Czech University of Life Sciences Prague
Faculty of Environmental Sciences

DIPLOMA THESIS

GIS and Artificial Neural Network-Based Approach for Integrated management in Costa Caparica, Portugal

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Supervisor of the thesis: Ing. Vojtěch Barták, Ph.D.

Declaration

I hereby declair that the work presented in this thesis is, to the best of my knowlede, origanal work, except as cited in the text. I have listed all literature and publications from which I have accquired information. The reserch was completed with the assistance of Vojtěch Barták.

Prague 19rd of April, 2016 Angeliki Peponi

CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

Faculty of Environmental Sciences

DIPLOMA THESIS ASSIGNMENT

Angeliki Peponi

Landscape Planning

Thesis title

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Objectives of thesis

This research aims to evaluate the past 41 years of coastline and land use dynamics and predict the next 13 years evolution, considering coastal systems morphometry and functional vegetation cover. These initial objectives, along with local socio-economic frameworks, lead to the main goal of this project which addresses future prediction of the state of the erosion for Integrated Coastal Zone Management (ICZM) and as a tool for stakeholders' decision making.

Methodology

To establish the balance between the sandy systems dynamics and the land use of the past 41years and to model the next 13 years evolution based on natural and anthropogenic predictions in order to support ICZM, it is necessary to estimate the beach dune system natural trends over the last 41 years, to assess the land use and land cover evolution in n-years and to estimate the natural and social values for the coastal area. To reach this goal GIS-ANN (Geographic Information Systems- Artificial Neural Networks) methodology is used to conduct sensitivity analyses on natural and social forces, dynamic relations in the dune-beach system which is an alternative method for ICZM.

The proposed extent of the thesis

46 – 60 pages

Keywords

ANN, ICZM, decision making, spatial analysis, land use conflict, erosion prediction

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Recommended information sources

1. Morgado P.,Gomes E., Costa N., 2014, Competing visions? Simulating alternative coastal futures using a GIS-ANN web application. Ocean & Coastal Management 101, 79-88
2. Daliakopoulos, I.N., Coulibaly, P., Tsanis, I.K., 2005. Groundwater level forecasting using artificial neural networks. Journal of Hydrology 309, pp.229–240.
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Expected date of thesis defence

2015/16 SS – FES

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Electronic approval: 15. 4. 2016

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Prague on 19. 04. 2016

Acknowledgements:

This diploma thesis has been prepared during an Erasmus internship which took place at the highly esteemed Institute of Geography and Spatial Planning (IGOT) of Lisbon University, Portugal. I would like to express my cordial gratitude to the authorities of IGOT and CZU for giving me the opportunity to participate in this training.

My deepest thanks and sincere appreciation are owed to my supervisor Ing. Vojtěch Barták, Ph.D for his encouragement, and creative and comprehensive advice throughout the process of this research.

It is a great pleasure to acknowledge my heartfelt thanks, gratitude and appreciation to Asst Prof Paulo Morgado Sousa, Ph.D of the Institute of Geography and Spatial Planning (IGOT) of Lisbon University, for his patience to pass on to me his knowledge and passion about the specific study. It was a great honor to work under his supervision, his kind and endless help, and his generous advice and support during the study.

Last but not least, I would like to thank SR Rsch Jorge Trindade of Center of Geography of IGOT and head of the team Coastal & Fluvial Systems (SLIF) for his key contribution to the project with his knowledge and experience and for his valuable guidance from the beginning to the end of this project.

ABSTRACT

Monitoring and managing populated coastal areas is a very important task which continues to be a difficult venture for interest groups. In this study, the use of Artificial Neural Networks and GIS are applied as a robust tool in integrated coastal zone management in the community of Costa Caparica, Lisbon, Portugal, by modeling and forecasting the erosion changes for the year 2021. Artificial Neural Networks present noteworthy advantages in comparison with other methods used for prediction and decision making in urban coastal areas. Multilayer perceptron (MLP) type of ANNs are used to conduct sensitivity analyses on natural and social forces, and dynamic relations in the dune-beach system of Costa Caparica, in order to give a prognosis of the erosion changes. Numerous tests were performed in order to train the network by changing the number of hidden layers and hidden layers nodes. The most suitable topology was one hidden layer with seven hidden nodes. The sensitivity analysis indicated that the variables amongst all the input variables to the model, which trigger the erosion changes in the study area, are the number of residents and households. The developed methodology appears fitted to reality; however some further steps would make it better suited to the purpose of the thesis.

Keywords:

ANN, ICZM, MLP, decision making, spatial analysis, land use conflict

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

LULC = land use land cover

CZs = coastal zones

CC= Costa Caparica

UN = United Nations

EU = European Union

EIA = environmental impact assessment

EEA = European economic area

ANN = artificial neural network

ICZM = integrated coastal zone management

MLP = multilayer perceptron

RBF = recurrent neural network

n.d = no date

SSE = sum of squared errors

MSE = mean squared errors

SOM = self-organized map

RL = reinforcement learning

CA = Cellular Automata

FD = fractal dimension

ABM = Agent-Based Modeling

GIS = geographic information systems

SSE-NNW = South Southeast to North Northwest

BP = before present (as present the date 1st of January 1950)

NW = Northwest

SE = Southeast

NAO = North Atlantic Oscillation

TEU's = twenty-foot equivalent unit

INA = National Statistic Institute

BP = Backpropagation

1 INTRODUCTION

The importance of coastal zones (CZ) in the environmental, economic, social, cultural, and recreational sector is commonly known. The land use and land cover (LULC) dynamics in CZs are changing due to the increase of inhabitation and urbanization largely due to the growth of the tourism industry and leisure activities as well as from sea level rise. The noticeable aftermath of these changes is the beginning of coastal erosion. Coastal erosion may cause coastal land loss and degradation, and must be considered in a calculated and careful manner. Land loss and degradation affect both directly and indirectly the coastal society by threatening human settlements, ports, coastal recreation areas, and wetlands other habitats and ecosystems, and so on, as well as by causing conflicts between coastal area users and interest groups.

In this study artificial neural networks and GIS are applied to predict erosion changes in the near future, to estimate the beach dune system natural trend over the last 41 years, the natural and social values for the study area and to assess the evolution of the land use and cover in n-years.

ANN is deemed a powerful tool for learning any non-linear input-output system and it can derive important features and trends from complex datasets. In coastal zones the relationships between human and environment and the hierarchical structures are characterized by nonlinearity; the underlying processes are either unknown or hard to understand. One of the most important attributes of ANN is that they are capable of adjusting to periodic changes and can identify patterns in complex natural nonlinear systems.

Modeling the prediction of the erosion changes using ANN has a huge potential for integrated coastal zone management studies. It will be a useful tool to plan and manage the area for sustainability and balanced land use. It will help the decision-makers and planers to understand the coastal dynamics by collective behavior of natural and human resources instead of individual behavior of single categorical variables and develop policies and plans for future development and appropriate management of the area.

The management of coastal areas constitutes a constant conflict owing to the co-existence of different interests and aims, so the integration of all these interests and all the physical and anthropogenic factors that cause significant erosion changes to the coastal environment of utmost importance and requires urgent attention.

2 PURPOSE AND AIMS OF THE THESIS

The intention of the study is to demonstrate the importance and complexity of the coastal zones, the necessity of an Integrated Coastal Zone Management (ICZM) and to explore alternative approaches and techniques to support ICZM.

The aim and the purpose of the current study are to analyze the study area, to establish the balance between the sandy systems dynamics and the land use of the past 41years, and to model the next 13 years evolution based on natural and anthropogenic predictions in order to support ICZM for the study area.

The approach will be used in order to reach the goal of the current study will be the development of a GIS-ANN (Geographic Information Systems- Artificial Neural Networks) methodology to conduct sensitivity analysis on natural and social forces, and dynamic relations in the dune-beach system.

The prediction of the erosion changes in the next 13 years (in 2021) will be the output of the current methodology.

3 REVIEW OF LITERATURE

3.1 INTEGRATED COASTAL ZONE MANAGEMENT (ICZM)

3.1.1 IMPORTANCE OF ICZM

Coastal zones (CZs) belong to the areas which are the most productive in the world. They provide valuable habitats and ecosystem services (provisioning, regulating, habitat or supporting and cultural services). The ecosystems of the coast often have great ecological value and also offer valuable perspectives on economic growth. They offer healthy food and fresh water, livelihoods, natural resources and energy production using the tidal power. In addition to, coastal zones are responsible for the nutrient cycle (carbon C, nitrogen N, phosphorus P), for the climate regulation, they moderate natural disturbances and some human diseases (TEEB 2015). CZs offer supporting ecosystem services such as soil formation and atmospheric oxygen and biomass production. Coastal areas continually attract humans for recreation, sightseeing, sports, boating, snorkeling and many other activities. CZs are touristic destinations, points of traffic and interaction and ongoing business zones. Coastal areas constitute historical and archeological sites. Last but not least the aesthetic of the coastal environment had been inspiration to many artists, poets and composers and enriches people's daily lives.

Coastal areas are affected by the anthropogenic pressure such as population growth, urbanization, expanding tourism, industry and energy production as well as by climate change, intensive agriculture, aquaculture and natural hazards (EEA 2006, Flannery et al. 2015). The CZ reflects the dynamic balance between the supply of sediment from the lithosphere and the removal and accumulation of the sediment from the hydrosphere by the action of the waves and currents. The action of waves and currents largely depend on the atmosphere. In this process (lithosphere-hydrosphere-atmosphere) the biosphere (bio-building reefs, bio-erosion, etc.) and the human getting involved (Hadjibiros & Panayotidis 2008). Anthropogenic stressors for the CZs derive from economic and commercial activities for instance marine transport, repairing or painting ships, loading and bunkering operations and wastewater emissions (Bebianno et al. 2015 ex. Bocchetti et al. 2008).The human's intervention in the coastal area in combination with the physical characteristics of the coast, lead to a new anthropogenic dynamic balance (Hadjibiros & Panayotidis 2008) which leads to ecosystem degradation and creates the need for sustainable development of the coastal zone.

The coastal environment is highly complex, vulnerable and sensitive[1]; therefore its management presents special difficulties. Long term management tools are necessary to protect the coastal resources and the sustainable use of them, to prevent biodiversity perdition, pollution, eutrophication, habitat devastation, land use conflicts and spatial restraints such as over-crowding. In order to develop appropriate management methods it is essential to have a good knowledge of the ecological and socioeconomic data (Dijk et al. 2016) and the dynamic changes of the coastal zone.

In the 1970s the first regional protocols and actions in terms of environmental protection had developed (Rochette & Bille 2012). In the last few decades of the last century the need for an integrated coastal zone management became visible due to the increasing coastal activity. In 1992 the UN Earth Summit of Rio established the ICZM as an acceptable alternative approach for sustainable management in coastal ecosystems (Sano et al. 2014). This approach also includes socioeconomic development of the coasts, and a stepping stone in this direction is the adoption of the ‘’Mediterranean Protocol on ICZM in 2008’’ (Rochette & Bille 2012, Dijk et al. 2016). Besides this protocol, EU has adopted two documents, the “Integrated Coastal Zone Management: the Strategy for Europe (COM/2000/547)’’ and the ‘’EU ICZM Recommendation (COM/2000/545)” in order to manage sustainably the coastal zones as well as other legislation (“EIA Directive 2001”, “WFD 2000/60/EC”, amongst others) (EAA 2006).

The application of the ICZM is a slow and long term process. It aims simultaneously to the maintenance of the structure and function of the coastal ecosystems, the sustainable economic management of resources of the coast and to the creation of functional social systems in local communities (Hadjibiros & Panayotidis 2008). ICZM is extensively recommended mechanism coping with long-term coastal challenges such as sea level rise, climate changes and managing the right balance with the short-term socio-economic conflicts (Figure 1) (EAA 2006).

[1] *Sensitivity* is used when discussing human impacts and *vulnerability* is about climate change-related issues (Kosyan & Velikova 2015)

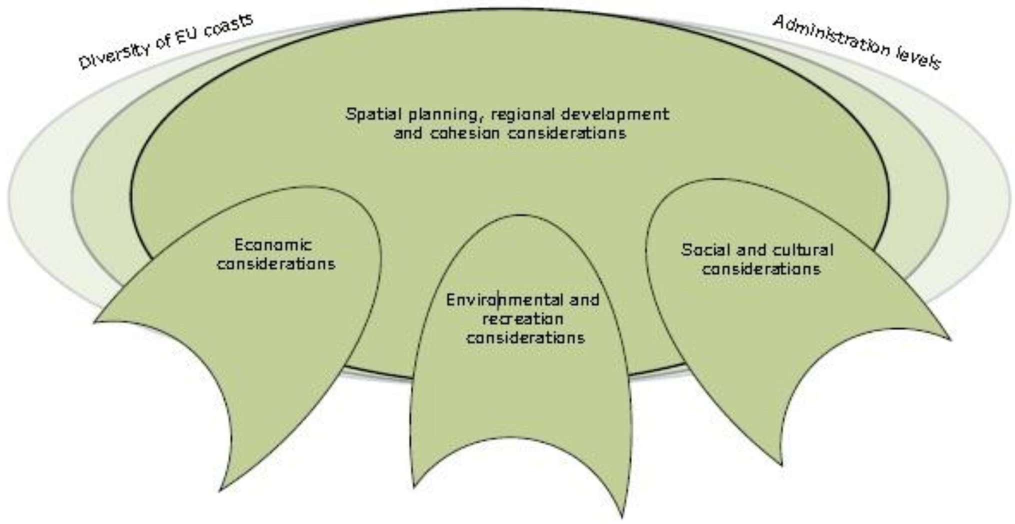


Figure 1: ICZM: the sea/land interface in a sustainable development perspective (EAA 2006).

3.1.2 DIFFERENT APPROACHES FOR ICZM

Different approaches and models have been applied over years for the integrated management of complex systems such as coastal zones. Mental models, system dynamics, participatory modeling of socio-environmental systems and combination of them are mainly approaches for integrated coastal zone management (Sano et al. 2014).

Mental models are individuals; created according to personal experiences, points of view and comprehensions of the surroundings. They are used to decision making, to analyze behaviors and logic. Understanding different stakeholder’s objectives is essential for effective management (Jones et al. 2011, Meliadou et al. 2012). System dynamics are conceptual and mathematical models; they are used as a general term for all approaches attempting to understand complex system behavior (Meliadou et al. 2012, Sano et al. 2014). In order to take advantage of the benefits of a mental model, aimed at solving an ecological problem and decision-making, a mental model takes the form of a conceptual model using cognitive mapping. “A cognitive map (Figure 2) is a qualitative model of a system, consisting of variables and the causal relationships between those variables” (Ozesmi & Ozesmi 2004).

