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Urbanization dynamics of Tehran city (1975–2015) using artificial neural networks

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ABSTRACT
Land-use dynamic is a major challenge for town and country planners especially in developing countries such as Iran. Iran has been under rapid urban expansion and population growth for past three decades which led to lack of resources, environmental deterioration and haphazard landscape development. In this paper, an attempt has been made to map the urbanization dynamics of Tehran in 40 years based on remote sensing imagery and by means of artificial neural networks. The presented scheme could be taken into consideration when planning initiatives aimed at surveying, monitoring, managing and sustainable development of the territory. Moreover, it can serve the experts in the fields of geography, urban studies and planning as a background for number of geographical analyses.

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1. Introduction

In the last century, tendency to urbanization and rapid population growth has increased significantly as a worldwide phenomenon (Mohammady & Delavar, 2016). Out of the global population, more than 3.5 billion live in urban areas which occupy above 2% (Grimm, Morgan Grove, Pickett, & Redman, 2000; Mohammady, Delavar, & Pijanowski, 2013a) of the earth's land area (OECD, 2012). Urban area is increasing faster than the urban population itself (Mohammady & Delavar, 2016; Tewolde & Cabral, 2011). Cities are becoming more attractive because of socioeconomic and political aspects. Cities are the main providers of employment, housing, education and health care (Angel, Parent, Civco, & Blei 2011) and the engine of the global economy, generating between 80% and 95% of the global gross domestic product (Cadena, 2011; Seto, Fragkias, Güneralp, Reilly, & Añel, 2011).

Land-use dynamics result from the complex interaction of many factors including policy, management, economics, culture, human behaviour and the environment (Dale, O'neill, Pedlowski, & Soutworth, 1993; Grimm et al., 2000; Houghton, 1994; Medley, Okey, Barrett, Lucas, & Renwick, 1995; Pijanowski, Brown, Shellito, & Manik, 2002; Turner, 1990; Vesterby & Heimlich, 1991; Wilder, 1985). It is critical to understand how land-use changes occur, since these anthropogenic processes can have broad impacts on the environment, altering hydrologic cycles (Steiner & Osterman, 1988), biogeochemical dynamics (Flintrop et al., 1996; Pijanowski et al., 2002), reduced open spaces and unplanned or poorly planned land development (Mohammady, 2014; Park, Jeon, Kim, & Choi, 2011). The challenges of urbanization are becoming more complex since recent rapid population growth and urban expansion that has concentrated in low and middle income countries (Angel et al., 2011; Giralt & Andrew, 2011). Thus, more attention should be given to the study of urbanization dynamics in these regions (Un-Habitat, 2012).

Urbanization in Iran during the last few decades has led to the expansion of housing and industry into previously open, low-populated areas that were originally natural areas and agricultural lands (Ahmadlou, Delavar, & Tayyebi 2016; Tayyebi, Pijanowski, & Tayyebi, 2011). Despite being one of the most urbanized regions in the developing countries (United Nations, 2014), there is a lack of up-to-date spatial information on the urban extent of cities and patterns of urbanization in Iran (Cohen, 2006). Developing accurate maps and spatial information of urban areas will help us better understand how population growth is influencing the trends and patterns of urbanization (Ahmadlou et al., 2016; Tayyebi, Delavar, Saeedi, Amini, & Alinia, 2008).

On the other hand, remote sensing technology for monitoring changes is widely used in different applications such as land-use/cover change (Demir, Bovolo, & Bruzzone, 2013; Salmon et al., 2013; Tayyebi et al., 2008), disaster monitoring (Brisco, Schmitt, Murnaghan, Kaya, & Roth, 2013; Volpi, Petropoulos, & Kanevski, 2013), forest and vegetation changes (Kaliraj, Meenakshi, & Malar, 2012; Markogianni, Dimitriou, &

