land

MDPI

Article

A Machine Learning Framework for Assessing Urban Growth of Cities and Suitability Analysis

Anne A. Gharaibeh [1], Mohammad A. Jaradat [2,3,*] and Lamees M. Kanaan [1]

[1] Department of City Planning and Design, College of Architecture and Design, Jordan University of Science and Technology, Irbid 22110, Jordan
[2] Department of Mechanical Engineering, College of Engineering, American University of Sharjah, Sharjah 26666, United Arab Emirates
[3] Department of Mechanical Engineering, College of Engineering, Jordan University of Science and Technology, Irbid 22110, Jordan
* Correspondence: mjaradat@aus.edu

Abstract: Rural–urban immigration, regional wars, refugees, and natural disasters all bring to prominence the importance of studying urban growth. Increased urban growth rates are becoming a global phenomenon creating stress on agricultural land, spreading pollution, accelerating global warming, and increasing water run-off, which adds exponentially to pressure on natural resources and impacts climate change. Based on the integration of machine learning (ML) and geographic information system (GIS), we employed a framework to delineate future urban boundaries for future expansion and urban agglomerations. We developed it based on a Time Delay Neural Network (TDNN) that depends on equal time intervals of urban growth. Such an approach is used for the first time in urban growth as a predictive tool and is coupled with Land Suitability Analysis, which incorporates both qualitative and quantitative data to propose evaluated urban growth in the Greater Irbid Municipality, Jordan. The results show the recommended future spatial expansion and proposed results for the year 2025. The results show that urban growth is more prevalent in the eastern, northern, and southern areas and less in the west. The urban growth boundary map illustrates that the continuation of urban growth in these areas will slowly further encroach upon and diminish agricultural land. By means of suitability analysis, the results showed that 51% of the region is unsuitable for growth, 43% is moderately suitable and only 6% is suitable for growth. Based on TDNN methodology, which is an ML framework that is dependent on the growth of urban boundaries, we can track and predict the trend of urban spatial expansion and thus develop policies for protecting ecological and agricultural lands and optimizing and directing urban growth.

Keywords: machine learning; Artificial Neural Network (ANN); GIS; urban growth; land suitability analysis; Time Delay Neural Network (TDNN)

check for updates

Citation: Gharaibeh, A.A.; Jaradat, M.A.; Kanaan, L.M. A Machine Learning Framework for Assessing Urban Growth of Cities and Suitability Analysis. *Land* **2023**, *12*, 214. https://doi.org/10.3390/land12010214

Academic Editor: Chuanrong Zhang

Received: 11 December 2022
Revised: 4 January 2023
Accepted: 6 January 2023
Published: 9 January 2023

1. Introduction

The urbanization process means transforming rural society into an urban one accompanied by changes in the landscape. However, urban expansion denotes transforming vacant land or natural environment to constructed urban fabrics including residential, industrial and infrastructure development [1].

In the year 1800 CE, the global urban population was about 3%; however, in the 1950s, this had increased to 30%, while studies in the 2000s indicated that more than 47% of the world's population was living in urban areas [2]. Based on both World Bank statistics for 2015 and the United Nations 2014 revision, the urban population now constitutes about 53.857% of the global population. In the study area of Jordan, the urban population reached 83% in 2014, which is an alarming percentage [3]. Estimates for 2050 indicate a further 12% increase in urban population globally, with Jordan specifically facing a 6% increase. More developed regions are no exception, with the urban population expected to reach 89% by 2050 in Jordan [3].

Understanding the urbanization process is no easy task, since it has evolved over the years as a result of a complex network of changes in human behavior or land use policy in addition to societal pressures and activities in cities making difficult any measured urban development, such as the effects of ethnicity, religion, culture, and lifestyle on spatial growth in urban areas [4].

Some countries were aware of the urban growth early in the 20th century. For example, the UK introduced laws that, if implemented, would ensure a greenbelt policy is followed to control sprawling [5]. More studies in America and China referred to it as an urban development boundary (UDB) providing guidelines for the decision-makers to control and plan urban boundaries [6]. The urban growth boundary (UGB) became the focus of many studies especially the ones using artificial intelligence [7]. Some studies refer the expansion to the growth in economic urban activities, while others consider it the main result of population growth [8]. Regardless of the reasons, the negative consequence is the encroachment of agricultural and ecological land usage, culminating in urban sprawl [9]. The outstanding growth in relation to the demand for expansion made it necessary to plan for future growth, and models such as Future Land Use Model (FLUS), Markov, Patch-generating Land Use Simulation (PLUS) and Artificial Neural Network (ANN) are employed to predict Land Use Land Cover (LULC) change [7,9–11]. Some Remote Sensing (RS) research offers essential information on LULC change in connection to Land Surface Temperature (LST) that is valuable for predicting changes that may impact climate change and assist policymakers in developing effective land resource management plans [12,13].

Over the years, urban growth models have proven to be effective in describing and predicting urban development, providing sufficient information to help planners make informed decisions about urban planning. An Artificial Neural Network (ANN) is used to find the urban growth boundary and is increasingly used in many fields because of its powerful attributes and software flexibility, especially since urban growth is highly non-linear through time [7,14].

Tayyebi et al. [7] used ANN for a comprehensive study of Tehran, Iran, to predict growth boundaries to limit urban expansion, upgrade urban services, ensure landscape maintenance, and aid environmental protection. Planners employed neural networks, remote sensing systems models, and geographic information systems to predict future urban growth boundaries for 2012 given a set of variables such as roads, slopes, green spaces, service stations, elevation, aspect, and built areas.

Another study in Iran [15] utilized ANN to study changes in land use in previous years in the city of Kermanshah and to predict future changes. In addition to data for the past 19 years, satellite images were used for each of the years 1987, 2000, and 2006. ANN and the Markov model were used to predict land use for the next 19 years, from 2006 to 2025. Others developed a methodology for delineating an urban development boundary based on the Minimum Cumulative Resistance (MCR) model and CA-Markov model [16,17]. Aithani et al. [18] generated urban growth zonation maps using feedforward ANN for Dehradun city. However, Al-Kheder in [19] utilized a fuzzy logic-based intelligent system to model urban growth using satellite images.

Suitability analysis can be defined as a model used to select a suitable spatial site to perform a particular function; it is one of the most important functions of geographic information systems (GIS), assisting in the choice of the site by applying specific parameters in making the selection, which describes the study area landmarks (terrain, road network, etc.), thus contributing the data required for spatial site suitability analysis. Some studies coupled GIS with genetic algorithms to optimize specific land uses based on demand and allocation criteria [20].

The present research focuses on suitability analysis to investigate and determine the optimum sites for urban growth of the city of Irbid, following input of the required data. GIS tools can identify and calculate the weights of the urban growth factors based on their importance, wherein lies the main challenge to achieving the appropriate analysis, in determining the relative weights.

In the available literature, studies have made use of the suitability analysis tool to determine sites best suited for population expansion and urban growth [21,22]; for determining the most suitable areas for rangelands [23]; and for determining the suitability trends for settlement [24]. In all of these studies, researchers used a wide range of factors depending on the nature of the study area and the elements influencing growth [19,25,26]. The determination of urban growth-dependent factors is based on choosing the most suitable direction, including physical factors (slope, elevation), environmental and topographical factors (such as agricultural land, valleys), accessibility factors (distance from main streets), as well as consideration of economic and social factors.

The study by Berry et al. [27] used suitability analysis to focus on increasing sea levels as a result of global climate change. Suitability analysis was based on the map overlay, with the integration of sea level rise expectations based on several factors: elevation, slope, distance to coast, rock type, land cover, and sea level rise.

Raddad in [28] conducted a study that employed suitability analysis to evaluate the most feasible places for development in the southeast Jerusalem region. Built-up areas, geopolitical categorization, agricultural land, the separation wall, settlement areas, highways, terrain, heritage, and water sensitivity zones were identified as the primary determinants influencing urban growth. He utilized Arc GIS processing modules to generate final suitability maps based on these variables. This study, however, reveals an anomaly in the spatial dimension of population distribution in Irbid, where expansion is taking place at the cost of agricultural land.

One of the main causes of this fast-growing urban expansion is the increasing number of refugees that immigrate to Jordan from neighboring countries suffering war and turmoil. They are mostly concentrated in GIM due to its location in the north of Jordan. Jordan refugee statistics for 2021 were 3,047,612.00 granted asylum, making up a percentage of 33.6% of the local residents [29]. Another cause of urban expansion is the local authority's decision to subdivide agricultural lands in the 2000s in Irbid and change the use to residential and services to absorb the increased number of refugees and locals returning home following the Iraq war. Another recent wave of refugees followed the Syrian war from 2011 onward. This has caused far more expansion than is needed in the next 50 years. This could not have happened without the Cities, Villages, and Buildings Planning Law No. 79 of 1966, which established zoning plans (Al-Tantheem) by the Ministry of Municipalities and Towns. This usually refers to zones on a municipal zoning map that are changed on a regular basis. The Al-Taqseem Law of 1968 established subdivision plans (Al-Taqseem), which are implemented per basin. Unfortunately, zoning is not a requirement for permission, and Al-Taqseem can be used in both zoning-enforced and unzoned regions [30]. Therefore, choosing Irbid to implement this AI methodology will be a beneficial task to develop and provide service to this municipality in particular.

