of 67. Farming experience ranged between 6 and 75 years with an average of 36 years. Agriculture was found to be mostly traditional in the area, with 74% of farmers having inherited this practice from their parents and never switched to other crops or to new irrigation systems. First-generation farmers were usually people who had been displaced during the civil unrest of 1975 and returned in the 1990s; thus they are the first to initiate farming in their family as they lived most of their lives away from the area and came back to exploit a rented land or their own land that was previously left barren. Farmers were either landowners (22%), tenants (52%) or both (26%). Land plots ranged between 0.2 and 25 ha. While 60% of farmers grew only bananas due to the relatively warm climate in the area and the soil type, the rest grew bananas and vegetables25. A majority of farmers (61%) claimed that their farming decisions were not affected by their spatial network. Moreover, 83% of farmers reported having been negatively affected by civil unrest and its repercussions. With regards to their perceptions on the potential impacts of climate change on their livelihood, the farmers

[25] Table SM1 in the Supplementary Material presents the production costs and gross income

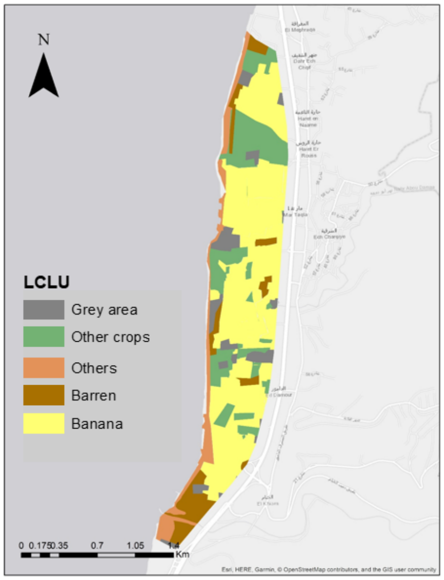
opined that a 24 % drop in the water availability will drop their produce yields on average by 50% and the price of their produce by around 40%. Interestingly, their predictions regarding the drop in yield were nearly twofold higher than those predicted by the FAO model (Equation 6).

5.3.2. ABM framework predictions

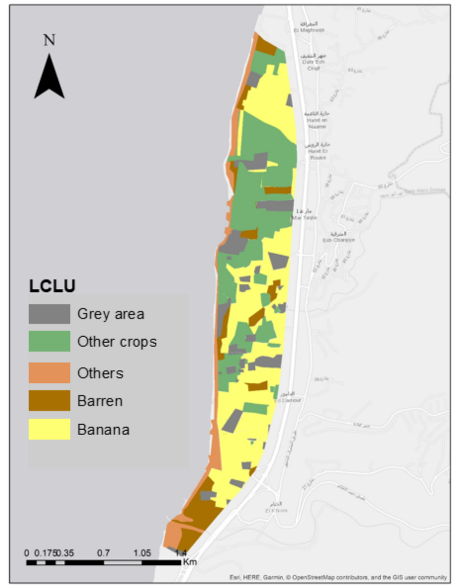
The evaluation of farmers' decisions using strictly economic-based rules predicted that by the end of the simulation (2032), the region will experience a 30% decrease in banana cropped areas mainly along the northern end of the study area and near the shoreline. Meanwhile, it was expected that there will be a 65% increase in the areas planted with crops other than bananas and a significant increase (86%) in grey areas (i.e., resorts, urban, industrial) (Figure 3, Table 4). Overall, the decision that had the highest probability of occurrence under the profit optimization utility pertained to changing crop type (Figure SM1). This was expected given that other crops tend to be more economically attractive as compared to bananas. Under profit optimization, the association of banana farming with local traditions is not accounted.

Predictions based on optimizing the social utility resulted in very different decision choices as compared to those generated based on adopting the economic utility. The two most recurrent responses were quitting farming without selling (35%) and changing crop type (31%) (Figure 3, Table 4). Assuming that farmers' decisions were exclusively a function of their social-based rules resulted in a future landscape, where banana-cropped lands decreased (28%) at the expense of an increase in other crop types (50%) and a relatively small expansion (16%) of grey areas. It also results in a 100% increase in the coverage of barren lands. These decisions reflect a willingness to adapt or quit farming without selling the land. Under the social utility, a high probability of quitting can be discerned along the Eastern parts of the coastal area that is dominated by traditional farmers, who have a lower tendency to change their agricultural practices. Moreover, the generated future landscape had a spatially diverse map of farmers' decisions (Figure SM1).

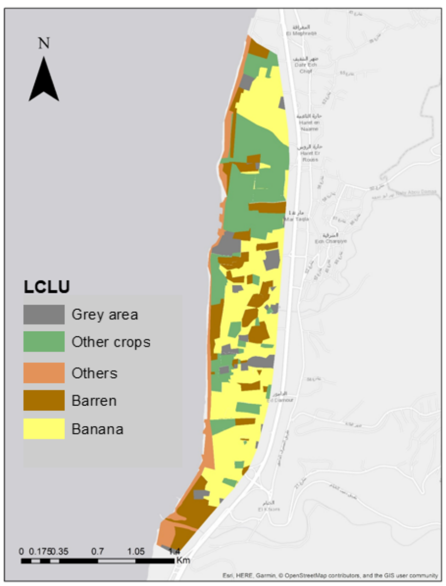
When farmers' decisions were based on optimizing the joint socio-economic attributes, the two most recurrent decisions were the adaptation options, namely changing the crop type (31%) and seeking a new water source (39%). The probability of selling the land was also found to be higher as compared to when farmers' decisions were driven by the social utility exclusively; but significantly lower than when decisions were purely based on economics. This highlights the impact that social values, traditions, and past incidences has on the probability that farmers to sell their land and allow urban sprawl (Figure 3, Table 4). The joint socio-economic utility forecasted a major change in the LULC by 2032, whereby banana plantations were expected to decrease by 28%, while areas planted with other crop types, such as vegetables and tropical fruits, were predicted to increase by 49%. Grey areas were equally expected to increase by 50%. The generated landscape reflects a compromise between the social values that aim to retain the land and the loss of economic profitability if the land is left barren. The latter increased by 71% as the quitting option had a high probability of being selected (Figure 3, Table 4).



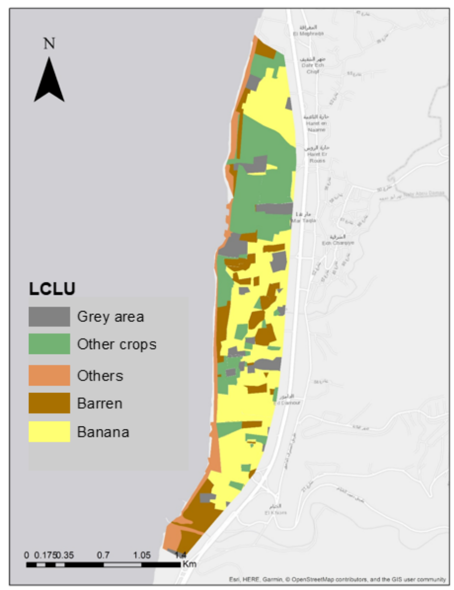
(a) Current LCLU (2017)



(b) Economic Optimization Utility



(c) Social Reasoned-Action Utility



(d) Combined Socio-economic Utility

Figure 3 Predicted LULC changes based on the utility functions at the end of the simulation

Grey area (i.e., resorts, urban, industrial); Other crops (vegetables, tropical fruits); Others (river and sandy beaches)

Table 4 Distribution of the probability of farmers' decisions across utilities at the end of the simulation

Decisio	Economic	Social Reasoned-	Combined Socio-

n	Optimization	Action	economic
NC	0	0	0
S	52	4	17
Q	0	35	13
CC	48	26	39
SW	0	26	26
CCSW	0	9	4

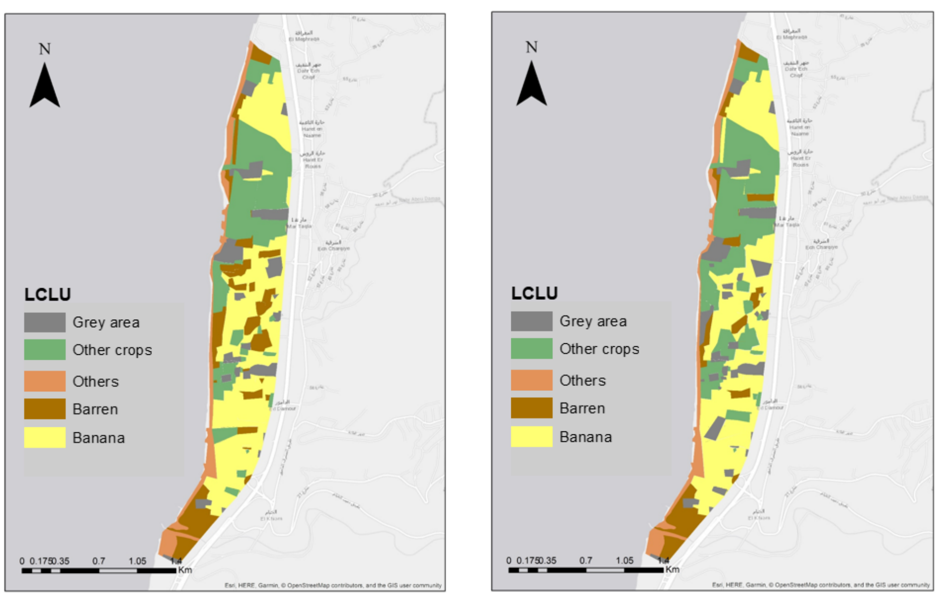
NC No change, S Sell, Q Quit, CC Change crop, SW Seek additional water, CCSW Change crop and seek additional water

5.3.3. ABM framework validation

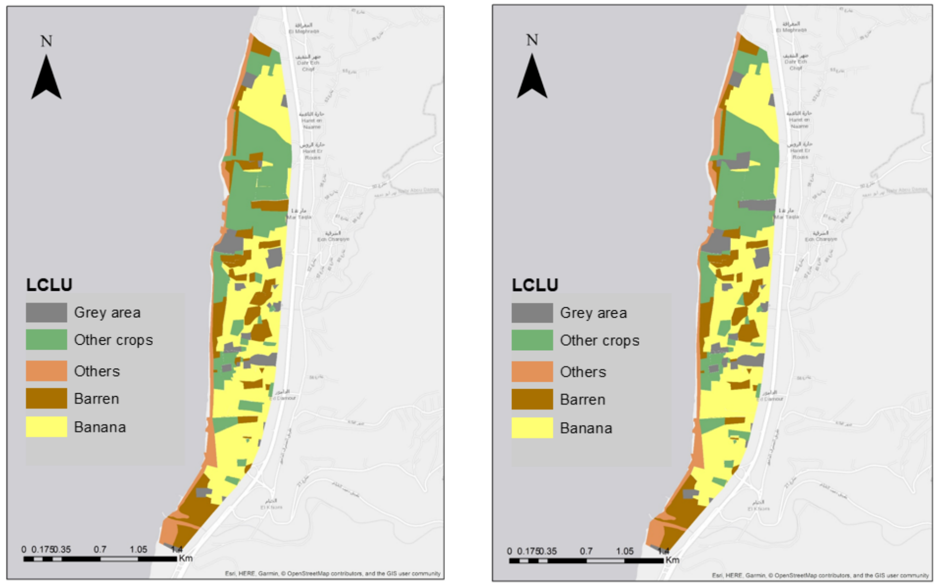
The 2032 LULC generated by the three different utilities were compared to the landscape that was based on the farmers' answers to the field questionnaire. The correspondence between the LULC map predictions generated from the economic-optimization utility and those generated from the farmers' answers was only 35% (Figure 4). The results of the Chi-Square Goodness of Fit test that compared the two maps indicated that the two were significantly different (p-value <0.05). The discrepancies tended to be highest in the parcels where the model predicted that farmers will sell their land but the survey showed that for most of these plots the farmers had opted to adapt or even quit rather than sell. The predictions also underestimated the banana-cropped and barren lands areas by 5 and 36%, respectively. Nevertheless, it overestimated the grey and other cropped areas by 86 and 67%, respectively.

The social reasoned-action utility generated a landscape that was closer to the 2032 LULC that was based on the farmers' responses (Figure 4). The two LULCs had a 70% concurrence. The Chi-Square Goodness of Fit Test between the simulated and survey data had a p-value of 0.05, indicating that the two LULC maps were marginally statistically different from each other at the 95% confidence level. The discrepancies between the model predictions and the farmers' responses were mostly due to the model over-predicting the "quitting" decision. Meanwhile, the model underestimated the coverage of future banana cropped and grey areas by 2 and 22%, respectively. It also overestimated the barren lands by 17% and the agricultural lands planted with crops other than banana by 7% (Figure 5).

For the combined socio-economic utility, the similarity between predictions and farmers' responses reached 83%. The Chi-Square Goodness of Fit test (p-value 0.77) indicated that the model predictions were not statistically different from those that were based on the field survey results. These findings ascertain that the combined socio-economic utility was able to predict farmers' decisions to a satisfactory level. Overall, the combined socio-economic utility underestimated banana cropped areas by 1.5%, while it overestimated the grey, barren and agriculture lands planted with crops other than banana slightly (0.01, 0.02 and 6%, respectively).



(a) Field-based survey
(b) Economic optimization



(c) Social reasoned-action ***(d) Combined socio-economic***

Figure 4 LULC based on the farmers' responses vs ABM predictions by the end of simulation period
Grey areas (i.e., resorts, urban, industrial); Other crops (vegetables, tropical fruits); Others (river and sandy beaches)

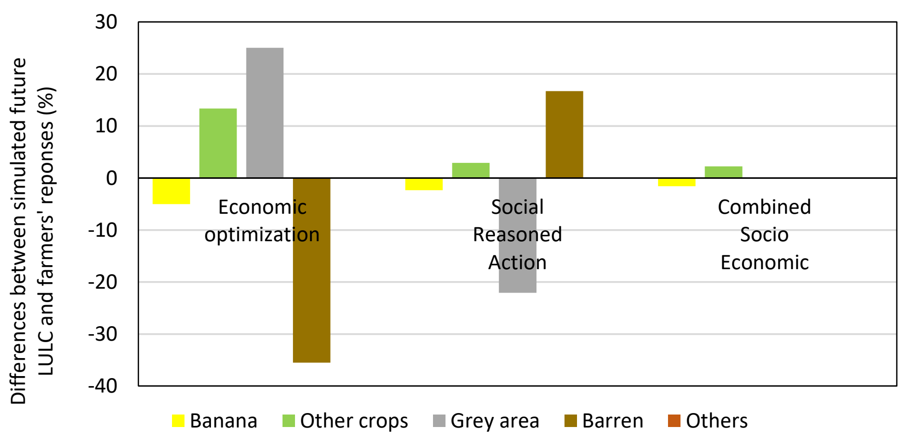


Figure 5 Percent differences between farmers' responses and model predicted LULC
Grey areas (i.e., resorts, urban, industrial); Other crops (vegetables, tropical fruits); Others (river and sandy beaches)

5.3.4. Sensitivity analysis

5.3.4.1. Effect of the spatial network (NE)

This scenario examined the impact that the spatial network has on predicting the future landscape. Figure 6 depicts the changes in the probabilities associated with the various decisions as the NE rate was varied. The selling decision, which ultimately leads to the expansion of urbanization, was found to be highly affected by changes in the spatial networking effect. When comparing the two extreme cases (NE=0 and NE=1), the median probability for selling increased from 15 to 30%. The results show a strong spatial network effect on the selling option, with a chain reaction initiated as the number of selling farmers increased. Moving between a low and a high NE, equally increased the median probability of quitting farming. That increased from 15 to 30%, leading to a shift in land use away from agriculture into barren lands. All other decisions were minimally affected by changes in the NE. The temporal evolution of the probabilities of the six decisions under different NE rates is presented in the Supplementary Material Figure SM2. Overall, when farmers were highly affected by their neighbors' decisions, they tended to adapt less over time; thus, the probability of changing crop type and/or seeking a new water source decreased over time.

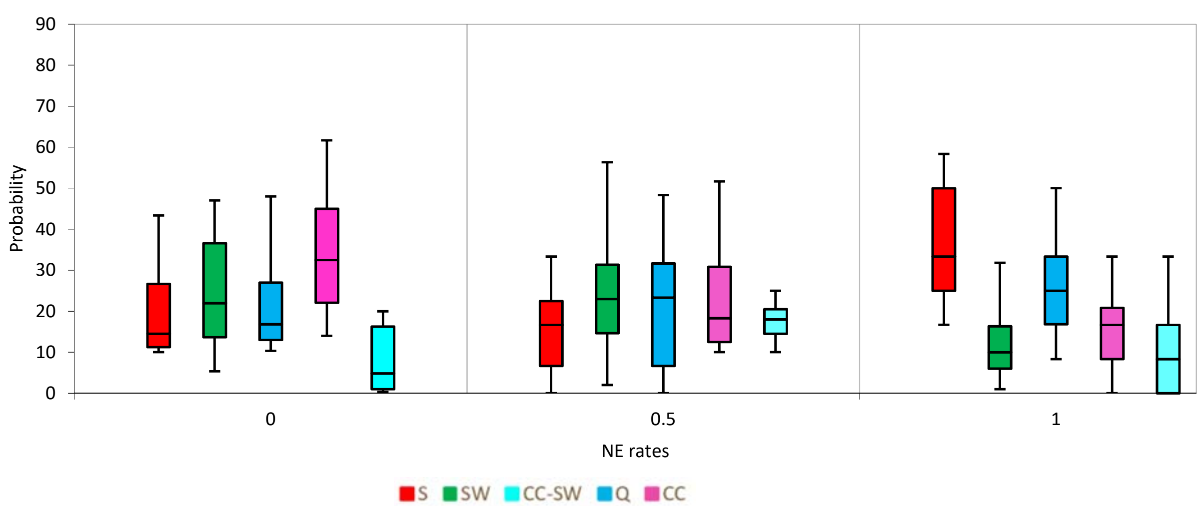


Figure 6 The probabilities of farmers' decisions as a function of varying the NE rate. Reported probabilities are for the end of the simulation (2032)

S Sell, Q Quit, CC Change crop, SW Seek additional water, CCSW Change crop and seek additional water, NE Impact of Neighbors (0-1)

5.3.4.2. Effects of varying the socio-economic weight (SE)

This scenario highlights how the economic and social utilities can affect the future state of the landscape over the simulation period. Various mean values for the αf/βf ratio were considered, namely 0.001, 0.01, 0.1, 1 and 2. Each of these means was used to draw random numbers for each farm from an exponential distribution that characterized the αf/βf ratio. Forty future simulations were conducted for each distribution. Figure 7 shows the distribution of the probabilities of the decisions as a function of varying the αf/βf ratio. As can be seen, the selling decision, which ultimately leads to urbanization expansion, was found to be highly affected by these rates. As expected, the impact of valuing the economic returns over the social features resulted in a significant increase in the probability of selling the land. The mean probability for selling remain around 0%, when the mean αf/βf was below 1. It then increased to 23% and 37%, when the αf/βf were set to 1 and 2, respectively. Therefore, the highest urbanization expansion was expected to occur when the decision-making process is heavily tied to economic profitability. Meanwhile, the decision of quitting farming decreased when the αf/βf rates increased above 1 (10 and 20% for αf/βf of 1 and 2), indicating that when the decision-making of farmers is highly driven by optimizing economic profitability, they do not quit farming and leave the land barren. They would opt for other options that are more gainful. When the impact of the social features on farmers' decision increased (αf/βf ratio below 1), the decision to quit farming increased and the option to change the crop type decreased. Therefore, the cultivation of bananas is expected to persist if social features have a dominant effect on farmers' decision.

