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Urban development modeling in Al Diwaniyah province of Iraq using RS-GIS

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Abstract

The rapid growth of the population and the consequent increase in migration to the cities during the past decades have caused the expansion of many urban areas. In this study, the growth and development of the urban areas of Al-Diwaniyeh during the recent decades using three categories: 1. urban limits layer extracted from land use maps during the period, 2. population density layers and 3. Degree of urbanization in the period 1975 to 2015 It was investigated, monitored and modeled. Modeling and forecasting for the future was done using layers of population density and degree of urbanization. The population density map for 2025 was implemented based on population changes in the last two decades using the multilayer artificial neural network method. While the prediction of the degree of urbanization was operationalized by creating and applying a multi-layer neural network model for 2030. The results of the study showed that the general trend of the expansion of Al-Diwaniye city limits during the period of 1975 to 205 was increasing. The degree of urbanization in Al Diwaniyah has been increasing since 1975. After 1975, the initial cores of the dense areas were formed, and gradually, in the following periods, the expansion of the urban areas of Al-Diwaniyeh was observed around the cores. The class of rural areas has shown an upward trend with a more uniform slope compared to other classes of the degree of urbanization. While after 1990, high density and low density classes with close areas have also gone through an upward trend. The rate of population density and, accordingly, the rate of population in Al-Diwaniye has been increasing between 1975 and 2015. The trend of maximum population changes has been downward; therefore, it can be claimed that the initial dense cores of the urban population of Al-Diwaniyeh have moved to the surrounding areas. In the estimated degree of urbanization in 2030, the class with high density has faced a decrease in area compared to the previous period. In general, the area of built-up areas in 2030 will increase compared to previous periods, but this will be achieved with a slower acceleration and slope compared to previous periods.

Keywords: RS-GIS; Degree of urbanism; Physical development of the city; Population density; Al-Divaniyeh

1. Introduction

One of the important aspects that can be raised in relation to urbanization management is to predict the growth of the city based on the trend and changes of its growth in the past by using different scenarios; The issue that has been emphasized in this research is the investigation of the growth of urban areas based on the observed changes using remote sensing satellite data and spatial analysis functions. In order to achieve a more accurate understanding of complex urban issues, researchers tried to use systematic analysis methods and modeling methods; Cities are inherently complex and non-linear systems. Understanding the urban system is the first step in modeling and the prerequisite of ecological encounters in the city, complex systems are systems with multiple variables that many possibilities must be considered in predicting their behavior. Therefore, these complexities make it difficult to use old models in modeling because they are static, linear, cumulative, interconnected and based on simple top-down theory (Cheng, 2003).

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2. Researches review

Urban development and the concentration of sustainable development facilities and infrastructures in large urban centers are among the obvious developments in many countries of the world (Liu, 2009). In the 1900s, only 13% of the world's population lived in cities, this share in it increased to 29% in 1950. This ratio reached 49% in 2005. According to the latest population projections of the United Nations, this figure could reach 60% by 2030. This means that out of the estimated 8 billion people for the whole world in 2030, it can be imagined that around 4.9 billion people will live in cities (United Nations, 2006). From the past to the present, various models have been developed by researchers to simulate the dynamic complexity of city growth and the growth process through the use of these models (Candau, 2002). Various models and theories have been proposed for urban development since the beginning of the 19th century, such as Von Thonen's theory, the model of concentric areas proposed by Burgess, and the theory of central positions proposed by Christaller. These models are experimental and based on observations. Such models are usually developed for special conditions and even special places and they cannot be used in other areas. On the other hand, the increase in the number of private cars in the late 1940s and early 50s caused the growth of cities to go out of their traditional physical form (Batty, 1976) and cities developed more based on the form of road networks.

Human activities and natural factors affect the change of land use over time. Spatial details play an important role in this process (White et al., 1997). Therefore, spatial modeling is the most appropriate method to model the process of land use changes (Chen et al., 2002). The development and progress of geographic information system (GIS) and remote sensing (RS) in providing appropriate spatial information in the 1990s and their use in spatial modeling of land use changes, facilitating the modeling of land use changes and urban development (Takayama et al., 1997). Therefore, spatial modeling methods were developed. In general, different approaches have been proposed for spatial modeling, which can be classified into five categories (Singh, 2003).