The primary objective of this study is to increase and broaden our understanding of spatial urban growth extent. It focuses on anticipating urban expansion so that strategies for land preservation and land use modification may be developed. The framework integrates machine learning (ML), geographic information systems (GIS), and image analysis for this purpose. The framework suggested is based on a Time Delay Neural Network (TDNN) that is dependent on equal time intervals of urban growth. In addition, it takes into account characteristics that influence land use change, such as soil fertility, the location of town and city centers, built-up areas, streams, and slopes. The ML-based prediction model is paired with Land Suitability Analysis, which includes both qualitative and quantitative data, in order to suggest analyzed urban expansion in the Greater Irbid Municipality, Jordan.

This paper is organized as follows: Section 2 covers the method, Section 3 illustrates and explains the prediction results and the suitability analysis, Sections 4 and 5 present the discussion and conclusions.

2. Methodology

Artificial neural networks (ANN) resemble the brain in two ways. 1—The network acquires knowledge from its surroundings via a learning process. 2—The strength of interneuron connections, termed "synaptic weights", is employed to store gained information [31]. ANN is composed of several layers, an input layer, one or more hidden layers and an output layer [7]. The training is achieved by exposing the network to examples of similar problems, and the network adapts itself (learns). After sufficient training, the neural network can model the problem data to the solutions, and it is then able to offer a solution to the problem [32]. During the training, the network predicts output and compares it with the correct available answer; if there is an output error, it works to modify the weights (w) of the links of each layer of the network and reprocesses the output. Time Delay Neural Network (TDNN) is among the ANNs. The TDNN consists of the lapped time delay with focused memory structure in the input layer of the network [33], where equal time intervals may be used as input data. Up to now, this network has not been used in urban growth forecasting, and it is worth investigating, especially where the data corresponded with equal intervals.

TDNN is a non-linear predictor that can train networks faster and easier with the least prediction errors [34]. This is completed based on the tapped delay line with a focused memory structure in the input layer of the network [33]. The more training it receives, the more accurate it can be.

As previously mentioned, this research aims to predict the boundary of the city of Irbid in 2025 by using TDNN and determining the best places for future urban growth of the city of Irbid based on selected criteria, namely: slope, soil fertility, streams, built-up area, and distance from the city center. The (TDNN), like other neural networks, consists of three layers: an input layer, an output layer and middle hidden layers. It relies on data input for specified time periods. In this research, the time period is optimized to be 10 years between the first and the second input; the Matlab software toolbox is utilized to implement and train the TDNN for prediction.

To predict the extent of urban growth in 2025 using (TDNN), training data were extracted from maps obtained from the Irbid municipality, as shown in Figure 1. The base of the analysis was Irbid Tal at the city center, which represents the kernel for the historical urban growth of the city. The growth maps from the center in each phase were used as input layers in the TDNN. Maps for the suitability analysis layers were created in GIS and other related software. The use of the TDNN allowed for working on a two-dimensional time series: one dimension is the time, while the other is the angle. In other words, the network would build its prediction based on an awareness of the growth radiuses (ρ) of all the angles (θ) rather than one angle only starting from the city center. The growth radius is transformed into the percentage of growth by dividing the new radius over the older one each time as follows:

$$G_r = \frac{\rho_c}{\rho_p} \tag{1}$$

where G_r is the growth percentage, ρ_c is the current radius, and ρ_p is the previous radius. In this series, each radius is normalized relative to the previous one, where if we had the value 2 for example, this meant that the current radius was twice the previous one. The values ranged between 1 and 6.9. The average in most years was about 1.98. The TDNN used in this work was a two-step time delay, which meant that the network takes the last two consequent radiuses and predicted the third one, as shown in Figure 2.

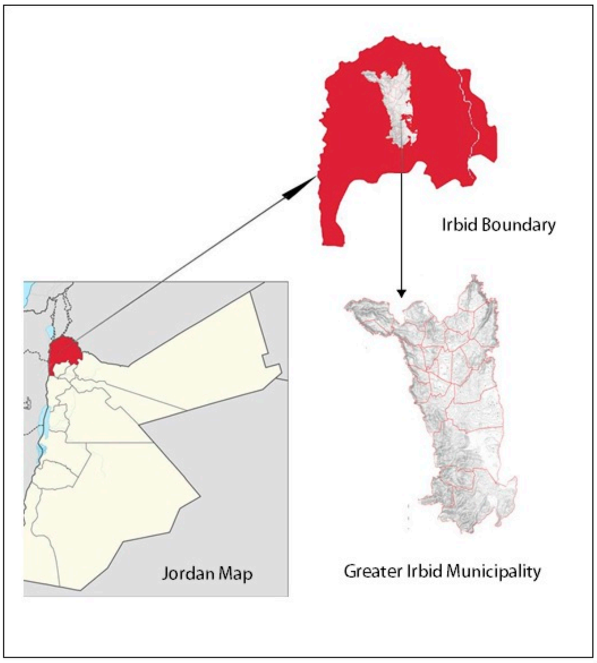


Figure 1. Study area. Map of Greater Irbid Municipality and City of Irbid boundaries (GIM, 2013) [35].

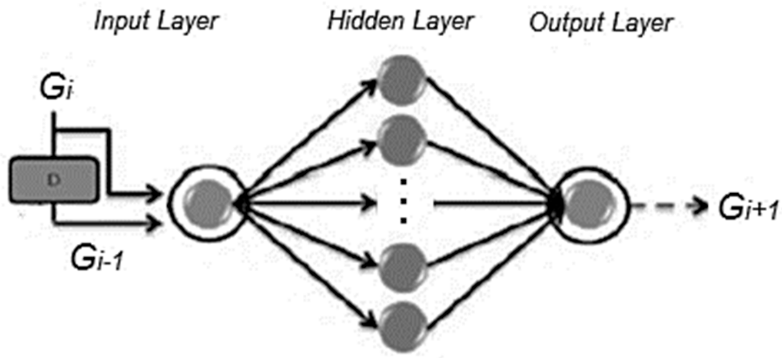


Figure 2. General structure for the TDNN [36].

To achieve the objectives of the TDNN network in providing the optimized input/output relationship for the predicted growth percentage G_{i+1}, the output layer collects the weighted inputs from the last hidden layer, and each hidden layer collects the weighted output from the previous layer until the first hidden layer, which collects the weighted inputs to the network as in Equations (2) and (3) [36].

$$G_{i+1} = F_o\left(\sum\nolimits_0^h w_{ho} A_h + b_o\right) \tag{2}$$

$$A_h = F_h(w_{1h} G_{i-1} + w_{jh} G_i + b_h) \tag{3}$$

where G_{i+1} is the growth percentage predicted by the network, F_o is the activation function of the neuron in the output layer, F_h is the activation function of the neuron in the hidden layer, w is the weight for the link to be optimized during training between the neurons, and b_o and b_h are the neuron bias for the output and hidden layers, respectively. A_h is the collected output from the hidden layer, h is the number of neurons in the hidden layer, and the number of inputs of the network is j. To reach the optimal weight during the training process, the backpropagation training approach is utilized, which is considered among the most popular approaches for multilayer NN weight optimization [36]. The objective function is to minimize the Mean Square Error (MSE) [37] between the terms of the actual

2D input series of the training data (Ga) and the equivalent estimation of the network (G_e) as in Equations (4) and (5) [36,38].

$$MSE = \frac{1}{m}\sum_{x=1}^{m} e^2(x) \quad (4)$$

$$e = G_a - G_e \quad (5)$$

where e is the error, and m is the length of the series for each angle in the training data.

Following the usage of neural networks in the prediction of the boundary of the city for 2025 (Figure 3), suitability analysis was performed to determine the most suitable areas for urban growth based on several criteria (topographical maps, soil fertility maps, distance from the city center, built-up areas, and maps indicating streams). Maps are created using GIS software (Figure 4).