When the αf/βf ratio increased above 1, banana cultivation in the study area was projected to be threatened. The median probability of changing the crop type increased to 30% when the ratio reached 2. As for the decision to seek a new water source, more farmers were willing to use groundwater for irrigation when the weight of the social features was high. The median probability of this decision remained almost constant at around 25%, when the mean of the αf/βf ratio was varied between 0.001 and 0.1. It decreased to less than 10% when the economic utility was given more weight. This can be attributed to costs associated with groundwater pumping that were incorporated in the ABM framework. The decision to change the crop type and seek a new water source at the same time was not affected by changes in the αf/βf ratio.

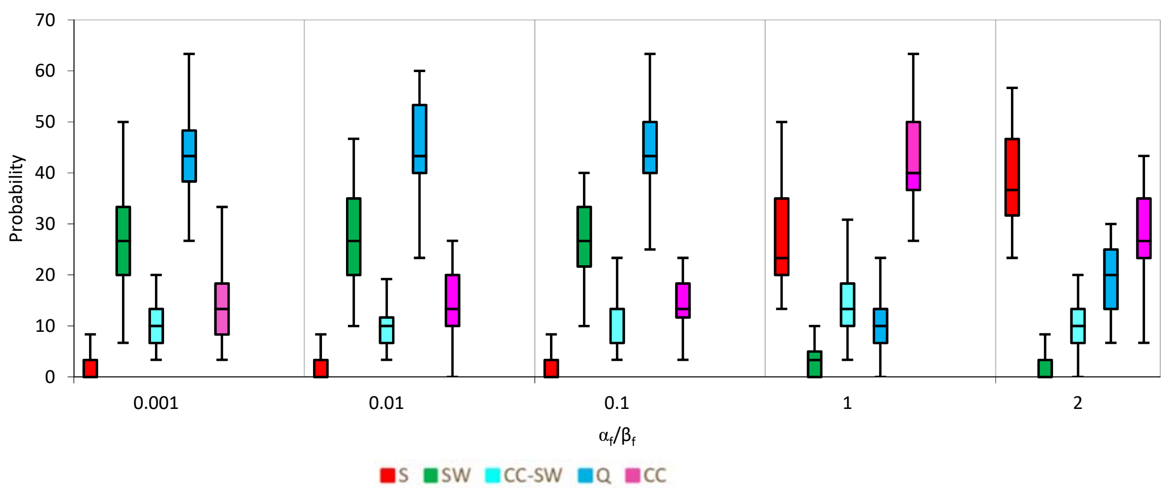


Figure 7 Probability of the different farmers' decisions in 2032 as the α_f/β_f ratio is varied

S Sell, Q Quit, CC Change crop, SW Seek additional water, CCSW Change crop and seek additional water, α_f Socio-economic weights ratio

The changes in the probabilities of farmers' decisions over time under various αf/βf rates are presented in the Supplementary Material Figure SM3. The results highlight the fact that when social features are more pronounced, farmers were more willing to keep the land barren rather than to sell. When the impact of the economic utility was stronger, the probability of adaptation (changing the crop type and/or seeking a new water source) decreased over time indicating that keeping the land under banana plantation is not robust and may dwindle over time.

5.3.4.3. Effects of changes in water availability

This scenario highlights the potential impacts that the change in water availability within the study area may have on the future landscape. Various predictions of the magnitude of the decrease in water availability were considered (Figure 8). When the drop in water availability was minor (median drop in water availability is 12%), a significant number of farmers tended to seek a new water source, either with or without changing their crop types. Under that scenario, nearly 21% of farmers will seek a new water source, while 22% would opt to seek a new water source and to change their crop type. The choice with the highest probability under that scenario was the decision to change the crop type. The median probability for that option was 45%. Changing crop type appears to be the most feasible and economically viable decision when the drop in water availability was limited to 12%. The decisions to sell or quit under were associated with low median probabilities of 5 and 9%, respectively indicating that when the decrease in water availability is still relatively low, farmers will try to adapt without giving up farming.

As the projected decrease in water availability increased, so did the probabilities of selling and quitting. When the drop was around 24%, the average probability of selling reached 11% while the decision to quit had a probability of 14%. When the drop reached 48%, the probabilities of selling or quitting increased further reaching 29% and 26%, respectively. Meanwhile, the probability associated with the decision to change crop type decreased significantly, reaching 12% when the future water availability was predicted to drop by 48%. This indicates that farmers appear to be less willing to adapt and keep farming when water scarcity is extreme, as this would require them to change their crops to drought tolerant crops, which they have no experience in farming, or to expect more frequent crop failures. The decision to seek a new water source had its probability significantly increase (from 21% to 35%) when water scarcity increased from 12 to 24%. Yet, the probability of that choice was 25% when the water scarcity reached 48%. The option to concomitantly change crop type and seek a new water source had its probability decrease as water scarcity became more pronounced. It decreased by half from 22%, when water scarcity was 12%, down to 11% and 10% when the scarcity increased to 24 and 48%, respectively. These results indicate that while farmers are willing to adapt and shift their agricultural practices and crops under low to medium water shortage scenarios, resilience and willingness to adapt appears to wane when water availability significantly decreases. Under such a case, they appear to opt towards selling their land and allowing their fields to urbanize or to turn into touristic resorts. As such, the decrease in water availability is expected to expand urbanization and limit banana farming in the region.

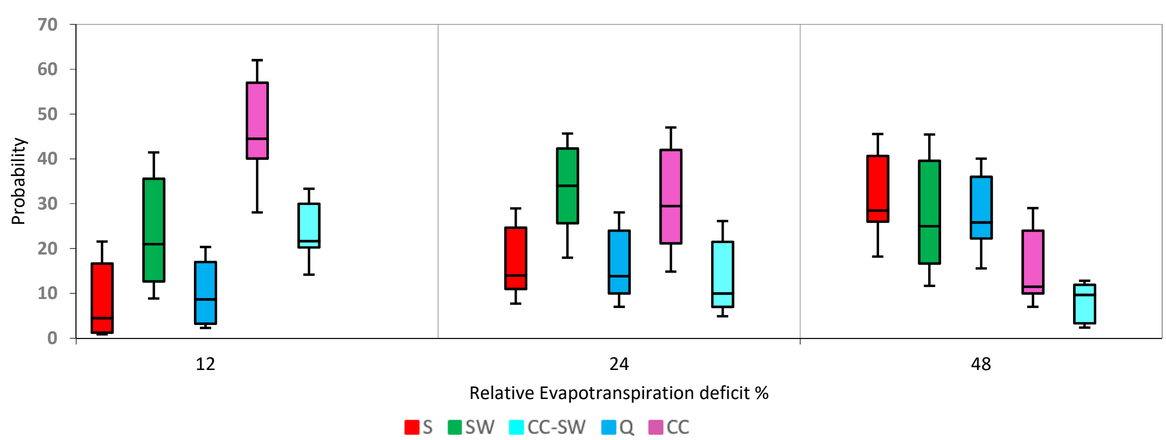


Figure 8 Probability of the 2032 decisions as a function of varying water availability
S Sell, Q Quit, CC Change crop, SW Seek additional water, CCSW Change crop and seek additional water

The temporal variability in the probabilities of various decisions under the different water availability scenarios is shown in the Supplementary Material (Figure SM4). When water shortages were high, the probabilities of the selling and quitting decisions were found to constantly increase over time. As for the adaptation decisions, their probabilities tended to drop over time across all water shortage rates.

5.4. Conclusion

The main objective of this study was to develop an integrated spatio-temporal ABM framework to predict farmers' decisions in the context of climate-induced water scarcity under varying utility optimization functions. The framework allows decision makers to forecast the behavior of farmers through a user-friendly platform with clear output visualization. It was tested at an agriculturally-dominated pilot area and validated against field survey data collected for this purpose. Model prediction that assumed that farmers were solely economically driven captured only 35% of the farmers' responses, while assuming that they were exclusively socially driven in their decisions correctly captured 69% of the field survey results. Meanwhile, linking their decisions to a combined socio-economic utility performed best; the conformity between farmers' response and model predictions reached 83%, which is considered satisfactory for predicting human decisions.

A sensitivity analysis showed that variations in the strength of the spatial network can have a high impact on the probabilities associated with selling or quitting farming. As such, the strength of its magnitude can have a significant impact on the rate at which the area urbanizes or the overall percentage that will be covered by barren lands. When farmers were highly affected by their neighbors' decisions they were found to adapt less over time. Changing the weights placed on the economic and social attributes equally affected the decisions about selling, quitting, and seeking new water sources. The highest urbanization expansion occurred when the decision-making process was based on economic profitability only. The probability of selling decreased in favor of opting to quit and leave the land barren, when social attributes were included. The decrease in water availability increased the rates of selling the land, leading to more urbanization- particularly when the farmers' decisions were based on economic optimization. While farmers were predicted to opt for changing their crops and seek new water sources under a future with low water shortages; they were predicted to stop farming and allow their lands to urbanize, when the future was predicted to have high water shortages.

In closure, we argue that farmers' decision-making processes are better represented when these decisions are concurrently linked to economic rules and social utilities. Moreover, the developed and tested ABM framework provides a powerful management tool that can be used by coastal managers that are aiming to protect fragile coastal agriculture from the encroachment of urbanization. The tool can help in defining and testing the impacts of proposed policies and/or the effects of changes to the physical and social forcing on future farming decisions and the feasibility of preserving coastal agriculture.

5.5. Acknowledgements

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CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

6.1. Summary and findings

This research is driven by the need to better understand, quantify, and predict farmers's behavior under the combined effect of climate change and anthropogenic stresses. It represents a branch of the agri-intelligence concerning strategic decision making to meet today's farming challenges with knowledge and confidence. The framework embraces a multi-disiplinary research methodology integrating various modules of decision making. The main objective is to deliver decision makers, in the context of agriculture, with a solid ground to be able to adapt autonomously and in real-time to intrinsic and extrinsic towards the sustainability and conservation of coastal natural resources. Hence the proposed framework helps in the development of a decision support tool for guiding farmers through a proper adaptation to stressors and effective management of their ressources. The framework was applied and validated in a pilot area representing a typical coastal agricultural Mediteranean area part of a small mountanious watershed.

The realization of this platform consisted of (1) the prediction of future landuse/landcover change in a small mountainous mediterranean watershed through a hybrid Morkov Chain- Cellular Automata process. The spatial-temporal model provided decision makers with a quantitative description of the LCLU past change and the projected direction and magnitude of change in the future; (2) the generation a physically-based hydrological model able to quantify the impacts of climate change on water resources availability in small mountanious mediterranean watersheds. The SWAT model source code was modified to improve the accuracy of runoff simulations in mountanious mediterranean watersheds governed by snowfall; (3) the assessment of the evolution of farmers' decision making processes over time while evaluating the efficiency of mental models and probabilistic models in modeling farmers' response to climate change. farmers' behaviors were examined and compared under climate change impacts using a combined quantitative (probabilistic) and qualitative (mental) approach; (4) the generation of an integrated spatial modeling framework that allows decision makers to forecast the behavior of farmers in the context of water scarcity. It proposes different decisional modules and evaluates their performance through field validation.

The landcover/landuse prediction model was validated at a 71% level. The 2032 predictions showed a significant 93% increase in urban areas of 2032 compared to 2017. Agricultural lands were also predicted to increase by 11% over the same period. Agricultural and urban areas will be growing at the expense of forest and grasslands that decrease by 5 and 73%, respectively while barren lands changed slightly (0.4%). These results showed that the natural equilibrium of the watershed is highly dictated by the population growth and corresponding needs, social beliefs and past experience. The spatial-temporal model provided decision makers with a quantitative description of the LCLU past change and the projected direction and magnitude of change in the future.

Runoff simulations under a modification in the SWAT snowmodule were found closer to observed measurements as reflected in an NSE increase from 7 to 28% and an R^2 from 21 to 44% between the original SWAT and its modified version. The modified snowmelt algorithm indicated an improvement in predicting future water availability whereby its corresponding decrease is expected to reach 24% in comparison to the 31% predicted without the source code modification. The proposed source code modifications to the snowmelt algorithm of SWAT appears to provide better insights about future water availability in snow-dominated watersheds that are increasingly under stress due to population growth and climate change.

The comparative assessment of the probabilistic and mental models returned dissimilarities with regards to some determinants and their impacts. Probabilistic models may miss some determinants that would invariably be mentioned by respondents to unstructured questions. Whereas mental models provide the direction of the relationship between determinants and decisions without specifying the rate of change. Therefore, using both models concomitantly may help in covering the largest trench of explanatory variables and provide a tracking of the weight and direction of their effect on the response in both qualitative and quantitative estimation.

The three ABMs that were created and validated against field data reported variabilities in terms of capturing farmers' responses. An economic-based ABM captured 35% of farmers' responses, while an exclusive social-based ABM exhibited a 69% compatibility with the field survey results, and a combined socio-economic ABM returned an 83% conformity with farmers' response, which is considered satisfactory in predicting human decisions. The sensitivity analysis showed that the spatial network can have a high impact on the probabilities of selling and quitting farming decisions as well as on the spread of urbanization and barren lands, both of which were predicted to increase with time. In contrast, when farmers are highly affected by their neighbors' decisions they tend to adapt less with time. The weights of economic and social attributes equally affected decisions about selling, quitting, and changing water source. The highest urbanization expansion occurred when the decision-making process was based on economic profitability only, with farmers opting to sell. The probability of selling decreased towards opting to just quit and leave the land barren when social attributes were included. A decrease in water availability increased the rates of selling the land, leading to more urbanization particularly under economic rules. While farmers are willing to shift their agricultural practices and crops under low to medium rates of water shortages, they will opt to leave the land to urbanization and tourism at high water shortages causing further urbanization and limiting traditional farming.

Placing all the puzzle pieces together, the integrated decision making platform that was developed captures the prediction of future faremers' behavior when accounting for empirical, social and economic aspects as well as highlighting some site-specific socio-cultural modules that may have high impact on the decision making process. In this context, some adaptation strategies may be suggested (1) for crop production such as switching to crops with higher tolerance to heat, drought and salinity, (2) to improve water catchment for groundwater availability through the enhancement of artificial recharge, (3) to develop alternate water sources such as desalination plants and wastewater recycling.

6.2. Recommendations for future work

Considering the ever-growing climate and anthropogenic stresses that continue to challenge food and agriculture sustainability, a significant need of greater efficiency within current farming resources is crucial. Hence the emergence of smart farming. This research targets one component of the global smart farming concept in small mountainous Mediterranean agricultural watersheds, namely the decision making process. Unleashing the full potential of smart agriculture requires the assessment of all the other components especially in watersheds that have not yet adopted the smart farming procedure. In this context recommendation for future work in such watersheds would ultimately targets (1) The platform which refers to the physical means with which information is acquired, being the specific elements through which objective data are obtained, (2) the data which includes the information directly retrieved from the parameters measured from the crop, soil, or ambient, (3) actuation which refers to the physical execution of an action commanded by the decision system, and is typically carried out by advanced equipment that can receive orders from a computerized control unit.

Finally, the essence resides in the implementation of such holistic approach for better management of the agricultural resources.

APPENDIX A- QUESTIONNAIRE

Oral Consent

An integrated econometric and agent based modeling framework for predicting farmers' decision making process towards improved water management

Dr. Mutasem El-Fadel

Ghinwa Harik

Hello. My name is Ghinwa Harik. I am a graduate student in the Department of Civil and Environmental Engineering at AUB. I would like to invite you to participate in a research study about farmers decision making vis-à-vis some controllable and uncontrollable surrounding environmental changes ; The primary aim of this study is to develop a decision making process that captures farmers' behavior in response to changes in water resources systems. This process is based on an integrated framework coupling socio-psychology, mathematical, econometric and hydrologic modeling into a spatially explicit system.

Before we begin, I would like to take a few minutes to explain why I am inviting you to participate and what will be done with the information you provide. You will be asked to participate in a short interview about your agricultural practices and what are you willing to change in the presence of environmental stresses. Please stop me at any time if you have questions about the study.

I am doing this study as part of my studies at AUB. I will be interviewing between 10 and 15 farmers with an age range between 20 and 50; and will use the information as the basis for my PhD thesis. I may also use this information in articles that might be published, as well as in academic presentations. Your individual privacy and confidentiality of the information you provide will be maintained in all published and written data analysis resulting from the study. The data will be stored with Ms. Ghinwa Harik with no public access to it.

Your participation should take approximately 30 minutes through a face to face interview in a private location in your working place. Please understand your participation is entirely on a voluntary basis and you have the right to withdraw your consent or discontinue participation at any time without penalty. The benefits which may reasonably be expected to result from this study is managing the water resources systems while taking into account farmers decisions and behaviors.

If at any time and for any reason, you would prefer not to answer any questions, please feel free to skip those questions. If at any time you would like to stop participating, please tell me. We can take a break, stop and continue at a late date, or stop altogether. You will not be penalized for deciding to stop participation at any time

If you have any questions, you are free to ask them now. If you have questions later, you may contact me via email gxh00@mail.aub.edu. If you have questions about your rights as a participant in this research, you can contact the following office at AUB: Email: irb@aub.edu.lb; Telephone: 00961 -1-350000 or 1 374374, ext: 5445

A copy of this consent form will be provided to you.