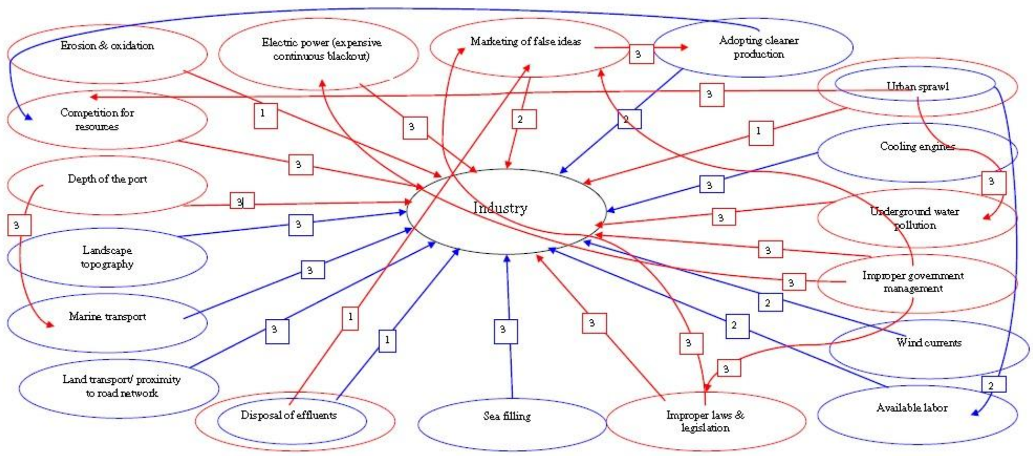


Figure 2: Example of cognitive map. Blue arrows show positive effect, red arrows negative effect. Comparative strengths of the above cause and effect relationships have a range of one (low) to three (high). (Meliadou et al. 2012).

Participatory approaches concern the stakeholder's engagement in environmental decision-making and problem-solving process. Stakeholder's participation is generally considered an important part of reaching agreements for policy decisions and part of superior management, but it can also lead to conflict between groups and difficulty in reaching decisions (Thaler & Keitel 2016). Different techniques of system dynamics are used to model and therefore to improve the stakeholder's incorporation in decision-making and implementation (Stave 2002).

A plethora of modeling techniques has been applied to approach numerous environmental complex problems such as coastal spatial dynamics from different perspectives. Cellular Automata modeling, Artificial Neural Networks modeling, Fractal modeling, Linear/Logistic Regression, Agent-Based Modeling and Decision Trees Modeling are present dominant promising methods (Triantakonstantis & Mountrakis 2012) to model land use and land cover changes. All of the above methods have been broadly applied to physical and human geography, integrating predictive modeling, which is a useful tool to support decision-making into management and planning.

Cellular Automata represent simple spatial dynamics systems composed by a grid of cells. Each cell has a state which depends on its previous state and on the state of the adjacent cells pursuant to some *transition rules* at each iteration (Figure3) (Kok et al. 2001,Triantakonstantis & Mountrakis 2012). CA have shown important advantages in modeling of land-use dynamics and coastal vulnerability modeling, particularly for policy and planning (Kok et al. 2001, Martins et al. 2012). Yet, their simplicity causes CA to be unable to represent real-world phenomena, there are limitations in their spatial parameters and *transition rules* (Rocha et al. 2007, Sante et al. 2010).

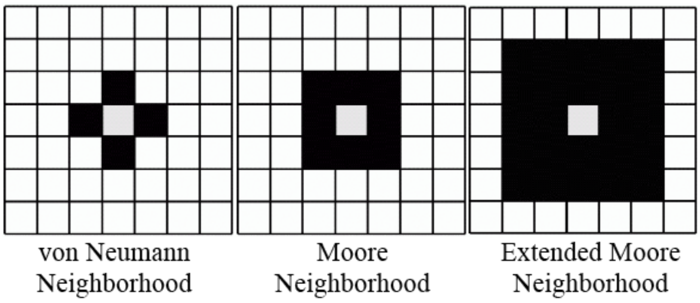


Figure 3: Examples of cellular automata neighborhoods (www.openabm.org).

Fractals are geometric objects which maintain their shape while undergoing any change of scale (*self-similarity*) and they contain elements with specific *embedded dimension* in a greater dimensional space. An essential asset of the fractals is the "*fractal dimension*", which is a non integer number which shows in which degree the fractal fills the embedding space (Baas 2002). Since earth materials have been considered as fractals of different dimensions in numerous studies, fractal geometry is progressively considered as a tool to model and quantify non-linear spatial complex objects (Hu et al. 2012). Nevertheless earth materials and phenomena are not always defined by *self-similarity* (Triantakonstantis & Mountrakis 2012 ex Halley et al. 2004). In addition, *fractal dimension* has significant restrictions. Using different techniques of FD in order to measure an object may lead to different outcomes. Furthermore there is the possibility that objects having different morphological attributes have equal FD, and objects that belong to the same fractal class to have drastically different FD (Triantakonstantis & Mountrakis 2012 ex Myint 2003). Fractal dimension methods have been applied to model coastal morhodynamics; shoreline evolution, bathymetry dynamics, wave's action, sediment transport and erosion in order to assess the impact of climate change and human pressure on coastal zones (Magar 2013). Fractals have been used as an alternative approach to model and predict urban growth and general land use changes (Triantakostantis 2012) thus this method could be used to support IZCM.

Linear and Logistic Regressions are statistical modelling techniques from a broad class of Linear and Generalized Linear Models, trying to explain the values of a dependent variable *(response)* by a certain combination of values of a set of (continuous or categorical) independent variables (*predictors*). For linear regression, the response variable is always continuous and the relation with predictors has a form of linear combination. In logistic regression, the response is dichotomous representing presence/absence of some event of interest. The output from regression methods is predicted value of the response, which in case of logistic regression takes a form of estimated probability of the event (Xu et al. 2013). However, linear and logistic regression modeling "is not able to capture non-linearity in the relationships between the dependent and independent variables or to address correlations between independent variables" (Triantakonstantis & Mountrakis 2012).

Agent-Based Modeling (ABM) applies in geography, ecology, anthropology and land use and land cover changes, as well as a tool to manage natural resource (Bell et al. 2015). The ABM is a simulation modeling technique consists of multiple types of agents and every agent has specific attributes (Entwisle et al. 2016). The foundation of ABM architecture is "a process-based model of decision making" which determines the actions of agents and the interactions between agents and other agents, likewise between agents and the environment (Figure 4) (Bell et al. 2015) according to a set of rules. An agent-based model shows complex behavior patterns and offers helpful information about the dynamics of the real-systems which simulates (Bonabeau 2002). An important limitation of this model is that ABM tools are infrequently used any further than with their initial development team (Bell et al. 2015) and this is because there is arbitrariness and complexity in defining of the initial conditions and interaction canon of agents, which can possibly lead to extremely different results (Triantakonstantis & Mountrakis 2012).

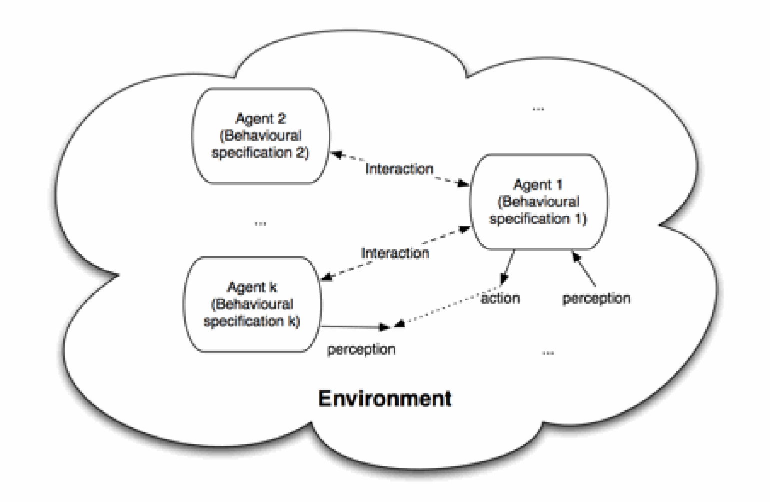


Figure 4: Analytical and descriptive, abstract model used to comment on other models, simulations, and agent based approach platforms (jasss.soc.surrey.ac.uk).

Decision tree modeling presents particular importance because they are able to create rules and are used to understand the structure of the model in an easy manner. The data are automatically divided into “sequential segments” using partition rules. Three basic steps construct a decision tree model. The first step concerns the *tree building* utilization “recursive splitting of nodes”. The second step includes the *pruning process*, the production of smaller trees with low complexity. In the last step, the tree which gives the lowest testing error is chosen. A limitation of this model is its structure which consists of only a simple algorithm which then allows for a general rule to arbitrarily form about the entire area. This leads to low spatial heterogeneity within the model. In addition, decision trees are *unstable* algorithms because subtly different *training samples* can generate significantly diverse classifiers (Triantakonstantis & Mountrakis 2012). A decision tree provides the structure for optimizing the decision process. Decision trees enhance the efficiency and uniformity of the process by displaying the order of the decisions which are made and by indentifying, delineating and expressing in a graphic model, the underlying patterns of the data interaction that are often ignored (Dewitt 1988). This is useful in order to ameliorate the decision making process and therefore to planning and management.

Artificial Neural Networks combined with Geographic Information Systems is an alternative approach that has been used in this particular study to predict geospatial phenomena and a tool to be used by and for future stakeholders’ decision making.

Amongst all the developed information technologies, GIS are considered an excellent tool to examine spatial distributions. The GIS software is developed to identify, manage analyze and demonstrate all information with geographical reference. Using GIS helps to see, comprehend, inquire, explain and visualize everything that takes place in the world in order to be able to see relationships, patterns and trends in a map, report or chart (Longley et al 2010). GIS offers a complete and precise information technology platform, with large database technology, advanced spatial analysis capability and computer graphic processing and ANNs have the dynamic ability to process nonlinear problems (Yalpir et al. 2014). In the following chapter, a detailed description of the origin, architecture and uses of ANN takes place.

3.2 ARTIFICIAL NEURAL NETWORKS

3.2.1 NATURE OF ANN

Artificial neural network is a system for processing information; it is designed to automatically detect knowledge in an analogous way to the neurological functions and the cognitive system of the human brain (Tsangaratos et al. 2014). The neural networks are an alternative tool to easily draw the hidden characteristics and the connections among the variables through large data sets, using non-linear models or initially unknown models (González 2008; Morgado 2012). In other words ANN mimics the way in which a biological nervous system operates in order to study, memorize, reason and build, using a variety of highly connected processing units. In the human brain, a neuron collects signals from a series of thin structures named *dendrites*. Using *axon* which is a fine long fiber, the neuron conducts electrical impulses. The axon is divided into numerous branches and every branch has a structure called *synapse,* which convert the electrical impulses, the information is then transmitted from one neuron to the other. When a neuron accepts information, it delivers an electrical impulse to the axon. The learning process is happening when the effectiveness of the synapses changes in order to change the influence of one neuron to another (Figure 5) (Stergiou & Siganos n.d.).

ANN is a dynamic system which allows a multivariate data analysis of nonlinear structural problems (Noack et al. 2014). ANN with the combination of GIS is a tool used for scenario building in order to solve complex problems ranging across many areas of research, and to help policymakers to develop better and proper future policies (Morgado et al. 2014).

ANNs are an alternative and more valid approach in solving geo-related problems, compared to other methods such as the mathematical-analytical approaches, Geo-statistical approaches like "Kriging'' and empirical or statistical approaches. Whereby, with ANN the availability of sparse and partial data and the limitation of knowledge about the relationships between variables and factors, is not an obstacle for its application (Noack et al. 2014). Methods of artificial intelligence such as ANNs have been applied to many studies for the modeling or prognosis of geospatial phenomena. Analytically, ANN techniques have shown prodigious performance, accurate prediction and satisfactory outcomes in landslide susceptibility mapping (Ermini et al. 2003; Conforti et al. 2012; Zare et al. 2012), in daily local forecasting of the global solar radiation (Amrouche & Pivert 2014), in assessment and forecasting the earth fracture hazards (Qiang et al. 2003), for land cover change detection in remote-sensing imagery (Zare et al. 2012) and in many other cases. According to Gopal and Kaufman 1998 ANN approach is superior “both in terms of predictive accuracy and model encompassing” compared to the benchmark methods for the spatial Interpolation of surface air temperatures. Furthermore, Artificial Neural Networks can provide a reliable flood system warning as they are able to predict flood levels along the stretches of stream with high accuracy using boundary water levels (Siddiquee & Hossain 2015), ANN can be used to forecast groundwater level as well (Daliakopoulos et al. 2009).

There are some studies wherein the performance of ANN techniques was lower than the conventional methods showing that it is not the best tool in all situations. Studies such as the estimation of the moisture content of tropical soils from digital color photographs using ANN delivered less accurate results than other methods used for the estimation (Zanetti et al. 2015). However, the results with ANN were still satisfactory and due to the important advantages of their simplicity and practicability and the reduction of run time and cost, ANN was considered a powerful tool for policy decisions.

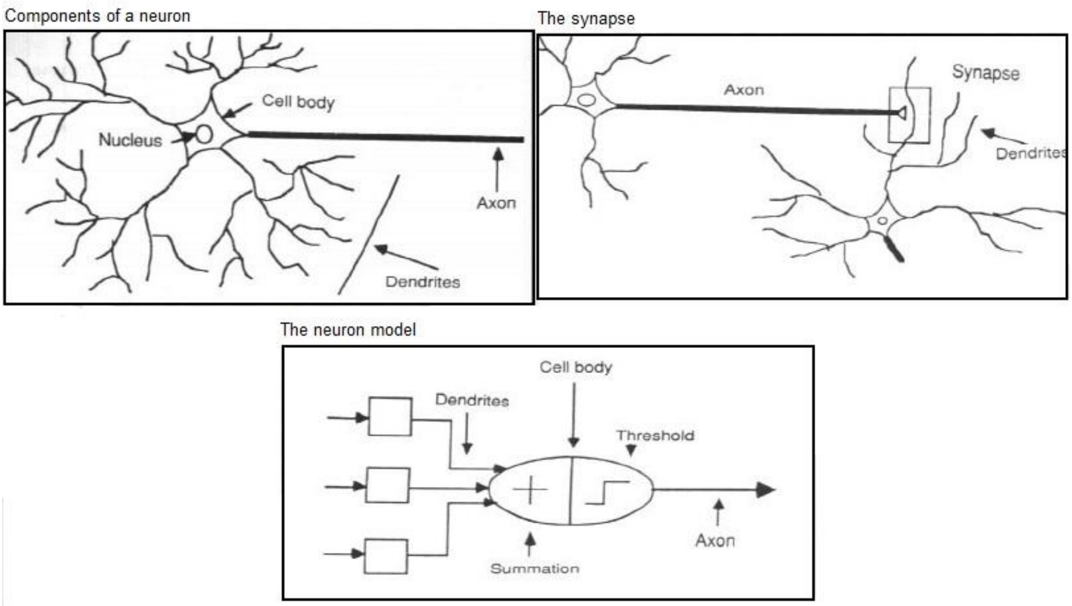


Figure 5: Neurons to Artificial Neurons (Stergiou & Siganos n.d.).