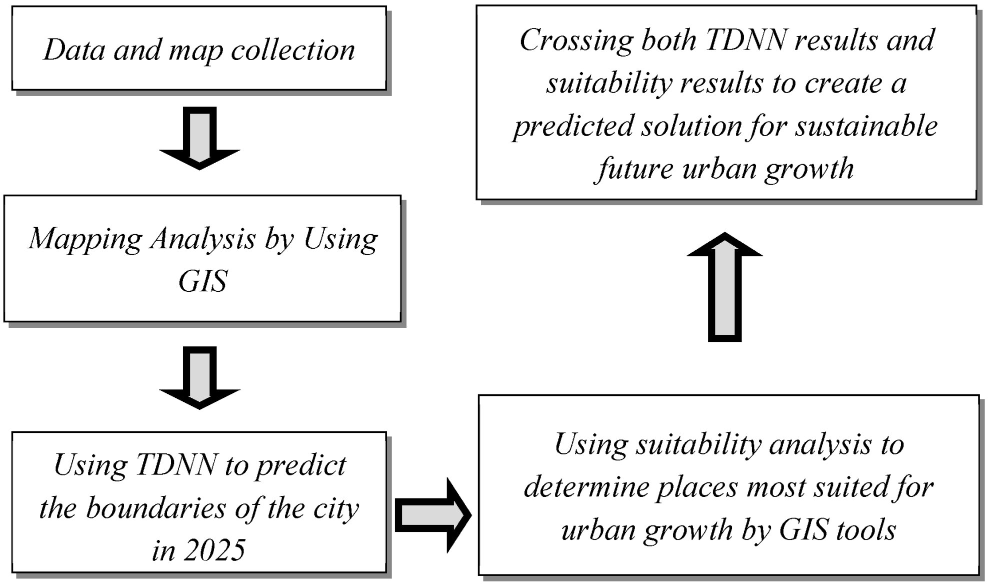


Figure 3. General structure of the proposed framework based on Time Delay Neural Network (TDNN).

Streams are important determinants that must be considered in order to preserve ecological corridors [28]. Distance from the major urban center and town agglomeration; closeness to services; level of city compactness; and physical limits to urban sprawl were all mentioned by [39,40]. Due to the importance of these factors, towns with a population of more than 11,000 people, based on Jordan's Department of Statistics report in 2015, were adopted as towns with urban centers (Table 1).

Table 1. Towns for which urban centers have been adopted in the suitability analysis [41].

Towns	Population Numbers	Towns	Population Numbers
Alhusun	*37,141*	*Beit ras*	*18,019*
Alsareeh	*19,227*	*Hawara*	*12,801*
Iydun	*18,592*	*Bushra*	*11,377*

Additionally, slope is one of the most important factors affecting planning and the direction of urbanization. Steep slopes are considered unsuitable for urban expansion because planning and construction are very expensive in these areas. Therefore, areas with a gradient of up to about 10% are suitable for residential development [28,42,43]. The increase in the urban built-up area makes it imperative to include this as a factor to encourage urban growth in vacant land [24]. Areas rich with fertile soil and agricultural land are worth protection and preservation [24]. After considering the previous literature and the considered variable weights, this research classified the variables and discussed each one based on the requirement of the place as well (Table 2).

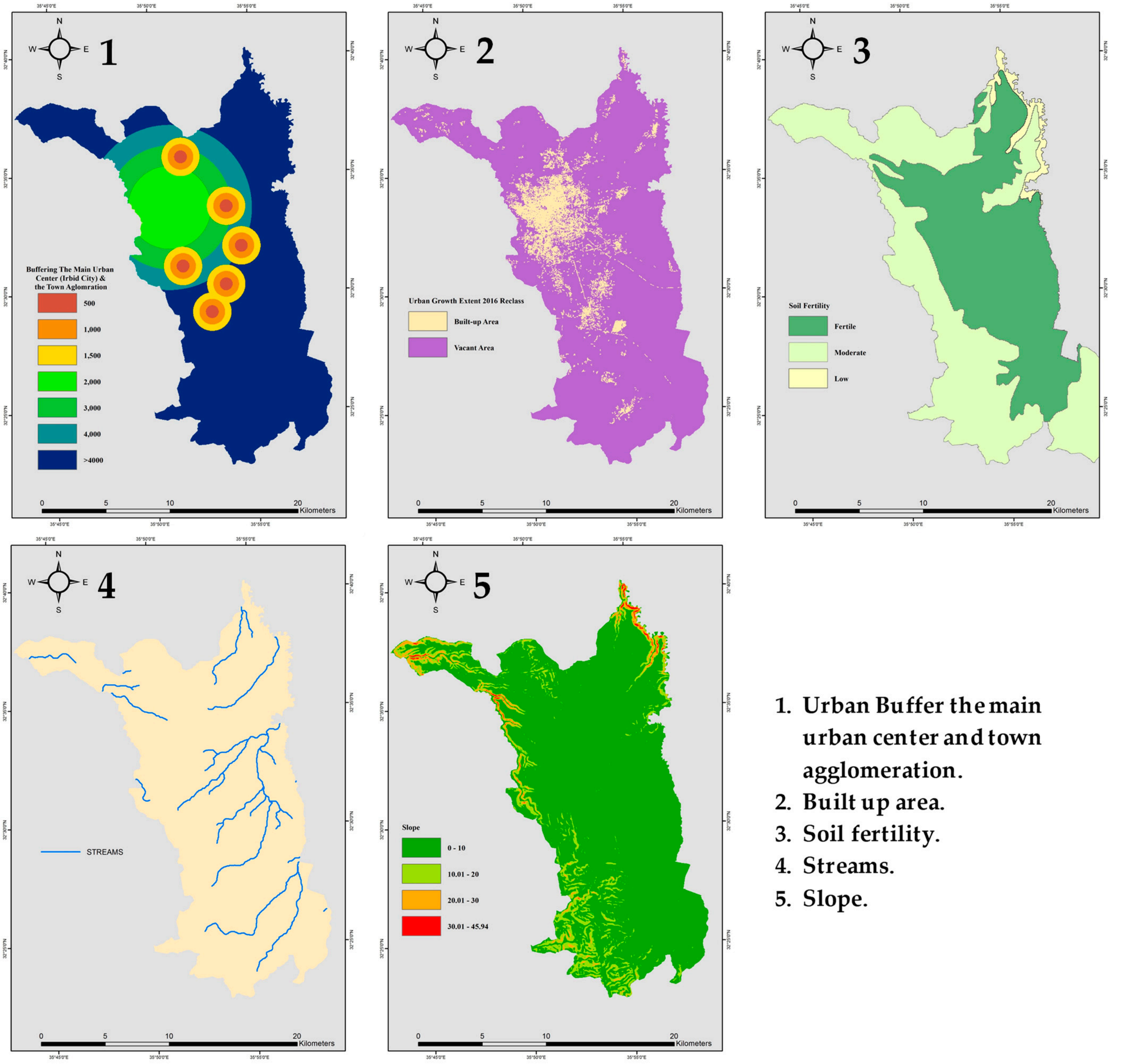


Figure 4. Variables affecting urban expansion in Irbid.

Table 2. Criteria classes and weighting.

Criteria	Classes	References	Weight	Weight Range	Note
Slope (degree)	0–10%	[24] [44] [43]	0.22	0.195	The slope factor in this research was given a weight based on the rate of the weight for the same factor in similar research. So, the weight = 0.19
	10.1–20%		0.3		
	20.1–30%	[28]	0.22		
	>30%		0.04		

Table 2. *Cont.*

Criteria	Classes	References	Weight	Weight Range	Note
Distance from the main urban center and town agglomeration	Main urban center 0–2000 m 2000–3000 3000–4000 Town center 0–500 m 500–1000 m 1000–1500 m	[39] [40]	0.22 0.26	0.24	Due to the population density of many towns in the study area, the urban center of the towns with a population of more than 11,000 was taken into consideration, including Huwwara, Al-Sareeh, Bushra, Idun, Beit-ras, and Al-Huson. To keep the towns and cities compact and prevent urban sprawl, the weight = 0.25
Streams (*m*) Buffering the water course with 40 m on either side of the center line.	0–40 m >40	[28] [45]	0.04 0.11	0.07	The study area is interspersed with many streams that have negative effects, especially flooding in the winter, so the weight = 0.11 based on [45].
Soil fertility	Fertile Moderate Low	[40] [22]	0.09 0.21	0.15	This factor was given the highest weight since the study area is rich in fertile soil and agricultural land and is being engulfed by urban growth. This is one of the most important factors that should control the future growth process so the weight = 0.3
Built-up area	Built-up Vacant land	[24] [45] [43]	0.13 0.15 0.12	0.133	The built-up area factor gained a weight of 0.15 based on [45]. The aim was to move away from the built-up area as it constituted an obstacle to growth

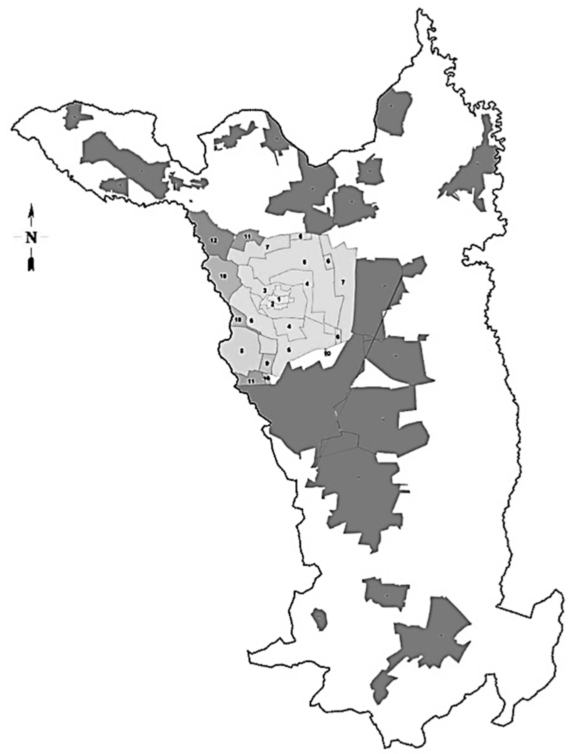
3. Results

3.1. Phases of Urban Expansion

The map of urban expansion of the Greater Irbid Municipality (GIM) is analyzed by separating each phase of the expansion using GIS tools (Figure 5 [46]). Earlier stages (1924–2001) were excerpted from GIM. Earth Explorer is the source for checking the later stages for specific years. We adopted and digitized the years 2005, 2010, and 2015.