Questionnaire

Nbr:
Date:

STRUCTURED QUESTIONNAIRE

Socio-demographic characteristics

1. Questionnaire ID

2. Parcel number

3. Age bracket

<15 15-20 20-40 40-64 >64

4. Highest level of education attained

Primary Middle High

5. Religion

6. Farming Experience

0-3 3-5 5-10 10-20 >

7. Relying on agriculture

<10% 25-50 50-75 75-100 1

8. Daily number of working hours

0-4 4-8 8-12 >12

9. Land tenure

Full owner Part owner Lease Other:

10. Number of workers on the field

11. Do you intend to pass on the farm to any member of your family once you stop farming?

☐ Yes

☐ No

☐ No, because I don't own the farm

☐ Don't know

12. If yes in what percentages?

13. Do you suppose that you could be the last generation in farming?

14. For how long has farming been a practice in your family?

First generation Traditional

15. How much is your land expropriation value? $/m2

16. Are you willing to sell? At what price.

Agricultural features

17. Land area

18. Type of practice:

Greenhouse Open field

19. What are your agricultural produce? Why do you cultivate this type of produce?

20. Roughly speaking, what percentage of your farm product do you sell?

_______% of my farm product is sold

21. What is the yield of the previous season?

22. What was the maximum reached yield? When?

23. What was the minimum reached yield? When?

24. What source of water you currently use?

Surface Ground Dam Rain Spring Public water

25. What is the percent irrigated area?

26. What is the type of irrigation used?

Surface Drip Sprinkler Other

27. Do you have any wells?

Yes No

28. What is its water quality?

Saline Fresh Brackish Other

29. Is the water tested?

Yes No

30. How much would you estimate the daily water needs?

31. How much do you actually spend on water on a monthly basis?

32. Are you satisfied with the actual water price?

33. How would you rate the actual water availability condition? (Bad – Good)

0 1 2 3 4 5

34. How would you rate the actual water quality? (Bad – Good)

0 1 2 3 4 5

35. How many months of the year water is needed the most?

36. How much do you actually spend on fertilizers on a monthly basis, seeds, equipment and human resources on a yearly basis?

Behavioral response

37. To what extent are you willing to adopt the same practices as your neighborhood? (low – high)

0 1 2 3 4 5

38. To what extent are you willing to adopt the same practices as your previous year? (low – high)

0 1 2 3 4 5

39. Who is your influencer in farming?

Neighbor	Market	Self education	Engineers	Employer	Family

40. In your opinion how good or bad would it be not changes in agricultural practices? (Bad – Good) 0-5
41. Would people who you respect in the farming industry be supportive if you don't change in agricultural practices? Y-N
42. Would not changing be feasible? Y-N
43. In your opinion how good or bad would it be to sell the land and drop agriculture? (Bad – good) 0-5
44. Would people who you respect in the farming industry be supportive if you sell the land? Y-N
45. Would selling be feasible? Y-N
46. In your opinion how good or bad would it be to quit agriculture? (Bad – good) 0-5
47. Would people who you respect in the farming industry be supportive if you quit agriculture? Y-N
48. Would quitting agriculture be feasible? Y-N
49. In your opinion how good or bad would it be to change the type of crops you cultivate? (Bad – Good) 0-5
50. Would people who you respect in the farming industry be supportive if you changed the type of crops? Y-N
51. Would changing crop types be feasible? Y-N
52. In your opinion how good or bad would it be to change the cropped area? (Bad – Good) 0-5
53. In what quantities?
54. Would people who you respect in the farming industry be supportive if you changed the cropped area? Y-N
55. Would changing the cropped area be feasible? Y-N
56. In your opinion how good or bad would it be to change the source of irrigation? (Bad – Good) 0-5
57. Would people who you respect in the farming industry be supportive if you changed the source of irrigation? Y-N
58. Would changing irrigation source be feasible? Y-N
59. In your opinion how good or bad would it be to change the type of crops and area you cultivate? (Bad – Good) 0-5
60. Would people who you respect in the farming industry be supportive if you changed the type of crops and cropped area?Y-N
61. Would changing crop types and area be feasible? Y-N
62. In your opinion how good or bad would it be to change the type of crops and irrigation source? (Bad – Good) 0-5
63. Would people who you respect in the farming industry be supportive if you changed the type of crops and irrigation source? Y-N
64. Would changing crop types and irrigation source be feasible? Y-N
65. In your opinion how good or bad would it be to change the cropped area and irrigation source? (Bad – Good) 0-5
66. Would people who you respect in the farming industry be supportive if you changed the cropped area and irrigation source? Y-N
67. Would changing the cropped area and irrigation source be feasible? Y-N

UNSTRUCTURED QUESTIONNAIRE

Mean summer temperature across the country are expected to increase up to 1.5^{o}C between 2008 and 2030. Future annual precipitation across the country are expected to decrease by ~20% in 2030 compared to 2008. What would you intend to do and why?

Can you please tell us more about your point of view and previous experience in agriculture, about the history of your family and the study area (its evolution in terms of socio-political status, economic, industrial and agricultural fields.)

*** I would like to keep the questionnaire anonymous**
Yes No

Thank You!

APPENDIX B- R CODE

```
a<- read.csv(file="E:/THESIS_LITANI/Litani/FIELD WORK/questionnaire
summary2_R.csv")
a$produce
ml <- relevel(a$RESPONSE, ref = "S")
ml
T1<- multinom(ml ~ Age  + Land_tenure + Farming_Experience_ + Relying_ag
+ produce + well  + water_quality , data=a)
summary(T1)
z <- summary(T1)$coefficients/summary(T1)$standard.errors
z
p <- (1 - pnorm(abs(z), 0, 1)) * 2
p
nullmod <- multinom(ml~1, data=a)
1-logLik(T1)/logLik(nullmod)
deviance(T1)
deviance(nullmod)
1-(deviance(T1)/deviance(nullmod))

T1<- multinom(ml ~   Farming_Experience_ + Relying_ag   + produce  +
water_availability  + water_quality  , data=a)
summary(T1)

a<- read.csv(file="E:/THESIS_LITANI/Litani/FIELD WORK/questionnaire
summary2_R.csv")
colnames(a)
ml <- relevel(a$RESPONSE, ref = "S")
T1<- multinom(ml ~   Age   + Land_tenure  + Farming_Experience_  + produce +
well , data=a)
summary(T1)
a$RESPONSE

#?
a<- read.csv(file="E:/THESIS_LITANI/Litani/FIELD WORK/questionnaire
summary3_R.csv")
ml <- relevel(a$RESPONSE, ref = "Q")
T1<- multinom(ml ~   Age   + Land_tenure + water_availability
+Farming_Experience_  + produce + well  + Relying_ag + well_quality  , data=a)
summary(T1)

z <- summary(T1)$coefficients/summary(T1)$standard.errors
z
p <- (1 - pnorm(abs(z), 0, 1)) * 2
p
summary(T1)$coefficients
exp(summary(T1)$coefficients)
summary(T1)$standard.errors
exp(coef(T1))
head(pp <- fitted(T1))
```

```
tail(pp <- fitted(T1))
?head
ggplot(pp)

T1<- multinom(ml ~   Land_tenure + Farming_Experience_  + longetivity   +
yield  + past_experience  , data=a)
summary(T1)
z <- summary(T1)$coefficients/summary(T1)$standard.errors
z
p <- (1 - pnorm(abs(z), 0, 1)) * 2
p
summary(T1)$coefficients
summary(T1)$standard.errors


T1<- multinom(ml ~    Land_tenure + Farming_Experience_   + longetivity   +
yield  + past_experience  , data=a)
summary(T1)
z <- summary(T1)$coefficients/summary(T1)$standard.errors
z
p <- (1 - pnorm(abs(z), 0, 1)) * 2
p
summary(T1)$coefficients
summary(T1)$standard.errors

T1<- multinom(ml ~ Land_tenure + Farming_Experience_  + longetivity    +
past_experience  , data=a)
summary(T1)
z <- summary(T1)$coefficients/summary(T1)$standard.errors
z
p <- (1 - pnorm(abs(z), 0, 1)) * 2
p
summary(T1)$coefficients
summary(T1)$standard.errors
```