3.2.2 ANN AS A TOOL FOR ICZM

Costal urban areas constitute complex-nonlinear systems where important erosion processes take place due to anthropogenic and physical activities (Medeiros & Cabral 2013). As I mentioned before, coastal zone areas continuously attract humans. Conflict of interest is inevitable as different stakeholders converge in an area with different intentions for land use. “Portman et al. (2012) states that integrated coastal zone management (ICZM) is a widely accepted approach for sustainable management of the coastal environment”.

Artificial Neural Networks have been used to interpret the evolution of coastal land use conflicts, by using an organized and systematic method to determine what information is important to consider when addressing conflicts and planning various policies (Montanari et al. 2014). ANN is a useful tool to understand the patterns of land use and land cover (LULC) changes in order to plan and manage sustainably vulnerable coastal areas (Qiang & Lam 2015). Neural Networks have significant advantages compared to other methods for prediction and decision making in coastal urban areas including that they are able to disclose the relationship between potential urban development and spatial characteristics (Maithani 2009; Medeiros & Cabral 2013). In addition, those using ANN can express various spatial development options in a specified area in order to perform a sensitivity analysis for contrasting options and to discover any relationship in causality between those options (Morgado et al. 2014).

3.2.3 ARTIFICIAL NEURAL NETWORK ARCHITECTURE

The majority of neural networks use sensitivity analysis techniques, which powerfully compare interdependent variables since they can make calculated changes in the inputs and monitor the produced changes in the output of the network. This leads to a model with advanced prognostic capabilities and user-friendly interpretable results (Morgado 2012). ANN consist of "layers of *neurons* or *processing elements*, which are interconnected by a set of correlation weights, they are recognized as a complex nonlinear mathematical function that converts input data to a desired output" (Tsangaratos et al. 2014). It is fundamental to define the architecture of a neural network, namely, the way in which the neurons may be ordered, and thus it is feasible to delineate the problems for which the network works (Gonzalves et al. 2012).

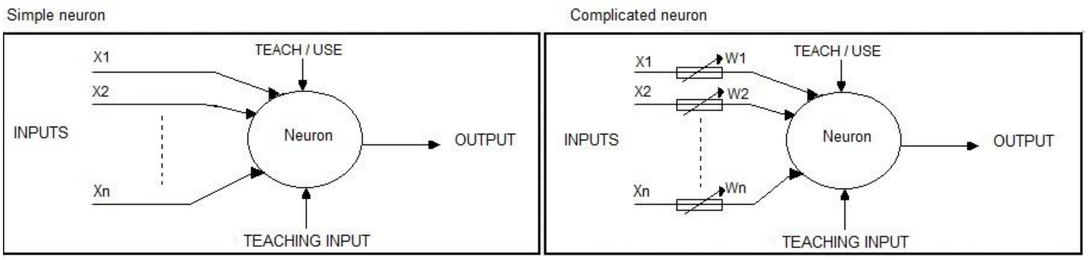


Figure 6: Different neuron's topology (Stergiou & Siganos n.d.).

The architecture of the network describes the number of layers, the number of neurons that are arranged in different layers and how the neurons connect within and in between these layers (Figure 6) (Maithani 2009). Restated, it is how the nodes are organized. In a neural network, a *node* constitutes the primary organizational unit; it can belong to an input, output or hidden layer node depending on its location and function. In the input layer the nodes accept the independent variables and the nodes in the output layer accept the dependent variables as well as broadcast information out of the network (Morgado et al. 2014). The nodes in the hidden layer are located between input and output node layers, mainly; they transform and distribute signals using hyperbolic-tangent-sigmoid (Tansig) or logarithm-sigmoid (Logsig) functions (Chitsazan et al. 2015 ex. Cybenko 1989). The hidden nodes in the hidden layer are responsible for finding the features and the patterns in the input data as well as to achieve nonlinear mapping between input and output variables (Zhang et al. 1998). More complicated ANNs use weighted inputs and each input influences the decision making by its weight value. Weight values related to individual nodes are called biases. Weight values are set during the training phase; when the network learns how to classify the input data according to their attributes (Leverington 2009). A *training algorithm* is applied to find the weights which can reduce an overall error measure, for instance, the sum of squared errors (SSE) or the mean squared errors (MSE) (Zhang et al. 1998). The training phase finishes after it has completed a defined number of repetitions or when the error is below a defined minimum (threshold).

The ANN can be described by a sequence of numbers; these numbers show the amount of neurons in each layer. For instance, a sequence 4-5-1 indicates four neurons in the input layer, five neurons in the hidden layer and one neuron in the output layer (see fig1.) (Maithani 2009).

3.2.4 CATEGORIZATION OF ANN

3.2.4.1 ANN LEARNING PARADIGM

In order for a neural network to execute some task, it is essential to define the connection between the units, and suitably determine the weights on these connections; the weights indicate the power of the influence. The determination of these weights is called *learning*, when the weights in a network are unchangeable referred to as a *fixed* network and when the weights may change in the network called *adaptive network* (Stergiou & Siganos n.d.). A neural network according to the learning role can be *supervised*, *unsupervised* and *reinforced* (Graves 2012; Sathya & Abraham 2013).

Supervised learning, in neural network parlance, is the estimation or the guess of the function between input-output pairs (*training set*) when the knowledge of the form of the function is limited or absent. The function learns how to train a data sample (*training set*) from a data source that an external teacher had classified and provides to the network (Orr 1996; Sathya & Abraham 2013). So, each output node is instructed on what the expected input response signals should be. *Supervised learning* neural networks are effective to solve linear and nonlinear problems as classification, plant control, forecasting, prediction and so on (Sathya & Abraham 2013). Paradigms of *supervised learning* are the *radial basis function networks* (RBF) and the *multilayer perceptron* (MLP) (Carcano et al. 2008).

In *unsupervised learning* networks there are no training signals at all (Graves 2012). The network ''identifies the pattern class information heuristically'' (Sathya & Abraham 2013). Unsupervised learning networks aim to organize the input data more effectively, for instance in clusters or categories, seeking similarity between the data. The networks which use *unsupervised learning* algorithms to indentify the hidden patterns in *unlabelled* (unclassified) input data are called Kohonen's Self-Organizing neural networks (SOM) and they don't use a providing error signal, as the *supervised learning* algorithms do, to learn and classify the information, instead they use information from a group of neurons (Sathya & Abraham 2013).

The *reinforcement learning* process reflects ideas from psychology. The RL algorithms learn using *trial and error* and *related reward* interactions with their environment in order to find optimal policies without having been taught by examples (Fu et al. 2014). Interacting with their environment, RL algorithms learn from the consequences (*penalty*) of their actions (Irodova & Sloan 2005). The learning agent receives rewards from its interaction (Fu et al. 2014) and to attain many rewards it is necessary to choose actions that have been tried and were rewarded (*exploitation*). To do so, the learning agent needs to try new actions, that haven't been chosen before (*exploration*). In supervised learning networks this dilemma of the balance of the swapping among *exploitation*- *exploration* does not occur (Sutton & Barto 1989).

3.2.4.2 DIRECTION OF SIGNAL PROPAGATION

Substantial parameters which define the type of neural network architecture are the direction of signal propagation, if it is forward or backward as well as the type and the level of the connection, and if it is completely connected or uses shortcuts (Noack et al. 2014). A *feedforward* architecture allows the link from a neuron in a layer to neurons in the next subsequent layer; the link among neurons to the same layer or to preceding layers is not feasable (Kavzoglu & Mather 2003), thus the output of one layer, does not influence that layer; the signals travel via one direction only, from input to output layer through the hidden nodes layer if it exists. They have a broad function in pattern recognition. From the other end of the spectrum, in the *feedback networks* the signal passes both directions creating loops (*feedback*) and cyclical connections. The *feedback networks* or *recurrent networks* constitute dynamic systems which are capable of modeling more multifaceted temporal relationships (Vos 2013). Different types of ANN architecture have been compared by many researchers to predict their capability for a wide range of applications and as a tool for decision making in various published papers and textbooks (Merkl 1996; Daliakopoulos et al. 2005; Carcano et al. 2008; Neagoe et al. 2012; Zare et al. 2012).

A *recurrent neural network* can be fully or partially connected. In a *fully* connected recurrent network, there is no separate input node layer, all nodes receive input from all the other nodes and it is feasible for a node to have input from itself. In the *partially recurrent network,* some of the nodes belong to feedforward topology and other nodes supply sequential context and obtain feedback from other nodes (Unadkat et al. 1999). The simplest form of *recurrent neural networks* (RNN) is the *Elman's partially recurrent network* which consists of the input layer, the hidden layer, and the output layer plus a *context (copy) layer* (Figure 7). The *context layer* represents the network memory of past events and is interconnected with the hidden layer (Daliakopoulos et al. 2005 ex. Haykin, 1999). "The connections from the hidden neurons loop back to themselves with a time step delay" (Vos 2013). The context node layer saves information in relation to the temporal sequence of the input data (Merkl 1996). Whereas *Elman network* emphasizes the sequence on input values, in the *Jordan recurrent network* the sequence of output values is emphasized (Unadkat et al. 1999).

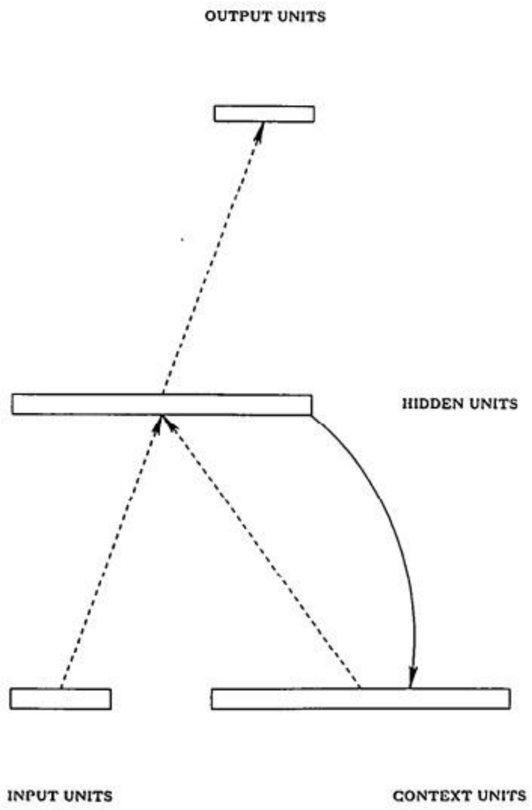


Figure 7: A simple recurrent network structure in which activations are copied from the hidden layer to context layer on a one-for-one basis. Dotted lines represent trainable connections (Elman 1990)

Radial basis function network (RBF) came into view as a variation of artificial neural network in the late 1980s. RBF was developed by Broomhead and Lowe (1988). It constitutes three layer feedforward architecture with multiple inputs and outputs, as well as a “linear output map between the hidden nodes and the output nodes” (Figure 8) (Li et al. 2010 ex Bianchini et al. 1995) (see fig.2). A RBF network can be linear or nonlinear if ‘’the basic functions can move or change size or if there is more than one hidden layer’’ (Orr 1996). The input nodes layer into a RBF network is nonlinear, the neurons of this layer are responsible for distributing the input information to the hidden layer. The hidden layer uses radial basis functions which are linked straight to the elements of the output layer. The output nodes layer is linear (Li et al. 2010; Zare et al. 2012 ex Haykin 1999). In radial functions the values of each point decrease or increase monotonically depending on the center position and the width. In a linear network all the parameters i.e the center point, the distance scale, and the exact shape of the radial function are all stable (Orr 1996). A characteristic radial function used by the hidden nodes in RBF networks is the Gaussian function (Orr 1996; Zare et al. 2012 ex Haykin 1999; Daliakopoulos et al. 2005; Li et al. 2010). “The centers and the widths of the Gaussian functions are set by unsupervised learning rules, and supervised learning is applied to the output layer” (Daliakopoulos et al. 2005 ex Haykin 1999). RBF neural networks usually learn more quickly than other feedforward networks (Daliakopoulos et al. 2005).

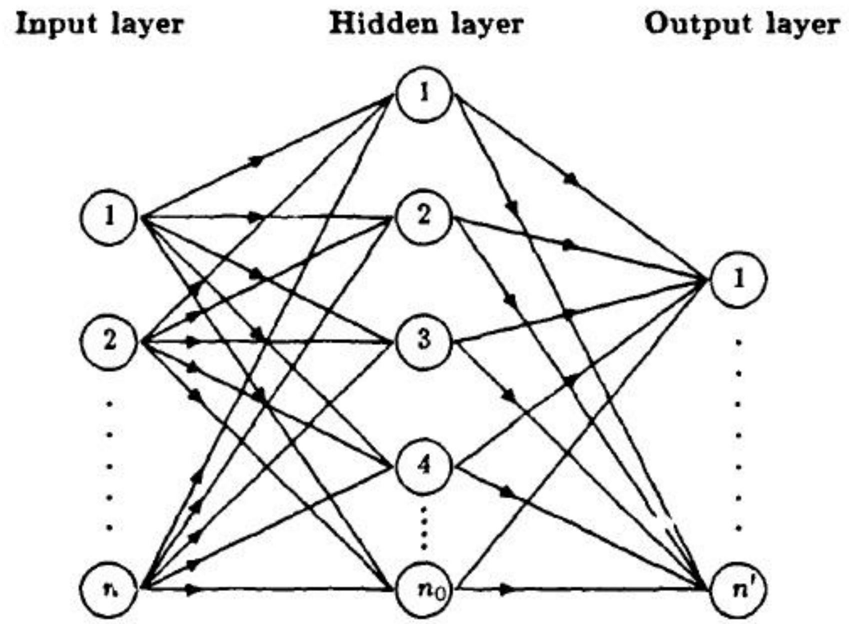


Figure 8: Scematic diagram of the feed-forward layered network model presented by the radial basis function expansion (Broomhead & Lowe, 1988).