The growth radius (ρ) was collected from the city center (Tal Irbid) to the boundary of each stage at a succession of equal angles (θ). This research experimented with a succession of 5 degree angles constituting a sum of 72 wedges, as shown in Figure 6.

The TDNN is adopted for the prediction process in the following years: (1955, 1965, 1975, 1985, 1995, 2005, and 2015). However, as a result of emigration in 1967, the population density increased, and urban expansion increased rapidly. There was a large difference between urban expansion in 1965 and 1975, which created illogical TDNN results. To eliminate the sudden jump, another experiment was performed by taking the years (1975, 1985, 1995, 2005 and 2015) as shown in Figure 7. Before the prediction process, the network was trained on the years 1975, 1985, 1995, and 2005 to predict 2015. However, in order for the data to be suitable for prediction, the growth radius was transformed into the percentage of growth by dividing the new radius over the older one each time, as in Equation (1). The average in most years was about 1.98. However, noticeably, in 1995–2005, larger values were registered, which was possibly because of the increased immigration to Jordan in this period due to the regional turmoil and instabilities in neighboring countries.



Phase	Year	Area (m^2)	Phase	Year	Area (m^2)	Phase	Year	Area (m^2)
1	*1924*	*285.739 K*	**6**	*1970*	*658.860 K*	**11**	*1994*	*1480.731 K*
2	*1953*	*596.792 K*	**7**	*1978*	*6134.087 K*	**12**	*2000*	*2443.510 K*
3	*1955*	*2770.525 K*	**8**	*1985*	*2999.913 K*	**13**	*2001*	*82312.254 K*
4	*1960*	*3286.844 K*	**9**	*1986*	*474.657 K*			
5	*1967*	*11396.903 K*	**10**	*1990*	*2820.436 K*			

Figure 5. Growth stages of greater Irbid municipality (GIM, 2005) [46].

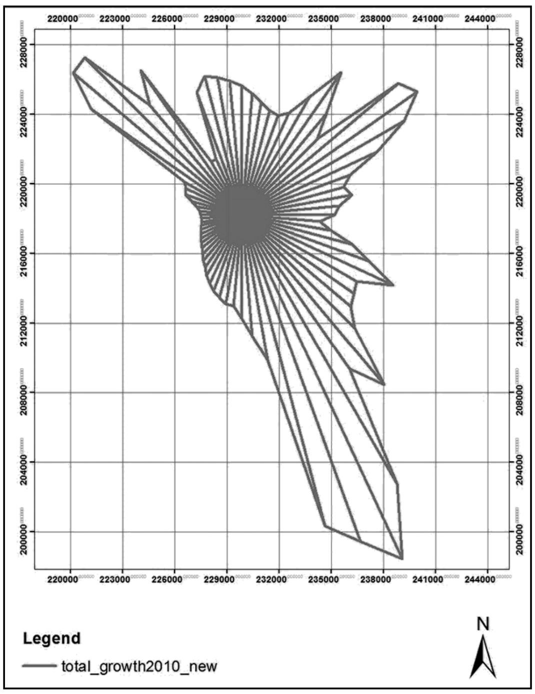


Figure 6. The succession of growth radiuses at θ = 5-degree angle for the 2010 stage using GIS.

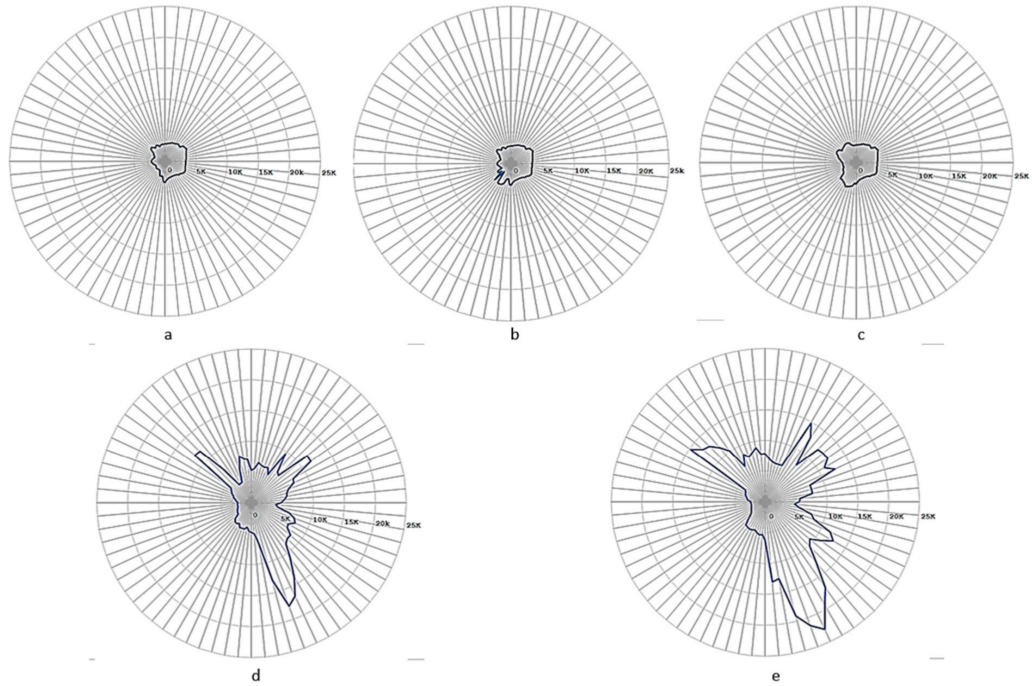


Figure 7. The succession of growth radiuses at θ = 5-degree angles for the years: 1975, 1985, 1995, 2005, and 2015, (**a**–**e**) respectively.

The general shape of the neural network and its components is shown in Figure 8; the number of inputs is 72 and the number of outputs is 72, which is equivalent to (360/5 = 72). Several iterations were made to reach the optimum network with the least error value starting from different random initial weights; 70% of the data was used for training. Finally, the network that had the least error consisted of two hidden layers; the first hidden layer consisted of five neurons and the second consisted of 71 neurons with the minimum MSE as shown in Figure 9.

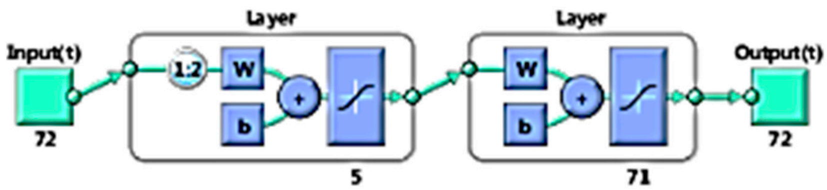


Figure 8. The general structure of TDNN.

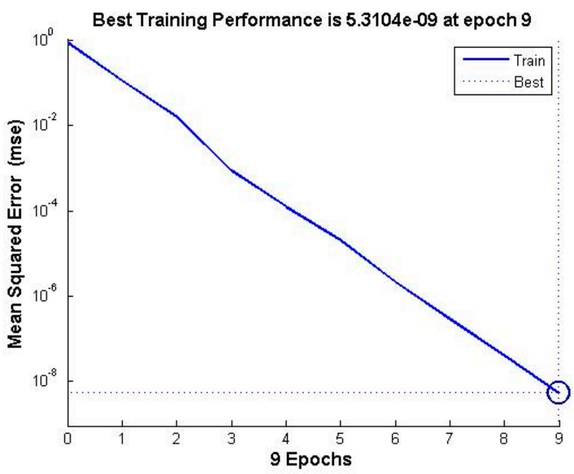


Figure 9. The mean square error of the network during the training epochs.

