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Monitoring land use and land cover changes in the mountainous cities of Oman using GIS and CA-Markov modelling techniques

Shawky Mansour[a,c,*], Mohammed Al-Belushi[b], Talal Al-Awadhi[a]

[a] Geography Department, College of Arts and Social Sciences, Sultan Qaboos University, Muscat, Oman
[b] Archaeology Department, College of Arts and Social Sciences, Sultan Qaboos University, Muscat, Oman
[c] Department of Geography and GIS, Faculty of Arts, Alexandria University, Alexandria, Egypt

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ABSTRACT

As a result of the socioeconomic transformation, the rapid urban expansion of cities and towns in the Gulf Cooperation Council (GCC) states has predominately led to tremendous pressure on the limited natural resources and loss of productive lands. Indeed, the spatial patterns of urbanisation and their impacts on mountain resources and environment have received little attention, particularly in Oman. Predicting urban growth in the mountainous cities has the potential to better understand the interaction between the spatial growth patterns and the mountain topography. This study aims to analyse spatiotemporal dynamics of land use/land cover (LULC) (2008–2018) and simulate urban expansion (2008–2038) in Nizwa city, Al Dakhliyah governorate, Oman. Cellular Automata (CA)-Markov and geospatial techniques were utilised to assess and project urban growth and land cover changes. The analysis was based on three maps of LULC at equal intervals derived from satellite imageries: Landsat TM for 1998, 2008 and 2018, along with topographic spatial layers (elevation, aspects, and terrain slopes) derived from the ASTER digital elevation model. In addition, other spatial parameters (population density, proximity to urban centres, and proximity to major roads,) were incorporated in the simulation process. The findings revealed that the actual LULC change during 2008–2018 was 12,014 ha of net urban growth (418.5 % change), while the simulated change was expected to be 14,985 ha by 2028, with a total of 37,465 ha increase in the built-up area and urban growth by 2038. Although the topographic variability will control LULC changes, the urban expansion overly will occupy the arable land across the valleys along with the flat areas. During the next two decades, the built-up areas will dominant, with a large percentage of vacant land (net loss 12,813 ha) and vegetation cover (net loss 35 ha) will be gradually converted into residential land use. The output of the simulations in this research could serve not only as spatial guidelines for monitoring future trends of LULC dynamics, but also address the threats and deteriorates of urban sustainability in the Omani mountainous cities. Furthermore, identifying bare soils and vegetation areas that are susceptible to urbanisation is of value for the national strategy of future urban planning in Oman.

1. Introduction and theoretical framework

Globally, the percentage of the urban population has dramatically increased from 14 % in 1900 to 29.1 % in 1950, reaching 54 % in 2014 and is expected to increase to 66 % in 2050 (UN, 2019). In developing countries, rapid urban growth initiated a transformation of urbanisation from small, clustered and fabric settlements into scattered and unplanned urban sprawl. Therefore, planners, governors and policy-makers face unprecedented challenges in managing urban communities. Consequently, global changes in land use land cover (LULC) and urban sprawl are subjects of great concern (Prestele et al., 2016; Long et al., 2007; Srivastava et al., 2012).

According to terrain and morphology, urban patterns in developing countries can be classified into various types, particularly coasts, deserts, plains, mountains, and upland. However, urban dynamics in mountainous cities remain poorly investigated and understood. Mountains cover a quarter of the earth surface, with almost 12 % of the world populations living in mountains and areas that are located in high elevations. Globally, populations living in mountainous urban zones are gradually increasing (FAO, 2014), for instance, in the developing countries, over one-quarter of mountain populations live in cities. The higher dynamic changes of LULC challenge policy makers and governors to manage new urban communities, especially in economic transition phases (You, 2017; Mohan et al., 2011; Zhang et al.,

* Corresponding author at: Department of Geography, College of Arts and Social Sciences, Sultan Qaboos university, P.O. Box: 42 Al-Khod P.C. 123, Muscat, Oman.
E-mail address: shmansour@squ.edu.om (S. Mansour).

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2011). The conversation of agricultural land into modern housing developments has been identified as a major driver of urbanisation in most developing countries (Khalifa, 2015; Phuc et al., 2014; Shahraki et al., 2011).

Since the recent oil boom (2002–2008) in the Gulf Cooperation Council (GCC) states (The United Arab Emirates, Bahrain, Saudi Arabia, Oman, Qatar and Kuwait), socio-spatial changes have taken place and major cities have achieved pronounced progress in urban development (Saif, 2009) However, the socioeconomic changes and oil revenues which oriented urban expansion also give rise to unplanned and irrational urban sprawl (Rizzo, 2014).

During the last decade, an obvious shift in the urban population has taken place in Oman. In 2016, Oman had the highest annual urban population growth (6.43 %) in the world, with the urban population reaching 83.56 % in 2017. Moreover, almost 25 % of the Omani urban population live in large cities (World Bank, 2019). This indicates that the rapid urbanisation process in Oman is not only driven by urban population growth, but also by several other forces, particularly socio-spatial changes, rural-urban migration, economic development, transportation and infrastructure construction. Moreover, in Oman, although land use regulations prohibit the conversion of agricultural land into other land use categories (MAF, 2019), urban expansion still reduces the area of agricultural land. Over the last three decades, the structure of mountainous settlements has changed from rural to predominately urban continents. The spatiotemporal development of urbanisation in Oman can be divided into two phases, pre-oil discovery when urban settlements were small and clustered, with slow urban growth change; in many cases, a small number of the population lived in a gated city surrounded by a wall, so that these cities were essentially independent, with higher degree of homogeneity among population groups. The second phase of urban growth was mainly associated with the discovery and revenues of oil, when transformational development and socio-economic changes began. Urban communities in Oman as well as in the other GCC states were quite simple, traditional and conservative (Bannerman, 1986).

The majority of urban agglomerations in most Omani cities are characterised by scattered settlements that are incomplete, not only with regard to service provision but also in spatial accessibility (von Richthofen, 2015v). The interconnectivity between settlements was weak and populations living in these areas usually travelled long distances to access public health, educational and basic need services (Al-Awadhi and Mansour, 2018). Despite the spread of this urban type which suffered from functional integration of the city, urban land areas generally rapidly expanded during the last two decades, but the growth rate varied greatly over time and space.

Urban sprawl and expansion of unplanned built-up areas over mountain valleys and basins certainly exerted tremendous pressure on the natural landscape (El Asmar and Taki, 2014; Seto et al., 2012). Consequently, environmental ecosystems are threatened and biodiversity declines due to human induced activities, such as establishing buildings, constructing road networks and creating infrastructure for basic services. In addition, such urban areas usually experience climate change risks, specifically urban heat islands and floods. Urban areas located in the mountains face rapid urbanisation, which puts serious population pressure on their fragile resources and environments, increasing the risk of landslides and flash floods. Moreover, in large urban mountain agglomerations, rapid urban growth may cause various problems in terms of basic services provision and coverage, in addition to disrupting the hydrological systems.

There is a lack of research regarding urban growth across the mountains of Oman, thus, this study aims to analyse spatiotemporal changes of mountainous urban in Oman using satellite images, employing advanced GIS algorithms. Understanding the spatiotemporal dynamic of LULC and predicting future urbanisation are crucial, particularly for sustainable development, formulating national development policies, and urban planning strategies. The study analysis adopts the Markov chain modelling technique, an effective method for quantitative simulation (Keshtkar and Voigt, 2016). The research questions are as follows:

- To what extent are the substantial changes in the mountain landscape due to urban growth along the Omani mountainous cities?
- What are the spatiotemporal divergences of LULC changes?
- What is the nature and trends of future urban growth in the Omani mountainous areas?

Spatial modelling and simulation have been used to address these research questions and the pattern and mechanism of mountainous urban growth in Oman can provide an important basis for identifying driving forces of expansion. In addition, such analysis can provide decision-makers with clear visions of controlling unplanned urban sprawl and promoting sustainable urban development and proper land management.