APPENDIX C- CADASTRAL MAP OF DAMOUR COAST

APPENDIX D- NETLOGO CODE

```
extensions [gis csv matrix]

globals [
  cities-dataset
	rivers-dataset
	WSs-dataset
	agrs-dataset
	Fs-dataset
  Fs-hru-dataset
  In-dataset
  Ur-dataset
  OS-dataset
  MAR-dataset
  DAM-dataset
  WWTP-dataset
  hruid1 hruid
 s4' s1' rd aws id fno  v m m1 n mu nu j u p i d b c b0 a1 ctry k In NE y1 y2 NC BR VR
WC R OA LA BA VA TA WE f flist x_list SE_CT-IS SE_CT SE_IS SE_S SE_Q
SE_NC  A ncol1
necol1 necol2 necol3 necol4 necol5 necol6 necol7 necol8 necol9 necol10 necol11
necol12 necol13 necol14 necol15 necol16 necol17 necol18 necol19 necol20 necol21
necol22 necol23 ECO CT']
breed [FARMs FARM]
breed [ F-labels F-label ]
breed [ river-labels river-label ]
breed [ WS-labels WS-label ]
breed [ agr-labels agr-label ]
breed [UITs UIT]

breed [residents resident]

breed [ pads pad ]
turtles-own [dec hru WTQ WTC UQ EUq EUn EUc EUcg EUcr EUi EUa EU ch]


to setup
  file-close-all
  ca
 setup-patches
 setup-env
 setup-features
; setup-AWSloc
; go
 setup-FARMs
; setup-DAMs
; setup-WWTPs
```

```
 ;setup-MARs
; setup-indus
 setup-urban
; setup-OSs
;setup-p
setup-u
;setup-neigh

  reset-ticks
end



to setup-patches
  ask patches [set pcolor scale-color green ((random 500) + 5000) 0 9000]
 ask patches with [pxcor mod 30 = 0 and pycor mod 30 = 0]
[
set plabel  (word "(" pxcor "," pycor ")")
]

end


to setup-env
  set WSs-dataset gis:load-dataset
"E:/THESIS_LITANI/Litani/GIS_data/highway_damour2017_polygon.shp"
 ; set rivers-dataset gis:load-dataset
"E:/THESIS_LITANI/Litani/GIS_data/damour_rivers.shp"
;  set agrs-dataset gis:load-dataset
"E:/THESIS_LITANI/Litani/GIS_data/Farms_locations.shp"
;  set Fs-hru-dataset gis:load-dataset
"E:/THESIS_LITANI/Litani/GIS_data/farms_HRU5.shp"
  set Fs-dataset gis:load-dataset
"E:/THESIS_LITANI/Litani/GIS_data/Farms_locations.shp"
  set Ur-dataset gis:load-dataset
"E:/THESIS_LITANI/Litani/GIS_data/urbn_ind_rec.shp"
end


to setup-features
gis:set-world-envelope (gis:envelope-of WSs-dataset)
let envelope-border gis:envelope-of WSs-dataset
gis:set-world-envelope envelope-border
   ask WS-labels [ die ]
  gis:set-drawing-color red
  gis:draw WSs-dataset 1

;  foreach gis:feature-list-of rivers-dataset [ vector-feature ->
```

```
;      let centroid gis:location-of gis:centroid-of vector-feature
;  ]
;
;     ask agr-labels [ die ]
;  gis:set-drawing-color 68
;  gis:draw agrs-dataset 1
;  foreach gis:feature-list-of agrs-dataset [ vector-feature ->
;      let centroid gis:location-of gis:centroid-of vector-feature
;  ]
;
;   ask river-labels [ die ]
;  gis:set-drawing-color blue
;  gis:draw rivers-dataset 1
;  foreach gis:feature-list-of rivers-dataset [ vector-feature ->
;      let centroid gis:location-of gis:centroid-of vector-feature
;  ]

 ;  ask F-labels [ die ]
 ; foreach gis:feature-list-of Fs-dataset [ vector-feature ->
 ;   gis:set-drawing-color black
  ;  gis:fill vector-feature 4.0
  ;]

end


to setup-u
set u []
  file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-
ECO.csv"
  if file-at-end? [ stop ]
  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
  set mu matrix:from-row-list  _datau
  set nu matrix:get-column mu 0
  ;print matrix:from-row-list nu
; print mu
ifelse item 1 nu = 0
  [print nu]
  [stop]
end

to setup-FARMs
  foreach gis:feature-list-of Fs-dataset  [ vector-feature ->
    set hruid gis:property-value vector-feature  "FID_1"
    set ctry gis:property-value vector-feature  "FID_1"
   set In gis:property-value vector-feature  "Index"
 set NE gis:property-value vector-feature  "neigh_effe"
```

```
;show NE
;    ask FARMS [
;    if NE != 0
;[ set b count FARMs-on neighbors
;    set c [color] of FARMs-on neighbors
;    set d [label] of FARMs-on neighbors
;  ]
;    ]


    file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-ECO.csv"
  if file-at-end? [ stop ]
  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-ECO.csv"
  set mu matrix:from-row-list  _datau
  set nu matrix:get-column mu 0


    let ctry2 gis:property-value vector-feature  "Id"
 ;   show ctry2
  ifelse ctry < FARM_nb + 1
    [let centroid gis:location-of gis:centroid-of vector-feature
          ;print gis:location-of gis:centroid-of vector-feature
         ; print centroid


   if not empty? centroid
 [create-FARMs  1
        [set xcor item 0 centroid
         set ycor item 1 centroid
         set color white set shape "house" set size 0.7
         set label ctry2 set label-color black

        ; go

;    set flist [1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23]
;    set x_list [0 2 5 5 3 3 3 5 4 4 4 4 4 5 4 4 4 5 5 5 2 6 4]

; show ctry2
;         let ii 0
; ask FARMs [
;   if ctry2 < 23
;           [  if item ctry2 x_list = 1 [if label = ctry2 [set color 4 set shape "house" set size 0.7]]
;             if item ctry2 x_list = 2 [if label = ctry2 [set color 15 set shape "house" set size 0.7]]
```

```
;            if item ctry2 x_list = 3 [if label = ctry2 [set color 96 set shape "house" set size
0.7]]
;            if item ctry2 x_list = 4 [if label = ctry2 [set color 126 set shape "house" set
size 0.7]]
;            if item ctry2 x_list = 5 [if label = ctry2 [set color 75 set shape "house" set size
0.7]]
;            if item ctry2 x_list = 6 [if label = ctry2 [set color 87 set shape "house" set size
0.7]]
;        ]]


     ]
   ]]
    [stop]

  ]


;  ifelse ctry2 < FARMERS_nb + 1
;        [ set label ctry set label-color black]
;        [stop]
;     ; show hru
;  ; print who
;  plot count turtles with [color = 4]
;  plot count turtles with [color = 15]
;
;; show NE
; if NE != 0
;[set b count FARMs-on neighbors
;    set c [color] of FARMs-on neighbors
;    set d [label] of FARMs-on neighbors
;          show c
;;           show ctry
;          if c != []
;[let a 0
; foreach c
;  [
;   if (a < 20)
;    [
;     ifelse (item a c = 87)
;      [
;; set color white
;;                 show ctry
;;                 show label
;  set _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
;  set mu matrix:from-row-list  _datau
;                print mu
```

```
;;                  set ctry ctry + 1
;;
;    set y1 matrix:get mu ctry 12
;   show y1
;set y2 y1 * 1.22
;show y2
;if y2 > 5
;   [set color 87]
;       ]
;
; [   ifelse (item a c = 75)
;     [
;; set color white
;;                  show ctry
;;                  show label
;  set _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
;  set mu matrix:from-row-list  _datau
;                print mu
;;                  set ctry ctry + 1
;;
;    set y1 matrix:get mu ctry 11
;   show y1
;set y2 y1 * 1.22
;show y2
;if y2 > 5
;   [set color 75]
;       ]
;
;[   ifelse (item a c = 126)
;     [
;; set color white
;;                  show ctry
;;                  show label
;  set _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
;  set mu matrix:from-row-list  _datau
;                print mu
;;                  set ctry ctry + 1
;;
;    set y1 matrix:get mu ctry 10
;   show y1
;set y2 y1 * 1.22
;show y2
;if y2 > 5
;   [set color 126]
;       ]
;
```

```
;[   ifelse (item a c = 15)
;     [
;; set color white
;;                 show ctry
;;                 show label
;  set _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
;  set mu matrix:from-row-list  _datau
;                print mu
;;                 set ctry ctry + 1
;;
;    set y1 matrix:get mu ctry 9
;   show y1
;set y2 y1 * 1.22
;show y2
;if y2 > 5
;   [set color 15]
;       ]
;
;   [   ifelse (item a c = 96)
;     [
;; set color white
;;                 show ctry
;;                 show label
;  set _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
;  set mu matrix:from-row-list  _datau
;                print mu
;;                 set ctry ctry + 1
;;
;    set y1 matrix:get mu ctry 8
;   show y1
;set y2 y1 * 1.22
;show y2
;if y2 > 5
;   [set color 96]
;       ]
;
; [   if (item a c = 4)
;     [
;; set color white
;;                 show ctry
;;                 show label
;  set _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
;  set mu matrix:from-row-list  _datau
;                print mu
;;                 set ctry ctry + 1
```

```
;;
;    set y1 matrix:get mu ctry 8
;   show y1
;set y2 y1 * 1.22
;show y2
;if y2 > 5
;   [set color 4]
;       ]
;
;                    ] ]
;             ]   ]]  ] ]
;     set a a + 1
;      ]
;
;; plot count turtles with [color = 4]
; ; histogram [color] of turtles
;                    ]
;
;     ]


    ;]


end

to setup-urban

    foreach gis:feature-list-of Ur-dataset  [ vector-feature ->
    set hruid1 gis:property-value vector-feature  "Id"
   ; show Id

    let ctry1 gis:property-value vector-feature  "Id"
    ;show ctry1
  ifelse ctry1 < UIT_nb + 1
    [let centroid gis:location-of gis:centroid-of vector-feature
          ;print gis:location-of gis:centroid-of vector-feature
         ; print centroid

   if not empty? centroid
 [create-residents  1
         [set xcor item 0 centroid
          set ycor item 1 centroid
           set color YELLOW set shape "building store" set size 1
          set hru hruid1
         ; set label ctry set label-color black
     ; show hru
  ; print who
```

```
      ]
  ]

    ]
    [stop]

  ]
end

to setup-neigh
  foreach gis:feature-list-of Fs-dataset  [ vector-feature ->
    set hruid gis:property-value vector-feature  "FID_1"
    set ctry gis:property-value vector-feature  "FID_1"
   set In gis:property-value vector-feature  "Index"
 set NE gis:property-value vector-feature  "neigh_effe"
  if NE != 0
[
      set b count FARMs-on neighbors
    set c [color] of FARMs-on neighbors
    set d [label] of FARMs-on neighbors
  ]
  ]
end

;to go
;file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/ALL_simp.csv"
;  if file-at-end? [ stop ]
;  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/ALL_simp.csv"
;  set mu matrix:from-row-list  _datau

;  ask FARMs [
;    set i 0
;    if i < FARMERS_nb + 1
; [ set nu matrix:get-row mu i
;    ;  show nu
; ]]
;
;;  set S matrix:get-column mu 15
;;      ;show S
;;  set BR matrix:get-column mu 8
;;      ;show BR
;;  set VR matrix:get-column mu 9
;;     ; show VR
;;  set WC matrix:get-column mu 10
;;     ; show WC
;;  set R matrix:get-column mu 11
```

```
;;     ; show R
;  set OA matrix:get-column mu 1
;      show OA
;  set LA matrix:get-column mu 2
;      show LA
;  set BA matrix:get-column mu 3
;      show BA
;  set VA matrix:get-column mu 4
;      show VA
;  set TA matrix:get-column mu 5
;      show TA
;  set WE matrix:get-column mu 6
;      show WE
;
;; ΔQ TO BE UPDATED AFTER SWAT
;set ΔQ -8.5 + 0.4 * ΔP_% - 0.8 * ΔT_C + 0.1 * ΔP_% * ΔT_C
;  show ΔQ
;SET A (1 - ΔP/ΔY * ΔY/ΔQ * abs(ΔQ) / 100)
;show A
;let A0 1 - ΔY/ΔQ * abs(ΔQ) / 100
;show A0
;
;  let s1 (map [ k1 -> k1 * A * A0 * 5040] BA)  ; REVENUE BANANA
;  show s1
;  let s2 (map [ k1 -> k1 * A * A0 * 2400 * 2.78] VA)   ; REVENUE VEG
2.78=1000/360
;  show s2
; ; output-print s2
;  let s3 (map [ k1 -> k1 * 1800] BA)  ; COST BANANA
;  show s3
;  let s4 (map [ k1 -> k1 * 1152] VA)   ; COST VEG
;  show s4
;  ;output-print s4
;  let s5 (map [ k1 -> k1 * Land_lease_LL/dnm.yr / 1500 ] LA)
;  show s5
;  let s6 (map [ k1 -> k1 * Water_price_LL/yr.dnm / 1500 ] TA)
;  show s6
;
;  let NC' (map + s1 s2)
;  let NC'' (map + s3 s4 )
;  let NC''' (map + s5 s6)
;  LET NC0 (map + NC'' NC''')
;  set NC (map - NC' NC0)
; SHOW 0
;  show NC'
; show NC''
; show NC'''
;  show NC
```

```
;  ;output-print NC
;
;  let S (map [ k1 -> k1 * Land_price_$/m2 * 1000] OA)
;  show S
; ; output-print S
;
;  let s3' (map [ k1 -> k1 * 5040] VA)
;  SET s4' (map [ k1 -> k1 * 2400 * 2.78] BA)
;  let s5' (map [ k1 -> k1 * 2333] BA) ; 2333 = UNIT COST VEGT/1500 X 1.8 X
1000/360
;  let s6' (map [ k1 -> k1 * 1800] VA) ; 1800 = UNIT COST BANANA/1500 X 1.8
;
;  SET s1' (map + s3' s4')
; let s2' (map +  s5' s6')
;  set CT' (map - s1' s2')
;  show CT'
;  output-print CT'
;
;
;  let s1'' (map [ k1 -> k1 *  5040] BA)  ; REVENUE BANANA
;  let s2'' (map [ k1 -> k1 * 2400 * 2.78] VA)   ; REVENUE VEG  2.78=1000/360
;  let s3'' (map [ k1 -> k1 * 1800] BA)  ; COST BANANA
;  let s4'' (map [ k1 -> k1 * 2333] VA)   ; COST VEG
;  let s5'' (map [ k1 -> k1 * Land_lease_LL/dnm.yr / 1500 ] LA)
;  let s6'' (map [ k1 -> k1 * Water_price_LL/yr.dnm / 1500 ] TA)
; let WC$ n-values 23 [ Well_cost_$ ]
;  let IS' (map + s1 s2)
;  let IS'' (map + s3 s4 )
;  let IS''' (map + s5 s6)
;  LET IS0 (map + IS'' IS''')
;  LET IS00 (map - IS' IS0)
;  LET IS (map - IS00 WC$)
;  output-print IS
;
;
;
;  let CT-IS (map - CT' WC$)
;  show CT-IS
;  output-print CT-IS
;
;    let NC1 item 0 NC
;   let NC2 item 1 NC
;   let NC3 item 2 NC
;   let NC4 item 3 NC
;   let NC5 item 4 NC
;   let NC6 item 5 NC
;   let NC7 item 6 NC
;   let NC8 item 7 NC
```

```
;    let NC9 item 8 NC
;    let NC10 item 9 NC
;    let NC11 item 10 NC
;    let NC12 item 11 NC
;    let NC13 item 12 NC
;    let NC14 item 13 NC
;    let NC15 item 14 NC
;    let NC16 item 15 NC
;    let NC17 item 16 NC
;    let NC18 item 17 NC
;    let NC19 item 18 NC
;    let NC20 item 19 NC
;    let NC21 item 20 NC
;    let NC22 item 21 NC
;    let NC23 item 22 NC
;    let row1 (list NC1 NC2 NC3 NC4 NC5 NC6 NC7 NC8 NC9 NC10 NC11 NC12
NC13 NC14 NC15 NC16 NC17 NC18 NC19 NC20 NC21 NC22 NC23)
;    show row1
;
;    let row2 (list 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0)
;  show row2
;
;  let CT1 item 0 CT'
;    let CT2 item 1 CT'
;    let CT3 item 2 CT'
;    let CT4 item 3 CT'
;    let CT5 item 4 CT'
;    let CT6 item 5 CT'
;    let CT7 item 6 CT'
;    let CT8 item 7 CT'
;    let CT9 item 8 CT'
;    let CT10 item 19 CT'
;    let CT11 item 10 CT'
;    let CT12 item 11 CT'
;    let CT13 item 12 CT'
;    let CT14 item 13 CT'
;    let CT15 item 14 CT'
;    let CT16 item 15 CT'
;    let CT17 item 16 CT'
;    let CT18 item 17 CT'
;    let CT19 item 18 CT'
;    let CT20 item 19 CT'
;    let CT21 item 20 CT'
;    let CT22 item 21 CT'
;    let CT23 item 22 CT'
;    let row4 (list CT1 CT2 CT3 CT4 CT5 CT6 CT7 CT8 CT9 CT10 CT11 CT12 CT13
CT14 CT15 CT16 CT17 CT18 CT19 CT20 CT21 CT22 CT23)
;    show row4
```

```
;
;   let SS1 item 0 S
;    let SS2 item 1 S
;    let SS3 item 2 S
;    let SS4 item 3 S
;    let SS5 item 4 S
;    let SS6 item 5 S
;    let SS7 item 6 S
;    let SS8 item 7 S
;    let SS9 item 8 S
;    let SS10 item 9 S
;    let SS11 item 10 S
;    let SS12 item 11 S
;    let SS13 item 12 S
;    let SS14 item 13 S
;    let SS15 item 14 S
;    let SS16 item 15 S
;    let SS17 item 16 S
;    let SS18 item 17 S
;    let SS19 item 18 S
;    let SS20 item 19 S
;    let SS21 item 20 S
;    let SS22 item 21 S
;    let SS23 item 22 S
;    let row3 (list SS1 SS2 SS3 SS4 SS5 SS6 SS7 SS8 SS9 SS10 SS11 SS12 SS13 SS14
SS15 SS16 SS17 SS18 SS19 SS20 SS21 SS22 SS23)
;    show row3
;
;
;    let IS1 item 0 IS
;    let IS2 item 1 IS
;    let IS3 item 2 IS
;    let IS4 item 3 IS
;    let IS5 item 4 IS
;    let IS6 item 5 IS
;    let IS7 item 6 IS
;    let IS8 item 7 IS
;    let IS9 item 8 IS
;    let IS10 item 9 IS
;    let IS11 item 10 IS
;    let IS12 item 11 IS
;    let IS13 item 12 IS
;    let IS14 item 13 IS
;    let IS15 item 14 IS
;    let IS16 item 15 IS
;    let IS17 item 16 IS
;    let IS18 item 17 IS
;    let IS19 item 18 IS
```

```
;    let IS20 item 19 IS
;    let IS21 item 20 IS
;    let IS22 item 21 IS
;    let IS23 item 22 IS
;    let row5 (list IS1 IS2 IS3 IS4 IS5 IS6 IS7 IS8 IS9 IS10 IS11 IS12 IS13 IS14 IS15
IS16 IS17 IS18 IS19 IS20 IS21 IS22 IS23)
;    show row5
;
;
;    let CT-IS1 item 0 CT-IS
;    let CT-IS2 item 1 CT-IS
;    let CT-IS3 item 2 CT-IS
;    let CT-IS4 item 3 CT-IS
;    let CT-IS5 item 4 CT-IS
;    let CT-IS6 item 5 CT-IS
;    let CT-IS7 item 6 CT-IS
;    let CT-IS8 item 7 CT-IS
;    let CT-IS9 item 8 CT-IS
;    let CT-IS10 item 9 CT-IS
;    let CT-IS11 item 10 CT-IS
;    let CT-IS12 item 11 CT-IS
;    let CT-IS13 item 12 CT-IS
;    let CT-IS14 item 13 CT-IS
;    let CT-IS15 item 14 CT-IS
;    let CT-IS16 item 15 CT-IS
;    let CT-IS17 item 16 CT-IS
;    let CT-IS18 item 17 CT-IS
;    let CT-IS19 item 18 CT-IS
;    let CT-IS20 item 19 CT-IS
;    let CT-IS21 item 20 CT-IS
;    let CT-IS22 item 21 CT-IS
;    let CT-IS23 item 22 CT-IS
;    let row6 (list CT-IS1 CT-IS2 CT-IS3 CT-IS4 CT-IS5 CT-IS6 CT-IS7 CT-IS8 CT-
IS9 CT-IS10 CT-IS11 CT-IS12 CT-IS13 CT-IS14 CT-IS15 CT-IS16 CT-IS17 CT-IS18
CT-IS19 CT-IS20 CT-IS21 CT-IS22 CT-IS23)
;    show row6
;
;
;  let list-of-rows (list row1 row2 row3 row4 row5 row6)
;  let BB matrix:from-row-list list-of-rows
;  SHOW BB
;  print matrix:dimensions BB
;
;  let COL1 matrix:get-column BB 0
;  let COL2 matrix:get-column BB 1
;  let COL3 matrix:get-column BB 2
;  let COL4 matrix:get-column BB 3
;  let COL5 matrix:get-column BB 4
```

```
;  let COL6 matrix:get-column BB 5
;  let COL7 matrix:get-column BB 6
;  let COL8 matrix:get-column BB 7
;  let COL9 matrix:get-column BB 8
;  let COL10 matrix:get-column BB 9
;  let COL11 matrix:get-column BB 10
;  let COL12 matrix:get-column BB 11
;  let COL13 matrix:get-column BB 12