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Kalivas, 2013), urban sprawl and modelling (Ahmadlou et al., 2016; Bagan & Yamagata, 2012; Emadodin, Taravat, & Rajaei, 2016; Mohammady & Delavar, 2016; Pijanowski, Tayyebi, Delavar, & Yazdanpanah, 2010; Pijanowski et al., 2014; Raja, Anand, Kumar, Maithani, & Kumar, 2013; Tayyebi, Pijanowski, & Tayyebi, 2011; Tayyebi et al., 2008) and hydrology (Dronova, Gong, & Wang, 2011; Taravat et al., 2016; Zhu, Cao, & Dai, 2011). Moreover, remote sensing technology provides a variety of ways to develop digital land-use information which is the basis for land-use planning (Tayyebi et al., 2008).

The use of machine learning models has increased substantially in remote sensing filed because of the advances in computing performance and the increased availability of powerful and flexible machine learning software (Skapura, 1996; Tayyebi et al., 2008). A combination of neural networks with remote sensing image data has been recently proposed for mapping the urbanization dynamics (Pijanowski et al., 2010; Tayyebi, Pijanowski, & Tayyebi, 2011).

However, to our knowledge, a detailed urbanization dynamics and development map of Tehran city over 40 years has not been presented so far in the literature which can serve the experts in the fields of geography, urban studies and planning as a background for number of geographical analyses.

Starting from these motivations, the purpose of the present paper is to automatically map and produce spatial information and describe urbanization dynamics and development between 1975 and 2015 in Tehran city which has changed significantly during the twentieth century (Main Map). Not only visualization, but also content of municipal plan have undergone number of changes in the last two centuries.

2. Study area

As a historical overview, Tehran was first built in 4000 BC (Municipality, 2016; Seger, 2013). Between 1850s and 1920s, it was a walled city with six gates (Figure 1) (Municipality, 2016; Seger, 2013). Figure 2 shows old settlements from 1868 to 1937 and a rapid urbanization from 1950s to 1970 that is created by historical maps and Arial photos. The surface area (located at a latitude and longitude of 35° 69′ 62″ N and 51° 42′ 30″ E) of Tehran city is a combination of mountain and plain and the altitude is between 945 and 2244 m above the sea level (Figure 3).

The climate of Tehran in the mountain is cold and semi-humid but in the southern and eastern areas are warm and dry (Peel, Finlayson, & McMahon, 2007). Like other cities in Iran, Tehran was experiencing rapid urbanization during six last decades that has an indication of the problem of over centralization. Tehran has been expanded because of political and economic centralization therefore the shape and external form of Tehran have changed greatly over the past decades. According to the spatial temporal patterns of urban growth in Tehran, Seifolddini and Mansourian (2014) divided urbanization process in Tehran into three major periods: rapid (1921–1976), very rapid (1976–1986) and slow growth rate (since 1986) (Seifolddini & Mansourian, 2014).

Between the 1950s and 2014, Tehran's population increased from about 1 million to more than 8.2 million (10.5% of the country) which made the city the world's seventeenth largest with the largest annual growth in Asia (Arsanjani, Kainz, & Mousivand, 2011; Geoinformation, 2016).

3. Methods

3.1. Pre-possessing phase

The methodology of this study is summarized and represented in Figure 4. Landsat images of Tehran acquired in every 5 years from 1975 to 2015 have been used for this study. Image subsets containing Tehran city were extracted to make classification process less time consuming and image interpretation more expedient and focused. The dataset was then projected in Geo (lat/long) projection and WGS84 datum. The line-tracing and edge-detection algorithms have been used to remove stripes in Landsat Enhanced Thematic Mapper Plus data caused by scan line corrector.

The whole dataset has been atmospherically and geometrically corrected which is caused by the effects of atmospheric particles through absorption and scattering of the radiation from the earth surface. The atmospheric correction has been shown to significantly improve the accuracy of image classification.