Another measure of how well the neural network has fit the data was the regression plot as shown in Figure 10. The regression plot illustrated the plot of the expected output based on associated target values. If the network had learned to fit the data well, the linear fit to this output–target relationship should closely intersect with the bottom-left and top-right corners of the plot [47].

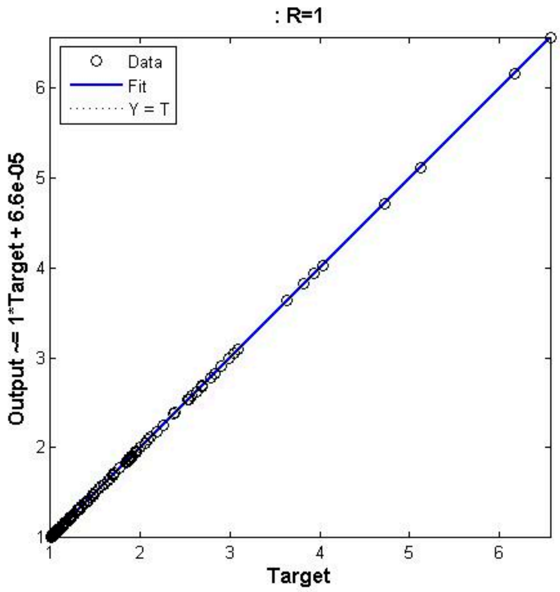


Figure 10. The regression plot measure of the suitability of TDNN.

Figure 11 illustrates a third measure of how well the neural network has fit data; the error histogram plot showed how the error sizes were distributed. Typically, most errors were near zero, with very few errors far from that. The value at the bottom of the blue rectangle is the error value. The value on the vertical axis is the number of times this error value appeared among the data.

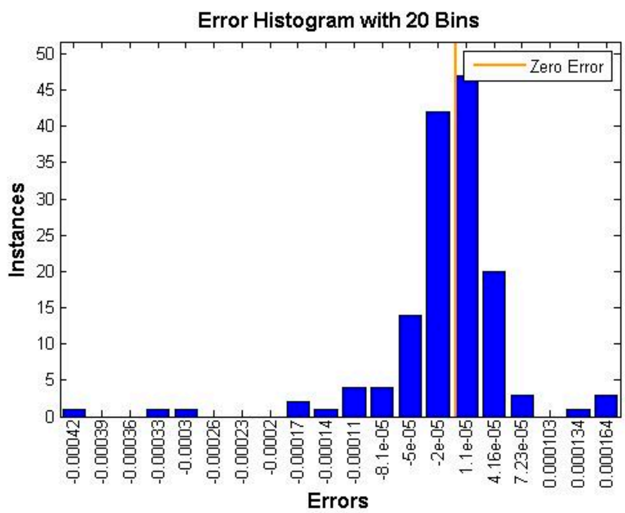


Figure 11. The error histogram measure of the suitability of the TDNN for data.

For presentation purposes, GIS was used to illustrate the existing and predicted maps. Each radius was drawn with an angle above the layer of 2015, as shown in Figure 12. As it is noticed, the results indicated that urban expansion was more prevalent in the eastern, northern, and southern areas and less in the west due to the presence of some valleys in this area.

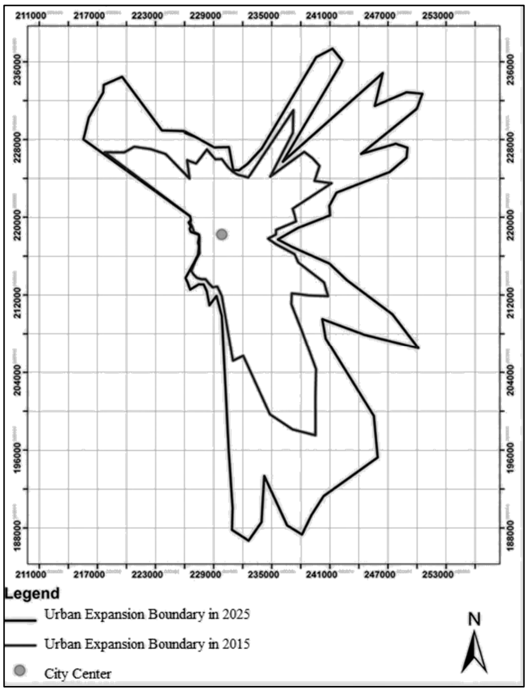


Figure 12. Prediction map for 2025 resulting from the use of TDNN.

Additionally, the urban growth boundary map illustrated that the continuation of urban growth in these areas will further impinge upon and diminish agricultural land, especially in the southern and eastern regions [48,49]. Unless prevented by urban development policies with firm and timely interventions of the concerned authorities, urban growth will continue to invade agricultural land.

3.2. Suitability Analysis

After obtaining the prediction map, the suitability analysis phase begins. Each variable is classified in a separate map (urban buffer, built-up area, soil fertility, streams, and slope) (Figure 13). The maps were reclassified and given weights depending on their importance and impact and depending on previous literature (Table 3). A multi-criteria analysis was made to create suitability maps by combining factors and weighting them. The resulting map was classified into three classes, namely: low suitability, moderate suitability, and high suitability for urban expansion (Figure 14).

Table 3. Criteria reclassification and weighting.

Criteria	Classes	Reclassified	Weight
Slope (degree)	0–10% 10.1–20% 20.1–30% More than 30%	4 (the best slope for growth) 3 2 0 (building restricted and challenging)	0.19
Distance from the main urban center and town agglomeration	Main urban center 0–2000 m 2000–3000 3000–4000 >4000 Town center 0–500 m 500–1000 1000–1500 >1500	 4 (the best for growth) 3 1 0 4 3 1 0	0.25

Table 3. *Cont.*

Criteria	Classes	Reclassified	Weight
Streams (m) Buffering the water course with 40 m on either side of the center line.	0–40 m More than 40	0 4	0.11
Soil fertility	Fertile Moderate Low	0 2 4	0.30
Built-up area	Built up Vacant land	0 4	0.15