A large body of literature has investigated land use dynamics as these changes have direct influences on population well-being and quality of life through the extent to which ecosystem elements are in balance. For instance, measuring and assessing the consequences of land use changes on natural resource preservation, production from agricultural land, air pollution, and access to potable water etc. have been previously reported (e.g. DeFries et al., 2007; Nuissl et al., 2009; Violin et al., 2011). Globally, the effects of urban growth on climate changes have been investigated (Kalnay and Cai, 2003; Grimmond, 2007; Satterthwaite, 2008; Ren et al., 2008; Martínez-Zarzoso and Maruotti, 2011), revealing that while urban areas and cities have potential sociodemographic benefits to shaping sustainable development and promote economic growth, urbanisation is also a significant threat to the environment and main cause of climate change, putting more populations and vulnerable communities at higher risk of disasters (Luber and McGeehin, 2008).

A second line of research on LULC changes has focused on understanding the impacts of land changes on environmental systems and communities (Mengistu and Salami, 2007; Yuan, 2008; Wu et al., 2013; Coskun et al., 2008). These studies have deployed GIS and remote sensing techniques, particularly to monitor urban expansions and explicitly model spatiotemporal growth and its effects on sustainability. Major progress in LULC analysis has been achieved mostly through adopting monitoring and simulation tools of advanced GIS and image processing (Singh et al., 2015; Paudel and Yuan, 2012; Rahman et al., 2011; Giri et al., 2013). Indeed, the seminal contributions of GIS and remote sensing methodologies are supported by an effective database of earth observations at global, regional and local scales, which have been employed daily to conduct comprehensive, accurate, invaluable analysis and measurements (Esch et al., 2018; Hagenlocher et al., 2012).

In recent decades, urban agglomerations in the GCC states (e.g., Oman, UAE and Saudi Arabia) as well as cities have recorded higher rates of urban growth (UN Habitat, 2016). Several factors are key drivers of such higher rates of urbanisation, particularly increased income and GDP rates, socioeconomic transformation and development, modernisation trends, fertility rates, car centred culture, and higher proportion of young people. Moreover, globalisation and modern transition have significant influences on land use changes and urban development across the GCC region (Rizzo, 2014). Accordingly, most large cities in the region have been transformed from villages into a metropolis (Furlan and Faggion, 2017).

Regarding spatial algorithms, spatial models and advanced GIS methods have been widely employed to explain LULC patterns, distribution and directions as well as predict the amount of land use changes. For example, the multisystem agent model combines the cellular landscape with agent-based simulation to optimise the decision making process of LULC dynamics (Schreinemachers and Berger, 2006; Le et al., 2008; Ralha et al., 2013). Similarly, generalised linear modelling was employed within the empirical GIS environment to model land use changes (Aspinall, 2004; Rutherford et al., 2008). Another type is aggregated multivariate regression, which was used to simulate urban dynamics, particularly assess dominate drivers and casual forces (Zang and Huang, 2006). A considerable amount of literature has been published on analysing spatiotemporal land use changes using the Markov chain model (Myint and Wang, 2006; Tang et al., 2007; Yang et al., 2012; Guan et al., 2011; Arsanjani et al., 2011; Al-sharif and Pradhan, 2014; Moghadam and Helbich, 2013; Rimal et al., 2018). The cellular automata (CA)-Markov model is a probabilistic model and potent simulator of predicting LULC changes compared to other model types of linear extrapolation models (Aaviksoo, 1993). The Markovian approach is a convenient model in predicting characteristics of spatial phenomena and commonly employed in geographical research (Clancy et al., 2010).

A more comprehensive investigation and description of the urban fabric, design and structure of cities in the GCC can be found in the literature (e.g. Al-Belushi, 2013; Wiedmann et al., 2012; Furlan and Faggion, 2015; Al Ghareebi, 2016; Aina et al., 2013). Nonetheless, little attention has been paid to mountainous cities and the nature of urbanisation, particularly the process and forces of growth and changes. Although mountainous urbanisation has been addressed globally in various regions such the European Alps (e.g. Zimmermann et al., 2010; Vigl et al., 2016; Fondevilla et al., 2016; Rutherford et al., 2008), southern Andes (e.g. Romero and Ordenes, 2004; Thies et al., 2014), China mountains (Zhao and Li, 2016; Yi et al., 2016; Ding and Peng, 2018), research which spatially investigates LULC changes in mountainous cities of the GCC states is still very rare. Very few studies have spatially analysed the urban context and structure using remote sensing techniques within the GCC states. For instance, Iman et al. (2016) examined urban morphology and changes in LULC in Mecca city, finding that urban dynamics and directions were influenced by mountain ranges and structures. In Oman, a strand of literature on urban physiognomy have been undertaken to essentially investigate the Omani urban fabric and designs (Richthofen, 2016; Al Gharibi, 2014; von Richthofen, 2016v; Richthofen, 2015). Most of the published research in this domain is linked to the seminal work regarding urbanisation in Oman which was edited by Nebel and Richthofe (2016) and involves many key aspects and topics of urban sustainability and development. However, quantitative methods or spatiotemporal measurements were not conducted.

Ultimately, explicit modelling research on spatial drivers, geographical factors and future predictions of the comprehensive urban process in the Omani cities and urban clusters has not been conducted. Specifically, the dynamics of mountainous urban patterns and its associated processes need to be spatially investigated. Consequently, the present study, through the integrated GIS and image processing approach, is the first attempt to bridge the gap in existing literature by simulating, modelling and predicting LULC dynamics of mountainous urban area in Oman. Monitoring and simulating urban growth across the mountainous cities of Oman result in useful information and spatial guidelines for decision-makers and policy managers not only in domains of urban sprawl, housing planning, and provision of public infrastructure but also in other critical issues in the mountainous cities such as ecological balance, vegetation shrinking and land degradation in urban areas.

2. Study area

Oman is mountainous, with most of the populous places located in mountain valleys and basins. The physical landscape of Oman is characterised by two large mountain ranges, Al Hajar Al Sharqy and Al Hajar Al Gharbi mountains (Eastern and western rocky or stone mountains), which cover the northern eastern and western part of the country. Al Jabal Al Akhdr, which is more than 3000 m height, is the highest mountain in the region (Fig. 1). Western Hajar's terrain is incised by dry valleys in which the major population clusters are located, whereas the more populated eastern Hajar has several urban settlements and towns, such as Ibra and Bidiyah (Allen, 2016).

The study area covers about 448.4 square kilometres including all urban agglomeration around Nizwa city is located in between latitudes of 22° 55′ 59 N and the longitude of 57° 31′ 59 E. It is an ancient city and located in the heart of Al Dakhliyah governorate at a crossroads between Muscat and the Hajar mountain range in the northern part of Oman. The city is the regional centre of the governorate and the largest city, located on the fringes of Al Jabal Al Akhdr Mountain, approximately 164 km from the capital Muscat. The total population of Nizwa city increased from 84,528 in 2010 to 123,396 inhabitants in 2017 (NCSI, 2019). Historically, Nizwa was previously the political capital of the Sultanate of Oman.

The climate is characterised as hot in the summer, with pleasant average temperatures in winter and rain fall, especially in the mountainous region of Al Jabal Al Akhdr. On average, the warmest month is July, while the coldest is January (World climates, 2019). The traditional market of Nizwa located in the city centre is famous for handicrafts, souvenirs and antiques and other items, and is the main tourist attraction in the city. The most important landscape feature in the city is Nizwa's splendid fort, which is one of the oldest and most impressive castles in the Sultanate of Oman, located in the inner part of the city and was built in 1660. Nizwa is famous for having the largest popular markets in Oman which include several local products, crafts and traditional industries, as well as gold and silver jewelry, wood and copper industry, textile and palm industries. Nizwa Fruit & Vegetable Market is the newest market built on the highest architectural specifications and play a crucial role in retail trading and linking rural to urban. In addition to small enterprises and retail activities, the city is also known as one of the top tourist destinations in Oman where various ancient monuments are located particularly castles, caves, forts, and waterfalls.