3.2. Classification phase

Artificial neural networks (ANNs) are powerful tools to quantify and model complex behaviour and patterns (Fischer & Abrahart, 2000; Mohammady, Delavar, & Pijanowski, 2013b; Pijanowski et al., 2002). The use of neural networks has increased substantially over the last several years because of the advances in computing performance (Pijanowski et al., 2010; Skapura, 1996) and the increased availability of powerful and flexible ANNs software. Their specific advantage lies not only in the enhancement of speed and efficiency in handling urban data but specifically in providing a tool to develop new theories and techniques (Diappi, Bolchim, & Buscema, 2004). ANNs are used for pattern recognition in many fields such as economics (Fishman, Barr, & Loick, 1991), medicine (Babaian, Miyashita, Von Eschenbach, Evans, & Ramirez, 1991), landscape classification (Brown, Lusch, & Duda, 1998), image analysis (Fukushima, Miyake, & Ito, 1983), pattern classification (Ritter, Logan, & Bryant, 1988), climate forecasting (Drummond, Joshi, &

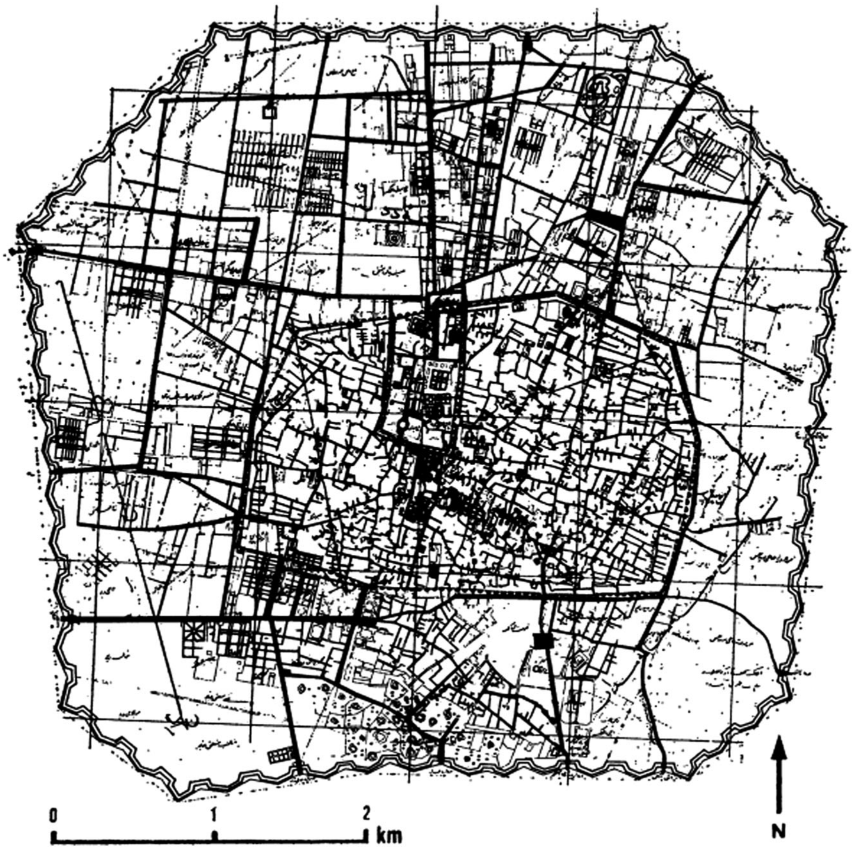

Figure 1. A historical map of Tehran in 1850s (Seger, 2013).

Sudduth, 1998; Panagoulia, 2006), remote sensing (Atkinson & Tatnall, 1997; Morris et al., 2005; Tayyebi et al., 2008), agricultural land suitability assessment (Wang, 1994), and land-use monitoring (Mohammady, Delavar, & Pijanowski, 2013a; Pijanowski et al., 2002; Tayyebi, Pijanowski, & Pekin, 2011; Zhang & Zhen, 2006).