Over the years, a large number of urban development growth models have been developed in developed countries and used to predict growth algorithms. But in developing countries, the number of studies that show the use of these models and their implementation has been less than needed (Al-shalabi et al., 2013). In general, many efforts have been made to build an urban growth model using different models and algorithms, which can be cellular automata with fuzzy logic (Liu, 2009), artificial neural network, Markov chain improved by genetic algorithm (Tang et al., 2007), evidence weighting (Soares-Filho et al., 2004) and the urban growth model SLEUTH, which has been widely used in the United States of America and other parts of the world. In the following, the most important studies and researches on urban growth monitoring and forecasting based on remote sensing data and GIS tools and functions are discussed:

In their study, Reno and Gotzke (2015) improved the SLEUTH model using Support Vector Machine (SVM) and evaluated its performance compared to binary logistic regression. Their study related the cellular automata SLEUTH model to the SVM machine learning method; A combination that caused the dynamic simulation of different types of urban growth along with various geophysical analyzes and socio-economic driving factors to be used simultaneously to determine the appropriate location for urban development.

In a study using Landsat satellite images, Sun et al. (2016) studied the physical growth of the capital of Honduras in South America. They used impervious surfaces extracted from satellite images to monitor the boundaries of the urban environment.

Liang et al. (2020), in a study, studied the sustainability of urban growth with the help of facilities, tools and data embedded in the Google Earth Engine (GEE) system over a 12-year period (2005 to 2016). Their study focused on the value of ecosystem services and acknowledged that the method implemented in studying the temporal dynamics and spatial variations of the sustainability of urban growth reveals.

Carneiro et al. (2021) prepared a land map of the urban environment using the time series analysis of remote sensing satellite images (1985 to 2018) in the GEE platform. They claimed that the high complexity of urban surfaces, characterized by the irregular shapes and variability of urban surfaces, was revealed through their study.

Bonacci et al. (2019) introduced a novel spectral index for extracting regions constructed from Landsat 8 satellite images. They named their index BLFEI. The said index was obtained from the combination of bands 3, 4, 6 and 7 of the Landsat 8 image and had higher efficiency and simplicity than similar indices.

In a study, Khai et al. (2019) compared land extraction indicators constructed using Landsat 8 and Sentinel 2 images. They compared the indices calculated with the bands of the images with the results obtained from the modeling using the Support Vector Machine (SVM) method. The results of their study showed that, in general, the spectral indices had a higher efficiency in extracting the constructed ranges than the SVM method.

In a study, Bai et al. (2020) proposed a new spectral index to estimate and extract built-up areas using Chinese GF-1 satellite images. They first analyzed the spectral curves of ground effects with the bands of GF-1 images and then introduced their index under the title of WE-NDBI. They acknowledged that their introduced index performed better than NDBI applied to Landsat 8 images for extracting built-up and urban areas.

Wardeh (2020) in a research was able to study the expansion of urban limits and the surrounding areas of the city of Met Salsil in Egypt. His research focused on the exploration of drivers and drivers of urban development, including population growth and density and road network. His study showed that the most important obstacle to urban growth is agricultural land. Finally, based on historical data, he predicted the growth of urban areas for the coming years.

3. Material and methods

Al-Diwaniyah, the capital of Al-Qadisiyah or Al-Diwaniyah province, is located in the south of central Iraq. Al Diwaniyah province is bordered by Babil province in the north, Wasit province in the northeast, Dhi Qar in the southeast, Mushani in the south, and Najaf province in the southwest.

More than 90% of the area of the province is made up of sedimentary plains created by the sediments of the Euphrates River and its tributaries. 4% of the area of Al Divaniyeh is made up of shallow areas, which are almost always below the water level due to its proximity to the groundwater level. . A part of the Euphrates River passes through this province, which is known as "Shat Al-Divanieh" in this region. Al-Diwaniyah is known for its fertile lands that provide a significant part of the food basket of the people of the region and other regions of Iraq.

The area of Al Divaniye province is 8507 square kilometers. Its population is around 1,500,000 people. The most important part of the economic activities of Al-Diwaniyah is based on agriculture. Due to the presence of flat and fertile lands, human resources and abundant water, this province alone can provide the basic needs of the country of Iraq. The most important agricultural products of this province are rice, wheat, barley, beans, cantaloupe and dates. Diwanieh Province is also active in the field of oil refining, and Diwanieh Refinery is one of the active units of the province.

The map of average air temperature and average annual precipitation of Al-Diwaniye province was prepared from TerraClimate data (Abatzoglou et al., 2018) with pixel dimensions of 4 km and over a period of more than 6 decades (1958 to 2021). In general, the average annual rainfall varies from 120 to 65 mm. While the average temperature changes in Al-Diwaniye province show the range of 26 to 24 degrees Celsius. Also, a digital elevation model (DEM) elevation map was extracted from the topographic radar shuttle with a pixel size of 30 meters for Al Divaniye province and city (Jarvis et al., 2008). In general, the elevation changes of Al-Diwaniye province show a range between 120 and -20 meters above the open sea level.