;  let COL14 matrix:get-column BB 13
;  let COL15 matrix:get-column BB 14
;  let COL16 matrix:get-column BB 15
;  let COL17 matrix:get-column BB 16
;  let COL18 matrix:get-column BB 17
;  let COL19 matrix:get-column BB 18
;  let COL20 matrix:get-column BB 19
;  let COL21 matrix:get-column BB 20
;  let COL22 matrix:get-column BB 21
;  let COL23 matrix:get-column BB 22
;
;  let min1 n-values 6 [ min COL1]
;  let max1 n-values 6 [ max COL1]
;  let yy1 (map - max1 min1)
;  let xx1 (map - col1 min1)
;  set ncol1 (map / xx1 yy1)
; show ncol1
;
;    let min2 n-values 6 [ min COL2]
;  let max2 n-values 6 [ max COL2]
;  let xx2 (map - COL2 min2)
;  let yy2 (map - max2 min2)
;  let ncol2 (map / xx2 yy2)
;
;      let min3 n-values 6 [ min COL3]
;  let max3 n-values 6 [ max COL3]
;  let xx3 (map - COL3 min3)
;  let yy3 (map - max3 min3)
;  let ncol3 (map / xx3 yy3)
;
;        let min4 n-values 6 [ min COL4]
;  let max4 n-values 6 [ max COL4]
;  let xx4 (map - COL4 min4)
;  let yy4 (map - max4 min4)
;  let ncol4 (map / xx4 yy4)
;
;        let min5 n-values 6 [ min COL5]
;  let max5 n-values 6 [ max COL5]
;  let xx5 (map - COL5 min5)
;  let yy5 (map - max5 min5)
```

```
;  let ncol5 (map / xx5 yy5)
;
;       let min6 n-values 6 [ min COL6]
;  let max6 n-values 6 [ max COL6]
;  let xx6 (map - COL6 min6)
;  let yy6 (map - max6 min6)
;  let ncol6 (map / xx6 yy6)
;
;       let min7 n-values 6 [ min COL7]
;  let max7 n-values 6 [ max COL7]
;  let xx7 (map - COL7 min7)
;  let yy7 (map - max7 min7)
;  let ncol7 (map / xx7 yy7)
;
;       let min8 n-values 6 [ min COL8]
;  let max8 n-values 6 [ max COL8]
;  let xx8 (map - COL8 min8)
;  let yy8 (map - max8 min8)
;  let ncol8 (map / xx8 yy8)
;
;       let min9 n-values 6 [ min COL9]
;  let max9 n-values 6 [ max COL9]
;  let xx9 (map - COL9 min9)
;  let yy9 (map - max9 min9)
;  let ncol9 (map / xx9 yy9)
;
;       let min10 n-values 6 [ min COL10]
;  let max10 n-values 6 [ max COL10]
;  let xx10 (map - COL10 min10)
;  let yy10 (map - max10 min10)
;  let ncol10 (map / xx10 yy10)
;
;       let min11 n-values 6 [ min COL11]
;  let max11 n-values 6 [ max COL11]
;  let xx11 (map - COL11 min11)
;  let yy11 (map - max11 min11)
;  let ncol11 (map / xx11 yy11)
;
;       let min12 n-values 6 [ min COL12]
;  let max12 n-values 6 [ max COL12]
;  let xx12 (map - COL12 min12)
;  let yy12 (map - max12 min12)
;  let ncol12 (map / xx12 yy12)
;
;       let min13 n-values 6 [ min COL13]
;  let max13 n-values 6 [ max COL13]
;  let xx13 (map - COL13 min13)
;  let yy13 (map - max13 min13)
```

```
;  let ncol13 (map / xx13 yy13)
;
;       let min14 n-values 6 [ min COL14]
;  let max14 n-values 6 [ max COL14]
;  let xx14 (map - COL14 min14)
;  let yy14 (map - max14 min14)
;  let ncol14 (map / xx14 yy14)
;
;       let min15 n-values 6 [ min COL15]
;  let max15 n-values 6 [ max COL15]
;  let xx15 (map - COL15 min15)
;  let yy15 (map - max15 min15)
;  let ncol15 (map / xx15 yy15)
;
;       let min16 n-values 6 [ min COL16]
;  let max16 n-values 6 [ max COL16]
;  let xx16 (map - COL16 min16)
;  let yy16 (map - max16 min16)
;  let ncol16 (map / xx16 yy16)
;
;       let min17 n-values 6 [ min COL17]
;  let max17 n-values 6 [ max COL17]
;  let xx17 (map - COL17 min17)
;  let yy17 (map - max17 min17)
;  let ncol17 (map / xx17 yy17)
;
;       let min18 n-values 6 [ min COL18]
;  let max18 n-values 6 [ max COL18]
;  let xx18 (map - COL18 min18)
;  let yy18 (map - max18 min18)
;  let ncol18 (map / xx18 yy18)
;
;       let min19 n-values 6 [ min COL19]
;  let max19 n-values 6 [ max COL19]
;  let xx19 (map - COL19 min19)
;  let yy19 (map - max19 min19)
;  let ncol19 (map / xx19 yy19)
;
;       let min20 n-values 6 [ min COL20]
;  let max20 n-values 6 [ max COL20]
;  let xx20 (map - COL20 min20)
;  let yy20 (map - max20 min20)
;  let ncol20 (map / xx20 yy20)
;
;       let min21 n-values 6 [ min COL21]
;  let max21 n-values 6 [ max COL21]
;  let xx21 (map - COL21 min21)
;  let yy21 (map - max21 min21)
```

```
;  let ncol21 (map / xx21 yy21)
;
;       let min22 n-values 6 [ min COL22]
;  let max22 n-values 6 [ max COL22]
;  let xx22 (map - COL22 min22)
;  let yy22 (map - max22 min22)
;  let ncol22 (map / xx22 yy22)
;
;       let min23 n-values 6 [ min COL23]
;  let max23 n-values 6 [ max COL23]
;  let xx23 (map - COL23 min23)
;  let yy23 (map - max23 min23)
;  let ncol23 (map / xx23 yy23)
;
;
;  let wf1 n-values 6 [ 0.3 ]
;  set necol1 (map * wf1 nCOL1)
;    let wf2 n-values 6 [ 0.8 ]
;  set necol2 (map * wf2 nCOL2)
;    let wf3 n-values 6 [ 0.8 ]
;  set necol3 (map * wf3 nCOL3)
;    let wf4 n-values 6 [ 0.8 ]
;  set necol4 (map * wf4 nCOL4)
;    let wf5 n-values 6 [ 0.2 ]
;  set necol5 (map * wf5 nCOL5)
;    let wf6 n-values 6 [ 0.2 ]
;  set necol6 (map * wf6 nCOL6)
;    let wf7 n-values 6 [ 0.2 ]
;  set necol7 (map * wf7 nCOL7)
;    let wf8 n-values 6 [ 0.5 ]
;  set necol8 (map * wf8 nCOL8)
;    let wf9 n-values 6 [ 0.5 ]
;  set necol9 (map * wf9 nCOL9)
;    let wf10 n-values 6 [ 0.5 ]
;  set necol10 (map * wf10 nCOL10)
;    let wf11 n-values 6 [ 0.5 ]
;  set necol11 (map * wf11 nCOL11)
;    let wf12 n-values 6 [ 0.5 ]
;  set necol12 (map * wf12 nCOL12)
;    let wf13 n-values 6 [ 0.5 ]
;  set necol13 (map * wf13 nCOL13)
;    let wf14 n-values 6 [ 0.5 ]
;  set necol14 (map * wf14 nCOL14)
;    let wf15 n-values 6 [ 0.3 ]
;  set necol15 (map * wf15 nCOL15)
;      let wf16 n-values 6 [ 0.2 ]
;  set necol16 (map * wf16 nCOL16)
;      let wf17 n-values 6 [ 0.3 ]
```

```
;  set necol17 (map * wf17 nCOL17)
;     let wf18 n-values 6 [ 0.3 ]
;  set necol18 (map * wf18 nCOL18)
;     let wf19 n-values 6 [ 0.3 ]
;  set necol19 (map * wf19 nCOL19)
;     let wf20 n-values 6 [ 0.3 ]
;  set necol20 (map * wf20 nCOL20)
;     let wf21 n-values 6 [ 0.6 ]
;  set necol21 (map * wf21 nCOL21)
;     let wf22 n-values 6 [ 0.7 ]
;  set necol22 (map * wf22 nCOL22)
;     let wf23 n-values 6 [ 0.7 ]
;  set necol23 (map * wf23 nCOL23)
;
;  let list-of-columns (list necol1 necol2 necol3 necol4 necol5 necol6 necol7 necol8
necol9 necol10 necol11 necol12 necol13 necol14 necol15 necol16 necol17 necol18
necol19 necol20 necol21 necol22 necol23)
;  SET ECO matrix:from-column-list list-of-columns
;  SHOW ECO


to go
file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/ALL_simp.csv"
  if file-at-end? [ stop ]
  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/ALL_simp.csv"
  set mu matrix:from-row-list  _datau
  view-SPE
  view-Ec
  view-SP
end

to view-SPE
   if SPE

   [file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/socio-eco2.csv"
  if file-at-end? [ stop ]
  let _datas csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/socio-eco2.csv"
  let socio-eco matrix:from-row-list  _datas

  show socio-eco
ifelse ΔQ = -24 [
  SET SE_NC matrix:get-row socio-eco 0
  show SE_NC

    SET SE_Q matrix:get-row socio-eco 1
  show SE_Q
```

```
  SET SE_S matrix:get-row socio-eco 2
 show SE_S

  SET SE_CT matrix:get-row socio-eco 3
 show SE_CT

  SET SE_IS matrix:get-row socio-eco 4
 show SE_IS

  SET SE_CT-IS matrix:get-row socio-eco 5
 show SE_CT-IS


 ask FARMs[
  set f 0
     set x_list (list ch)
 while [f < FARMERS_nb  ]
 [
  let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

    show maxval

;    show FARM f
;     ;show who

   if maxval = item f SE_NC [
    set ch 1
    print "NC"
    show f
      set x_list lput ch x_list
   set color 4
  ]
   if maxval = item f SE_S [
    set ch 2
    print "S"
    show f
      set x_list lput ch x_list
   ;set color 15
    ]
      if maxval = item f SE_Q  [
    set ch 3
    print "Q"
    show f
      set x_list lput ch x_list
   ;set color 15
   ]
```

```
  if maxval = item f SE_CT [
    set ch 4
    print "CT"
    show f
      set x_list lput ch x_list
;  set color 126
     ]
  if maxval = item f SE_IS [
    set ch 5
    print "IS"
    show f
      set x_list lput ch x_list
 ; set color 75
     ]
  if maxval = item f SE_CT-IS [
    set ch 6
    print "CT-IS"
    show f
      set x_list lput ch x_list
        ;  set color 87
  ]

show x_list
set f f + 1


  ]]]

  [let g 0.02 * ΔQ + 1.5
      let gg n-values 24 [ g ]
    sET SE_NC matrix:get-row socio-eco 0
    sET SE_NC (map * gg  SE_NC )
 show SE_NC

  SET SE_Q matrix:get-row socio-eco 1
     show SE_Q

  SET SE_S matrix:get-row socio-eco 2
      show SE_S

  SET SE_CT matrix:get-row socio-eco 3
    sET SE_CT (map * gg  SE_CT )
 show SE_CT

  SET SE_IS matrix:get-row socio-eco 4
    sET SE_IS (map * gg  SE_IS )
 show SE_IS
```

```
   SET SE_CT-IS matrix:get-row socio-eco 5
     sET SE_CT-IS (map * gg  SE_CT-IS )
  show SE_CT-IS


  ask FARMs[
   set f 0
      set x_list (list ch)
  while [f < FARMERS_nb  ]
  [
   let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

     show maxval

;     show FARM f
;      ;show who

    if maxval = item f SE_NC [
     set ch 1
     print "NC"
     show f
       set x_list lput ch x_list
    set color 4
  ]
    if maxval = item f SE_S [
     set ch 2
     print "S"
     show f
       set x_list lput ch x_list
    ;set color 15
     ]
       if maxval = item f SE_Q  [
     set ch 3
     print "Q"
     show f
       set x_list lput ch x_list
    ;set color 15
    ]
    if maxval = item f SE_CT [
     set ch 4
     print "CT"
     show f
       set x_list lput ch x_list
  ;  set color 126
      ]
    if maxval = item f SE_IS [
     set ch 5
```

```
     print "IS"
     show f
       set x_list lput ch x_list
   ; set color 75
       ]
    if maxval = item f SE_CT-IS [
     set ch 6
     print "CT-IS"
     show f
       set x_list lput ch x_list
         ;  set color 87
    ]

show x_list
set f f + 1


    ]]]




    foreach gis:feature-list-of Fs-dataset  [ vector-feature ->
    set hruid gis:property-value vector-feature  "FID_1"
    set ctry gis:property-value vector-feature  "FID_1"
   set In gis:property-value vector-feature  "Index"
 set NE gis:property-value vector-feature  "neigh_effe"

     file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-
ECO.csv"
  if file-at-end? [ stop ]
  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
  set mu matrix:from-row-list  _datau
  set nu matrix:get-column mu 0

    let ctry2 gis:property-value vector-feature  "Id"
 ;   show ctry2
  ifelse ctry < FARM_nb + 1
    [let centroid gis:location-of gis:centroid-of vector-feature
          ;print gis:location-of gis:centroid-of vector-feature
         ; print centroid



   if not empty? centroid
 [create-FARMs  1
        [set xcor item 0 centroid
```

```
        set ycor item 1 centroid
        set color white set shape "house" set size 0.7
        set label ctry2 set label-color black

 show ctry2

 ask FARMs [
   if ctry2 < FARMERS_nb
          [  if item ctry2 x_list = 1 [if label = ctry2 [set color 4 set shape "house" set size
0.7]]
            if item ctry2 x_list = 2 [if label = ctry2 [set color 15 set shape "house" set size
0.7]]
            if item ctry2 x_list = 3 [if label = ctry2 [set color 96 set shape "house" set size
0.7]]
            if item ctry2 x_list = 4 [if label = ctry2 [set color 126 set shape "house" set size
0.7]]
            if item ctry2 x_list = 5 [if label = ctry2 [set color 75 set shape "house" set size
0.7]]
            if item ctry2 x_list = 6 [if label = ctry2 [set color 87 set shape "house" set size
0.7]]
   histogram [color] of FARMs       ]

        ]


     ]
    ]]
   [stop]
;
; show ECO

  ]

   ifelse Well_cost_$ = 4800 [
  SET SE_NC matrix:get-row socio-eco 0
  show SE_NC

   SET SE_Q matrix:get-row socio-eco 1
  show SE_Q

   SET SE_S matrix:get-row socio-eco 2
  show SE_S

   SET SE_CT matrix:get-row socio-eco 3
  show SE_CT

   SET SE_IS matrix:get-row socio-eco 4
  show SE_IS
```

```
   SET SE_CT-IS matrix:get-row socio-eco 5
  show SE_CT-IS


  ask FARMs[
    set f 0
       set x_list (list ch)
  while [f < FARMERS_nb  ]
  [
    let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

      show maxval

;     show FARM f
;      ;show who

    if maxval = item f SE_NC [
     set ch 1
      print "NC"
      show f
        set x_list lput ch x_list
    set color 4
  ]
    if maxval = item f SE_S [
      set ch 2
      print "S"
      show f
        set x_list lput ch x_list
    ;set color 15
     ]
        if maxval = item f SE_Q  [
      set ch 3
      print "Q"
      show f
        set x_list lput ch x_list
    ;set color 15
    ]
    if maxval = item f SE_CT [
      set ch 4
      print "CT"
      show f
        set x_list lput ch x_list
  ;  set color 126
       ]
    if maxval = item f SE_IS [
      set ch 5
```

```
     print "IS"
     show f
       set x_list lput ch x_list
  ; set color 75
       ]
    if maxval = item f SE_CT-IS [
     set ch 6
     print "CT-IS"
     show f
       set x_list lput ch x_list
         ;  set color 87
    ]

show x_list
set f f + 1


    ]]]

    [let h 4800 / Well_cost_$
         let hh n-values 24 [ h ]
     sET SE_NC matrix:get-row socio-eco 0
      show SE_NC

    SET SE_Q matrix:get-row socio-eco 1
      show SE_Q

    SET SE_S matrix:get-row socio-eco 2
       show SE_S

    SET SE_CT matrix:get-row socio-eco 3
       show SE_CT

    SET SE_IS matrix:get-row socio-eco 4
     sET SE_IS (map * hh  SE_IS )
  show SE_IS

    SET SE_CT-IS matrix:get-row socio-eco 5
     sET SE_CT-IS (map * hh  SE_CT-IS )
  show SE_CT-IS


  ask FARMs[
    set f 0
      set x_list (list ch)
  while [f < FARMERS_nb  ]
  [
```

```
   let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

     show maxval

;    show FARM f
;     ;show who

   if maxval = item f SE_NC [
    set ch 1
     print "NC"
     show f
       set x_list lput ch x_list
   set color 4
 ]
   if maxval = item f SE_S [
     set ch 2
     print "S"
     show f
       set x_list lput ch x_list
   ;set color 15
    ]
       if maxval = item f SE_Q  [
     set ch 3
     print "Q"
     show f
       set x_list lput ch x_list
   ;set color 15
   ]
   if maxval = item f SE_CT [
     set ch 4
     print "CT"
     show f
       set x_list lput ch x_list
 ;  set color 126
      ]
   if maxval = item f SE_IS [
     set ch 5
     print "IS"
     show f
       set x_list lput ch x_list
  ; set color 75
      ]
   if maxval = item f SE_CT-IS [
     set ch 6
     print "CT-IS"
     show f
       set x_list lput ch x_list
```

```
      ;  set color 87
   ]

show x_list
set f f + 1


   ]]]




   foreach gis:feature-list-of Fs-dataset  [ vector-feature ->
   set hruid gis:property-value vector-feature  "FID_1"
   set ctry gis:property-value vector-feature  "FID_1"
  set In gis:property-value vector-feature  "Index"
 set NE gis:property-value vector-feature  "neigh_effe"

    file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-
ECO.csv"
  if file-at-end? [ stop ]
  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
  set mu matrix:from-row-list  _datau
  set nu matrix:get-column mu 0

   let ctry2 gis:property-value vector-feature  "Id"
 ;   show ctry2
  ifelse ctry < FARM_nb + 1
   [let centroid gis:location-of gis:centroid-of vector-feature
      ;print gis:location-of gis:centroid-of vector-feature
      ; print centroid



  if not empty? centroid
 [create-FARMs  1
      [set xcor item 0 centroid
       set ycor item 1 centroid
       set color white set shape "house" set size 0.7
       set label ctry2 set label-color black

 show ctry2

 ask FARMs [
  if ctry2 < FARMERS_nb
         [  if item ctry2 x_list = 1 [if label = ctry2 [set color 4 set shape "house" set size
0.7]]
```

```
            if item ctry2 x_list = 2 [if label = ctry2 [set color 15 set shape "house" set size
0.7]]
            if item ctry2 x_list = 3 [if label = ctry2 [set color 96 set shape "house" set size
0.7]]
            if item ctry2 x_list = 4 [if label = ctry2 [set color 126 set shape "house" set size
0.7]]
            if item ctry2 x_list = 5 [if label = ctry2 [set color 75 set shape "house" set size
0.7]]
            if item ctry2 x_list = 6 [if label = ctry2 [set color 87 set shape "house" set size
0.7]]
  histogram [color] of FARMs       ]

        ]


     ]
   ]]
  [stop]
;
; show ECO

 ]


   ifelse Land_price_$/m2 = 130 [
 SET SE_NC matrix:get-row socio-eco 0
 show SE_NC

   SET SE_Q matrix:get-row socio-eco 1
 show SE_Q

   SET SE_S matrix:get-row socio-eco 2
 show SE_S

   SET SE_CT matrix:get-row socio-eco 3
 show SE_CT

   SET SE_IS matrix:get-row socio-eco 4
 show SE_IS

   SET SE_CT-IS matrix:get-row socio-eco 5
 show SE_CT-IS


 ask FARMs[
   set f 0
      set x_list (list ch)
 while [f < FARMERS_nb  ]
```

```
 [
   let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

     show maxval

;    show FARM f
;     ;show who

   if maxval = item f SE_NC [
    set ch 1
     print "NC"
     show f
       set x_list lput ch x_list
   set color 4
 ]
   if maxval = item f SE_S [
     set ch 2
     print "S"
     show f
       set x_list lput ch x_list
   ;set color 15
    ]
       if maxval = item f SE_Q  [
     set ch 3
     print "Q"
     show f
       set x_list lput ch x_list
   ;set color 15