The paradigm of ANN architecture used in this study is the Multilayer Perceptron (MLP) (Figure 9). Its application to study complex systems like coastal zones seems logical. MLP is a supervised learning algorithm which can be used for pattern recognition. The MLP is a three layer feedforward neural network; it contains an input node layer, the hidden node layer and an output node layer. The neurons in the input layer broadcast data to the next layer and the neurons in the hidden and output layers are responsible for further processing of data. The neurons in the input layer connect to a subsequent hidden and then output layer and provide weighted inputs to which every neuron in the hidden and output layers respond (Maithani 2009).

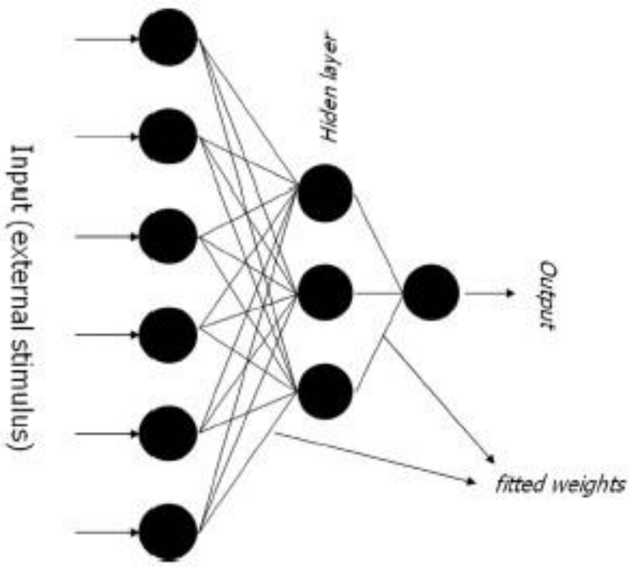


Figure 9: MLP architecture (Morgado et al. 2014).

4 CHARACTERISTICS OF THE STUDY AREA - COSTA CAPARICA, PORTUGAL

4.1 GEOGRAPHY OF COSTA CAPARICA

Costa Caparica belongs to Lisbon region, district of Setubal and the municipality of Almada. It is located ten kilometers south west of Lisbon city near to Almada city on the southern bank of the Tagus River and close to the river mouth (Figure 10). Costa Caparica is easily accessible from Lisbon, using public transportation (boat, train or buses), or using private vehicle crossing the Ponte de Abril suspension bridge.

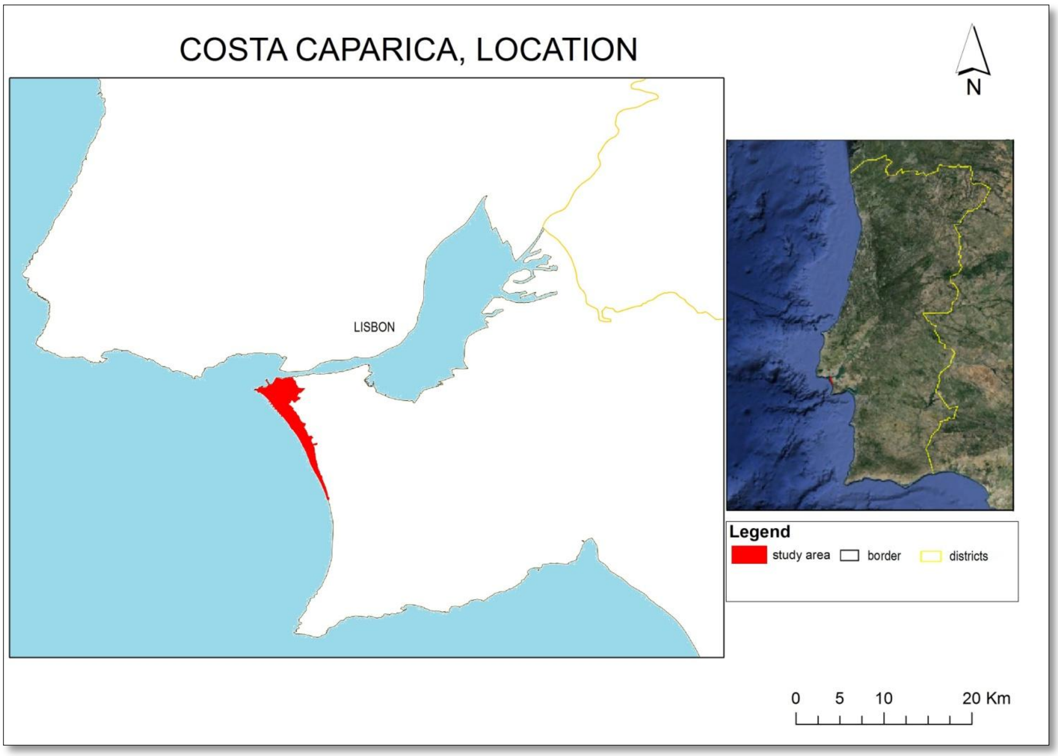


Figure 10: Location of study area (author).

The town of Costa Caparica was a traditional fishing village and after the excessive construction during the 80’s and 90’s turned into a touristic resort with no character and no former picturesque landmarks left. The coastline of Costa Caparica consists of more than a thirty kilometers stretch of golden sand beaches to fit all different kinds of beachgoers. Beaches ranging from developed and crowded urban centers to less developed sparsely inhabited coastline. Close to Cabo Espichel the sandy stretch merges with acacia and eucalyptus trees as well as sienna colored cliffs. The main activity on the Costa Caparica coast is tourism and sports, particularly surf. It represents the largest unbroken beach in Portugal. Surf schools, bars and restaurants are built along the coast and they operate all year long.

4.2 GEOMORPHOLOGY OF COSTA CAPARICA

The coastline of Portugal extends more than a thousand kilometers and 44% contains beaches. The Portuguese coast presents diverse geomorphologic characteristics. Dunes and sandy beaches, high cliffs and low rocky coasts, lagoons and barrier islands compose the coastal geomorphology of the country (Semeoshenkova & Newton 2015). The geomorphologic feature that covers the greater part of the coastline is the relatively stable transgressive dunefields. These dunefields demonstrate important sedimentation in the littoral system periodically throughout the geological history. Since the Middle Pleistocene, dune deposits constitute the decisive factor for the formation of the littoral zone of Portugal. The driving force for the formation and movement of these transgressive dunefields is periods of higher aeolian activity (Costas et al. 2012).

Morphologically, the study area has an arc shape with orientation SSE-NNW. It represents an extensive coastal plain along the shoreline up to a fossil cliff. The sea bathymetry of the area is characterized as mild; the slope is gradual and the bathymetric lines are nearly parallel to the shoreline (Veloso-Gomes & Pinto 2002). Geomorphologically, the study area is the Caparica cliff-top dune which consists of a transgressive dunefield situated in the western- central side of the Setubal Peninsula, on the Atlantic Coast. It is formed lying on a terrace situated about fifty meters above the mean sea level. The dunefield goes up to 4.5 kilometers from the shoreline to the edge of the cliff and has a 45 square kilometers surface. The coastal plain extends 25 kilometers in length to the south (Costas et al. 2012).

Geologically, the study area consists of alluvium deposits with a south to north orientation, as a result of tides-waves-river flow phenomena and refraction/ diffraction patterns. The Caparica fossil cliff is a tremendously important feature of the area; it is located south of the Costa Caparica town and extends to Albufeira lagoon. In 1884 the area was characterized as a protected area (Veloso-Gomes & Pinto 2002). The cliff composed of unconsolidated fluvial sediments from the Pliocene correlated to the onshore Tagus paleovalley and played a major role in the development of the geomorphology. The Costa Caparica beach system depends in a great degree on the estuary inputs of the Tagus River as well. Storms and floods influence the amount of sedimentation in the estuary. A rough estimation of sediments that the estuary receives is $77X10^6$ ton per year and in dry years the discharges of the estuary to the sea are 0.4 to $1X10^6$ tons (Veloso-Gomes & Pinto 2002). In 1983/84 the average rates of sedimentation were 1.1 to 1.5 centimeters per year, in the years from 1928 to 1986 just 65% of all sediments remained in the system and currently there are substantial silt deposits in the upstream estuary for the reason that the area can naturally retain sediments and the river capacity has been reduced (Silva & Ferreira 2014).

The northern part of this paleocliff is protected from wave caused erosion although sub-aerial denudation degrades the slope of the cliff (Figure 11). This is contrary to the southern part of the cliff which is dramatically eroded by waves (Costas et al. 2012).

Figure 11: Northern part of the paleocliff, Costa Caparica, Lisbon, Portugal (author).

The coastal plain -on the northern part- is subject to dramatic human pressure resulting in serious erosion problems. Erosion prevention measures have been taken, such as artificial nourishment and shoreline armoring (Figure 12). On the central part -north of Fonte da Telha beach (Figure 13)- there are two separate foredune fields. Foredune is a dune ridge (as at the landward margin of a beach) relatively to completely stabilized by vegetation. The landward foredune is about two hundred meters in width and consists of a forest which was planted in the later part of the twentieth century in order to stabilize the dunes. The seaward foredune is around eighty meters in width and consists of Ammophila sp. patches. The maximum height of these two foredunes is around twelve meters. According to Antunes and Pais the cliff top dune formation can be dated around 1190±90 BP (Costas et al. 2012).

Figure 12: Shoreline artificial protection from erosion (author).

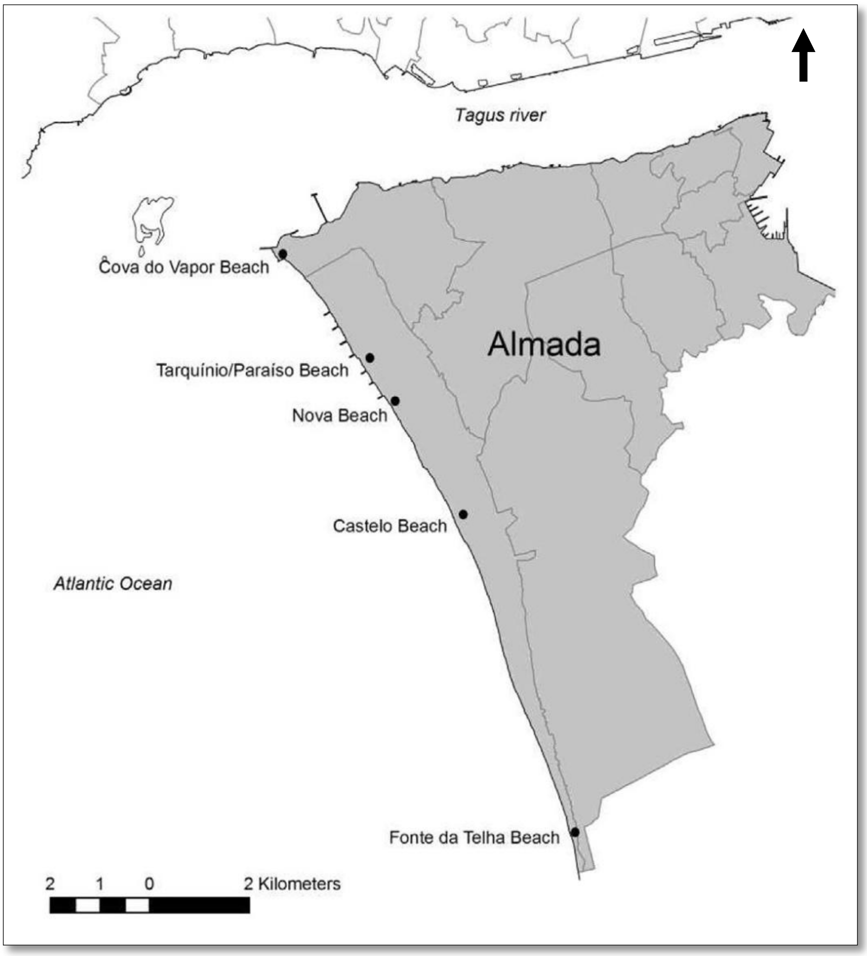


Figure 13: Costa Caparica, beach extension (Silva & Ferreira 2014).

The coastal plain, due to its low topography and the fragility of the sand dune system, is vulnerable to flooding (Schmidt et. al 2014). In addition, the high energy waves and the sediment drift place the study area as one of the most exposed to erosion and floods in Portugal (Semeoshenkova & Newton 2015). The general swell period of the waves, in the area, is between three seconds and sixteen seconds with local medium spectral directions S-20-W to WNW. The most frequent local waves have directions of 260º to 290º, heights of 0.5 meters to 2.5 meters and a period of five to eight seconds. In the study area, semi-diurnal tides occur of an approximate 12h 25 m tide cycle, South to North. The velocities of the tides in the Tagus estuary are intense with low heights. They go beyond 2.0 m/s during the flood, and 1.8 m/s during the ebb, in the spring. The average values are 1.5 m/s and 1.4 m/s respectively. In Costa Caparica near to the river inlet the tides are less strong with values 0.2m/s and directions South to North due to the closed circuit (Veloso-Gomes & Pinto 2002).

The sediment drift has a South to North direction owing to the direction of the coastal currents. As mentioned before, the sedimentation in the area depends on the Tagus estuary. From the 1920's to the 1950's, the Tagus basin had a significant impact on the sedimentation in the area. During this time period, the shoreline retreat was huge, receding around one hundred meters (Veloso-Gomes & Pinto 2002).

Sandy coastal zones are vulnerable due to the dynamic sea- land balance. The morphology of the coastal dunes and their species composition are the result of alterations of the shoreline (advance or retreat) over years caused by climatic changes, vegetation cover, sediment deposits, storm episodes and sea level. Presently, the main reason behind shifts in the shoreline as well as the change in vegetation and the cause of erosion and degradation to the function and structure to the coastal zone is the human activity. Sandy shoreline ecosystems provide essential ecosystem services. Besides economical, recreational and cultural services they stabilize and protect the coastline from wind and wave energy. It is necessary to manage and protect the geomorphological and ecological attributes of the coastal systems in order to preserve them (Calva et. al 2013).