After a successful pre-possessing phase, a supervised model based on Multilayer Perceptron (MLP) neural networks has been used for classification. From the range of network types suitable for classification applications (Ito & Omatu, 1997), multilayer feed forward networks algorithms are the most widely used models in remote sensing (Hinton & Sejnowski, 1986).

An activation function defines the output of a neuron in terms of the linear combination of inputs (Bishop, 1995). It is sometimes desirable to have the activation function range from −1 to +1, in which case the activation function assumes an anti-symmetric form with respect to the origin. For the corresponding form of a sigmoid function, we may use the hyperbolic tangent function defined by:

$$o = \tanh(s),$$

$$s = \sum_{k=1}^{n} i_k . w_k,$$

where 's' is cumulative input, 'w' is weight of input, 'i' is value of input, 'n' is number of inputs, and 'k' is number of neuron. The MLP used in this study has four input layers, one hidden layer and two outputs. Single hidden layer networks are found to be sufficient for most classification problems (Kanellopoulos & Wilkinson, 1997; Lippmann, 1989; Paola & Schowengerdt, 1997; Yuan, Van Der Wiele, & Khorram, 2009). Pixel selection for train/test sets has been done randomly and repeated three times. From each image, 85,000 pixels were extracted for train/test net. The number of about 20,000 training cycles was sufficient to get the network learned.

Several attempts have been made to properly select the number of units to be considered in the hidden layers of the MLP. Architecture 4-12-2 has been finally chosen for its good performance in terms of classification accuracy, root-mean-square error, and training time.

For accuracy assessment, from each sub-image, 10,000 pixels have randomly been selected, and then,

Table 1. The values of accuracy, commission and omission error (In %) achieved by ANNs.

	Omission	Commission	Accuracy
2015	3.03	1.65	96.97
2010	3.00	1.80	97.00
2005	5.06	1.65	94.94
2000	9.91	8.20	90.09
1995	9.64	8.20	90.36
1990	12.19	9.40	87.81
1985	9.32	1.80	90.68
1980	7.62	1.65	92.38
1975	10.58	10.24	89.42