Topographically, the study area can be divided into three distinct regions: the mountainous area located to the north and northeast (Fig. 2), middle area broadly dominated by uplands and lower mountains, with some new urban extensions, and flat land, a basin surrounded by mountains containing an oasis of palm trees stretching for eight kilometres along the sides of the two main valleys. In this part of the study area, large urban agglomerations of villa housing style are located. In contrary, the traditional and rural roots of urban settlements can be found along dray valleys that extend from north to south. Similarly, ancient heritage houses and lanes mirror architecture development in the center of Nizwa Wilayat.

3. Methods of data acquisition and analysis

Landsat images (1998, 2008, and 2018) were collected from the official webpage of the US Geological Survey (USGS).The spatial resolution of images are 15*15 m pixel size. The images were geo-referenced and projected as the Universal Transverse Mercator (UTM) within Zone 40 N - Datum World Geodetic System (WGS) 1984 (Table 1). Fig. 3 illustrates the methodological framework of utilizing the CA–Markov model within GIS platform to simulate and project future LULC changes in the study area.

The Landsat images of L1T indicates precision and terrain corrected data which provides systematic radiometric and geometric accuracy by incorporating ground control points (GCPs). A rectification and georeferencing process for 1998, 2008, and 2018 Landsat images was performed using 8, 12, and 15 ground-control points respectively. The digital topographic map of 1:50 000 scale and the Global Positing System (GPS) were the source of the selected GCPs. Generally, road intersections, valleys, hills and building of public infrastructure were identified as major GCPs and these references are located near the corners and the middle of the study area. Comparisons of the GCPs points against common points in the images revealed that georeferencing was accurate within 1 pixel (15 m). The vector map layers were generated using various vector and grid data formats, such as

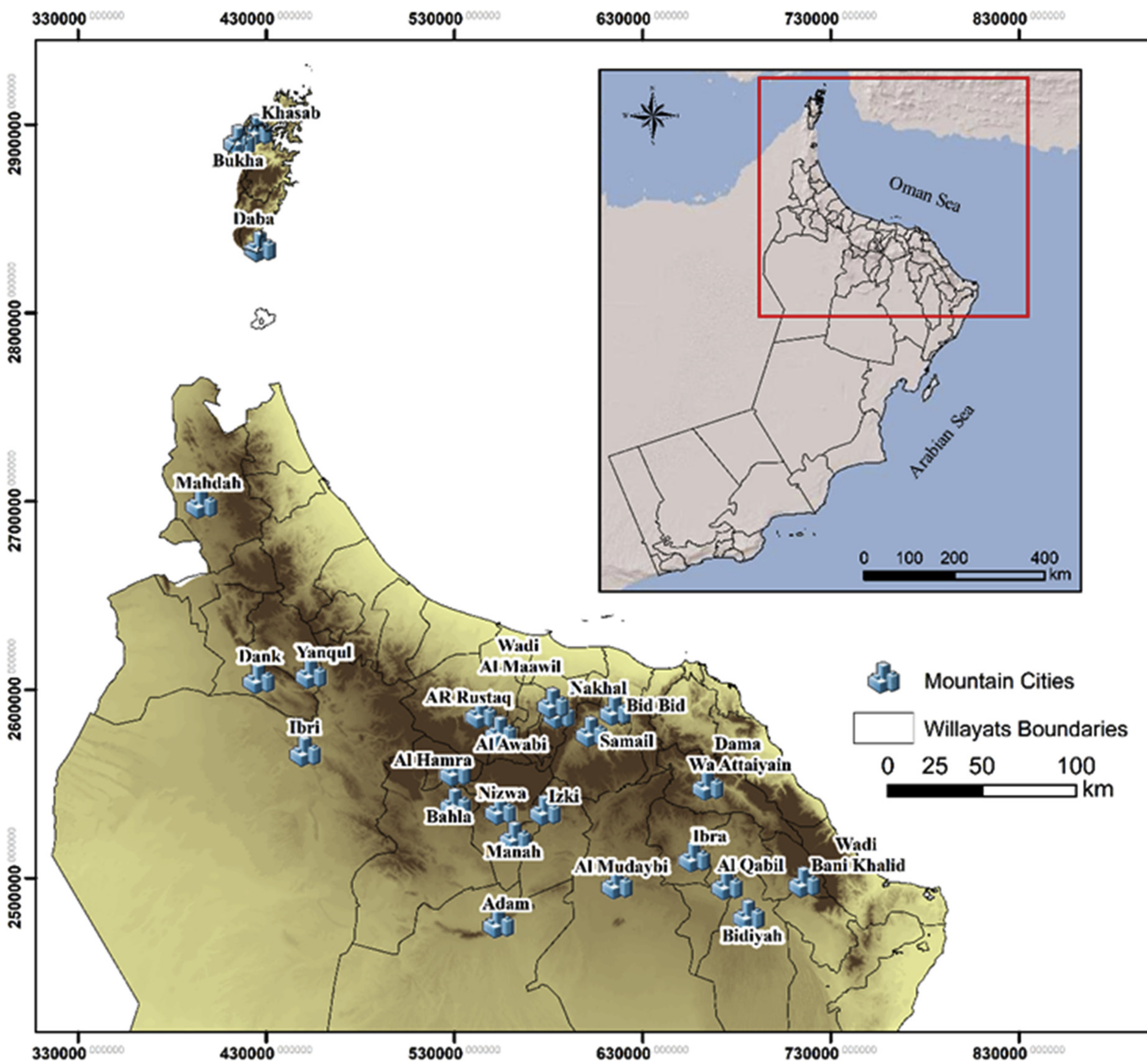

Fig. 1. The main cities in northern Oman.

population settlements and density, highways and roads, urban centres, and digital elevation model (DEM) 30 m resolution which was used to generate slopes, aspects and area elevation. In this analysis, LULC classification was implemented based on five classes and a brief description of major LULC classes is provided in Table 2. The adopted LULC classification comprises consistency in the definition of each class and a clear distinction of class boundaries on the basis of the heterogeneity of natural and human features on the study area. Further, this classification is a scale-independent where it can be viable at any spatial scale or level of details.

3.1. Suitability maps

The formation of suitability maps for each land use class is influenced by spatial factors and constraints, with the parameters denoting the suitability of a location to be developed using continuous values (Fig. 4). The constraint is created as a Boolean image comprising only values of 0 and 1, limiting the specific spatial location where a value of 0 indicates that the locations that do not meet the criteria of growth and are not suitable for change in the future, whereas a value of 1 indicates that the location meets the developed criteria and has potential to change to another land use class. Table 3 represents the parameters of suitability analysis, function of rating, the calculated weights and rationale to suitability. To examine the multicollinearity among the independent variables, the Band Collection Statistics tool in ArcGIS was utilized and a correlation matrix was generated. The output indicated that the values of the coefficients were less than 0.4 which means no redundancy among the variables.

Suitability criteria were used to define the suitability of land use changes of a specific LULC class for each pixel, with 0 representing no suitability and 255 indicates the highest suitability of land use changes (Fig. 5).