4.3 CLIMATE OF COSTA CAPARICA

The Portuguese climate varies from the northern part of the country to the southern and from the mainland to the coast. Generaly in Portugal, the extreme precipitation volume and the average precipitation spatial gradients are one of the highest compared to other European countries; the precipitation per year is above 2500mm in the NW and below 400mm in the SE (Soares et. all 2015). In the region of Costa Caparica, a typical Mediterranean climate occurs in conjunction with the combination of tropical and mid latitude climate characteristics because it faces the Atlantic Ocean. The Portuguese climate is characterized by seasonal distribution of precipitation; smooth wet winters and dry warm summers are. The precipitation patterns clearly show that there are wet and dry years. The monthly and seasonal precipitation patterns are determined by the North Atlantic Oscillation (NAO) index (Costas et al. 2012).

The NAO is a large scale pattern of natural climate variability which has significant impacts on the climate of the regions around the North Atlantic, particularly in Western Europe. NAO index is characterized by the difference of the surface sea level pressure from the sub-tropical Azores Islands to sub-polar near Iceland. High pressures are around the Azores and low pressures are near Iceland. Positive and Negative NAO phases boost this climate pattern with variable spatial distribution of precipitation. Therefore, when the NAO is in a positive phase, the storms and precipitation, as well as the temperatures which are related to the air volume coming from lower latitudes, are increasing in the northern hemisphere. Simultaneously in southern Europe the precipitation and the volume of storms are decreasing. When NAO is in a negative phase there is a decrease of storms, precipitation and temperatures in northern Europe and an increase of storms, precipitation and temperatures in southern Europe (Dahlman 2009).

The winds in Costa Caparica are 48% northerlies and 17% consist of westerly and southwesterly winds. The wind pattern is stable all year long with significant augmentation of northerlies towards the summer season (Costas et al. 2012 ex. Alcoforado 1992).

According to researches and data records the study area appears extremely prone to the global climate changes. A considerable warming and decrease in precipitation started taking place during the beginning of 21st century (Costas et al. 2012) and it can have serious negative impacts on the Portuguese water cycle and therefore to essential parts of the country's economy such as agriculture, forestry, water supply and energy production (Soares et. all 2015).

4.4 CONFLICT OF LAND USES IN COSTA CAPARICA

Costa Caparica is an important second-home urban center with 16,000 inhabitants, which is oriented to tourism. It constitutes a major destination for holidays and surfing due to its high quality of water and sand (Morgado et. al 2014) and its location. Costa Caparica is situated 10 km west of Almada, which is demographically one of the densest areas in the country, and it belongs to the Lisbon metropolitan area. Surfing in Costa Caparica started in the decade of sixties and nowadays, Costa Caparica's waves form a significant part in the social and economic sector of the area. According to Silva and Ferreira (2014) the economic value of the waves in Costa Caparica is between 46,635.12 to 1,022,789.52 euros, taking into account an estimation of 22,000 surfers per year.

It is important to have knowledge of the economic value of the coastal resources and the uniqueness of the coastal systems for better coastal management in order to protect them against unrestrained urban development and other threats. Natural threats to coastal systems of the study area, as mentioned in a previous chapter are the massive alterations on sediment deposits and therefore the erosion rates of the shoreline.

Figure 14: Urbanization in Costa Caparica coast (author).

In this beach stretch which extents more than 13 kilometers, conflicts of interest take place between different stakeholders and it is necessary that it be addressed. Conflicts on the distribution of land uses relevant to tourism, leisure, harbor/ dry docks, residential and commercial land uses are present in the area and various stakeholders, for instance tourists, residents and local administrators contribute actively to the potential development of the area (Figure 14, 15). Each of these groups have their vision of development, and all in favor of their personal interests (Morgado et. al 2014).

Another major subject which adds more tension to the existing divisive situation of the study area, is the project of the Lisbon Port Authority to create a container terminal in Trafaria. Trafaria is a fishing village of 6,000 inhabitants north of Costa Caparica and it is included within the boundary of the study area. The terminal will use 105 hectares of a total area of 300 hectares and it will serve the transport of two million TEU's annually. The new terminal raises a controversy because the same area has another project which has been suggested by local and national environmental organizations. This project focuses on the protection and re-naturalization of the landscape. Residents and fishermen and beachgoers are largely opposed to the development of the new terminal as well (Morgado et. al 2014).

Knowing the main threats to the quality of the coastal systems and understanding the situation that prevails amongst the different stakeholders could prevent the negative impacts on both local community and economy and lead to a better integrated coastal management of the area.

Figure 15: Different stakeholders; beachgoers, fishermen, surf schools, restaurants and residences (author).

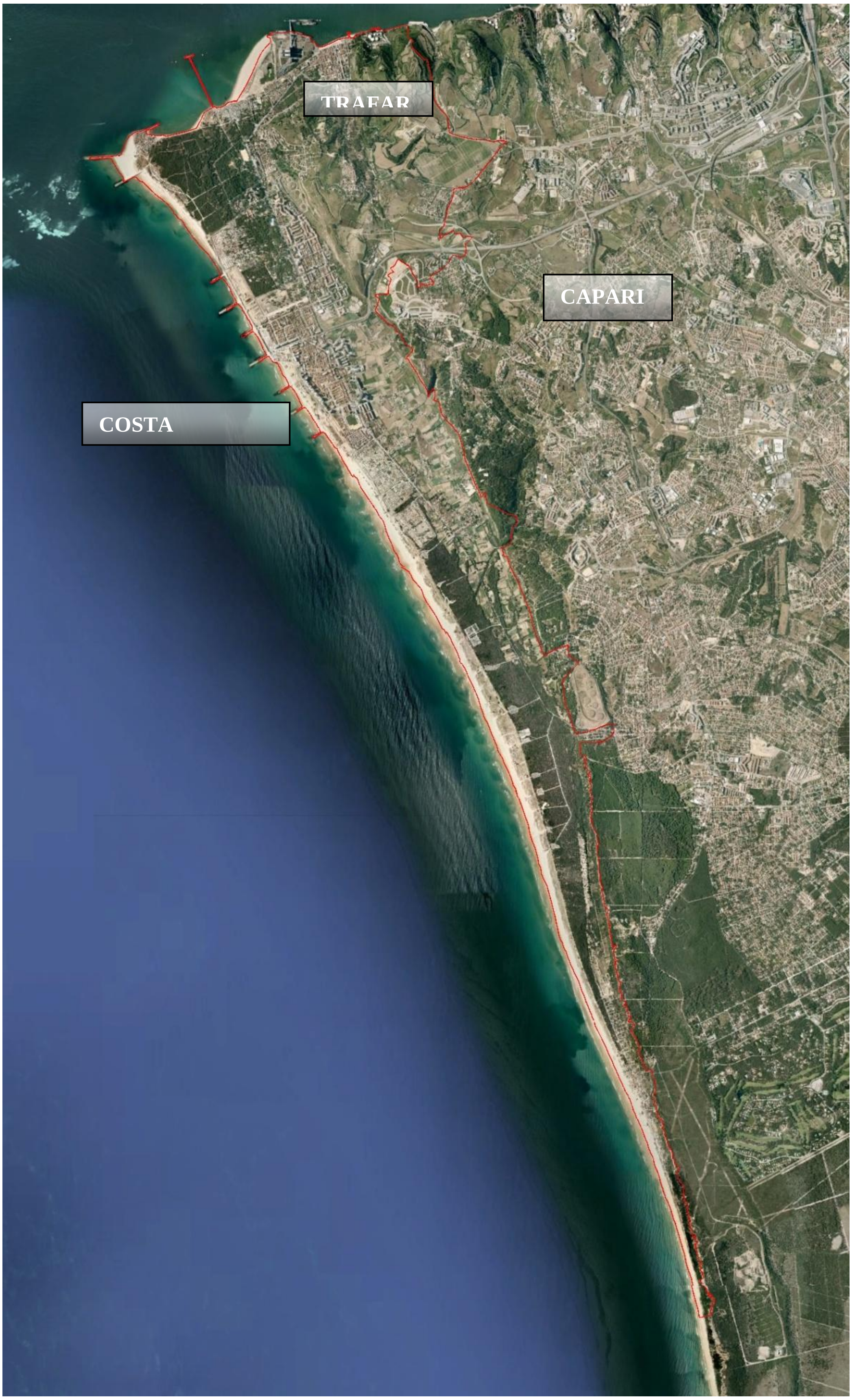


Figure 16: Aerial photography with the boundary of the study area in red color (author).

5 METHODOLOGY

After the analysis of the study area, significant issues arose concerning its land use and land cover. In order to establish the balance between the sandy systems dynamics and the land use of the past 41years, and to model the next 13 years evolution based on natural and anthropogenic predictions in order to support ICZM, it is necessary to estimate the beach dune system natural trends over the last 41 years, to assess the land use and land cover evolution in n-years and to estimate the natural and social values for the coastal area. To reach this goal GIS-ANN (Geographic Information Systems- Artificial Neural Networks) methodology is used to conduct sensitivity analyses on natural and social forces, and dynamic relations in the dune-beach system (which is an alternative method for ICZM).

5.1 DATA USED AND SPATIAL DATABASE CONSTRUCTION

In this study, social/demographic, economic and environmental data have been used. Data is acquired from the 2001 and 2011 Census found on the Portuguese National Statistic Institute (INA), from satellite images and from local measurements found on the master thesis “Dinamica da linha de costa e vulnerabilidade a erosao no setor nao artificializado do arco Caparica-Espichel” of N.F. Pereira, 2015.

Specifically, the data that have been used from the INA concerns the number of residents in the years 2001 and 2011, the corine land cover for the years 2000 and 2006 and the number of households in 2001 and 2011. The files are clipped on the boundary of the study area using geoprocessing tools in GIS.

Data about the different shorelines over different years have been taken from the N.F. Pereira’s master thesis. These different shorelines have been classified into different decades; 60s, 80s, 90s and currently in a GIS environment. Using these shorelines as a base, the erosion plots have been created in the areas where there is retreat of the shoreline between 60s and 80s, 80s and 90s, and 90s to present respectively. Thereafter the ridge of the paleocliff and the boundary of the *grey dune* were mapped. To understand the role of erosion, it was deemed important to calculate the minimum distance from each different shoreline to the paleocliff. The distance was added to the erosion plots layers mentioned before. Another crucial factor, which plays a significant role in order to see the erosion activity of the area, was to find the vegetated and non vegetated areas within the grey dune, as the vegetation stabilizes the dune and lack of vegetation causes erosion. To do so, satellite images are classified into two categories; vegetated (gridcode 1) and non vegetated (gridcode 0) using Iso Cluster Unsupervised Classification in GIS. The produced classified raster files were merged, converted to layers and clipped to the boundary of the grey dune.

All the data was converted from GIS layers to raster with a cell size of 3m using the raster file with the boundary of the area as a mask, and then from raster to ASCII using a GIS conversion tools. Afterwards, using IDRISI Taiga software, the ASCII files were exported to stat files (from grid data to tabular data) in order to be used by ANN in the STATISTICA program. Some of the data set did not contain information for all the pixels within the study area. In these pixels with no information, zero values were added in order to work the model.

The input data were classified into dependent and independent variables. Analytically, 10 variables were used for this study (9 independent variables and one dependent variable) in order to have one output. The dependent variable is the file with the current erosion plots. The independent variables are the files with the number of residents in the years 2001 and 2011, the corine land cover for the years 2000 and 2006, and the number of households in 2001 and 2011. In addition, the file with the vegetated and non vegetated areas within the grey dune, and the files with the erosion plots in the grey dune for the decades 60s to 80s and 80s to 90s were used, making the rest of the independent variables. As mentioned before, the variable with the erosion plots in present years (ER2008_R) is the dependent variable.

VARIABLES	**CODE**	**VARIABLES**	**CODE**
Resident population -2001	RESID01_	N^{O} of households - 2011	ALOJ11_3
Resident population - 2011	RESID11_	Area of erosion plots - 60s to 80s	ER6080_R
Corine Land Cover - 2000	CORNL00_	Area of erosion plots - 80s to 90s	ER8090_R
Corine Land Cover - 2006	CORN06_	Area of erosion plots - currently	ER2008_R
N^{O} of households - 2001	ALOJ01_3	Area of vegetated and non vegetated plots - currently	VEG_RCID

Table 1: Legend of variables (author).

5.2 METHODS

Based on the literature review, ANNs have been used as a powerful tool to address land use conflicts and to predict land cover changes for planning and management. After exporting and calibrating the input data, the selection of the type of the neural network follows. In this study the feed-forward Multilayer Perceptron (MLP) type of neural networks which belongs to ANN supervised techniques have been applied.

Different algorithms have been tried in order to train the network. Examples of algorithms commonly used to train Multilayer Perceptrons are the Back propagation algorithm, the Conjugate Gradient Descent, the Quasi-Newton and the Levenberg-Marquard. The Back propagation is one of the most useful training algorithms and the most appropriate for training multilayer perceptrons. One of the reasons is that it requires low memory and can very rapidly approach an acceptable error. The Conjugate gradient descent is a good generic algorithm with fast convergence; it is an advanced method for training MLP. For networks with multiple output units and/or high quantities of weights (more than a few hundred), it is the suggested approach (StatSoft, Inc. 2013). The Quasi-Newton constitutes an advanced method of training MLP with fast convergence as well, however, it is less numerically stable than Conjugate Gradient Descent and it has high memory requirements. It is recommended for almost all the networks with small numbers of weights (less than a couple hundred). Conjugate gradient descent and Quasi-Newton calculate the errors as the sum of the error gradients on each training case, whereas Back propagation calculates the local gradient of each weight with respect to each case during training and the weights are updated once per training case. Levenberg-Marquardt is a tremendously fast algorithm in the appropriate conditions (low-noise regression problems with the standard sum-squared error function). In the present study a combination of Back propagation and Conjugate Gradient Descent have been tried to train the network. Ultimately, in this study, Back propagation has been used for the network training.

Using MLP and GIS the prediction of the areas prone to erosion changes in 2021 was constructed in order to be used for future planning and management of the land cover changes and land use conflicts in Costa Caparica.

5.2.1 IMPLEMENTATION OF THE ANN MODEL

Having decided the independent and dependent variables (Figure 17), the next step is to define the type of neural network (MLP) (Figure 18) and then to design the topology and architecture of the network. In this phase it is important to define the number of input nodes, of hidden layers and hidden nodes and the number of output nodes (Figure 19).