   ]
   if maxval = item f SE_CT [
     set ch 4
     print "CT"
     show f
       set x_list lput ch x_list
 ;  set color 126
      ]
   if maxval = item f SE_IS [
     set ch 5
     print "IS"
     show f
       set x_list lput ch x_list
  ; set color 75
       ]
   if maxval = item f SE_CT-IS [
     set ch 6
     print "CT-IS"
     show f
```

```
        set x_list lput ch x_list
          ;  set color 87
    ]

show x_list
set f f + 1

    ]]]

    [let o Land_price_$/m2 / 130
         let oo n-values 24 [ o ]
      sET SE_NC matrix:get-row socio-eco 0
       show SE_NC

    SET SE_Q matrix:get-row socio-eco 1
       show SE_Q

    SET SE_S matrix:get-row socio-eco 2
      sET SE_S (map * oo  SE_S )
        show SE_S

    SET SE_CT matrix:get-row socio-eco 3
        show SE_CT

    SET SE_IS matrix:get-row socio-eco 4
        show SE_IS

    SET SE_CT-IS matrix:get-row socio-eco 5
       show SE_CT-IS


  ask FARMs[
    set f 0
       set x_list (list ch)
  while [f < FARMERS_nb  ]
  [
    let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

      show maxval

;     show FARM f
;      ;show who

    if maxval = item f SE_NC [
     set ch 1
      print "NC"
      show f
```

```
        set x_list lput ch x_list
    set color 4
  ]
    if maxval = item f SE_S [
      set ch 2
      print "S"
      show f
        set x_list lput ch x_list
    ;set color 15
     ]
        if maxval = item f SE_Q  [
      set ch 3
      print "Q"
      show f
        set x_list lput ch x_list
    ;set color 15
    ]
    if maxval = item f SE_CT [
      set ch 4
      print "CT"
      show f
        set x_list lput ch x_list
  ;  set color 126
       ]
    if maxval = item f SE_IS [
      set ch 5
      print "IS"
      show f
        set x_list lput ch x_list
   ; set color 75
        ]
    if maxval = item f SE_CT-IS [
      set ch 6
      print "CT-IS"
      show f
        set x_list lput ch x_list
          ;  set color 87
    ]

show x_list
set f f + 1


    ]]]
```

```
   foreach gis:feature-list-of Fs-dataset  [ vector-feature ->
   set hruid gis:property-value vector-feature  "FID_1"
   set ctry gis:property-value vector-feature  "FID_1"
  set In gis:property-value vector-feature  "Index"
 set NE gis:property-value vector-feature  "neigh_effe"

    file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-
ECO.csv"
  if file-at-end? [ stop ]
  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
  set mu matrix:from-row-list  _datau
  set nu matrix:get-column mu 0

   let ctry2 gis:property-value vector-feature  "Id"
;   show ctry2
  ifelse ctry < FARM_nb + 1
   [let centroid gis:location-of gis:centroid-of vector-feature
        ;print gis:location-of gis:centroid-of vector-feature
       ; print centroid



  if not empty? centroid
 [create-FARMs  1
       [set xcor item 0 centroid
        set ycor item 1 centroid
        set color white set shape "house" set size 0.7
        set label ctry2 set label-color black

 show ctry2

 ask FARMs [
  if ctry2 < FARMERS_nb
         [  if item ctry2 x_list = 1 [if label = ctry2 [set color 4 set shape "house" set size
0.7]]
          if item ctry2 x_list = 2 [if label = ctry2 [set color 15 set shape "house" set size
0.7]]
          if item ctry2 x_list = 3 [if label = ctry2 [set color 96 set shape "house" set size
0.7]]
          if item ctry2 x_list = 4 [if label = ctry2 [set color 126 set shape "house" set size
0.7]]
          if item ctry2 x_list = 5 [if label = ctry2 [set color 75 set shape "house" set size
0.7]]
          if item ctry2 x_list = 6 [if label = ctry2 [set color 87 set shape "house" set size
0.7]]
  histogram [color] of FARMs       ]
```

```
        ]


     ]
    ]]
   [stop]
;
; show ECO

  ]

]
end

to view-Ec
   if Ec

   [file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/eco.csv"
  if file-at-end? [ stop ]
  let _datas csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/eco.csv"
  let socio-eco matrix:from-row-list  _datas

  show socio-eco
ifelse ΔQ = -24 [
  SET SE_NC matrix:get-row socio-eco 0
  show SE_NC

    SET SE_Q matrix:get-row socio-eco 1
  show SE_Q

    SET SE_S matrix:get-row socio-eco 2
  show SE_S

    SET SE_CT matrix:get-row socio-eco 3
  show SE_CT

    SET SE_IS matrix:get-row socio-eco 4
  show SE_IS

    SET SE_CT-IS matrix:get-row socio-eco 5
  show SE_CT-IS


  ask FARMs[
    set f 0
       set x_list (list ch)
  while [f < FARMERS_nb  ]
```

```
 [
   let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

     show maxval

;     show FARM f
;      ;show who

    if maxval = item f SE_NC [
     set ch 1
      print "NC"
      show f
        set x_list lput ch x_list
    set color 4
  ]
    if maxval = item f SE_S [
      set ch 2
      print "S"
      show f
        set x_list lput ch x_list
    ;set color 15
     ]
        if maxval = item f SE_Q  [
      set ch 3
      print "Q"
      show f
        set x_list lput ch x_list
    ;set color 15
    ]
    if maxval = item f SE_CT [
      set ch 4
      print "CT"
      show f
        set x_list lput ch x_list
  ;  set color 126
       ]
    if maxval = item f SE_IS [
      set ch 5
      print "IS"
      show f
        set x_list lput ch x_list
   ; set color 75
        ]
    if maxval = item f SE_CT-IS [
      set ch 6
      print "CT-IS"
      show f
```

```
        set x_list lput ch x_list
          ;  set color 87
    ]

show x_list
set f f + 1


    ]]]

    [let g 0.02 * ΔQ + 1.5
          let gg n-values 24 [ g ]
      sET SE_NC matrix:get-row socio-eco 0
      sET SE_NC (map * gg  SE_NC )
  show SE_NC

    SET SE_Q matrix:get-row socio-eco 1
       show SE_Q

    SET SE_S matrix:get-row socio-eco 2
        show SE_S

    SET SE_CT matrix:get-row socio-eco 3
      sET SE_CT (map * gg  SE_CT )
  show SE_CT

    SET SE_IS matrix:get-row socio-eco 4
      sET SE_IS (map * gg  SE_IS )
  show SE_IS

    SET SE_CT-IS matrix:get-row socio-eco 5
      sET SE_CT-IS (map * gg  SE_CT-IS )
  show SE_CT-IS


  ask FARMs[
    set f 0
       set x_list (list ch)
  while [f < FARMERS_nb  ]
  [
    let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

      show maxval

;     show FARM f
;      ;show who
```

```
  if maxval = item f SE_NC [
   set ch 1
    print "NC"
    show f
      set x_list lput ch x_list
  set color 4
]
  if maxval = item f SE_S [
    set ch 2
    print "S"
    show f
      set x_list lput ch x_list
  ;set color 15
   ]
      if maxval = item f SE_Q  [
    set ch 3
    print "Q"
    show f
      set x_list lput ch x_list
  ;set color 15
  ]
  if maxval = item f SE_CT [
    set ch 4
    print "CT"
    show f
      set x_list lput ch x_list
;  set color 126
     ]
  if maxval = item f SE_IS [
    set ch 5
    print "IS"
    show f
      set x_list lput ch x_list
 ; set color 75
      ]
  if maxval = item f SE_CT-IS [
    set ch 6
    print "CT-IS"
    show f
      set x_list lput ch x_list
        ;  set color 87
  ]

show x_list
set f f + 1


  ]]]
```

```
   foreach gis:feature-list-of Fs-dataset  [ vector-feature ->
   set hruid gis:property-value vector-feature  "FID_1"
   set ctry gis:property-value vector-feature  "FID_1"
  set In gis:property-value vector-feature  "Index"
 set NE gis:property-value vector-feature  "neigh_effe"

    file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-
ECO.csv"
  if file-at-end? [ stop ]
  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
  set mu matrix:from-row-list  _datau
  set nu matrix:get-column mu 0

   let ctry2 gis:property-value vector-feature  "Id"
 ;   show ctry2
  ifelse ctry < FARM_nb + 1
   [let centroid gis:location-of gis:centroid-of vector-feature
        ;print gis:location-of gis:centroid-of vector-feature
       ; print centroid



  if not empty? centroid
 [create-FARMs  1
       [set xcor item 0 centroid
        set ycor item 1 centroid
        set color white set shape "house" set size 0.7
        set label ctry2 set label-color black

 show ctry2

 ask FARMs [
  if ctry2 < FARMERS_nb
         [  if item ctry2 x_list = 1 [if label = ctry2 [set color 4 set shape "house" set size
0.7]]
          if item ctry2 x_list = 2 [if label = ctry2 [set color 15 set shape "house" set size
0.7]]
          if item ctry2 x_list = 3 [if label = ctry2 [set color 96 set shape "house" set size
0.7]]
          if item ctry2 x_list = 4 [if label = ctry2 [set color 126 set shape "house" set size
0.7]]
          if item ctry2 x_list = 5 [if label = ctry2 [set color 75 set shape "house" set size
0.7]]
```

```
          if item ctry2 x_list = 6 [if label = ctry2 [set color 87 set shape "house" set size
0.7]]
  histogram [color] of FARMs       ]

        ]


     ]
   ]]
  [stop]
;
; show ECO

  ]

   ifelse Well_cost_$ = 4800 [
 SET SE_NC matrix:get-row socio-eco 0
 show SE_NC

   SET SE_Q matrix:get-row socio-eco 1
 show SE_Q

   SET SE_S matrix:get-row socio-eco 2
 show SE_S

   SET SE_CT matrix:get-row socio-eco 3
 show SE_CT

   SET SE_IS matrix:get-row socio-eco 4
 show SE_IS

   SET SE_CT-IS matrix:get-row socio-eco 5
 show SE_CT-IS


 ask FARMs[
   set f 0
      set x_list (list ch)
 while [f < FARMERS_nb  ]
 [
   let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

     show maxval

;     show FARM f
;      ;show who
```

```
    if maxval = item f SE_NC [
     set ch 1
      print "NC"
      show f
        set x_list lput ch x_list
    set color 4
  ]
    if maxval = item f SE_S [
      set ch 2
      print "S"
      show f
        set x_list lput ch x_list
    ;set color 15
     ]
        if maxval = item f SE_Q  [
      set ch 3
      print "Q"
      show f
        set x_list lput ch x_list
    ;set color 15
    ]
    if maxval = item f SE_CT [
      set ch 4
      print "CT"
      show f
        set x_list lput ch x_list
  ;  set color 126
       ]
    if maxval = item f SE_IS [
      set ch 5
      print "IS"
      show f
        set x_list lput ch x_list
   ; set color 75
        ]
    if maxval = item f SE_CT-IS [
      set ch 6
      print "CT-IS"
      show f
        set x_list lput ch x_list
          ;  set color 87
    ]

show x_list
set f f + 1


    ]]]
```

```
    [let h 4800 / Well_cost_$
         let hh n-values 24 [ h ]
      sET SE_NC matrix:get-row socio-eco 0
       show SE_NC

    SET SE_Q matrix:get-row socio-eco 1
       show SE_Q

    SET SE_S matrix:get-row socio-eco 2
        show SE_S

    SET SE_CT matrix:get-row socio-eco 3
        show SE_CT

    SET SE_IS matrix:get-row socio-eco 4
      sET SE_IS (map * hh  SE_IS )
  show SE_IS

    SET SE_CT-IS matrix:get-row socio-eco 5
      sET SE_CT-IS (map * hh  SE_CT-IS )
  show SE_CT-IS


  ask FARMs[
    set f 0
       set x_list (list ch)
  while [f < FARMERS_nb  ]
  [
    let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

      show maxval

;     show FARM f
;      ;show who

    if maxval = item f SE_NC [
     set ch 1
      print "NC"
      show f
        set x_list lput ch x_list
    set color 4
  ]
    if maxval = item f SE_S [
      set ch 2
      print "S"
      show f
```

```
      set x_list lput ch x_list
   ;set color 15
    ]
      if maxval = item f SE_Q  [
     set ch 3
     print "Q"
     show f
       set x_list lput ch x_list
   ;set color 15
   ]
   if maxval = item f SE_CT [
     set ch 4
     print "CT"
     show f
       set x_list lput ch x_list
  ;  set color 126
      ]
   if maxval = item f SE_IS [
     set ch 5
     print "IS"
     show f
       set x_list lput ch x_list
  ; set color 75
       ]
   if maxval = item f SE_CT-IS [
     set ch 6
     print "CT-IS"
     show f
       set x_list lput ch x_list
         ;  set color 87
   ]

show x_list
set f f + 1


   ]]]




   foreach gis:feature-list-of Fs-dataset  [ vector-feature ->
   set hruid gis:property-value vector-feature  "FID_1"
   set ctry gis:property-value vector-feature  "FID_1"
  set In gis:property-value vector-feature  "Index"
 set NE gis:property-value vector-feature  "neigh_effe"
```

```
    file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-ECO.csv"
  if file-at-end? [ stop ]
  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-ECO.csv"
  set mu matrix:from-row-list  _datau
  set nu matrix:get-column mu 0

    let ctry2 gis:property-value vector-feature  "Id"
;   show ctry2
  ifelse ctry < FARM_nb + 1
    [let centroid gis:location-of gis:centroid-of vector-feature
         ;print gis:location-of gis:centroid-of vector-feature
        ; print centroid



   if not empty? centroid
 [create-FARMs  1
        [set xcor item 0 centroid
         set ycor item 1 centroid
         set color white set shape "house" set size 0.7
         set label ctry2 set label-color black

 show ctry2

 ask FARMs [
   if ctry2 < FARMERS_nb
          [  if item ctry2 x_list = 1 [if label = ctry2 [set color 4 set shape "house" set size 0.7]]
            if item ctry2 x_list = 2 [if label = ctry2 [set color 15 set shape "house" set size 0.7]]
            if item ctry2 x_list = 3 [if label = ctry2 [set color 96 set shape "house" set size 0.7]]
            if item ctry2 x_list = 4 [if label = ctry2 [set color 126 set shape "house" set size 0.7]]
            if item ctry2 x_list = 5 [if label = ctry2 [set color 75 set shape "house" set size 0.7]]
            if item ctry2 x_list = 6 [if label = ctry2 [set color 87 set shape "house" set size 0.7]]
   histogram [color] of FARMs       ]

         ]


     ]
    ]]
   [stop]
```

```
;
; show ECO

 ]


   ifelse Land_price_$/m2 = 130 [
 SET SE_NC matrix:get-row socio-eco 0
 show SE_NC

   SET SE_Q matrix:get-row socio-eco 1
 show SE_Q

   SET SE_S matrix:get-row socio-eco 2
 show SE_S

   SET SE_CT matrix:get-row socio-eco 3
 show SE_CT

   SET SE_IS matrix:get-row socio-eco 4
 show SE_IS

   SET SE_CT-IS matrix:get-row socio-eco 5
 show SE_CT-IS


 ask FARMs[
   set f 0
      set x_list (list ch)
 while [f < FARMERS_nb  ]
 [
   let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

     show maxval

;     show FARM f
;      ;show who

   if maxval = item f SE_NC [
    set ch 1
     print "NC"
     show f
       set x_list lput ch x_list
   set color 4
 ]
   if maxval = item f SE_S [
     set ch 2
```

```
      print "S"
      show f
        set x_list lput ch x_list
    ;set color 15
     ]
        if maxval = item f SE_Q  [
      set ch 3
      print "Q"
      show f
        set x_list lput ch x_list
    ;set color 15
    ]
    if maxval = item f SE_CT [
      set ch 4
      print "CT"
      show f
        set x_list lput ch x_list
  ;  set color 126
       ]
    if maxval = item f SE_IS [
      set ch 5
      print "IS"
      show f
        set x_list lput ch x_list
   ; set color 75
        ]
    if maxval = item f SE_CT-IS [
      set ch 6
      print "CT-IS"
      show f
        set x_list lput ch x_list
          ;  set color 87
    ]

show x_list
set f f + 1

    ]]]

    [let o Land_price_$/m2 / 130
          let oo n-values 24 [ o ]
      sET SE_NC matrix:get-row socio-eco 0
       show SE_NC

    SET SE_Q matrix:get-row socio-eco 1
       show SE_Q

    SET SE_S matrix:get-row socio-eco 2
```

```
  sET SE_S (map * oo  SE_S )
    show SE_S

 SET SE_CT matrix:get-row socio-eco 3
    show SE_CT

 SET SE_IS matrix:get-row socio-eco 4
    show SE_IS

 SET SE_CT-IS matrix:get-row socio-eco 5
   show SE_CT-IS


ask FARMs[
 set f 0
   set x_list (list ch)
while [f < FARMERS_nb  ]
[
 let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

  show maxval

;    show FARM f
;     ;show who

 if maxval = item f SE_NC [
  set ch 1
  print "NC"
  show f
    set x_list lput ch x_list
 set color 4
]
 if maxval = item f SE_S [
  set ch 2
  print "S"
  show f
    set x_list lput ch x_list
 ;set color 15
  ]
    if maxval = item f SE_Q  [
  set ch 3
  print "Q"
  show f
    set x_list lput ch x_list
 ;set color 15
 ]
 if maxval = item f SE_CT [
```

```
     set ch 4
     print "CT"
     show f
       set x_list lput ch x_list
  ;  set color 126
      ]
    if maxval = item f SE_IS [
     set ch 5
     print "IS"
     show f
       set x_list lput ch x_list
   ; set color 75
       ]
    if maxval = item f SE_CT-IS [
     set ch 6
     print "CT-IS"
     show f
       set x_list lput ch x_list
         ;  set color 87
    ]

show x_list
set f f + 1


    ]]]




    foreach gis:feature-list-of Fs-dataset  [ vector-feature ->
    set hruid gis:property-value vector-feature  "FID_1"
    set ctry gis:property-value vector-feature  "FID_1"
   set In gis:property-value vector-feature  "Index"
 set NE gis:property-value vector-feature  "neigh_effe"

     file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-
ECO.csv"
  if file-at-end? [ stop ]
  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
  set mu matrix:from-row-list  _datau
  set nu matrix:get-column mu 0

    let ctry2 gis:property-value vector-feature  "Id"
 ;   show ctry2
  ifelse ctry < FARM_nb + 1
    [let centroid gis:location-of gis:centroid-of vector-feature
```

```
         ;print gis:location-of gis:centroid-of vector-feature