3.2. Markov chain (MC)

In order to predict LULC changes across the study area, CA Markov method was performed within Terrset software package. The Markov model is a stochastic model used to simulate randomly changing and continuous surfaces. It is also a theory based on the assumption that the future state of any object depends mainly upon the current state, not on the previous states. In LULC changes, the model describes quantities of conversion states between land classes and calculates rates of transfer among various land use types (Sang et al., 2011). The changes in LULC are generated based on computing the probability matrix of transition. Markov model is generally well-known in predicting systems of continuous phenomena in geographic research, particularly urban growth and land cover changes. Predicating LULC changes is calculated as follows:

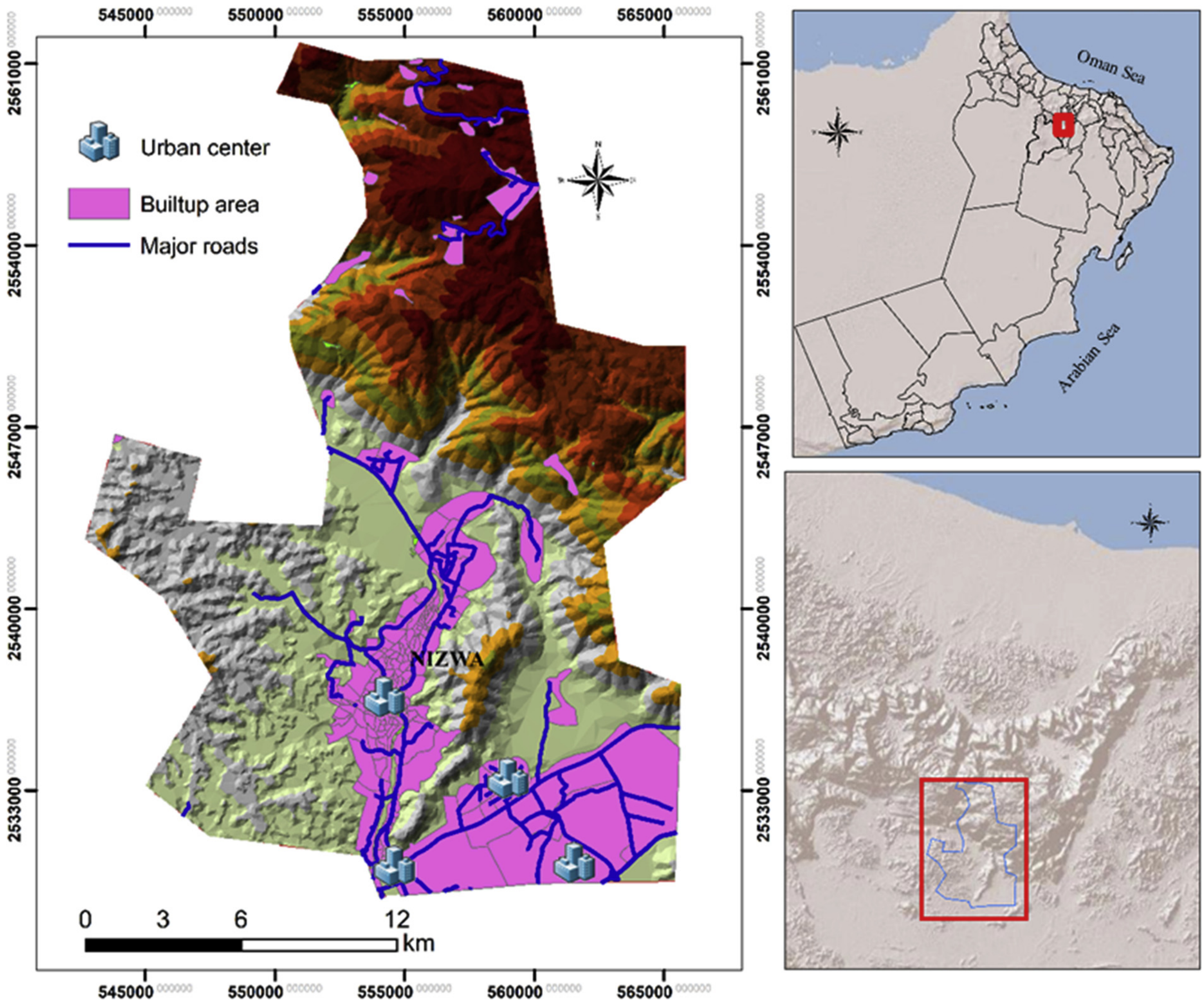

Fig. 2. The study area location.

$$S(t+1) = P_{ij \times s(t)} \tag{1}$$

Where S (t), S (t + 1) are the phenomenon or system status at time t or $t+1$; P_{ij} is the transition probability matrix in a state which is calculated as the following:

$$P = P_{ij} = \begin{bmatrix} P_{11} & p_{12}\cdots & p_{1n} \\ P_{21} & p_{22}\cdots & p_{2n} \\ p_{n1} & p_{n2}\cdots & p_{nn} \end{bmatrix} \tag{2}$$

$(0 \leq \text{pij} < 1 \text{ and } \sum_{j=1}^{N} p_{ij} = 1, \ (i, j = 1,2, \ldots..n)$.

Where, P is the Markov transition matrix, i,j is the LULC type in the first and second time, P_{ij} denotes the probability of LULC type i to change into type j, N refers to the number of LULC classes in the region.

3.3. Cellular automata-Markov (CA-Markov)

Markov chain alone is not sufficient for simulation and predicting of LULC dynamics because it does not consider spatial distribution of each land category or the spatial direction of growth (Ghosh et al., 2017). Consequently, a cellular automata model was combined with Markov chain to consider the spatial structure and geographic directions of LULC changes. CA-Markov is a combination of cellular automata, Markov chain, multi criteria, multi objective land allocation, and LULC prediction, adding spatial contiguity structure and the knowledge of land use geographic distribution to the Markov chain analysis (Surabuddin Mondal et al., 2013; Kumar et al., 2016). The CA-Markov model simulates changes of multi categories of LULC based on the concept of spatial proximity, an essential factor of leading change events (Arsanjani et al., 2013). In the study area, each cell has five LULC states representing urban land classes and in the CA-Markov model, each cell has five cases that represent LULC classes across the study areas. This is computed as follows:

Table 1
Details of Landsat satellite images.

Images	Resolution	Path/raw	Date of acquisition	Product type	Cloud cover
Landsat 5 T M	15*15m	158/044	13 September 1998	L1T[a]	0.00 %
Landsat 5 T M	15*15m	158/044	11November 2008	L1T[a]	0.00 %
Landsat 8 T M	15*15m	158/044	23 November 2018	L1T[a]	0.00 %