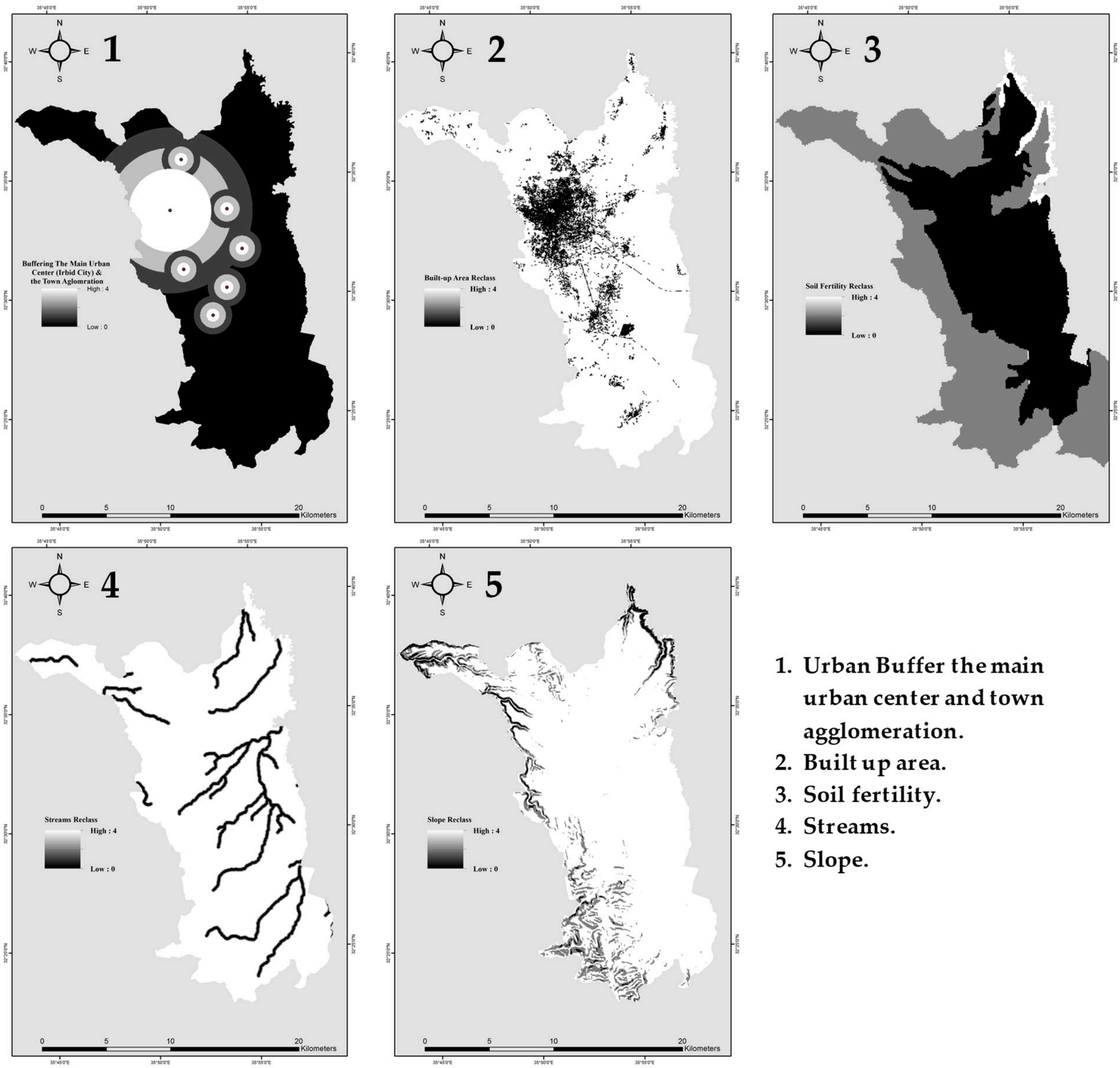
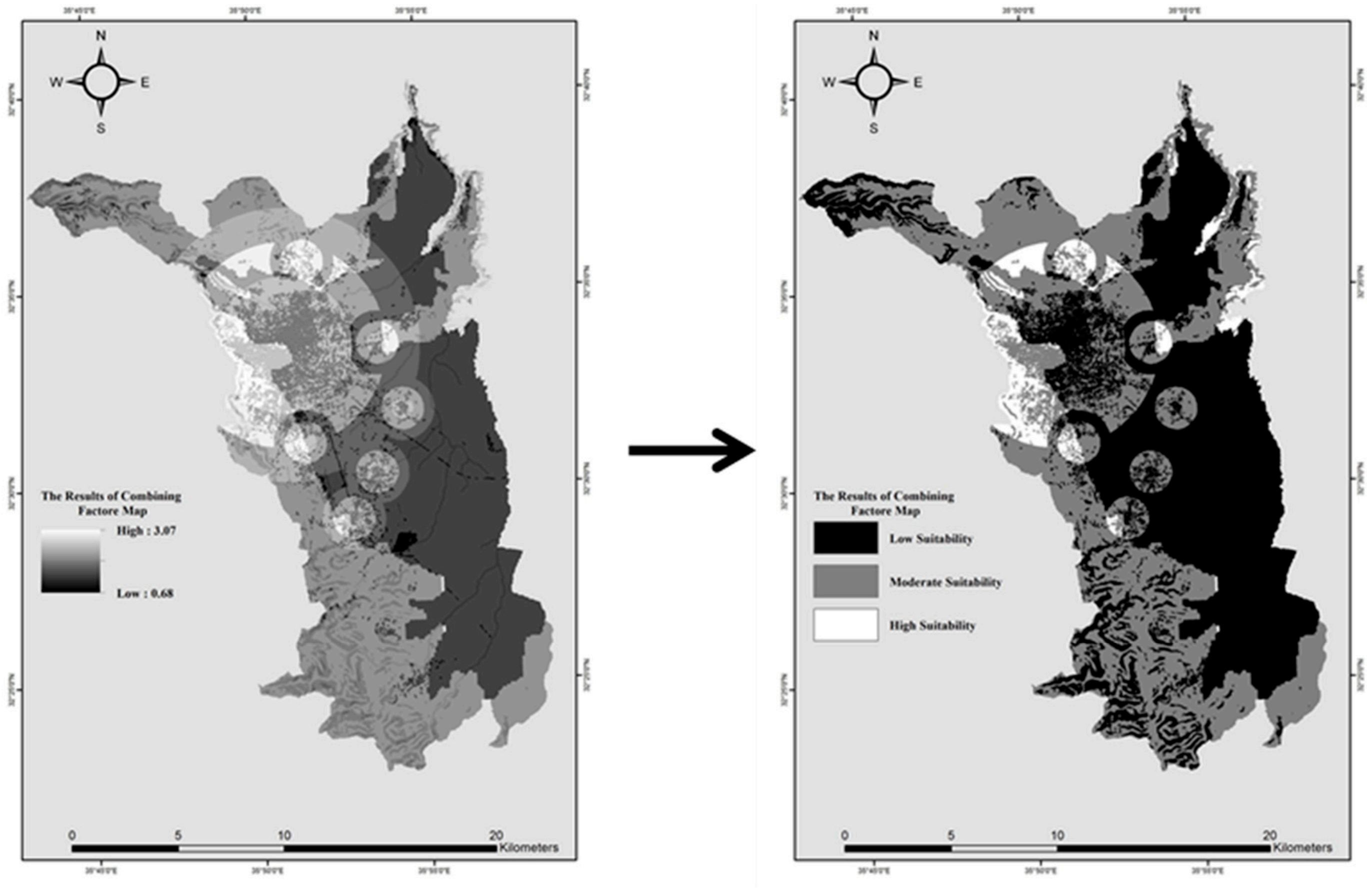


Figure 13. The factors after reclassified.



The result of combining factors map The result of suitability analysis

Figure 14. The result of combining factors and suitability analysis.

3.3. Juxtaposing the Suitability Analysis and the TDNN Map

Factors with higher weights (white color) were a major influence to make the region suitable for growth. The results indicated that many of the areas suitable for urban growth are located around urban centers (Figure 14). Therefore, we recommend that the city grows vertically and fill the vacant city parcels with more development. This will create a more compact urban fabric while preserving agricultural lands. Most of the areas located between 52 degrees and 120 degrees (2 and 1) and 282 degrees and 300 degrees (4 and 3) had a medium suitability (Figure 15). They grow from the city center toward the north or south in general. The eastern areas are more suited for agricultural land because of the soil fertility and their nature as plains. This answers the research question concerning the preferred direction of urban growth and land suitability for urban growth.

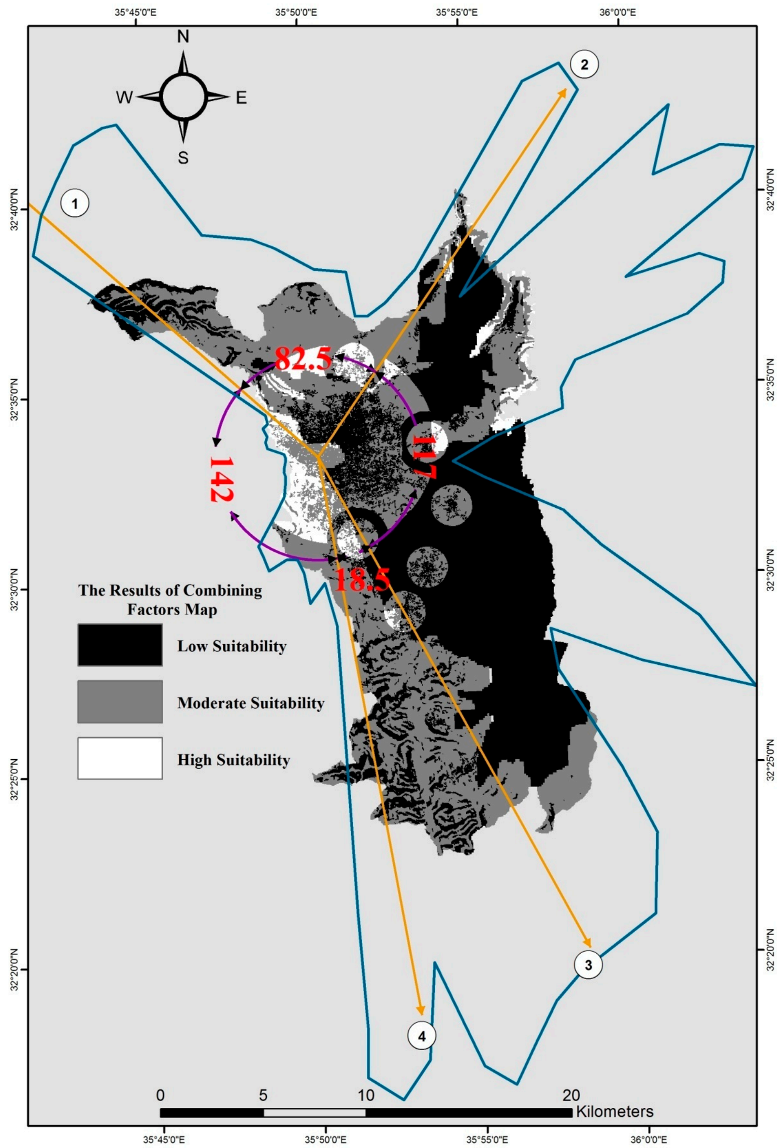


Figure 15. The result of suitability analysis overly and TDNN prediction for 2025. Line color representation: blue is the expected urban growth extent, yellow are the lines delimiting the preferred angle of growth between the arrows 1&2 and 3&4. Delimited angles between 2&3 and 1&4 define the unwanted growth direction avoiding fertile soils (117°) and rugged terrains (142°) respectively.