        ; print centroid



   if not empty? centroid
 [create-FARMs  1
        [set xcor item 0 centroid
         set ycor item 1 centroid
         set color white set shape "house" set size 0.7
         set label ctry2 set label-color black

 show ctry2

 ask FARMs [
   if ctry2 < FARMERS_nb
          [  if item ctry2 x_list = 1 [if label = ctry2 [set color 4 set shape "house" set size
0.7]]
            if item ctry2 x_list = 2 [if label = ctry2 [set color 15 set shape "house" set size
0.7]]
            if item ctry2 x_list = 3 [if label = ctry2 [set color 96 set shape "house" set size
0.7]]
            if item ctry2 x_list = 4 [if label = ctry2 [set color 126 set shape "house" set size
0.7]]
            if item ctry2 x_list = 5 [if label = ctry2 [set color 75 set shape "house" set size
0.7]]
            if item ctry2 x_list = 6 [if label = ctry2 [set color 87 set shape "house" set size
0.7]]
   histogram [color] of FARMs       ]

         ]


      ]
    ]]
   [stop]
;
; show ECO

  ]

]
end

to view-SP
  if SP

   [file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/socio.csv"
```

```
  if file-at-end? [ stop ]
  let _datas csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/socio.csv"
  let socio-eco matrix:from-row-list  _datas

  show socio-eco
if ΔQ = -24 [
  SET SE_NC matrix:get-row socio-eco 0
  show SE_NC

    SET SE_Q matrix:get-row socio-eco 1
  show SE_Q

    SET SE_S matrix:get-row socio-eco 2
  show SE_S

    SET SE_CT matrix:get-row socio-eco 3
  show SE_CT

    SET SE_IS matrix:get-row socio-eco 4
  show SE_IS

    SET SE_CT-IS matrix:get-row socio-eco 5
  show SE_CT-IS


  ask FARMs[
    set f 0
       set x_list (list ch)
  while [f < FARMERS_nb  ]
  [
    let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

      show maxval

;     show FARM f
;      ;show who

    if maxval = item f SE_NC [
     set ch 1
      print "NC"
      show f
        set x_list lput ch x_list
    set color 4
  ]
    if maxval = item f SE_S [
      set ch 2
```

```
     print "S"
     show f
       set x_list lput ch x_list
   ;set color 15
    ]
       if maxval = item f SE_Q  [
     set ch 3
     print "Q"
     show f
       set x_list lput ch x_list
   ;set color 15
   ]
   if maxval = item f SE_CT [
     set ch 4
     print "CT"
     show f
       set x_list lput ch x_list
 ;  set color 126
      ]
   if maxval = item f SE_IS [
     set ch 5
     print "IS"
     show f
       set x_list lput ch x_list
  ; set color 75
      ]
   if maxval = item f SE_CT-IS [
     set ch 6
     print "CT-IS"
     show f
       set x_list lput ch x_list
         ;  set color 87
   ]

show x_list
set f f + 1


   ]]]

;    [let g 0.02 * ΔQ + 1.5
;         let gg n-values 24 [ g ]
;      sET SE_NC matrix:get-row socio-eco 0
;      sET SE_NC (map * gg  SE_NC )
;  show SE_NC
;
;    SET SE_Q matrix:get-row socio-eco 1
;       show SE_Q
```

```
;
;    SET SE_S matrix:get-row socio-eco 2
;        show SE_S
;
;    SET SE_CT matrix:get-row socio-eco 3
;      sET SE_CT (map * gg  SE_CT )
;  show SE_CT
;
;    SET SE_IS matrix:get-row socio-eco 4
;      sET SE_IS (map * gg  SE_IS )
;  show SE_IS
;
;    SET SE_CT-IS matrix:get-row socio-eco 5
;      sET SE_CT-IS (map * gg  SE_CT-IS )
;  show SE_CT-IS
;
;
;  ask FARMs[
;    set f 0
;       set x_list (list ch)
;  while [f < FARMERS_nb  ]
;  [
;    let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)
;
;      show maxval
;
;;     show FARM f
;;      ;show who
;
;    if maxval = item f SE_NC [
;     set ch 1
;      print "NC"
;      show f
;        set x_list lput ch x_list
;    set color 4
;  ]
;    if maxval = item f SE_S [
;      set ch 2
;      print "S"
;      show f
;        set x_list lput ch x_list
;    ;set color 15
;     ]
;        if maxval = item f SE_Q  [
;      set ch 3
;      print "Q"
;      show f
```

```
;        set x_list lput ch x_list
;    ;set color 15
;    ]
;    if maxval = item f SE_CT [
;      set ch 4
;      print "CT"
;      show f
;        set x_list lput ch x_list
;  ;  set color 126
;      ]
;    if maxval = item f SE_IS [
;      set ch 5
;      print "IS"
;      show f
;        set x_list lput ch x_list
;   ; set color 75
;       ]
;    if maxval = item f SE_CT-IS [
;      set ch 6
;      print "CT-IS"
;      show f
;        set x_list lput ch x_list
;          ;  set color 87
;    ]
;
;show x_list
;set f f + 1
;
;
;    ]]]
;
;
;
;
;    foreach gis:feature-list-of Fs-dataset  [ vector-feature ->
;    set hruid gis:property-value vector-feature  "FID_1"
;    set ctry gis:property-value vector-feature  "FID_1"
;   set In gis:property-value vector-feature  "Index"
; set NE gis:property-value vector-feature  "neigh_effe"
;
;     file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-
ECO.csv"
;  if file-at-end? [ stop ]
;  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
;  set mu matrix:from-row-list  _datau
;  set nu matrix:get-column mu 0
;
```

```
;    let ctry2 gis:property-value vector-feature  "Id"
; ;   show ctry2
;  ifelse ctry < FARM_nb + 1
;    [let centroid gis:location-of gis:centroid-of vector-feature
;          ;print gis:location-of gis:centroid-of vector-feature
;         ; print centroid
;
;
;
;   if not empty? centroid
; [create-FARMs  1
;         [set xcor item 0 centroid
;          set ycor item 1 centroid
;          set color white set shape "house" set size 0.7
;          set label ctry2 set label-color black
;
; show ctry2
;
; ask FARMs [
;   if ctry2 < FARMERS_nb
;            [  if item ctry2 x_list = 1 [if label = ctry2 [set color 4 set shape "house" set size
0.7]]
;              if item ctry2 x_list = 2 [if label = ctry2 [set color 15 set shape "house" set size
0.7]]
;              if item ctry2 x_list = 3 [if label = ctry2 [set color 96 set shape "house" set size
0.7]]
;              if item ctry2 x_list = 4 [if label = ctry2 [set color 126 set shape "house" set
size 0.7]]
;              if item ctry2 x_list = 5 [if label = ctry2 [set color 75 set shape "house" set size
0.7]]
;              if item ctry2 x_list = 6 [if label = ctry2 [set color 87 set shape "house" set size
0.7]]
;   histogram [color] of FARMs       ]
;
;          ]
;
;
;      ]
;    ]]
;   [stop]
;;
;; show ECO
;
;  ]
;
;    ifelse Well_cost_$ = 4800 [
;  SET SE_NC matrix:get-row socio-eco 0
;  show SE_NC
```

```
;
;    SET SE_Q matrix:get-row socio-eco 1
;  show SE_Q
;
;    SET SE_S matrix:get-row socio-eco 2
;  show SE_S
;
;    SET SE_CT matrix:get-row socio-eco 3
;  show SE_CT
;
;    SET SE_IS matrix:get-row socio-eco 4
;  show SE_IS
;
;    SET SE_CT-IS matrix:get-row socio-eco 5
;  show SE_CT-IS
;
;
;  ask FARMs[
;    set f 0
;       set x_list (list ch)
;  while [f < FARMERS_nb  ]
;  [
;    let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)
;
;      show maxval
;
;;     show FARM f
;;      ;show who
;
;    if maxval = item f SE_NC [
;     set ch 1
;      print "NC"
;      show f
;        set x_list lput ch x_list
;    set color 4
;  ]
;    if maxval = item f SE_S [
;      set ch 2
;      print "S"
;      show f
;        set x_list lput ch x_list
;    ;set color 15
;     ]
;        if maxval = item f SE_Q  [
;      set ch 3
;      print "Q"
;      show f
```

```
;       set x_list lput ch x_list
;    ;set color 15
;    ]
;    if maxval = item f SE_CT [
;      set ch 4
;      print "CT"
;      show f
;        set x_list lput ch x_list
;  ;  set color 126
;      ]
;    if maxval = item f SE_IS [
;      set ch 5
;      print "IS"
;      show f
;        set x_list lput ch x_list
;   ; set color 75
;       ]
;    if maxval = item f SE_CT-IS [
;      set ch 6
;      print "CT-IS"
;      show f
;        set x_list lput ch x_list
;          ;  set color 87
;    ]
;
;show x_list
;set f f + 1
;
;
;    ]]]
;
;    [let h 4800 / Well_cost_$
;          let hh n-values 24 [ h ]
;      sET SE_NC matrix:get-row socio-eco 0
;       show SE_NC
;
;    SET SE_Q matrix:get-row socio-eco 1
;       show SE_Q
;
;    SET SE_S matrix:get-row socio-eco 2
;        show SE_S
;
;    SET SE_CT matrix:get-row socio-eco 3
;        show SE_CT
;
;    SET SE_IS matrix:get-row socio-eco 4
;      sET SE_IS (map * hh  SE_IS )
;  show SE_IS
```

```
;
;    SET SE_CT-IS matrix:get-row socio-eco 5
;      sET SE_CT-IS (map * hh  SE_CT-IS )
;  show SE_CT-IS
;
;
;  ask FARMs[
;    set f 0
;       set x_list (list ch)
;  while [f < FARMERS_nb  ]
;  [
;    let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)
;
;      show maxval
;
;;     show FARM f
;;      ;show who
;
;    if maxval = item f SE_NC [
;     set ch 1
;      print "NC"
;      show f
;        set x_list lput ch x_list
;    set color 4
;  ]
;    if maxval = item f SE_S [
;      set ch 2
;      print "S"
;      show f
;        set x_list lput ch x_list
;    ;set color 15
;     ]
;        if maxval = item f SE_Q  [
;      set ch 3
;      print "Q"
;      show f
;        set x_list lput ch x_list
;    ;set color 15
;    ]
;    if maxval = item f SE_CT [
;      set ch 4
;      print "CT"
;      show f
;        set x_list lput ch x_list
;  ;  set color 126
;       ]
;    if maxval = item f SE_IS [
```

```
;      set ch 5
;      print "IS"
;      show f
;        set x_list lput ch x_list
;   ; set color 75
;        ]
;    if maxval = item f SE_CT-IS [
;      set ch 6
;      print "CT-IS"
;      show f
;        set x_list lput ch x_list
;          ;  set color 87
;    ]
;
;show x_list
;set f f + 1
;
;
;    ]]]
;
;
;
;
;    foreach gis:feature-list-of Fs-dataset  [ vector-feature ->
;    set hruid gis:property-value vector-feature  "FID_1"
;    set ctry gis:property-value vector-feature  "FID_1"
;   set In gis:property-value vector-feature  "Index"
; set NE gis:property-value vector-feature  "neigh_effe"
;
;     file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-
ECO.csv"
;  if file-at-end? [ stop ]
;  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
;  set mu matrix:from-row-list  _datau
;  set nu matrix:get-column mu 0
;
;    let ctry2 gis:property-value vector-feature  "Id"
; ;   show ctry2
;  ifelse ctry < FARM_nb + 1
;    [let centroid gis:location-of gis:centroid-of vector-feature
;          ;print gis:location-of gis:centroid-of vector-feature
;         ; print centroid
;
;
;
;   if not empty? centroid
; [create-FARMs  1
```

```
;        [set xcor item 0 centroid
;         set ycor item 1 centroid
;         set color white set shape "house" set size 0.7
;         set label ctry2 set label-color black
;
; show ctry2
;
; ask FARMs [
;   if ctry2 < FARMERS_nb
;          [  if item ctry2 x_list = 1 [if label = ctry2 [set color 4 set shape "house" set size
0.7]]
;            if item ctry2 x_list = 2 [if label = ctry2 [set color 15 set shape "house" set size
0.7]]
;            if item ctry2 x_list = 3 [if label = ctry2 [set color 96 set shape "house" set size
0.7]]
;            if item ctry2 x_list = 4 [if label = ctry2 [set color 126 set shape "house" set
size 0.7]]
;            if item ctry2 x_list = 5 [if label = ctry2 [set color 75 set shape "house" set size
0.7]]
;            if item ctry2 x_list = 6 [if label = ctry2 [set color 87 set shape "house" set size
0.7]]
;   histogram [color] of FARMs       ]
;
;         ]
;
;
;     ]
;    ]]
;   [stop]
;;
;; show ECO
;
;  ]
;
;
;    ifelse Land_price_$/m2 = 130 [
;  SET SE_NC matrix:get-row socio-eco 0
;  show SE_NC
;
;    SET SE_Q matrix:get-row socio-eco 1
;  show SE_Q
;
;    SET SE_S matrix:get-row socio-eco 2
;  show SE_S
;
;    SET SE_CT matrix:get-row socio-eco 3
;  show SE_CT
;
```

```
;    SET SE_IS matrix:get-row socio-eco 4
;  show SE_IS
;
;    SET SE_CT-IS matrix:get-row socio-eco 5
;  show SE_CT-IS
;
;
;  ask FARMs[
;    set f 0
;       set x_list (list ch)
;  while [f < FARMERS_nb  ]
;  [
;    let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)
;
;      show maxval
;
;;     show FARM f
;;      ;show who
;
;    if maxval = item f SE_NC [
;     set ch 1
;      print "NC"
;      show f
;        set x_list lput ch x_list
;    set color 4
;  ]
;    if maxval = item f SE_S [
;      set ch 2
;      print "S"
;      show f
;        set x_list lput ch x_list
;    ;set color 15
;     ]
;        if maxval = item f SE_Q  [
;      set ch 3
;      print "Q"
;      show f
;        set x_list lput ch x_list
;    ;set color 15
;    ]
;    if maxval = item f SE_CT [
;      set ch 4
;      print "CT"
;      show f
;        set x_list lput ch x_list
;  ;  set color 126
;      ]
```

```
;    if maxval = item f SE_IS [
;      set ch 5
;      print "IS"
;      show f
;        set x_list lput ch x_list
;   ; set color 75
;        ]
;    if maxval = item f SE_CT-IS [
;      set ch 6
;      print "CT-IS"
;      show f
;        set x_list lput ch x_list
;          ;  set color 87
;    ]
;
;show x_list
;set f f + 1
;
;    ]]]
;
;    [let o Land_price_$/m2 / 130
;          let oo n-values 24 [ o ]
;      sET SE_NC matrix:get-row socio-eco 0
;       show SE_NC
;
;    SET SE_Q matrix:get-row socio-eco 1
;       show SE_Q
;
;    SET SE_S matrix:get-row socio-eco 2
;      sET SE_S (map * oo  SE_S )
;        show SE_S
;
;    SET SE_CT matrix:get-row socio-eco 3
;        show SE_CT
;
;    SET SE_IS matrix:get-row socio-eco 4
;        show SE_IS
;
;    SET SE_CT-IS matrix:get-row socio-eco 5
;       show SE_CT-IS


  ask FARMs[
    set f 0
       set x_list (list ch)
  while [f < FARMERS_nb  ]
  [
```

```
   let maxval max (list item f SE_NC item f SE_Q item f SE_S item f SE_CT item f
SE_IS item f SE_CT-IS)

      show maxval

;     show FARM f
;      ;show who

    if maxval = item f SE_NC [
     set ch 1
      print "NC"
      show f
        set x_list lput ch x_list
    set color 4
  ]
    if maxval = item f SE_S [
      set ch 2
      print "S"
      show f
        set x_list lput ch x_list
    ;set color 15
     ]
        if maxval = item f SE_Q  [
      set ch 3
      print "Q"
      show f
        set x_list lput ch x_list
    ;set color 15
    ]
    if maxval = item f SE_CT [
      set ch 4
      print "CT"
      show f
        set x_list lput ch x_list
  ;  set color 126
       ]
    if maxval = item f SE_IS [
      set ch 5
      print "IS"
      show f
        set x_list lput ch x_list
   ; set color 75
        ]
    if maxval = item f SE_CT-IS [
      set ch 6
      print "CT-IS"
      show f
        set x_list lput ch x_list
```

```
        ;  set color 87
    ]

show x_list
set f f + 1


    ]]]





    foreach gis:feature-list-of Fs-dataset  [ vector-feature ->
    set hruid gis:property-value vector-feature  "FID_1"
    set ctry gis:property-value vector-feature  "FID_1"
   set In gis:property-value vector-feature  "Index"
 set NE gis:property-value vector-feature  "neigh_effe"

     file-open "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-ECO/SOCIO-
ECO.csv"
  if file-at-end? [ stop ]
  let _datau csv:from-file "E:/THESIS_LITANI/Litani/FIELD WORK/SOCIO-
ECO/SOCIO-ECO.csv"
  set mu matrix:from-row-list  _datau
  set nu matrix:get-column mu 0

    let ctry2 gis:property-value vector-feature  "Id"
 ;   show ctry2
  ifelse ctry < FARM_nb + 1
    [let centroid gis:location-of gis:centroid-of vector-feature
         ;print gis:location-of gis:centroid-of vector-feature
        ; print centroid



   if not empty? centroid
 [create-FARMs  1
        [set xcor item 0 centroid
         set ycor item 1 centroid
         set color white set shape "house" set size 0.7
         set label ctry2 set label-color black

 show ctry2

 ask FARMs [
   if ctry2 < FARMERS_nb
           [  if item ctry2 x_list = 1 [if label = ctry2 [set color 4 set shape "house" set size
0.7]]
```

```
            if item ctry2 x_list = 2 [if label = ctry2 [set color 15 set shape "house" set size
0.7]]
            if item ctry2 x_list = 3 [if label = ctry2 [set color 96 set shape "house" set size
0.7]]
            if item ctry2 x_list = 4 [if label = ctry2 [set color 126 set shape "house" set size
0.7]]
            if item ctry2 x_list = 5 [if label = ctry2 [set color 75 set shape "house" set size
0.7]]
            if item ctry2 x_list = 6 [if label = ctry2 [set color 87 set shape "house" set size
0.7]]
  histogram [color] of FARMs       ]

        ]


     ]
    ]]
  [stop]
;
; show ECO

  ]


end


to view-FARM-neighb
  if show-FARM-neighb

  [ask FARMs [
   set i who
   if who < FARM_nb
     [ set b0 count turtles-on neighbors
   if b0 > 10
      [inspect FARM i
       ; show label

        ]
    ]
  ]
]
end



to inter-FARM-neigh-U
   set i 1
```

```
   ask FARMs [
 ifelse i < FARMERS_nb
      [
   set b count FARMs-on neighbors
   set c [color] of FARMs-on neighbors
   set d [label] of FARMs-on neighbors
;show d
;show  c
  ; show i
   if c = [126]
          [show i]
;    [ set a1 matrix:get mu i 1
;      show a1
;      set a1 a1 * 1.23
;      if a1 > 5
;              [set color 126]]
set i i + 1
  ]

  [stop]

  ]
;ask FARMs [
;    if c = [126 87 15]
;    [ set a1 matrix:get mu i 1
;      show a1
;      set a1 a1 * 1.23
;      if a1 > 5
;      [set color 126]
;  ]
 ; ]

End
```