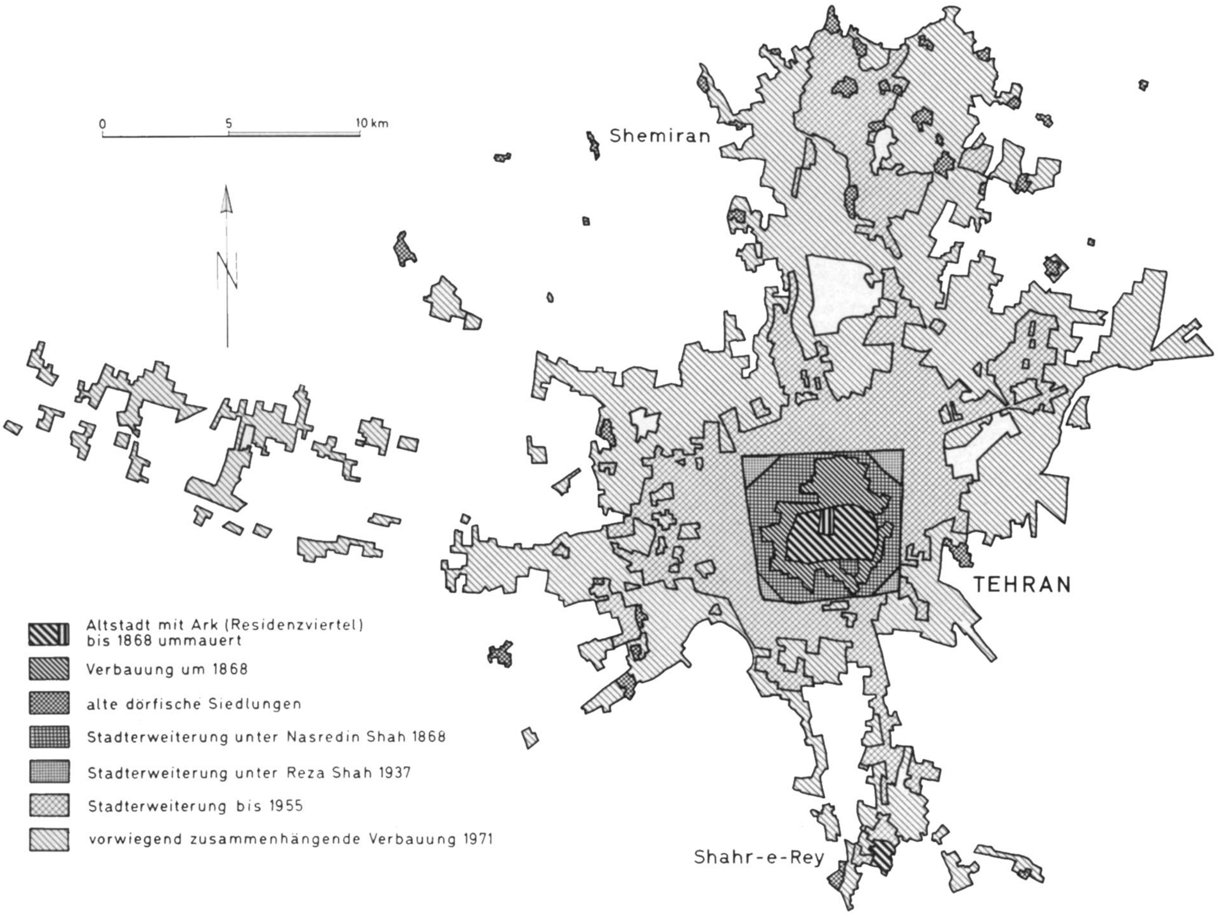

Figure 2. Development of the residential area of Tehran from 1868 to 1971 (Seger, 1975).