4. Discussion

If we want to be governed by this predictive study and maintain more resilient urban growth, we must create policies to control the urban edge, the permissible areas of growth, and the tolerable densities. We must think of re-zoning the city and nominate the types of buildings that suit the multi-cultural melting pot we are experiencing in this part of the world. As it seems, there will be more people to settle in secured urban areas, and we must be prepared to handle forecasts. We must think of our future and long-term interests in growing our foods in the places most suited for that and in the places that have the ability to grow abundant amounts of basic foods to create food security. With the United Nation's sustainable development goals (SDGs), this issue has an enormous importance for the coming generations: in particular, Zero Hunger (SDG 2), Sustainable Cities and Communities (SDG 11), Climate Action (SDG 13), and Life on Land (SDG 15) [50].

If we continue conducting business as usual, we will end up with overly expanded metropolitan areas, unaffordable infrastructures, the loss of agricultural lands, and most probably, loss of identity. There is an opportunity to develop a better organized spatial strategy that considers both the scope and capacity of urban growth as well as the need for urban green spaces to accommodate expanding populations. This is an opportunity to preserve ecological corridors, renovate heritage buildings, and organize land uses.

It is in our interest to encourage people to live in their home towns and prevent rural urban migration, which is another cause of this outstanding urban growth. Since most people tend to have daily commutes to obtain services at their urban centers, it is wise to serve them in their hometowns and prevent excessive commuting and the tendency to immigrate to urban areas to fulfill consumption aspirations. A study concentrating on the rural–urban relationship in the north of Jordan revealed that the commutes were not based on obtained jobs at the urban center but rather in search of attractive and necessary services [51]. Therefore, most of this sprawling is not essential. If we are discussing policies, we also have to consider providing services especially entertainment and shopping in addition to job opportunities at key rural locations to prevent the rural–urban migration and the fast-growing urban areas.

This study demonstrated how the TDNN predictive tool, coupled with suitability analysis, can predict and weigh urban growth. This is similar to other methods but with more precise outputs as a result of the self-learning tool and the suitability analysis. The machine learning tools allow self-correction and adaptation to change. The more it learns, the more precise the prediction. When such tools are accessible to decision makers, they can modify and study growth and manage city requirements with great precision. Giving building permits, preparing infrastructures, proposing services, and many other land uses will be made easier for them. With such predictive tools that are able to learn and evolve every day, we can also plan for resource management to lead a more resilient growth.

5. Conclusions

The purpose of this research is to predict the boundary of urban growth in GIM in 2025 by using ANN as a model, specifically TDNN to support the planning process and help decision-makers see the future status of the city. This was expected to aid them in the future expansion of the city and prepare for greater sustainability in the foreseeable future. The research is based on the analysis of the urban expansion map throughout history, using the resulting data from the analysis as input for TDNN, and by employing suitability analysis of the resulting expected growth. Results indicated that urban growth will be significantly southward, with little northward and eastward, and very limited westward. The results showed that 51% of the region is unsuitable for growth, 43% is moderately suitable and only 6% is suitable for growth. The ML model is very useful in determining the future of the city based on learning from previous spatial urban growth.

We note from the analysis that the eastern and southeastern areas are generally unsuitable for urban growth due to the fertility of the land there and the presence of agricultural land in abundance in addition to the increased distance from the city center. The area in the proximity to the city center was suitable for growth despite the presence of a built-up area. Suitability was strongly affected by other factors, such as the soil, which despite being fertile has not so far been used as agricultural land because of urban growth.

Since the more suitable lands for urban expansion are the lands within the urban areas and in close proximity to their centers, the results highlight the importance of densification in this case. Densification will save agricultural land and create more sustainable and manageable urban growth. Smaller towns also act as sub-centers that will help with densification and more controllable urban growth. Encouraging growth on the hillier sides of the city toward the southwest is another foreseen alternative. The more challenging slopes will provide more bare land than agricultural lands with moderate suitability for urban growth. This will result in a more linear city footprint but a more resilient existence in this part of the country. The waves of refugees in this part of the world keep coming to Jordan as things escalate within the Middle East region. Enforcing policies to direct growth appears to be critical for the city in order to control its excessive urban growth activities and create a more resilient future with a served city limit and reduced sprawl. Based on the demonstrated results, this work can be further extended in the future and applied to other growing cities.

Author Contributions: The work was developed and implemented as part of the thesis work by L.M.K. and supervised by the project advisors; A.A.G. and M.A.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Shenghe, L.; Sylvia, P. *Spatial Patterns and Dynamic Mechanisms of Urban Land Use Growth in China: Case Study in Beijing and Shanghai*; IIASA Interim Report; IIASA: Laxenburg, Austria, 2002.
2. United Nations. *Department of Economic and Social Affairs. Population Division Population Distribution, Urbanization, Internal Migration and Development: An International Perspective*; United Nations: New York, NY, USA, 2011.
3. United Nations. *World Urbanization Prospects, United Nations, 2014 revision, Department of Economic and Social Affairs*; United Nations: New York, NY, USA, 2015.
4. Herold, M.; Goldstein, N.C.; Clarke, K.C. The spatiotemporal form of urban growth: Measurement, analysis and modeling. *Remote Sens. Environ.* **2003**, *86*, 286–302. [CrossRef]
5. Han, A.T.; Go, M.H. Explaining the national variation of land use: A cross-national analysis of greenbelt policy in five countries. *Land Use Policy* **2019**, *81*, 644–656. [CrossRef]
6. Zheng, B.; Liu, G.; Wang, H.; Cheng, Y.; Lu, Z.; Liu, H.; Zhu, X.; Wang, M.; Yi, L. Study on the Delimitation of the Urban Development Boundary in a Special Economic Zone: A Case Study of the Central Urban Area of Doumen in Zhuhai, China. *Sustainability* **2018**, *10*, 756. [CrossRef]
7. Tayyebi, A.; Pijanowski, B.; Tayyebi, A. An urban growth boundary model using neural networks, GIS and radial parameterization: An application to Tehran, Iran. *Landsc. Urban Plan.* **2011**, *100*, 35–44. [CrossRef]
8. Gao, L.; Tao, F.; Liu, R.; Wang, Z.; Leng, H.; Zhou, T. Multi-scenario simulation and ecological risk analysis of land use based on the PLUS model: A case study of Nanjing. *Sustain. Cities Soc.* **2022**, *85*, 104055. [CrossRef]
9. Feng, D.; Bao, W.; Fu, M.; Zhang, M.; Sun, Y. Current and Future Land Use Characters of a National Central City in Eco-Fragile Region—A Case Study in Xi'an City Based on FLUS Model. *Land* **2021**, *10*, 286. [CrossRef]
10. Xu, T.; Zhou, D.; Li, Y. Integrating ANNs and Cellular Automata–Markov Chain to Simulate Urban Expansion with Annual Land Use Data. *Land* **2022**, *11*, 1074. [CrossRef]
11. Cağlıyan, A.; Dağlı, D. Monitoring Land Use Land Cover Changes and Modelling of Urban Growth Using a Future Land Use Simulation Model (FLUS) in Diyarbakır, Turkey. *Sustainability* **2022**, *14*, 9180. [CrossRef]
12. Hussain, S.; Mubeen, M.; Karuppannan, S. Land use and land cover (LULC) change analysis using TM, ETM+ and OLI Landsat images in district of Okara, Punjab, Pakistan. *Phys. Chem. Earth Parts A/B/C* **2022**, *126*, 103117. [CrossRef]
13. Hussain, S.; Mubeen, M.; Ahmad, A.; Majeed, H.; Qaisrani, S.A.; Hammad, H.M.; Amjad, M.; Ahmad, I.; Fahad, S.; Ahmad, N.; et al. Assessment of land use/land cover changes and its effect on land surface temperature using remote sensing techniques in Southern Punjab, Pakistan. *Environ. Sci. Pollut. Res.* 2022, pp. 1–17. [CrossRef]
14. Triantakonstantis, D.; Mountrakis, G. Urban Growth Prediction: A Review of Computational Models and Human Perceptions. *J. Geogr. Inf. Syst.* **2012**, *4*, 26323. [CrossRef]
15. Razavi, B.S. Predicting the Trend of Land Use Changes Using Artificial Neural Network and Markov Chain Model (Case Study: Kermanshah City). *Res. J. Environ. Earth Sci.* **2014**, *6*, 215–226. [CrossRef]
16. Yi, S.; Zhou, Y.; Li, Q. A New Perspective for Urban Development Boundary Delineation Based on the MCR Model and CA-Markov Model. *Land* **2022**, *11*, 401. [CrossRef]
17. Gharaibeh, A.; Shaamala, A.; Obeidat, R.; Al-Kofahi, S. Improving land-use change modeling by integrating ANN with Cellular Automata-Markov Chain model. *Heliyon* **2020**, *6*, e05092. [CrossRef] [PubMed]
18. Maithani, S.; Arora, M.K.; Jain, R.K. An artificial neural network based approach for urban growth zonation in Dehradun city, India. *Geocarto Int.* **2010**, *25*, 663–681. [CrossRef]
19. Al-Kheder, S.; Wang, J.; Shan, J. Fuzzy inference guided cellular automata urban-growth modelling using multi-temporal satellite images. *Int. J. Geogr. Inf. Sci.* **2008**, *22*, 1271–1293. [CrossRef]
20. Gharaibeh, A.A.; Ali, M.H.; Abo-Hammour, Z.S.; Al Saaideh, M. Improving Genetic Algorithms for Optimal Land-Use Allocation. *J. Urban Plan. Dev.* **2021**, *147*, 04021049. [CrossRef]
21. Jiao, S.; Gao, Q.; Wei, C.-Y.; Liu, B.; Li, X.-D.; Zeng, G.-M.; Yuan, Z.-X.; Liang, J. Ecological suitability evaluation for urban growth boundary in red soil hilly areas based on fuzzy theory. *J. Cent. South Univ.* **2012**, *19*, 1364–1369. [CrossRef]