APPENDIX E SUPPLEMENTARY MATERIAL CHAPTER 5

Table SM1 Field-based Economic indicators

	Cost	Revenue $/ha	Reference
Irrigation	**$/ha** 600	-	Damour municipality, 2019
Land	-	0.01-0.02	Damour municipality, 2019 Field survey IMF, 2019
Groundwater ($ per plot)	[1]Drilling permit/ cost: 333 / 1275 Pumping permit/ cost: 250 /2800	-	Damour municipality, 2019 Nassif, 2016 Khadra, & Stuyfzand, 2014 IMF, 2019
Banana cultivation	**$/ha** 18,000	50,400	[2]Field survey, 2019 IMF, 2019 FAO, 2019 FAO, 2018
Greenhouses	**$/ha** 23,330	66,660	Farmers interviews, 2019 FAO, 2007 IMF, 2019 FAO, 2020

[1]Drilling permit and costs paid once. Pumping permits paid once a year. Pumping costs paid per well.
Inflation rate: 2.7% /year
[2] Data was collected through a field survey using a questionnaire covering Socio-demographic characteristics, Agricultural features and Behavioral response. 60% of farmers grew only bananas due to the relatively warm climate in the area and the soil type; while the rest grew bananas and vegetables (refer to paper)

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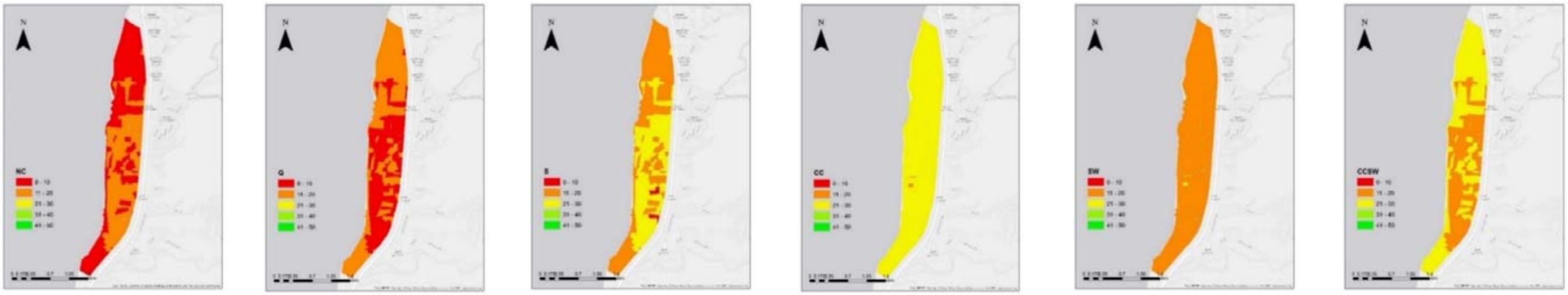
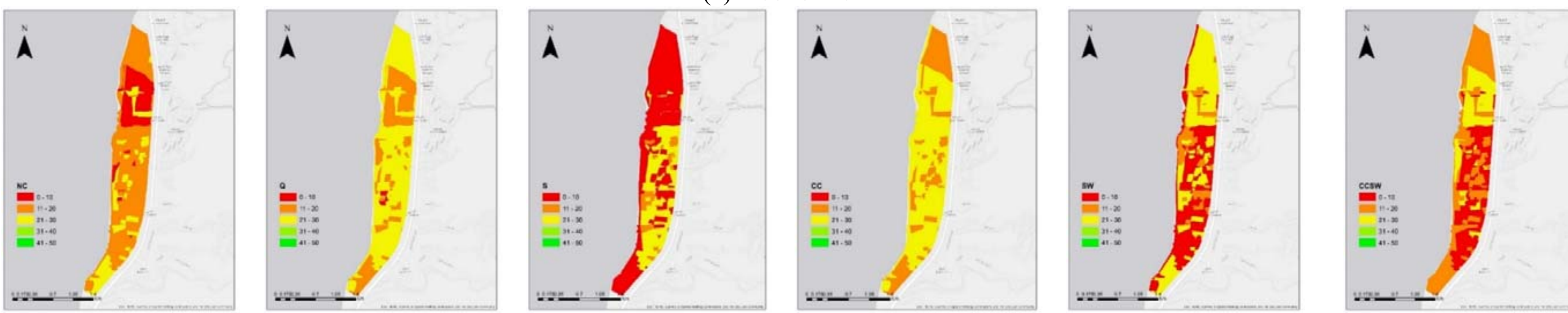
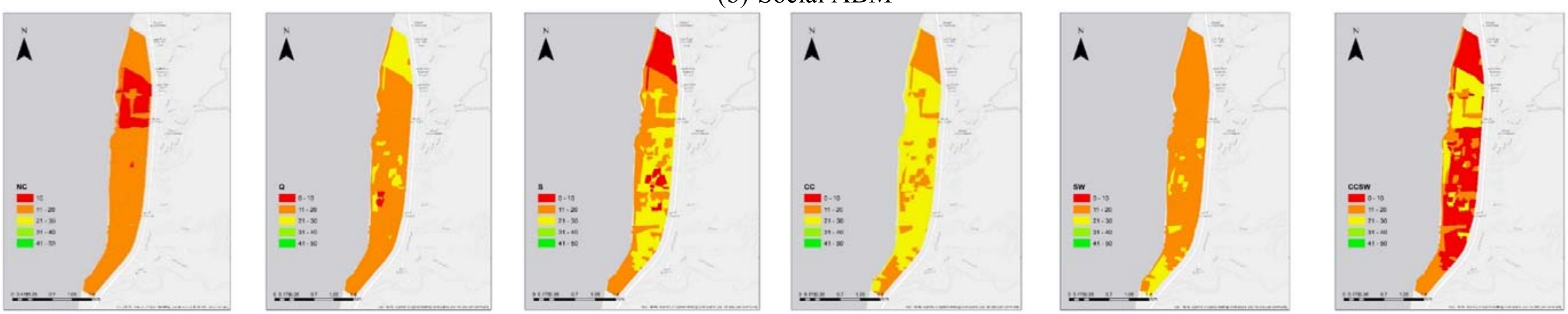


(a) Economic ABM



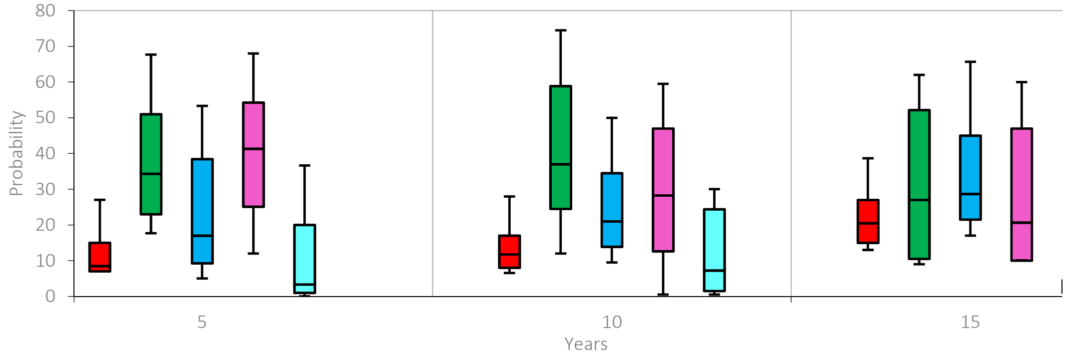
(b) Social ABM



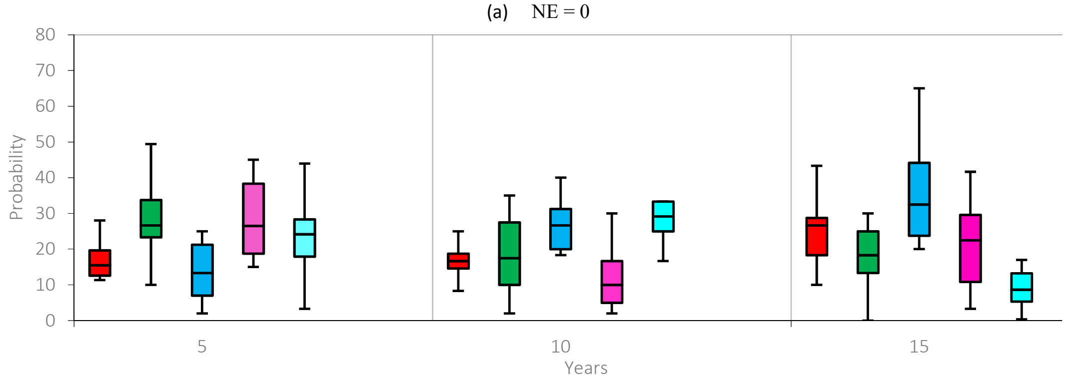
(c) Socio-economic

Figure SM1 Probability of choice of decision alternatives under the three ABM at the end of 2032

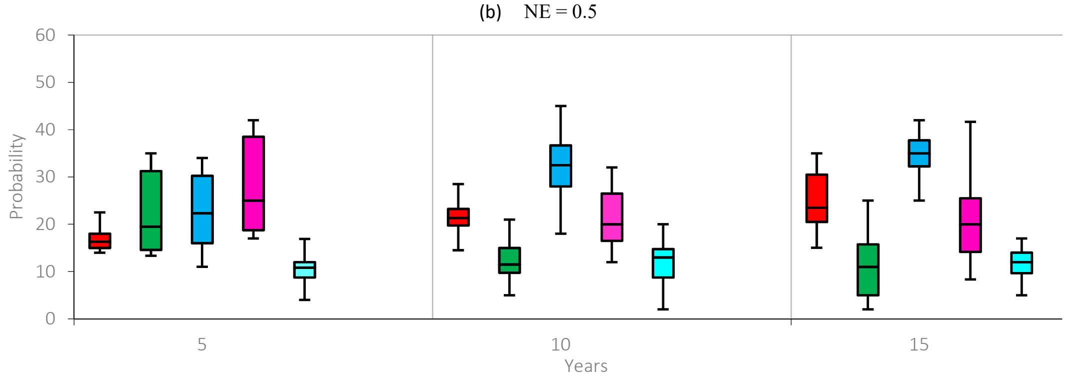
NC No change, S Sell, Q Quit, CC Change crop, SW Seek additional water, CCSW Change crop and seek additional water



(a) NE = 0



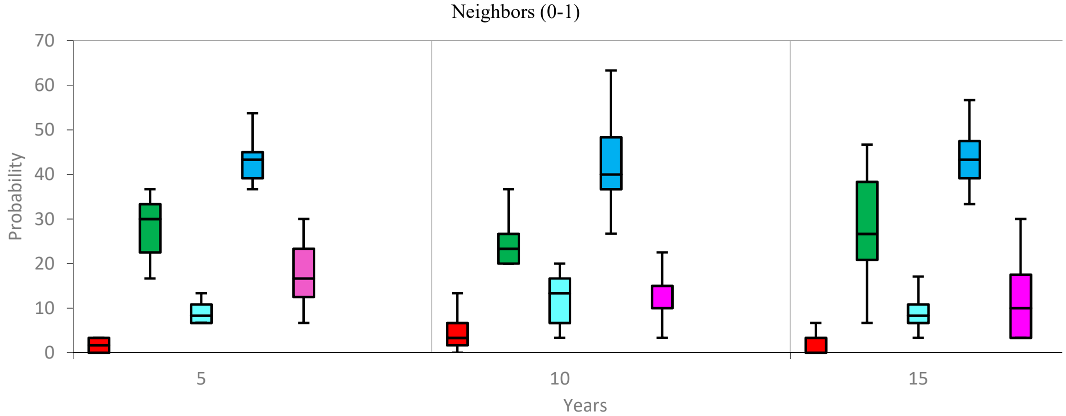
(b) NE = 0.5



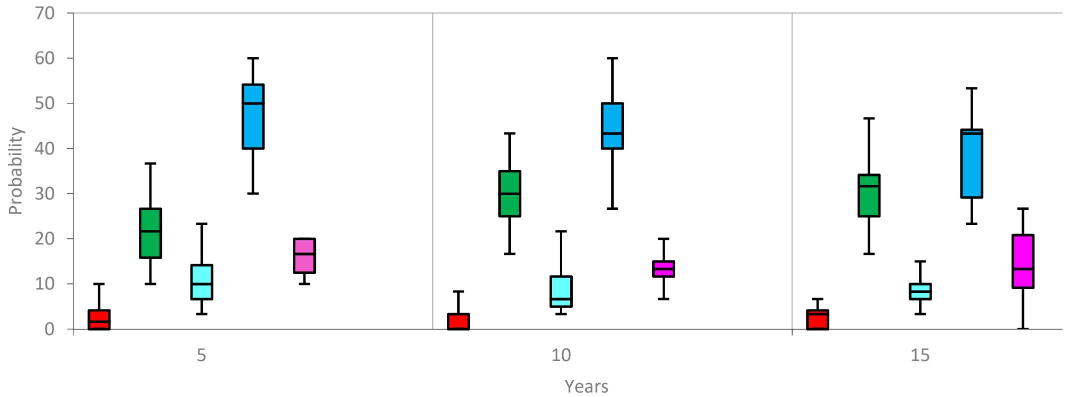
(c) NE = 1

Figure SM2 Probability of the 5 years-step decisions for different NE rates

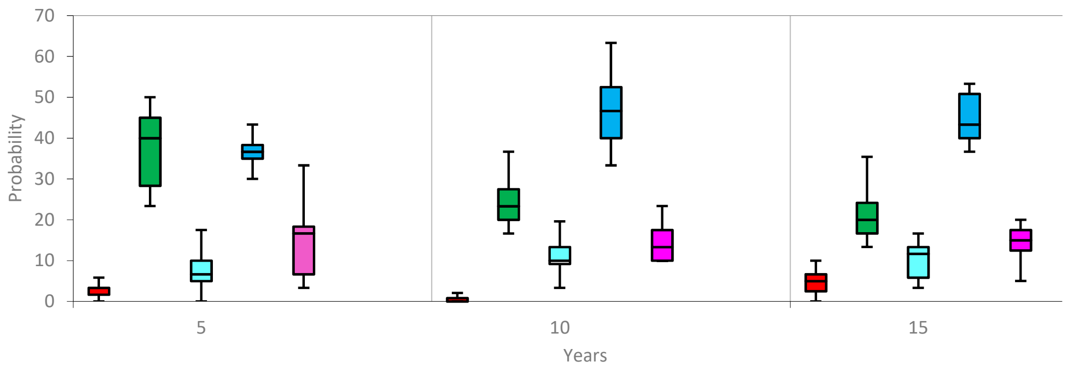
S Sell, Q Quit, CC Change crop, SW Seek additional water, CCSW Change crop and seek additional water, NE Impact of Neighbors (0-1)



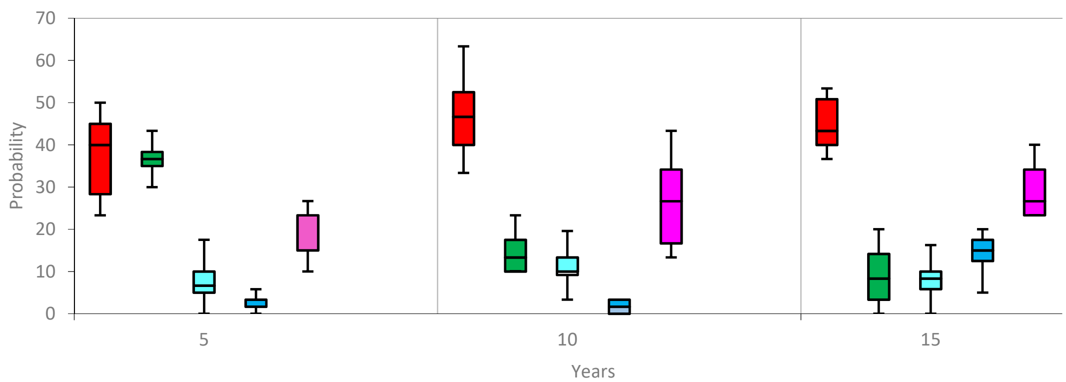
(a) α = 0.001



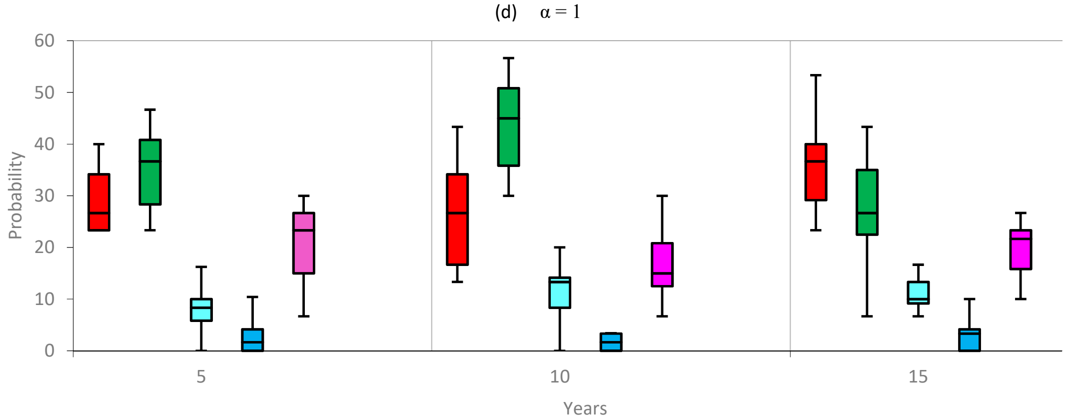
(b) $\alpha = 0.01$



(c) $\alpha = 0.1$



(d) $\alpha = 1$

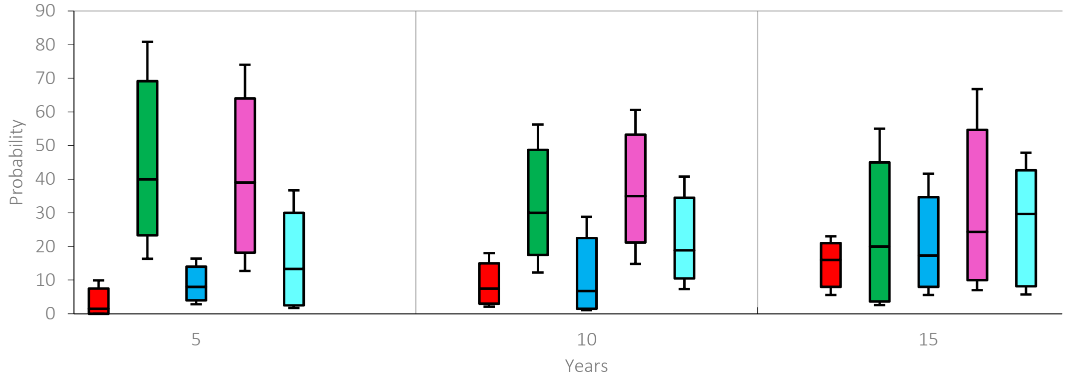


(e) α = 2

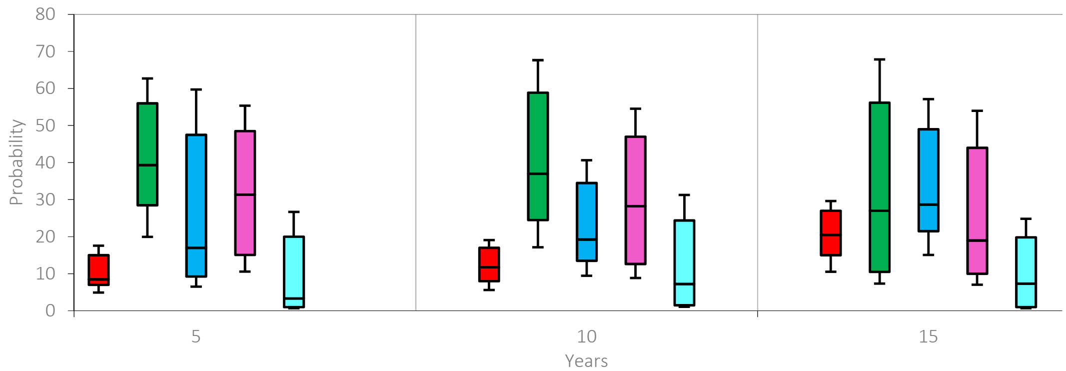
S SW CC-SW Q CC

Figure SM3 Probability of the 5 years-step decisions for different *α* rates

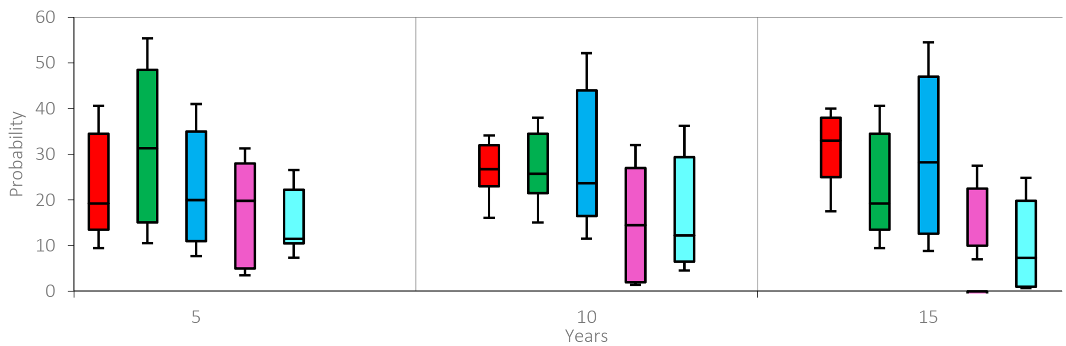
S Sell, Q Quit, CC Change crop, SW Seek additional water, CCSW Change crop and seek additional water, α Socio-economic weights ratio



(a) 12%



(b) 24%



(c) 48%

S SW CC-SW Q CC

Figure SM4 Probability of the 5 years-step decisions for different water availability decrease rates

S Sell, Q Quit, CC Change crop, SW Seek additional water, CCSW Change crop and seek additional water

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