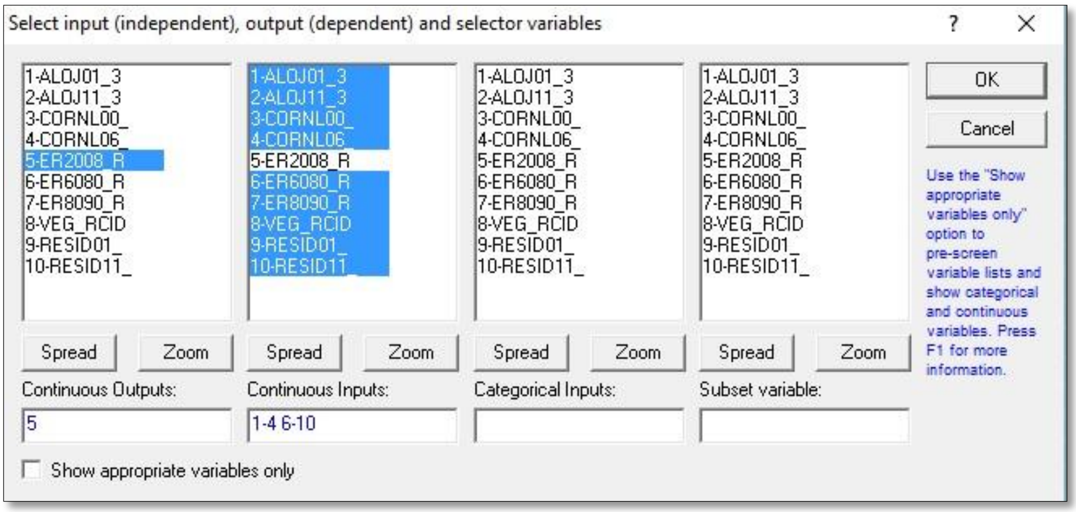


Figure 17: Selection of independent and dependent variables, STATISTICA (author).

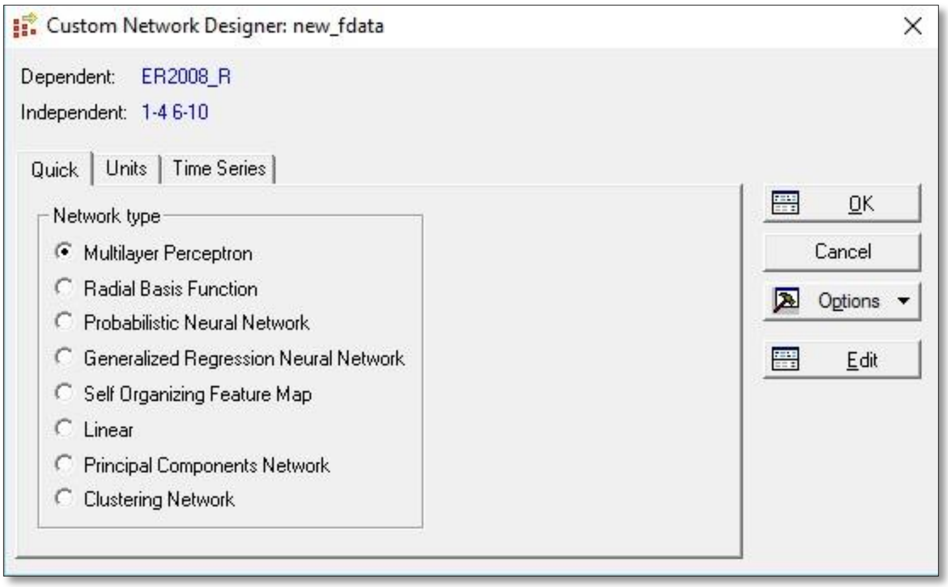


Figure 18: Selection of the type of neural network (MLP) STATISTICA, (author).

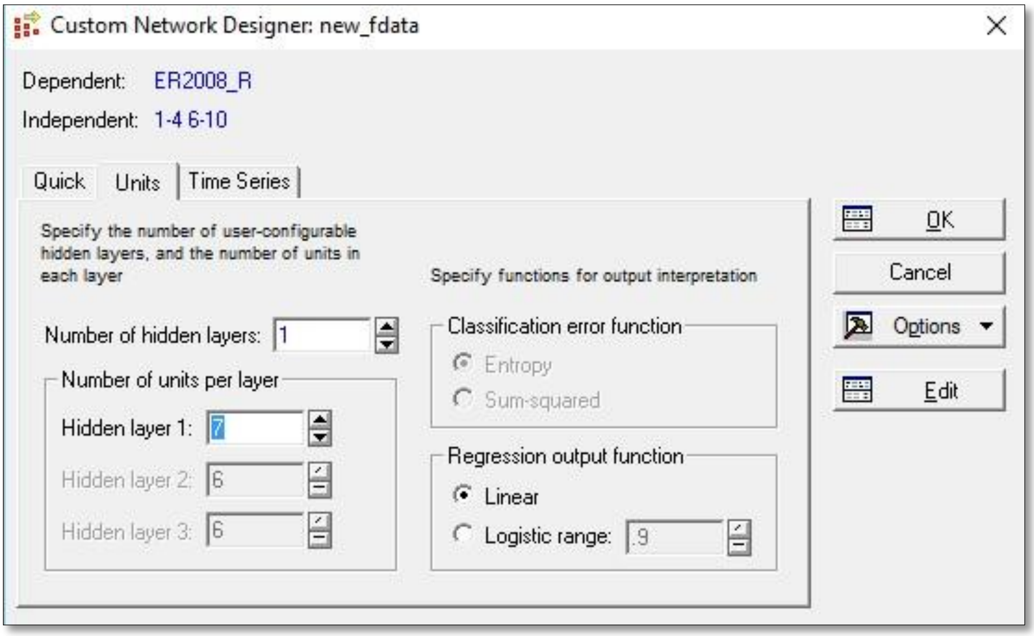


Figure 19: Selection of network topology (9:1:7:1) STATISTICA (author).

Subsequently, the training and validation samples are chosen and the network training starts. The standard training procedure for multilayer perceptron consists of two-phases (Figure 20). In the first phase a brief and fast spurt of back propagation takes place with a moderate training rate. This fulfills the "*gross convergence*" stage and for some cases it is adequate and it is not necessary to continue to the second phase.

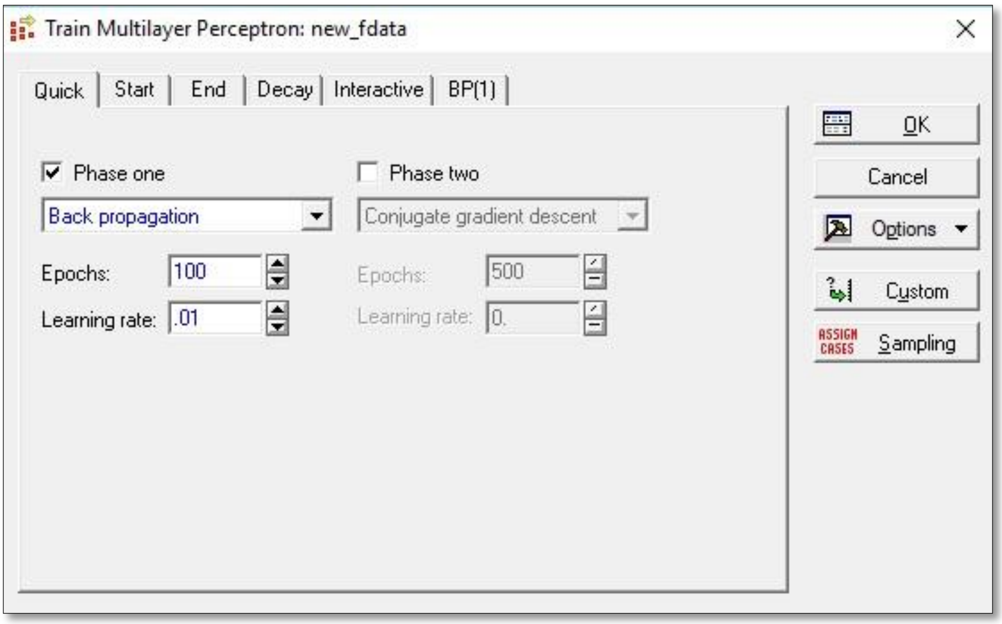


Figure 20: Selection of signal propagation (Back propagation) and phase/s of training procedure (One phase) STATISTICA (author).

The second phase constitutes a lengthy run of conjugate gradient descent, which is a stronger algorithm and more unlikely to encounter convergence issues because back propagation has been used before. When the network training is completed, a graph of the error function, per epoch (iteration) on the training and/or selection subsets, is created, as well as a table with the results of the training phase (Figure 26, Table 3 on the following chapter). Then the sensitivity analysis and the predictions are followed.

The training data is by default the 70% of the total data, therefore the selection is made randomly by the machine. The training/selection and test data must be representative of the underlying mode. If the training data is not representative, then the model is compromised. The network is trained with the training set in order to adjust the weights. The selection set is used to tune the parameters of the network and to confirm that the network does not over fit. Using the test set, it is feasible to evaluate how the network performs in unseen data, so to verify the predictive ability of the network (generalization). The error function is used to evaluate the performance of the neural network during the training. In order to do prediction, it is necessary to have a trained network. The error function measures the proximity of the network predictions to the targets and how much weight adjustment should be applied to every iteration by the training algorithm (Morgado 2012).

In the present study the network topology was the combination of 9 input nodes, 1 hidden layer with 7 hidden nodes and 1 output (9:1:7:1). Different network topologies and directions of signal propagation have been tried in order to conclude the final combination (9:2:6:3:1, 9:2:5:5:1, 9:2:4:3:1, 9:2:6:6:1). The network was trained in one phase with Back propagation algorithm. For all of the training tests, the maximum number of training samples defined was 1802181 samples. In other words, the total amount of data was used for training data and no selection data was made.

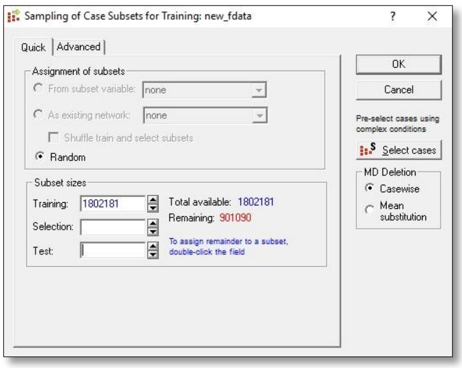


Figure 21: Selection of the training samples (total available samples) STATISTICA (author).

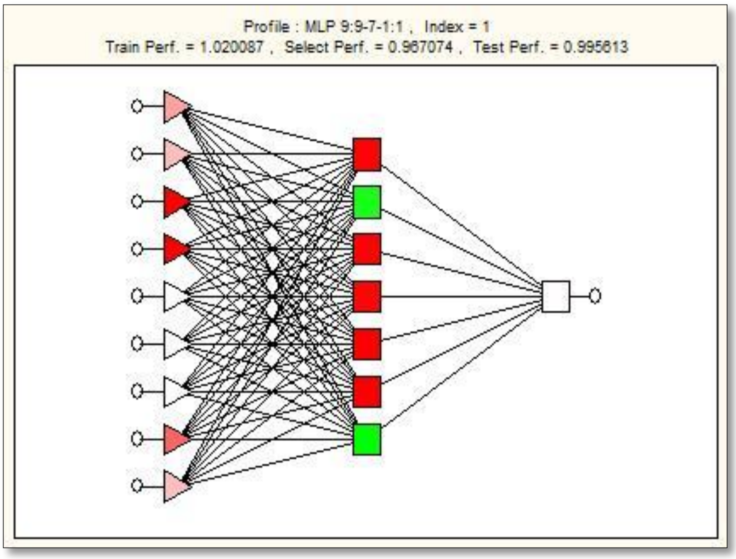


Figure 22: Network topology 9:1:7:1. The train performance, selection performance and test performance are similar which means that the generalization ability of the network is satisfactory (author).

The back propagation algorithm uses the available training data and trains the network iteratively. On every iteration (Epoch), all the training sets are introduced to the network each time. After the network's execution output values are produced, the output values are compared with the desired outputs present in the data set and the error between the true and desired outcome is used to shift the weights in the network so that the error has a higher probability of being lower. The algorithm has to make a compromise between the various cases, trying to change the weights so that the overall error throughout the entire training set is reduced.

After the network training, the sensitivity analysis of the inputs to the neural network is conducted. The sensitivity analysis shows the importance of the input variables by that specific neural network. It can give a better understanding about the usefulness of each variable. Sensitivity analysis illustrates the variables which can be ignored when following analyses and the variables which must always be kept. The results of the sensitivity analysis for different network topologies are presented on the following chapter, (Table 2).

Following the sensitivity analysis is the predictions for 2021 which indicates the areas with changed erosion values, mostly due to the number of residents and households. Clicking on the box "prediction" a spreadsheet of the model predictions is created (Figure 23, 24). The output tables contain two columns; the first one shows the value of each pixel of the erosion plots for the year 2008, and the second column the predicted value of each pixel of the erosion plots for the year 2021.

This table was converted from statistica files to ASCII, then to Raster and finally to GIS feature in order to create a visual representation in map form which can be appropriately interpreted.