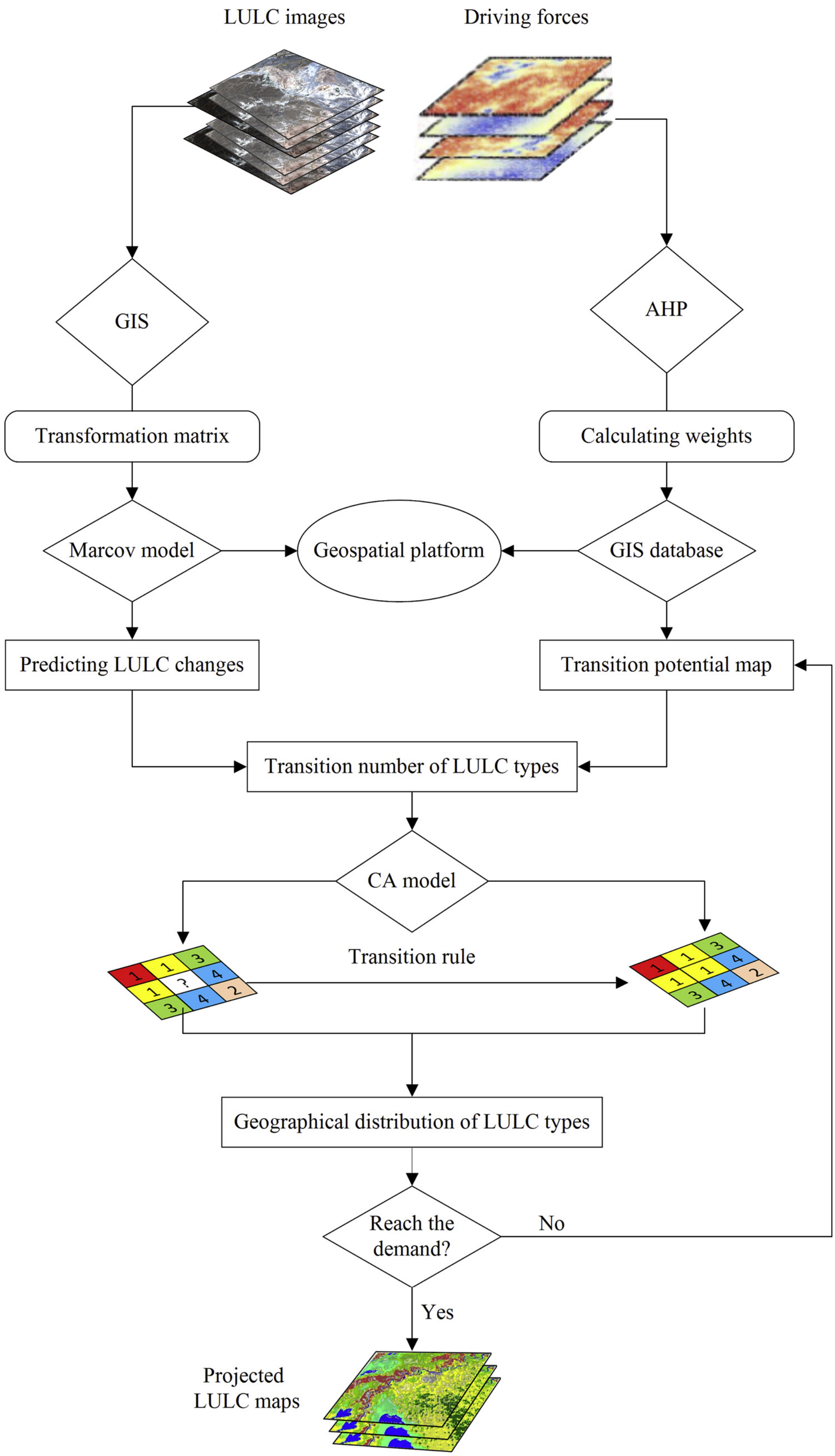

Fig. 3. Flowchart of the applied methodology framework for modelling LULC changes.

Table 2
Characteristics of land use/land cover (LULC) types.

LULC type	Description
Built-up area	Developed environment including all residential, commercial and industrial areas, urban agglomerations and transportation infrastructure
Vegetation	Total plant cover which encompasses mixed palm trees, gardens, inner city recreational areas, cultivated lands, grasslands, and agricultural areas
Bare land	Open land that has no buildings and is not being used, often bare soils, it can be used for several purposes, particularly for residential, agricultural and industrial use
Rocky land	Land dominated by rocky blocks or consists of large areas of rock which almost cover the entire landscape
Mountains	Large landforms that rise above the surrounding lands and rugged terrains

$$t_{LULCij} = \begin{cases} 1 = Vegetation \\ 2 = Builtup\ area \\ 3 = Baren\ land \\ 4 = Rocky\ outcro \\ 5 = Mountains \end{cases}$$

The transformation of cells from time $\boldsymbol{t}$ to another $\boldsymbol{t+1}$ is a function of its cell state, its neighbourhood proximity, and a set of transition rules. The evolution of cells can be calculated as follows:

$$t+1_{LULCi,j} = f\left((t_{LULCi,j}).\ (t_{Si,j}).\ (t_{Px,y,i,j}).\ (t_{Nij})\right) \tag{3}$$

Where $t+1_{LULCi,j}$ indicates the potential status of cell *i.j* to change at time $t+1$ while $t_{LULCi,j}$ represents states of cell *i.j* at time *t*. $t_{Si,j}$ illustrates suitability indices of cell *i.j* at time *t*. $t_{Px,y,i,j}$ specifies the probability of cell *i.j* to change from x to y. t_{Nij} denotes a neighbourhood index of cell *i.j*.

In CAM model, the transition rule is computed according to suitability indices, neighbourhood indices, and transition probabilities. In this study, the multi criteria evaluation (MCE) suitability maps were created utilising weighted linear combination as follows:

$$t_{Si,j} = \sum_{m=1}^{M} t_{xi,j}.\ w_m.\ c_m \tag{4}$$

Where $t_{Si,j}$ represents suitability index for cell *i.j* at time *t*, while $t_{xi,j}$ refers to a score of criteria m for cell *i.j* at time *t*. w_m indicates the weight which is given to each criteria and c_m signifies a Boolean value of growth constraints.

The transition rule was also calculated based on the transition potential of each cell, which is calculated based on changes of LULC classes of two periods as follows:

$$t_{Px,y,i,j,} = \mathrm{p}\{x_t = y_a x_{t1} = a_x\} \tag{5}$$

$t_{Px,y,i,j,}$ denotes the probability of cell *i,j* to change from activity *a x* to

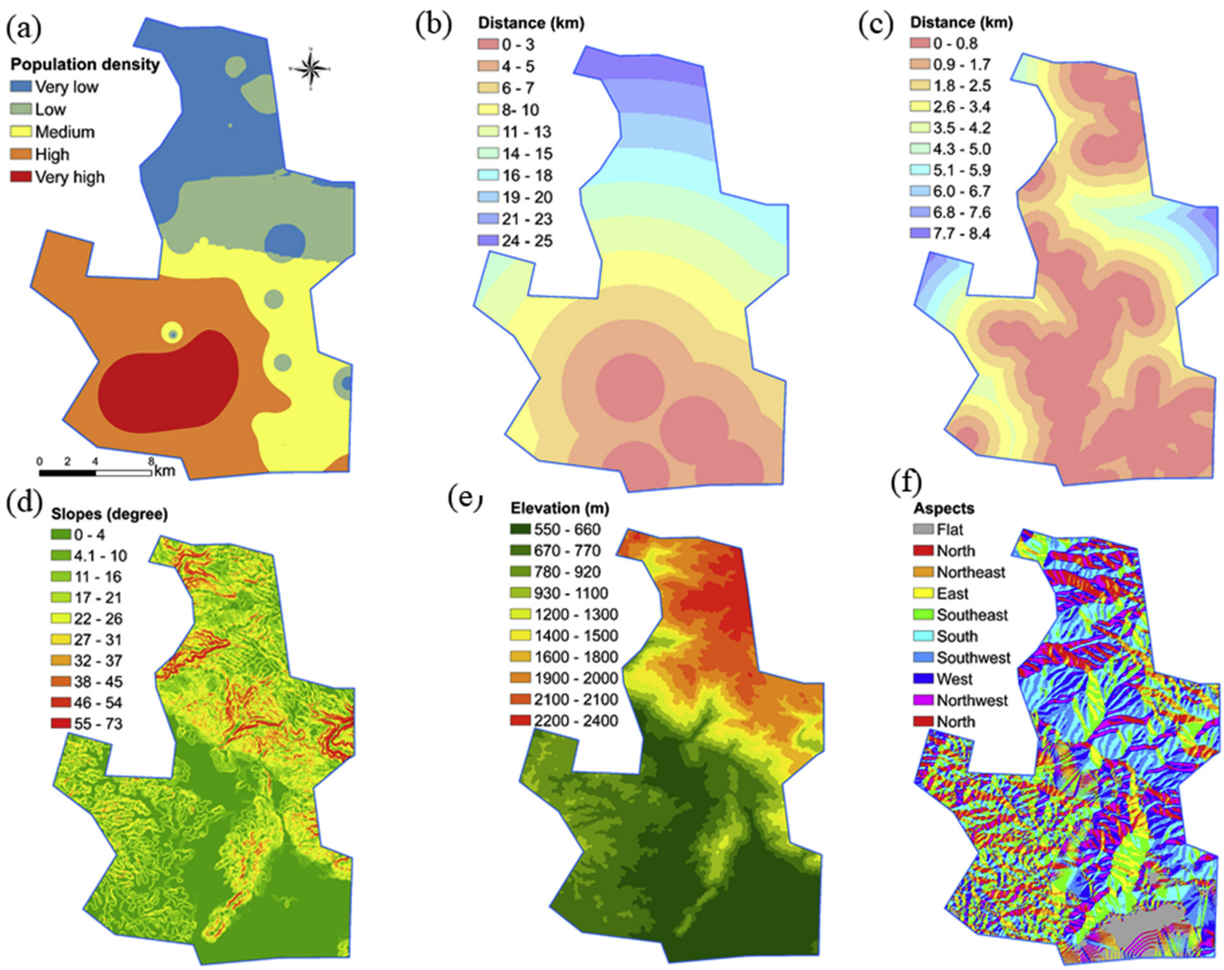

Fig. 4. Urban growth contributing factors (a) population density, (b) proximity to urban centres, (c) proximity to major roads, (d) slopes, (e) elevations, and (f) aspects.