In addition, Statistical and mathematical models were investigated along with different spectral indices for this issue, which are not presented here.

4. Results

The first category includes population density products, urbanization degree layers and global settlements (GHSL). The population layers include the time series of the population data of the global project known as WorldPop, in the form of spatial layers during the period from 2000 to 2020 globally, mainly from the implementation of machine learning methods on the data obtained from censuses on an annual basis and They have been prepared in the time division of hectares. (Gaughan et al., 2013). Another source of population layers that included population density in 1975, 1990, 200 and 2015 was GHSL layers.

Based on the design and implementation of modern spatial data mining technologies, GHSL data have relied on automatic processing and knowledge extraction and analysis from a large amount of heterogeneous data such as satellite images with appropriate resolution, census data and voluntary geographic information sources. This data set includes the distribution of population density per pixel for the reference time periods of 1975, 1990, 200 and 2015. GHSL settlement layers are the result of implementing a rural-urban settlement classification model adopted by GHSL.

The model generated the degree of urbanization of each grid in integration with GHSL built-up areas and GHSL population grid data for the reference periods. GHSL classification is based on a scheme called DEGURBA. The DEGURBA model is a people-based definition of cities and settlements: the scheme serves as the main input using a 1 km2 cell that calculates the population at a given point in time. DEGURBA distinguishes population grid cells into three main classes: urban centers (cities), urban clusters (cities and suburbs), and rural grid cells (base). These class abstractions are respectively transformed into high-density clusters (HDC), low-density clusters (LDC), and rural grid cells in the preparation of GHSL layers (Pesaresi and Sergio, 2016).

The second category includes layers of land use and multi-time land cover. Monitoring the growth and expansion of Al-Diwaniyeh urban environment based on the built-up land use extraction from the land use layers of the European Space Agency (ESA) under the title The Land Cover CCI Climate Research Data Package (CRDP) in three time periods of 1994, 2004 and 2014 and interest The 10-meter land use layer was operationalized in 2020. The 10-meter layer of land use has been produced by the European Space Agency using Sentinel 2 images in 2020 as a global coverage.

The third layer of average monthly values of climatological elements, including precipitation and air temperature, in the study area from 2000 to the end of 2021. Also, the 30-meter digital elevation model or DEM layer of the study area extracted from ASTER images, in order to display elevation changes and extract The slope map of Al Divaniye province was received and used. These layers and data were not directly used in the analyses

The fourth category includes satellite images. Satellite images were mainly used as a background to display other layers of information. For this purpose, the average natural color composition of Landsat 8 satellite images was used in images with less than 10% cloud cover.

5. Discussion

Modeling and forecasts for the coming years were done using layers of population density and degree of urbanization. The population density map for 2025 was implemented based on population changes in the last two decades using the multilayer artificial neural network method. The inputs of the neural network were formed by the layers of population density in the years 2000, 2005, 2010 and 2015. While modeling and predicting the degree of urbanization by creating and applying a multi-layer neural network model was operationalized for 2030. The input data layers of the neural network were the layers of the degree of urbanization in the time periods of 1975, 1990, 200 and 2015.

The results are as follows:

Although the general trend of the expansion of the urban limits of Al-Diwaniyeh during the time period of 1975 to 205 has been increasing, but in the 10-year period between 2004 and 2014, urbanization and urbanization have been accelerated.

The degree and intensity of urbanization in Al Diwaniyah has been increasing since 1975. However, the acceleration of urbanization has not been uniform. After 1975, the initial cores of high-density areas were formed, and over time, the expansion of the urban areas of Al Divaniyeh around the cores has been observed.

The class of rural areas has shown an upward trend with a more uniform slope in comparison with other classes of the degree of urbanization. While after 1990, the high density and low density classes with areas close to each other have gone through an upward trend, but at the same time, the distance between their shares of the total area of the classes in 2015 was lower than ever.

The rate of population density and consequently the rate of population in Al-Diwaniyeh has been increasing between 1975 and 2015.

The average population density and consequently the population of the study area has been associated with a significant increase. While the standard deviation of the population density during the period from 1975 to 2015 has been growing parallel to the increase in the population, which indicates the increase in the inhomogeneous distribution of the population in the studied time period. Also, the trend of maximum population changes has been downward; therefore, it can be claimed that the initial dense cores of the urban population of Al-Diwaniyeh have moved to the surrounding areas.

The population density map forecast for 2025 was implemented based on the population data of the last twenty years and by applying the multi-layer artificial neural network method.