22. Mohammed, K.S.; Elhadary, Y.A.E.; Samat, N. Identifying Potential Areas for Future Urban Development Using Gis-Based Multi Criteria Evaluation Technique. In *SHS Web of Conferences*; EDP Sciences: Les Ulis, France, 2016; p. 03001. [CrossRef]
23. Jafari, S.; Zaredar, N. Land Suitability Analysis using Multi Attribute Decision Making Approach. *Int. J. Environ. Sci. Dev.* **2010**, *1*, 441–445. [CrossRef]
24. Omar, N.Q.; Raheem, A.M. Determining the suitability trends for settlement based on multi criteria in Kirkuk, Iraq. *Open Geospat. Data Softw. Stand.* **2016**, *1*, 10. [CrossRef]
25. Bagheri, M.; Sulaiman, W.N.A.; Vaghefi, N. Application of geographic information system technique and analytical hierarchy process model for land-use suitability analysis on coastal area. *J. Coast. Conserv.* **2013**, *17*, 1–10. [CrossRef]
26. Kumar, M.; Shaikh, V.R. Site suitability analysis for urban development using GIS based multicriteria evaluation technique. *J. Indian Soc. Remote Sens.* **2013**, *41*, 417–424. [CrossRef]
27. Berry, M.; BenDor, T.K. Integrating sea level rise into development suitability analysis. *Comput. Environ. Urban Syst.* **2015**, *51*, 13–24. [CrossRef]
28. Raddad, S. Integrated GIS and multi criteria evaluation approach for suitability analysis of urban expansion in south eastern Jerusalem region–Palestine. *Geogr. Inf. Syst.* **2016**, *5*, 24–31.
29. Macrotrends. Jordan Refugee Statistics 1960–2022. 2022. Available online: https://www.macrotrends.net/countries/JOR/jordan/refugee-statistics (accessed on 1 December 2022).
30. UN-Habitat's Urban Practices Branch, Planning, Finance and Economy Section. Urban Planning & Infrastructure in Migration Contexts, Irbid Spatial Profile, Jordan. A report in Collaboration of UN-Habitat, Greater Irbid Municipality, and Swiss State Secretariat for Economic Affairs (SECO). 2022. Available online: https://unhabitat.org/sites/default/files/2022/04/220411-final_irbid_profile.pdf (accessed on 1 December 2022).
31. Jensen, R.R.; Binford, M.W. Measurement and comparison of Leaf Area Index estimators derived from satellite remote sensing techniques. *Int. J. Remote Sens.* **2004**, *25*, 4251–4265. [CrossRef]
32. Zhou, L. Integrating Artificial Neural Networks, Image Analysis and GIS for Urban Spatial Growth Characterization. Ph.D Thesis, College of Social Sciences and Public Policy, Florida State University, Tallahassee, FL, USA, 2012; pp. 1–154.
33. Hagan, M.; Demuth, H. *Neural Network Design*; PWS Publishing: Boston, MA, USA, 1996.
34. Winograd, T. Shifting viewpoints: Artificial intelligence and human–computer interaction. *Artif. Intell.* **2006**, *170*, 1256–1258. [CrossRef]
35. Al-Kofahi, S.D.; Gharaibeh, A.A.; Bsoul, E.Y.; Othman, Y.A.; Hilaire, R.S. Investigating domestic gardens' densities, spatial distribution and types among city districts. *Urban Ecosyst.* **2019**, *22*, 567–581. [CrossRef]
36. Saadeddin, K.; Abdel-Hafez, M.F.; Jaradat, M.A.; Jarrah, M.A. Optimization of Intelligent Approach for Low-Cost INS/GPS Navigation System. *J. Intell. Robot. Syst.* **2014**, *73*, 325–348. [CrossRef]
37. Negnevitsky, M. *Artificial Intelligence*, 1st ed.; Harlow Addison-Wesley: Boston, MA, USA, 2011.
38. Jaradat, M.A.K.; Abdel-Hafez, M.F. Non-Linear Autoregressive Delay-Dependent INS/GPS Navigation System Using Neural Networks. *IEEE Sens. J.* **2016**, *17*, 1105–1115. [CrossRef]
39. Liu, Y.; Hu, Y.; Long, S.; Liu, L.; Liu, X. Analysis of the Effectiveness of Urban Land-Use-Change Models Based on the Measurement of Spatio-Temporal, Dynamic Urban Growth: A Cellular Automata Case Study. *Sustainability* **2017**, *9*, 796. [CrossRef]
40. Alanbari, M.A.; Al-Ansari, N.; Jasim, H.K. GIS and Multicriteria Decision Analysis for Landfill Site Selection in Al-Hashimyah Qadaa. *Nat. Sci.* **2014**, *6*, 282–304. [CrossRef]
41. Department of Statistics (DOS). Main Results of the General Census of Population and Housing 2015. Published in 2016. 2016. Available online: http://dosweb.dos.gov.jo/products/census_mainresults2015/ (accessed on 1 December 2022).
42. Aliani, H.; Ghanbari Motlagh, M.; Danesh, G.; Aliani, H. Land suitability analysis for urban development using TOPSIS, WLC and ANP techniques (Eastern cities of Gilan-Iran). *Arab. J. Geosci.* **2021**, *14*, 1276. [CrossRef]
43. Satir, O. Mapping the Land-Use Suitability for Urban Sprawl Using Remote Sensing and GIS Under Different Scenarios. Master's Thesis, Department of Landscape Architecture, Faculty of Agriculture, Yuzuncu Yil University, Van, Turkey, 2016.
44. Ahmad, F.; Goparaju, L.; Qayum, A. Agroforestry suitability analysis based upon nutrient availability mapping: A GIS based suitability mapping. *AIMS Agric. Food* **2017**, *2*, 201–220. [CrossRef]
45. Kaoje, I.U.; Dankani, I.M.; Ishiaku, I. Site Suitability Analysis for Municipal Solid Waste Disposal in Birnin Kebbi, Nigeria. *IOSR J. Humanit. Soc. Sci.* **2016**, *21*, 1–10. [CrossRef]
46. *Growth Stages of Greater Irbid Municipality*; Greater Irbid Municipality (GIM): Irbid, Jordan, 2005.
47. Beale, M.; Martin, T.H.; Howard, B.D. *MATLAB Neural Network Toolbox User's Guide (version R2017b)*; The MathWorks, Inc.: Natick, MA, USA, 2017; p. 158.
48. Gharaibeh, A.A.; Shaamala, A.H.; Ali, M.H. Multi-Criteria Evaluation for Sustainable Urban Growth in An-Nuayyimah, Jordan; Post War Study. *Procedia Manuf.* **2020**, *44*, 156–163. [CrossRef]
49. Gharaibeh, A.A.; Jaradat, R.A.; Okour, Y.F.; Al-Rawabdeh, A.M. Landscape Perception and Landscape Change for the City of Irbid, Jordan. *J. Archit. Plan.* **2017**, *29*, 89–104.

50. UN General Assembly, Transforming Our World: The 2030 Agenda for Sustainable Development, 21 October 2015. A/RES/70/1. Available online: https://www.refworld.org/docid/57b6e3e44.html (accessed on 1 January 2023).
51. Gharaibeh, A.A.; Alhamad, M.N.; Al-Hassan, D.A.; Abumustafa, N.I. The impact of the spatial configuration of socioeconomic services on rural–urban dependencies in Northern Jordan. *GeoJournal* **2022**, *87*, 4475–4490. [CrossRef] [PubMed]