Table 3
Factors and weights for urban suitability map.

Parameters	Functions	Rating of suitability	Rationale to suitability	Data source
Population density	Linear decreasing	Very high = high suitability High to medium = decreasing suitability Low to very low = lowest suitability	Highly suitable lands close to densely populated settlements; this type of land is more attractive for the population than areas close to sparsely populated settlements (von Richthofen, 2016; von Richthofen, 2015v)	Population density 2017, National Center for Statistics and Information (NCSI), Oman.
Proximity to urban centre	J-shape decreasing	1 km to 7.2 km = high suitability 8 km to 15 km = decreasing suitability 15 km to 25 km = lowest suitability	Vacant land close to the urban centre is more suitable for new residential housing units; the closer the distance, the higher the land price (Heim et al., 2018)	Urban settlements 2018, National Center for Statistics and Information (NCSI), Oman.
Proximity to major roads	J-shape decreasing	100 m to 2.5 km = high suitability 2.5 km to 5 km = decreasing suitability 5 km to 8.5 km = lowest suitability	Land close to highway and major roads is more accessible and more valuable; consequently, suitable for housing and urban growth (Richthofen, 2016).	Road network 2018, Supreme Committee of Town Planning and Ministry of Housing, Oman.
Slopes	J-shape decreasing	0 degree to 21 degree = high suitability 22 degree to 31 degree = decreasing suitability 32 km to 73 degree = lowest suitability	The steeper the slopes, the less suitable the land for urban growth; the lower the slopes, the more suitable for residential and build up expansion (Nebel & Von Richthofen, 2016)	Slopes generation from, DEM (40 m), USGS: source: http://www.edc.usgs.gov
Elevations	J-shape decreasing	550 m to 1000 m = high suitability 1100 m to 1500 m = decreasing suitability 1600 m to 2400 m = lowest suitability	Lower elevation, flat land is more suitable for urban expansion than higher elevation (Seto et al., 2011)	Elevations generation from DEM (40 m), USGS: http://www.edc.usgs.gov
Aspects	J-shape decreasing	SE to SW = high suitability North to NE = decreasing suitability NW = lowest suitability	The aspect shows in which direction urban growth is expanding; the directions-facing slopes are less suitable for urban growth (Mansour et al., 2019)	Aspects generation from DEM (40 m), USGS: source: http://www.edc.usgs.gov

activity $a\ y$.

The third element of calculating the transition rule is the neighbourhood indices which is calculated as follows:

$$t_{N_{i,j}} = \sum t_{N\,i,j}\,/24 \tag{6}$$

The $t_{N_{i,j}}$ was computed based on the extended Moore neighbourhoods which is a contiguity 5 × 5 filter, that is, each cell is surrounded by a matrix which composed by 5 × 5. A Moore neighborhood filter was utilized to capture local interaction among cells. The filter is a regular squared lattice and it is composed of a central cell and eight surrounding cells. This size of the neighbourhood was applied since it allows the influences of surrounding cells on the central one.

4. Findings

4.1. Model validation

To validate the model and evaluate its reliability in predicting LULC for projected years 2028 and 2038, the observed maps of the actual LULC for the year 2008 and 2018 were compared with the projected map for the same years. The validation process was based on the Kappa Index of Agreement (KIA), which is widely utilised in validating LULC predictions (e.g. Wang and Maduako, 2018; Hua, 2017; Parsa et al., 2016). The index comprises several statistical K parameters: kappa for no information (K_{no}), kappa for grid cell level location ($K_{location}$), kappa for stratum-level location ($K_{locationStrata}$), and kappa standard (Kstandard). Kappa values of 0 indicates agreement between the actual and projected map, which is known as equals chance agreement. The kappa index has an upper (+1) limit which denotes a total agreement and lower (-1) limit which refers to agreement less than chance (Congalton, 1991; Pontius, 2001; Parsa et al., 2016). The kappa k parameters reveal the accuracy of the modelling process and are used to assess model simulation, when the k parameter values are above 0.80, the statistics are accurate and satisfactory (Viera and Garrett, 2005).

In this study, the validation process was computed to the total LULC classes using the validate function in Terrset software. The Kappa statistics (K) were assessed to measure how closely the instances classified between actual and projected maps of the years 2008 and 2018 (Fig. 6). The output of the validation process (Table 4) exhibited robust agreement between the projected and reference maps, consequently accurate prediction between the observed and simulated LULC of the 2008 and 2018.

Although all Kappa parameters in 2018 were higher than 2008, they were all higher than 0.8 in both years, ranging from 0.8050 to 0.9170, which can be described as substantial agreement to almost perfect agreement (Hyandye and Martz, 2017).

4.2. Transition probability matrices

From the transition probabilities between maps of 1998 and 2008, the transition probability matrix for 2008 was computed following Eqs. 4 and 5. The Markov matrix (Table 5) showed that except for vegetation class, the remaining classes are stable in time. For instance, the matrix has high diagonal values, particularly for built-up areas, rocky outcrops and mountains, whereas vegetation and bare land are less stable classes. In addition, the conversion and LULC changes are towards built-up areas, followed by bare lands and rocky outcrop areas. The transition probability also revealed that in general, the change was oriented towards the increase of built-up areas in which vast bare lands were developed into housing units and residential areas.

The transition probabilities matrix between 2008 and 2018 for predicting LULC changes in 2028 and 2038 is presented in Table 6. Noticeably, bare lands, vegetation and rocky outcrops contribute significantly to urban growth and landscape changes across the study area with probabilities values of 0.64, 0.48 and 0.32 respectively. The