Multi-layer artificial neural network method was used to model and predict the population and the degree of urbanization in the study area. The approach of this method for predicting population density and degree of urbanization was based on regression and classification methods, respectively.

In order to predict the population in 2025, the layers of population density in 2005, 2010, 2015 and 2020 were used as the input layers of the built and validated model. Therefore, the output was the population density map in 2025.

Modeling and prediction of the degree of urbanization map for 2030 was implemented based on the information of the degree of urbanization of the last 40 years from 1975 to 2015 and by applying the method of multi-layer artificial neural networks. The input information layers of the proposed network were the layers of the degree of urbanization in the mentioned time period.

In the estimated degree of urbanization in 2030, the class with high density has faced a decrease in area compared to the previous period. While the area of low-density areas and rural areas have increased and remained stable, respectively. It can be inferred that in general, the area of built areas in 2030 will increase compared to previous periods, but this will be achieved with a slower acceleration and slope compared to previous periods.

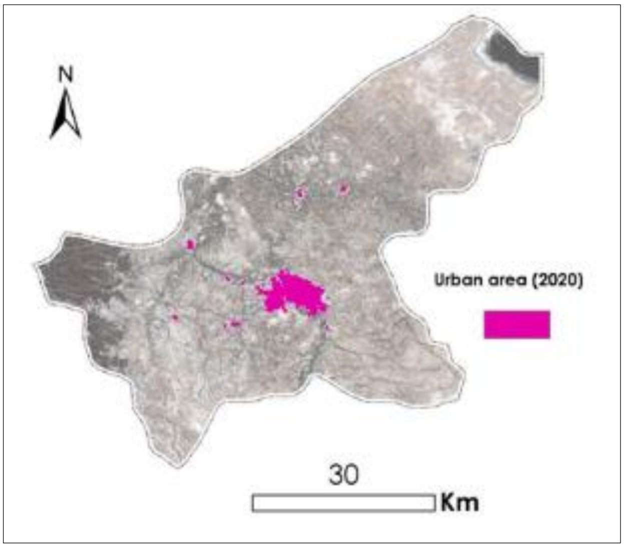

Figure 1 Al-Diwaniyah city boundaries in 2020

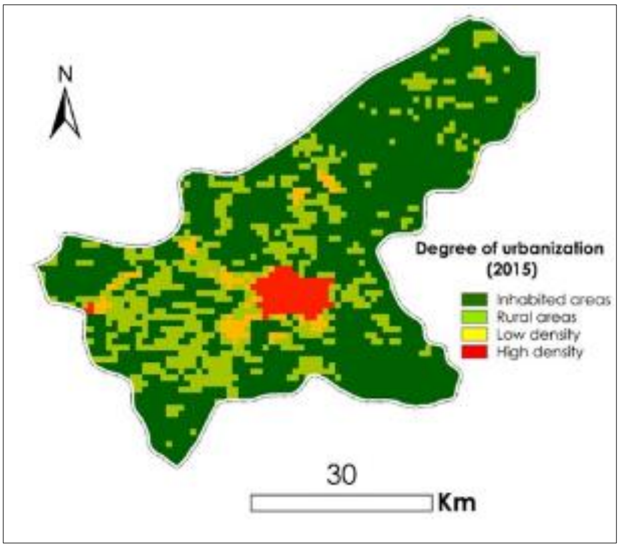

Figure 2 The map of the degree of urbanization of Al-Diwaniyeh in the period of 2015