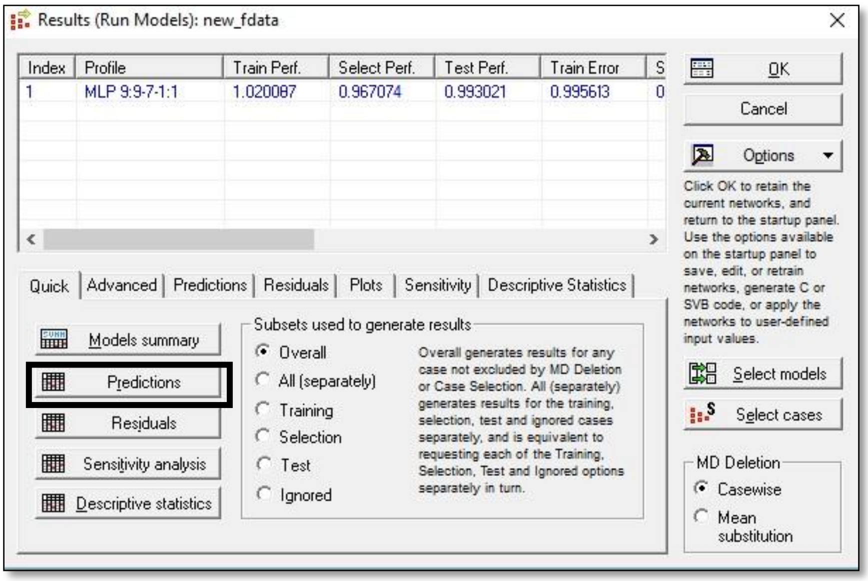
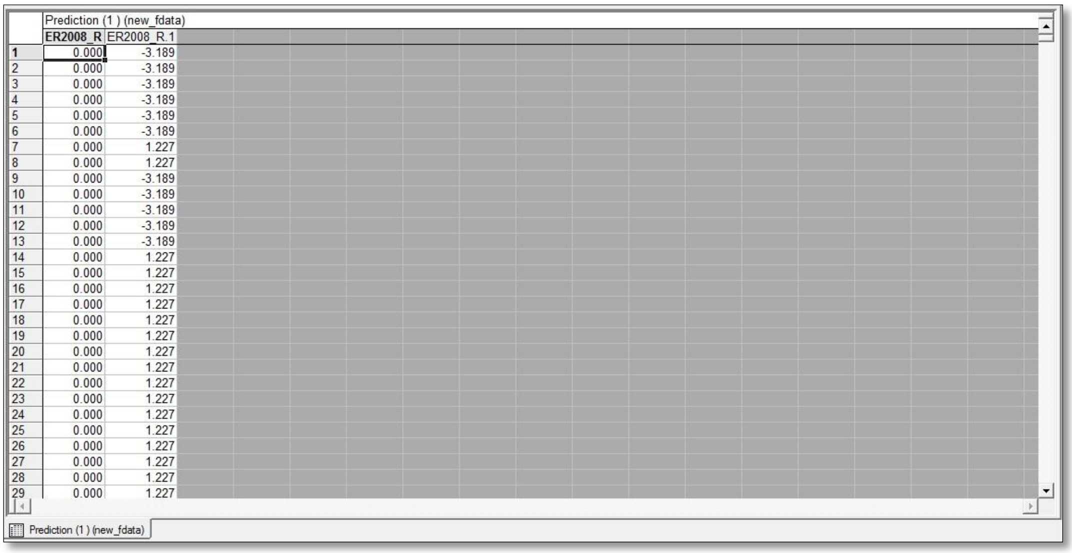


Figure 23: Prediction (MLP, Back propagation) STATISTICA (author).



Prediction (1) (new_fdata)

	ER2008_R	ER2008_R.1
1	0.000	-3.189
2	0.000	-3.189
3	0.000	-3.189
4	0.000	-3.189
5	0.000	-3.189
6	0.000	-3.189
7	0.000	1.227
8	0.000	1.227
9	0.000	-3.189
10	0.000	-3.189
11	0.000	-3.189
12	0.000	-3.189
13	0.000	-3.189
14	0.000	1.227
15	0.000	1.227
16	0.000	1.227
17	0.000	1.227
18	0.000	1.227
19	0.000	1.227
20	0.000	1.227
21	0.000	1.227
22	0.000	1.227
23	0.000	1.227
24	0.000	1.227
25	0.000	1.227
26	0.000	1.227
27	0.000	1.227
28	0.000	1.227
29	0.000	1.227

Figure 24: Prediction Results (MLP, Back propagation) STATISTICA (author).

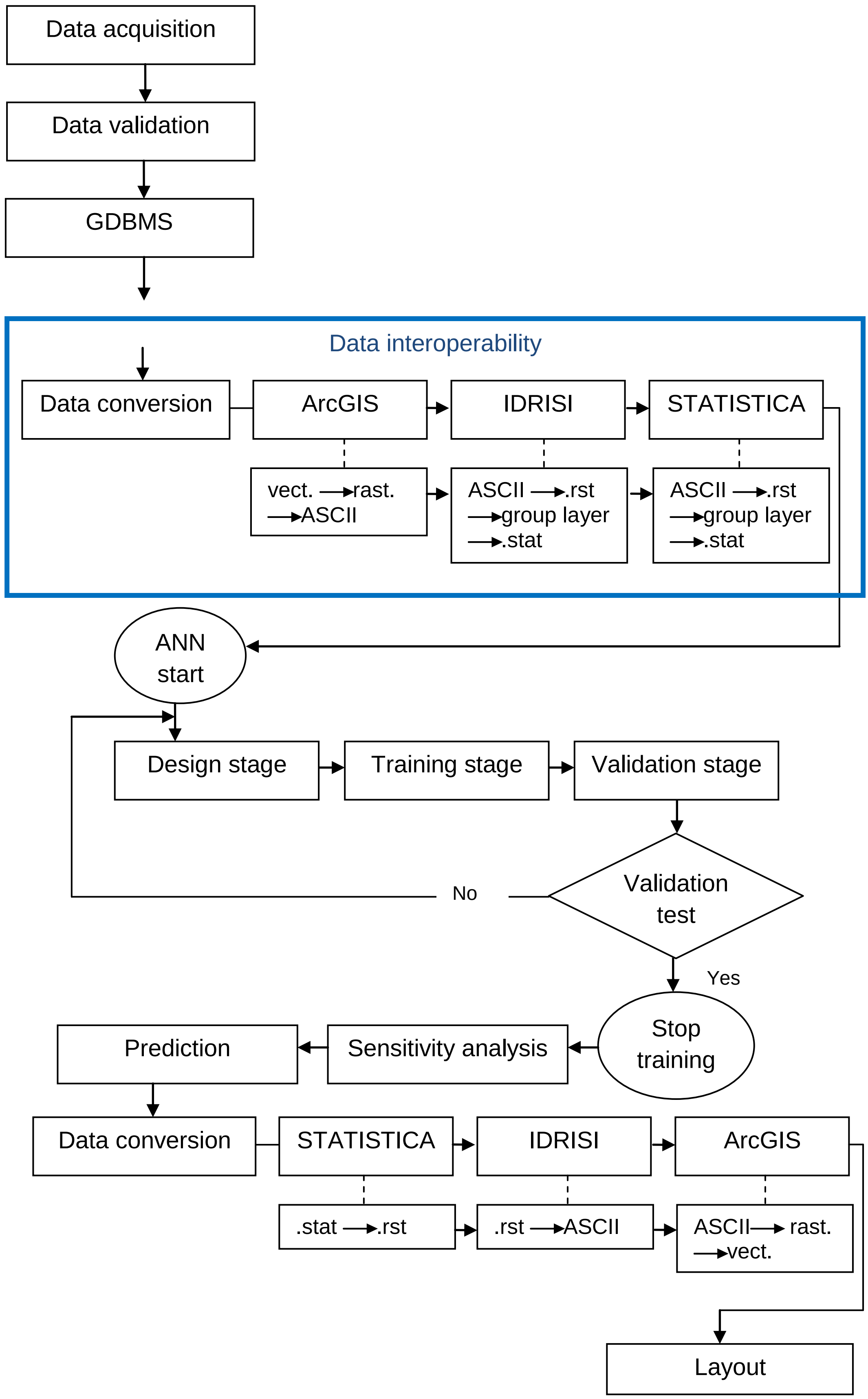


Figure 25: Physical Model of the current study (author).

6 RESULTS

After training the network several times, the results show that all the variables are relevant for the study. Looking at the numbers of the variables ratio on the different sensitivity analysis result tables (Table 2), there is no significant difference between the weights of the variables. This leads to no need for further network training because it can cause noise in the model and during training. Finally the network was trained with nine inputs one hidden layer with seven hidden nodes and one output (9:1:7:1).

A	Sensitivity Analysis – network 9:2:6:3:1								
	ALOJ01_3	ALOJ11_3	CORNL_00	CORNL06_	ER6080_R	ER8090_R	VEG_RCID	RESID01_	RESID11_
Ratio	1.000451	0.999655	0.999669	1.004549	1.017696	1.000097	1.007850	1.005299	1.000919
Rank	6.000000	9.000000	8.000000	4.000000	1.000000	7.000000	2.000000	3.000000	5.000000
B	Sensitivity Analysis – network 9:2:6:6:1								
	ALOJ01_3	ALOJ11_3	CORNL_00	CORNL06_	ER6080_R	ER8090_R	VEG_RCID	RESID01_	RESID11_
Ratio	1.047523	0.999605	1.002351	1.000591	1.018752	1.000064	1.011311	1.004844	0.999059
Rank	1.000000	8.000000	5.000000	6.000000	2.000000	7.000000	3.000000	4.000000	9.000000
C	Sensitivity Analysis – network 9:2:5:5:1								
	ALOJ01_3	ALOJ11_3	CORNL_00	CORNL06_	ER6080_R	ER8090_R	VEG_RCID	RESID01_	RESID11_
Ratio	1.012291	1.001607	0.998228	1.001061	1.013966	0.999958	1.001469	1.198692	1.003025
Rank	3.000000	5.000000	9.000000	7.000000	2.000000	8.000000	6.000000	1.000000	4.000000
D	Sensitivity Analysis – network 9:2:4:3:1								
	ALOJ01_3	ALOJ11_3	CORNL_00	CORNL06_	ER6080_R	ER8090_R	VEG_RCID	RESID01_	RESID11_
Ratio	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
Rank	4.000000	7.000000	2.000000	5.000000	3.000000	9.000000	8.000000	1.000000	6.000000
E	Sensitivity Analysis – network 9:1:7:1								
	ALOJ01_3	ALOJ11_3	CORNL_00	CORNL06_	ER6080_R	ER8090_R	VEG_RCID	RESID01_	RESID11_
Ratio	1.031465	1.002228	1.029465	1.078573	1.018142	0.999928	1.005138	1.115673	1.020041
Rank	3.000000	8.000000	4.000000	2.000000	6.000000	9.000000	7.000000	1.000000	5.000000

Table 2: Results of Sensitivity Analysis for different network topology (A,B,C,D,E). The rank shows which of the variables influence more the output and has a range of one (high) to nine (low). The ratio shows how relevant are the variables for the study (author).

Index	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Test Error	Training/ Members	Inputs	Hidden (1)	Hidden (2)
1	MLP 9:9-7-1:1	1.020087	0.967074	0.995613	0.012059	0.034072	0.023768	BP1b	9	7	0

Table 3: Results of the network training (9:1:7:1) STATISTICA (author).

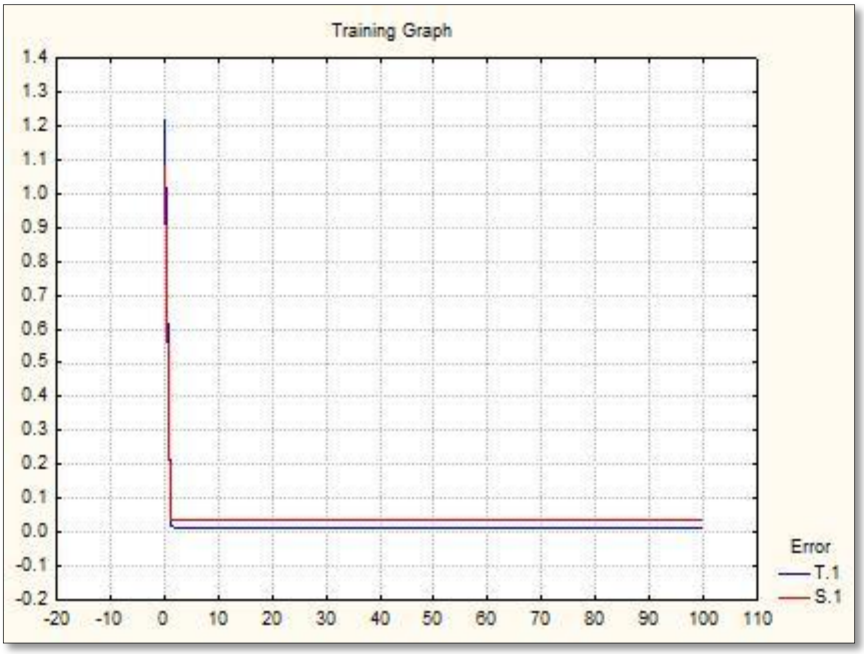


Figure 26: Training graph for the network 9:1:7:1. It shows the error function per epoch on the training and selection subsets. It is used to determine how well the neural network is performing during iterative training and execution.

Comparing all of the different results of the different trainings the variables of the number of the residents and the households seems to have a greater effect than the other variables in the areas vulnerable to erosion in the near future (rank-Table 2).

Knowing the variables that most affect the erosion parameter in the future, the standard network prediction was generated. The result of the predicted values for the network's output has been mapped (Figure 28). Different areas (polygons) with different colors were created to show where major, medium or minor erosion changes will take place in relation with the rest of the variables in 2021. The color yellow indicates the areas that are affected less, the color orange shows the areas that are affected moderately; the color red indicates the areas that are highly affected and white shows the areas where there is no erosion change.

The extent of the area of the different degrees of erosion risk was calculated for the year 2021 within the study area (Table 4). The pie chart below (Figure 27) illustrates that more than half of the total area will probably undergo medium level of erosion changes and the areas where the erosion level is less possible to change in the future constitute almost a quarter of the total area. Furthermore, less than a fifth of the total area is likely to have high erosion change level and only one in twenty of the area will not appear erosion changes.

EROSION CHANGE LEVEL	AREA/ m^2
Low	4305289.813234
Medium	9026291.059202
High	2123576.39112
No change	764323.845085
SUM	16219481.1086

Table 4: Extent of the area of different degrees of erosion risk in 2021, CC (author).

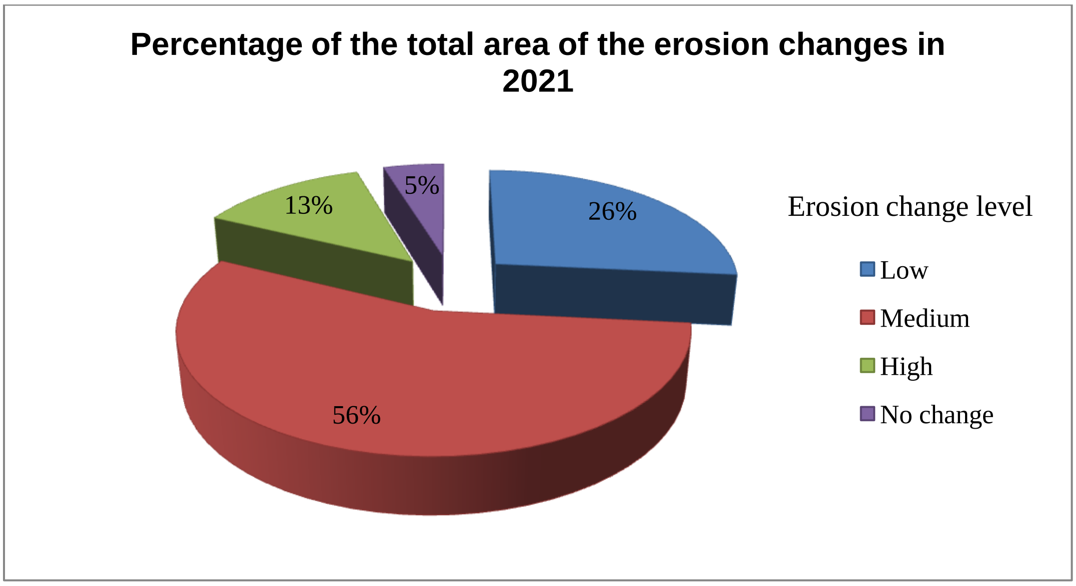


Figure 27: Percentage of the areas with different erosion change level in 2021, CC (author).