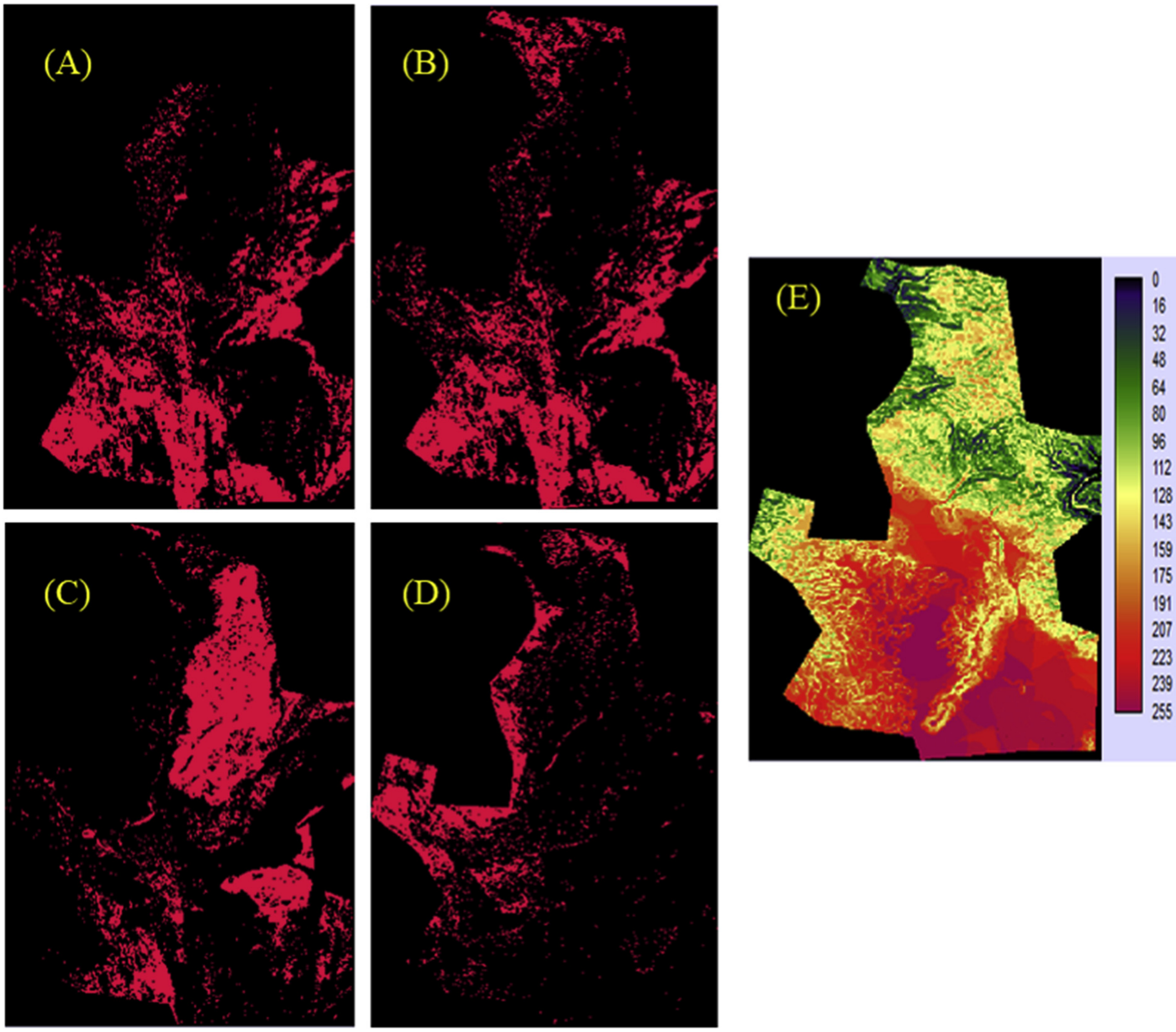

Fig. 5. Suitability maps for (A) built-up, (B) vegetation, (C) bare land, and (D) rocky land (0 indicates no suitability and 255 indicates the highest suitability).

mountainous area has a relatively small probability (0.020) to change to built-up and urban lands.

4.3. LULC dynamics

The dynamic changes of LULC categories for the years 2008, 2018, 2028, and 2038 are presented in Fig. 7. Across the study area, vegetation slightly declined from 0.57 % of the total area in 2008 to 0.51 % in 2018, where this class has lost 10.5 ha as a result of conversion into mainly housing units and residential properties (Table 7). Likewise, the bare land areas decreased from 46.8 in 2008 to 29.3 % in 2018, resulting in a loss of 37.6 ha. However, the built-up areas increased from almost 6 % in 2008 to 31 % in 2018; this conversion gains have come mainly from bare land and vegetation classes.

Fig. 8 shows the output of LULC dynamics and spatial growth during one decade (2008–2018). The change, particularly in residential class, can be classified into four areas: southeast towards the Izky-Farg highway, Taymissah area in the southwest, the far east towards Barket El Moz and the north, mainly from Nizwa Castle towards the Tanouf. The residential development obviously followed transportation routes, mainly infilling around existing developed areas. However, the increased built-up was more pronounced in the south and east directions.

4.4. LULC future predictions

The transition probability matrix of 2008–2018 was used to predict LULC changes in the future 20 years up to 2038. The map of 2018 was set as a starting year to forecast LULC changes in 2028. Similarly, to predict urban dynamics in 2038, the map of 2028 was set as a starting year utilising the same transition probability matrix of the 2008–2018 period. According to the successful simulation of LULC change patterns and distribution in 2018, future changes of urban landscape were projected across the study area from 2018 till 2038 (Fig. 8). The map of 2028 shows that Nizwa city will experience a noticeable increase in residential and housing section, specifically in the middle part and across the east. In 2028, this category is expected to occupy 14,985 ha forming almost 34 % of the total area (Table 8), which indicates remarkable future expansion of the urban landscape. The spatial patterns of this residential growth are characterised by linear directions, particularly along major transportation routes with distinguished nodes and clusters around core urban areas. The rapid growth in the built-up category is contrasted by a substantial decline in bare lands and vegetation cover, whereas changes in rocky outcrops and mountainous lands are less noticeable compared to vegetation and arable lands that are decreasing significantly due to urbanisation and residential expansion.

Fig. 9 also shows a fundamental increase in the built-up areas, which will dominate the landscape, while a large percentage of bare soils and vegetation will be gradually converted into residential land

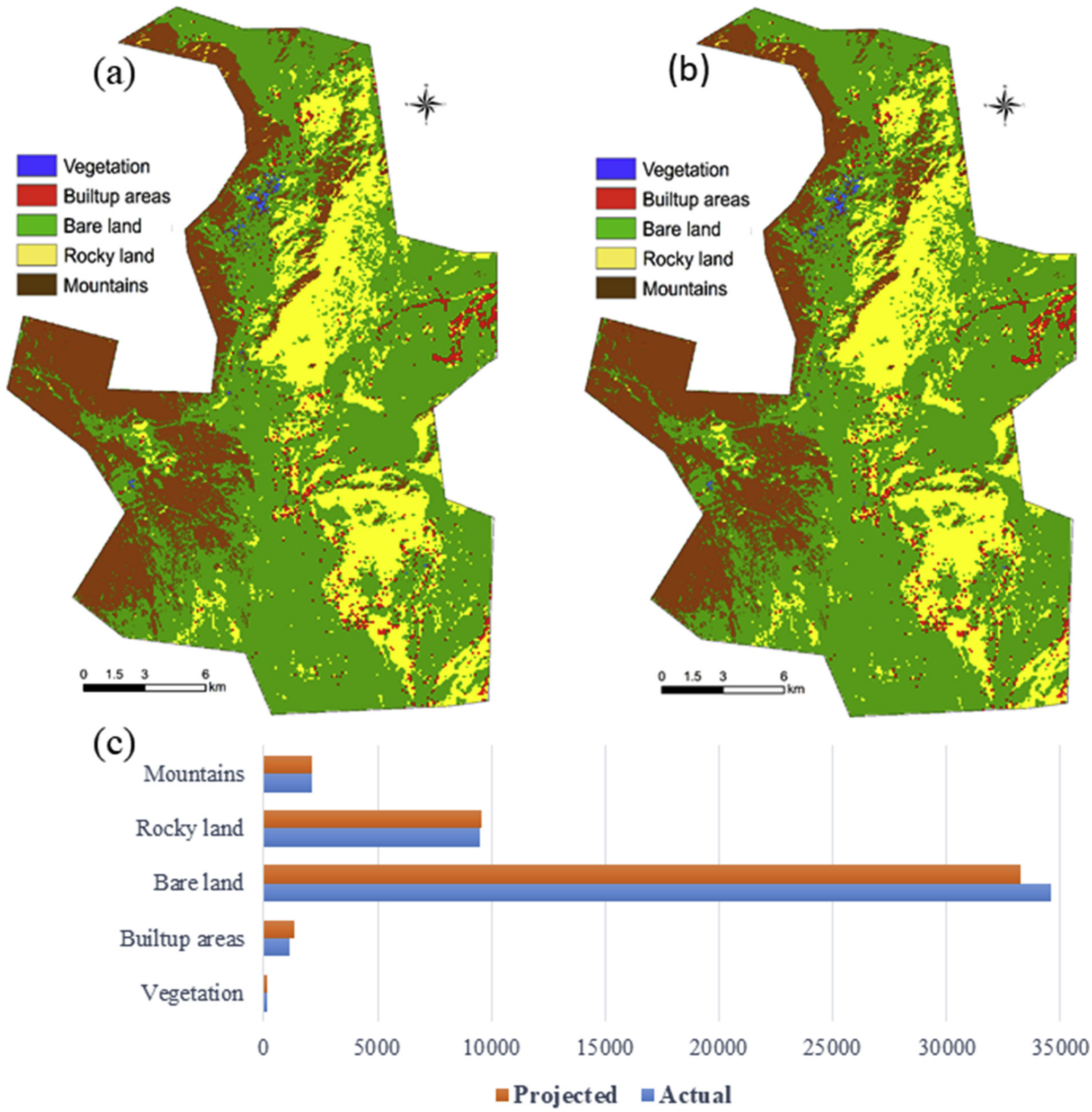

Fig. 6. The output of Kappa analysis: the actual LULC map (a), the predicted LULC map, the differences of area size of each LULC type in hectares.

use. Furthermore, the major conversion of bare land and farms of date palm trees into built-up areas is expected to take place in the middle and southern parts of Nizwa. For example, the percent of built-up area is estimated to increase from 38.18 % in 2028 to 48.25 % in 2038 (Table 8), while bare land and vegetation are expected to witness a decline from 25.27 % and 0.03 % in 2028 to 14.50 % and 0.021 % in 2038 respectively. Spatial distribution patterns of the predicted LULC changes are in accordance with the fact that the majority of previous and future urban growth is concentrated around and expanding upon existing core urban areas and transportation lines.