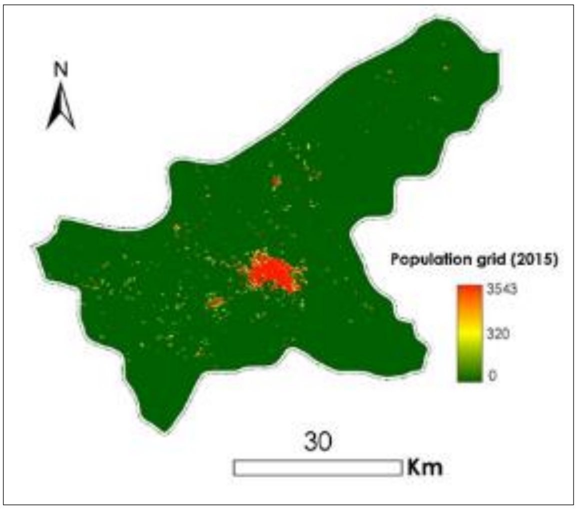

Figure 3 Al Diwaniyah population density map in 2015

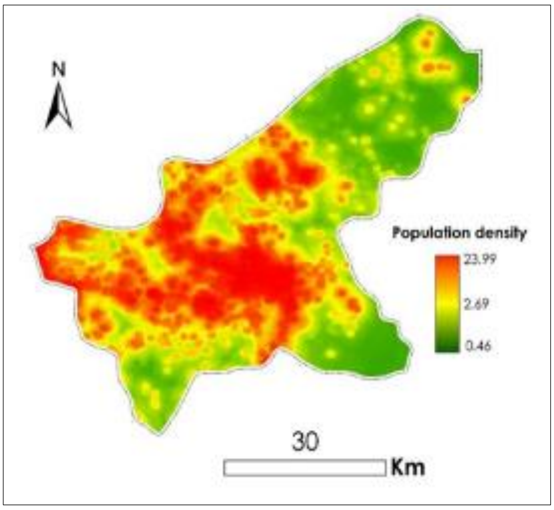

Figure 4 Projected map of population density in 2025

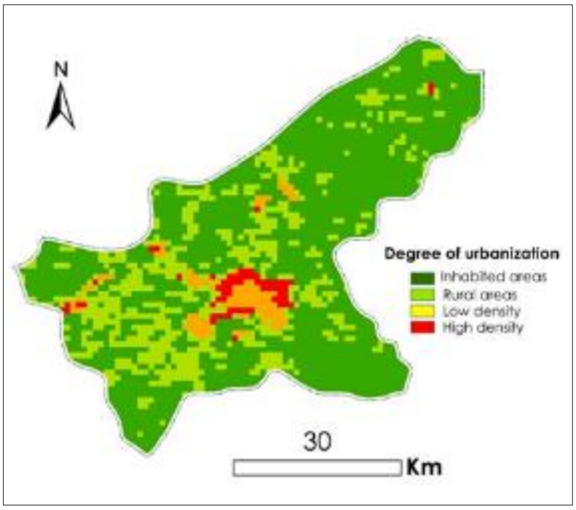

Figure 5 Projected map of the degree of urbanization in 2030 for Al Diwaniyah

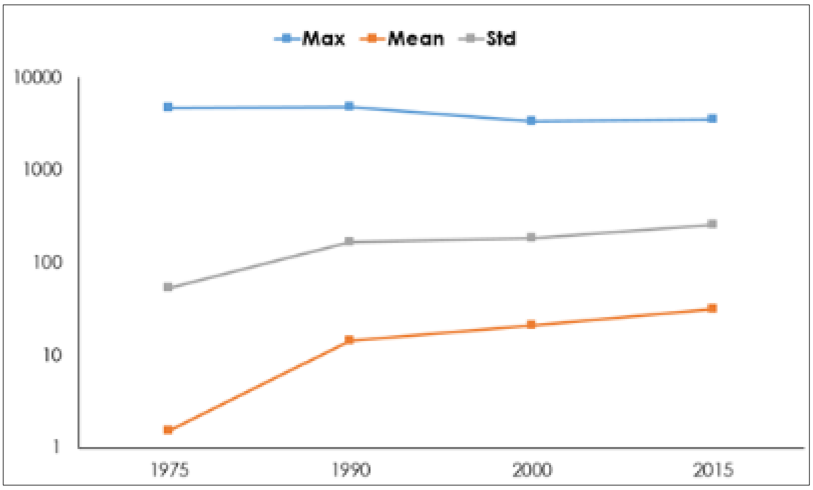

Figure 6 Statistical characteristics of the population density of Al-Diwaniyeh during the period from 1975 to 2015

6. Conclusion

The general result is that: the average population density and, accordingly, the population of the study area has increased, the degree and intensity of urbanization is increasing, the standard deviation of population density during the period from 1975 to 2015 has a growing trend parallel to the increase in population, and the degree of urbanization in the year 2030 classes with high density have faced a decrease in area compared to the previous period.

Suggestion

It is suggested to use the SLEUTH model in future studies in order to model and predict the physical growth of the city in certain time horizons. Although the SLEUTH model requires a lot of time to run (on average and assuming average hardware conditions), it is one of the best and most specialized methods of predicting urban physical growth. Of course, it is suggested to implement the above model based on the estimation of the physical growth of the city, by using human data and especially population data.

It is suggested that in future researches, in addition to flat growth forecasting, i.e. two-dimensional forecasting, the height dimension should also be included in the modeling and forecasts. With the help of emerging technologies such as LIDAR, by spending reasonable and recoverable costs, valuable actions can be taken regarding the modeling of the growth of the vertical dimension of urban environments

Compliance with ethical standards

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Disclosure of conflict of interest

There is no conflict of interest in preparing and submitting this scientific article.

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