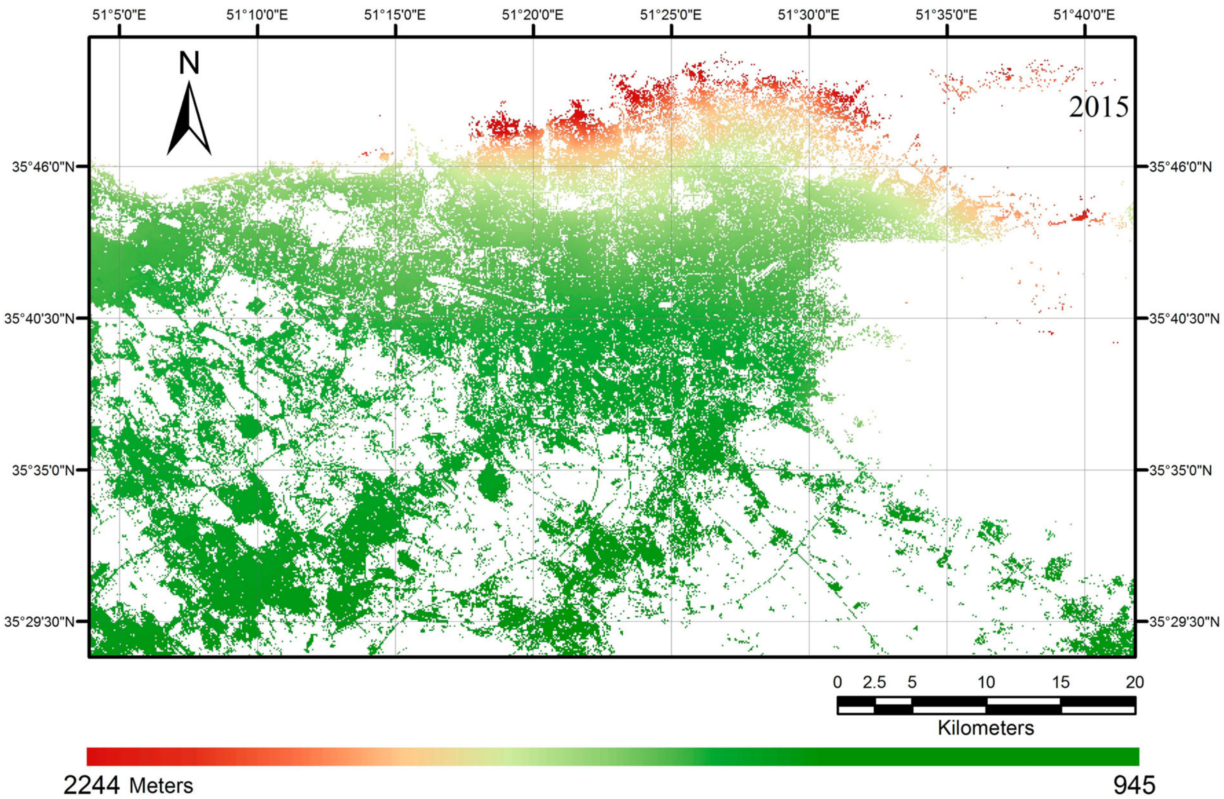

Figure 3. The elevation map of Tehran.

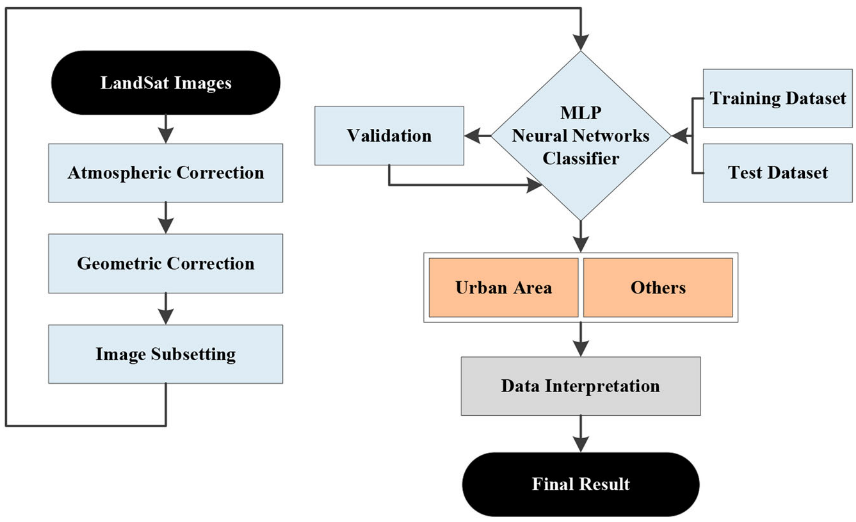

Figure 4. Schematic representation of the methodology.

labelling is made by visual interpretation. The distance for measuring commission error and omission error is set as 1 pixel. The results of the accuracy assessment applied to the different years are displayed in Table 1. In order to improve aesthetic and cartographic quality of the maps, Bezier interpolation algorithm has been used for smoothing sharp angles in polygon outlines.

4. Conclusions

The aim of this study was to represent the spatial and temporal structure of Tehran city from 1975 to 2015 based on Landsat imagery by means of ANNs. The map reflects the development of Tehran and it can therefore serve as basis for a number of geographic or urbanistic studies, planning and contribute to better public awareness. These maps as well as the proposed model and methodology can also be used to assess the different aspects and impacts of rapid growth and expansion of Tehran city in the recent decades for the interdisciplinary and multidisciplinary research and investigation.

Software

Python 3.5 programming software for the pre-processing phase and the Stuttgart neural network simulator (SNNS) developed at the University of Stuttgart, Stuttgart, Germany, were used in implementing the Neural Networks classification algorithm (Zell et al., 1995). QGIS 2.14 software was used for mapping and visualization.

Disclosure statement

No potential conflict of interest was reported by the authors.

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