The areas more vulnerable to erosion changes according to the map and analysis of the study area are located within the grey dune, in the borders of the dune and the fossil cliff, close to the river Tagus inlet, and in the part of the coastal zone which is more developed and has more human traffic. The areas where the urbanized part of Costa Caparica takes place are less prone to erosion changes.

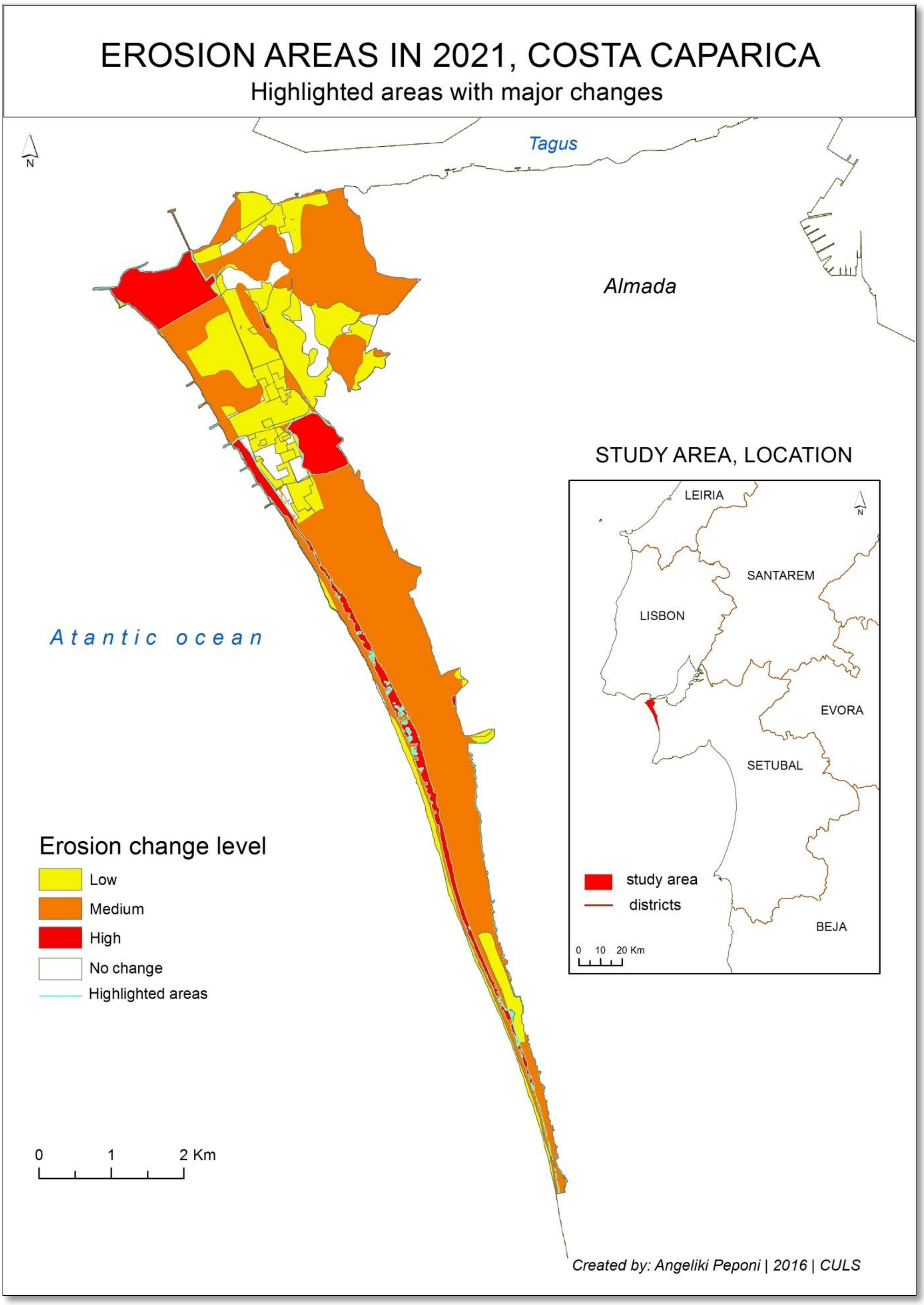


Figure 28: Map of the areas prone to erosion changes in 2021 (author).

7 DISCUSSION

7.1 DISCUSSION OF METHODOLOGY

The implementation of the methodology was satisfactory, but not entirely in accordance with the original concept. The reason for this was the non-availability of further suitable data for the study area. Issues with data acquisition, selection, validation, storage, management and visualization were raised. The larger and better the data set is the more superior the capability to acquire knowledge, learn local agent dynamics and perform more reliable sensitivity analysis. The data on the variables must belong to at least two different time periods in order for the machine to learn from the past and to be capable of predicting the future conditions. Not all the data were available in two time periods, so the result was that fewer variables were used for the study.

Data were acquired from different sources, in different formats, for different areas within the study area and with different scale, thus for all acquired and selected data, geometric and topologic validation was applied in order to reduce some computing errors. Two types of data were used; biophysical and social-economical-demographic which cover different areas within the study area. There is the dune field where there is not social-economical-demographic and the urbanized part where there are not biophysical features. However, these two subareas are located in close proximity to one another, and after having studied the area, it is correct to say that there is pressure to the dune which causes erosion, from the urbanized part of the area. So, in order to discover in which degree these social-economical-demographic variables are affecting the dune and vice versa, it is necessary to include every single available variable in the model. To do so zero values were added as information in the empty pixels.

All the datasets were needed to have the same number of columns and rows, in order to be finally integrated into one Statistica file and introduced to the neural network. In order to set the scale of the analysis, the dimension of the study area as well as the type of the problem were taken into account. Different scales were tried (cell size: 1, 10, 5m) until concluding with the final scale (cell size: 3m).The same cell size was applied to all raster datasets.

According to the literature review multilayer perceptron is considered the most commonly used type of ANNs. A MLP model was adopted in this study and overall, the use of MLP technique for studying the coastal systems in Costa Caparica was performed optimally. The model is fitted to reality and suits the purpose. However to be able to say with certainty that it is the best supervised ANN type for this kind of study, it would be necessary to train the network with other ANN types. A good example would be the comparison of MLP and radial basis function networks (RBF).

7.2 DISCUSSION OF RESULTS

The sensitivity analysis showed that the most important variables which affect the level of erosion changes is 2021 are the number of residents and the number of households. Here, it is important to clarify that people and urbanization are two different factors which, from one perspective, can combine to contribute to the cause of degradation of the nature environment but conversely are not necessarily analogs. In other words, where there is an increase of urbanization there is no implied growth of population and vice versa. They are two different ideas which affect the dynamics of the coastal system differently. Households/urbanization principally modifies the hydrological and sedimentation regimes as well as the nutrients and chemical pollutants dynamics. Urbanization creates impervious surfaces resulting in the increase of surface runoff and the decrease of groundwater and waterway discharges. The quality of surface runoff also is changed because it contains increased loads of sediment, nutrients and pollutants. All of these affect the biota and physical environment. Population density affects the carrying capacity of the coastal zone. Population’s change in size, composition and distribution affect the coastal systems by altering the land uses and land cover of the area.

The output of the neural network is a map which illustrates the areas of the study area prone to erosion changes in 2021. These areas are categorized in low, medium, major and no changes. This implies that in the areas with major changes, it is more likely that changes in the erosion state will occur, than in the areas of the category medium or low changes. In the areas with “no change” the erosion in 2021 will be at the same level as present (2008). As mentioned before, the areas with major erosion changes are situated within the grey dune, in the borders of the dune and the fossil cliff, close to the river Tagus inlet, and in the part of the coastal zone which is more developed and has more human traffic. With an understanding of the coastal dynamics, the results seem accurate. Dune erosion is caused naturally by the Aeolian activity (deflation) and the wind action. Human activities such as excessive trampling, driving vehicles over dunes, construction and so on, affect the erosion of the areas. A cliff is a landform produces by erosion processes and weathering, so it is logical that the areas in close proximity to the cliff are prone to erosion changes. Areas close to river mouth are characterized by general instability because they meander and change shape due to tidal inlets.

At this point of the study, there is no specification to which degree the erosion variable for the areas with erosion change will be changed. It is not known whether the erosion is going to decrease or increase.

To be able to know, and make the model more fitted to reality, it is necessary to use more data and to have different attribute values for the erosion which is the dependent variable of the ANN model. Instead of having the size of the areas in the erosion variable as in the current study, you must have a classification of the erosion in three levels to be able to answer the questions of: what will affect the erosion changes? Where will the erosion changes happen? And in which degree? Now it is possible to answer only the first two questions.

One step further would be to build different scenarios which represent different alternative images of the future by changing the values in the input variables depending on the conflicts for the spatial development of the area. The current study constitutes a “business as usual (BAU)” scenario with the action “Do nothing”. Which means the values of variable stayed as normal.

8 CONCLUSIONS

Why is it important to apply ICZM? And why use a GIS-ANN approach for ICZM?

Coastal zones belong to the areas which are the most productive in the world. The Coastal Ecosystems provides a wide range of services to human beings. Nowadays, coastal ecosystems belong to the most intensively used and vulnerable natural systems worldwide. A sustainable management and use of coastal zones is crucial. An ICZM is the key tool to take into consideration the vulnerability of the coastal ecosystems and landscapes, the plethora of activities and different uses and the interactions between marine and terrestrial parts of CZ. The IZCM aims, amongst others, to endorse balance between the coastal uses and to take into account the economic and environmental strengths and weakness of different policies and strategies with the scope to guarantee the most valuable use of the coastal zone. The application of the ICZM is a slow and long term process. Various methods and techniques and different approaches have been used over the years as a tool for ICZM. In the current study, Artificial Neural Networks have been applied in order to predict the areas within the study area in Costa Caparica which are prone to erosion changes by the year 2021. Erosion is a crucial variable which leads to instability of the coastal dynamics of the area. Knowing the areas susceptible to erosion can help managers and decision-makers to design a sustainable plan for future development.

ANN is a dynamic system for processing information which allows a multivariate data analysis of nonlinear structural problems. ANNs are an alternative and more valid approach with significant advantages compared to other methods for the prognosis of geo-related phenomena in coastal areas such as erosion changes.

Why use a MLP for the methodology?

In this study the feed-forward Multilayer Perceptron (MLP) type of neural networks was applied to conduct sensitivity analyses on natural and social forces, and dynamic relations in the coastal system, in order to predict the areas vulnerable to erosion within the borders of the study area by examining all the different variables which influence the dynamics of the coastal system. MLP according to the literature is the most commonly used network architecture that has been used to solve nonlinear problems as classification and prediction. MLP presents a high performance in pattern recognition.

Which variables affect the most the output?

Having trained the network numerous times with varied topology, the different variables that were used seem relevant for the study. The difference between the weights of the variables is not major. For this reason further network training it is not required. However, in all the different trainings the numbers of residents and the households have more effect than the other variables on the areas vulnerable to erosion in the near future (2021). Anthropogenic activities can cause and prevent erosion. Erosion and human activities modify and disturb directly and indirectly the coastal zones resulting in changes to the coastal environment and natural processes.

Prediction, why is it important?

The results of the study indicate the areas with the highest, the medium and the lowest erosion stability by the year 2021. Knowing the areas where the erosion state is likely to change or not change within the study area, and the variables that most effect the erosion changes in spatial and temporal time scales, is a useful tool for the integrated management of the area. Moreover, this quantitative understanding of the erosion changes is essential for the establishment of rational policies in order to regulate development in the coastal zone.

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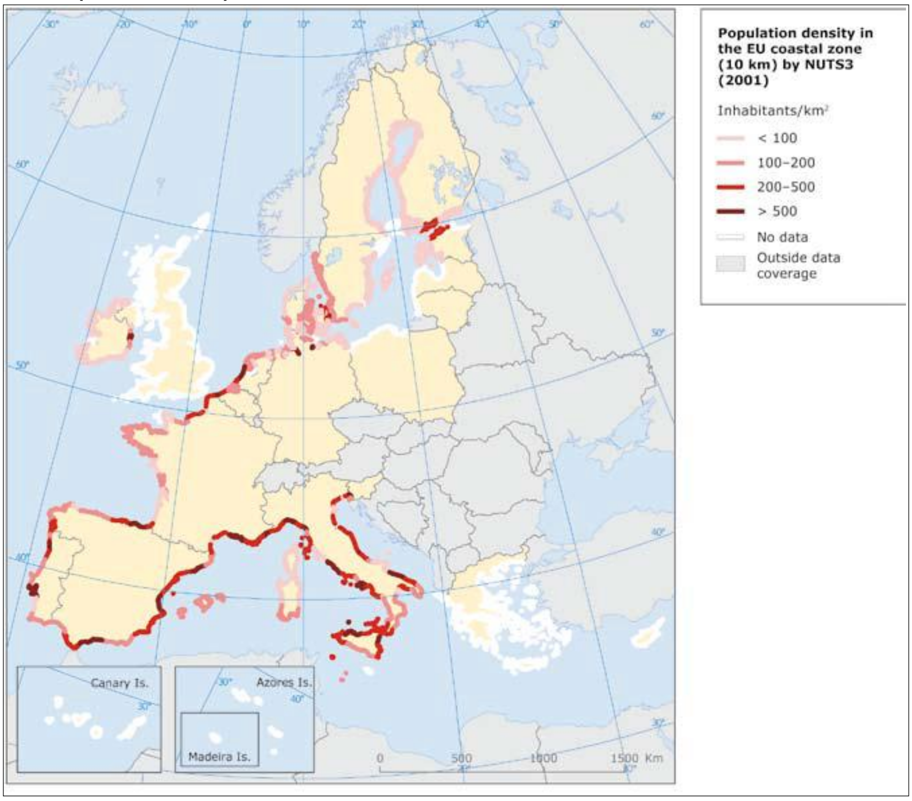
1 MAP POPULATION DENSITY IN THE EUROPEAN COASTAL ZONE (0-10km) IN 2001 (EEA, 2006)



2 MAP POPULATION IN COASTAL SETTLEMENTS (2001), (EAA, 2006)