5. Discussion

One of the main aims of this research was to investigate the spatiotemporal characteristics of urban expansion in the mountainous regions of Oman. Landsat images (1998, 2008, and 2018), topographical

Table 4
Kappa coefficients of land use/land cover (LULC) types.

	Overall Kappa		Kappa coefficients for 2018 LULC types				
Kappa parameters	2008	2018	Vegetation	Builtup	Bare land	Rocky	Mountains
K_{no}	0.8702	0.9170	0.9251	0.8163	0.8365	0.9518	0.9392
$K_{location}$	0.8631	0.8953	0.8732	0.8672	0.8721	0.9427	0.9212
$K_{locationStrata}$	0.8631	0.8953	0.8390	0.9031	0.8297	0.9475	0.9487
$K_{standard}$	0.8050	0.8425	0.8113	0.8574	0.8037	0.9058	0.8842

Table 5
Transition probability matrix between 1998 and 2008 for predicting the LULC in 2018.

	Vegetation	Builtup	Bare land	Rocky	Mountains
Vegetation	0.0381	0.1076	0.2407	0.3554	0.2925
Builtup	0.0096	0.8851	0.2285	0.469	0.2045
Bare land	0.0044	0.1018	0.7023	0.4799	0.1116
Rocky	0.0051	0.102	0.4262	0.5519	0.1147
Mountains	0.0028	0.0867	0.4207	0.4363	0.5326

Table 6
Transition probability matrix between 2008 and 2018 for predicting the LULC in 2028.

	Vegetation	Builtup	Bare land	Rocky	Mountains
Vegetation	0.0019	0.4839	0.2282	0.0027	0.2333
Builtup	0.0066	0.2546	0.4025	0.0055	0.0909
Bare land	0.0048	0.6432	0.3068	0.0089	0.1194
Rocky	0.0052	0.3251	0.3289	0.5035	0.1374
Mountains	0.0041	0.0204	0.0039	0.2532	0.7183

and socioeconomic data were used to project future LULC dynamics in an Omani mountainous city. The CA-Markov model and multi criteria suitability analysis were combined with advanced spatial metric techniques to simulate spatial patterns of urban development up to 2038. The model was validated using reference data of 2018 and it exhibited satisfactory reliability. The findings clearly indicated that urban built-up areas would expand over bare soils and vegetation, with a large proportion of both categories converted into urban land, suggesting that Nizwa city is at a stage of increasing tendency for urban expansion.

Focusing on the spatial patterns of future urban growth in the Omani mountainous cities, the model successfully predicted directions of urban expansion in Nizwa. In addition, these directions were impacted by vigorous driving forces, such as topography, including slopes and elevation, and accessibility which incorporates proximity to major roads and urban cores. The effects of urban growth are often relatively challenging to policymakers and planners, specifically in the mountainous regions where establishing infrastructure and basic utilities is intricate and costly. Nevertheless, the spatial modelling process of future urban growth in the Omani mountainous cities is potentially helpful in various domains. Firstly, it determines spatiotemporal patterns and trends of growth, secondly, it is capable of simulating interactions between urban development and surrounding landscape, thirdly, it can effectively generate several scenarios of growth and their impact on urban ecosystems, and finally, the output of the CA-Markov can be indispensable to planning guidelines to foresee and examine possible

Table 7
The actual and simulated LULC changes in hectares.

	2008		2018		2008–2018	2008–2018 changes
	Area (ha)	% of total area	Area (ha)	% of total area	Area (ha)	% changes*
Vegetation	276	0.57	246.9	0.516	−29.1	−10.54
Builtup	2870.27	5.96	14884.21	31.094	12013.94	418.56
Bare land	22544.66	46.80	14052.85	29.357	−8491.81	−37.67
Rocky land	12383.4	25.71	12263.75	25.619	−119.65	−0.97
Mountains	10094.51	20.96	6421.46	13.415	−3673.05	−36.39

* The percentage of changes for each land use class was calculated by dividing the net area change between 2008–2018 by class area in 2008.

future LULC growth and the environmental socioeconomic associations in mountainous cities.

The dynamic of built-up areas is associated with urban population growth (You, 2017; Mohan et al., 2011; Zhang et al., 2011; Khalifa, 2015; Phuc et al., 2014), specifically the rise in population size due to natural increase and higher fertility as well as rural-urban migration. The Omani population of Nizwa Willayat reached 76,849 inhabitants in 2015, which is estimated to nearly double (149,246) by 2040 (NCSI, 2019). Accordingly, the increasing tendency of expansion of urban agglomerations is initially associated with the increased future population. The simulation results revealed a substantial increase in the built-up and residential category, for example, in 2038, it is projected that 7,596 ha will be added to the current area size of the built-up area across Nizwa city. Besides the increase in the urban population, this rapid expansion of built-up areas is due to several reasons, particularly the culture of a single-family home (where Omani people do not prefer to live in a flat) and large residential plots which increase housing area sizes. Although constructing new roads is a major driving force of urban growth, car transportation and over dependency on automobiles certainly causes fragmentation of urban fabric and traffic congestion in less dense urban areas. Furthermore, lacking proper planning policies may lead to urban sprawl, consequently destruction of open spaces and vegetation cover. Indeed, the growth of residential and housing lands in Nizwa city happens mostly at the outer edges, on the converted agricultural land and over bare soils. In general, the fragmentation of vegetation and bare lands tended to increase in areas that neighbour existing higher residential densities.

Land use dynamics in the mountainous cities of Oman describe the influences of human footprints on ecological, hydrological and environmental structures, where the higher the level of intensively land use changes, the more destructive effects on the ecological balance of

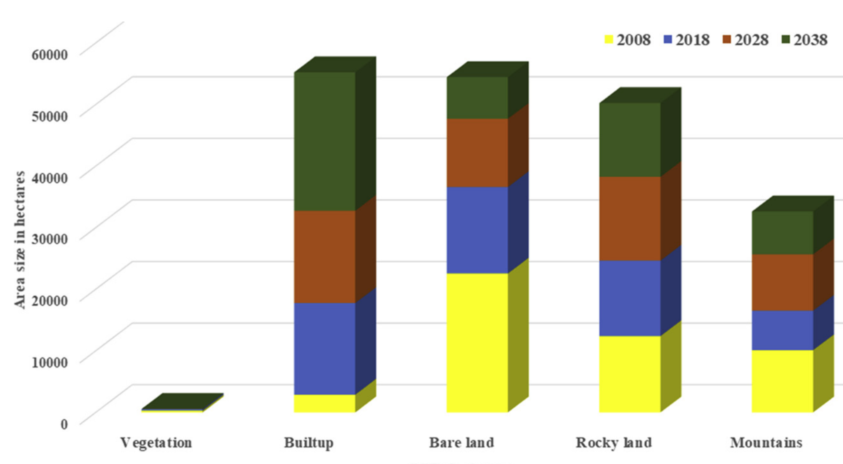

Fig. 7. The dynamic changes of LULC classes for the years 2008, 2018, 2028, and 2038.

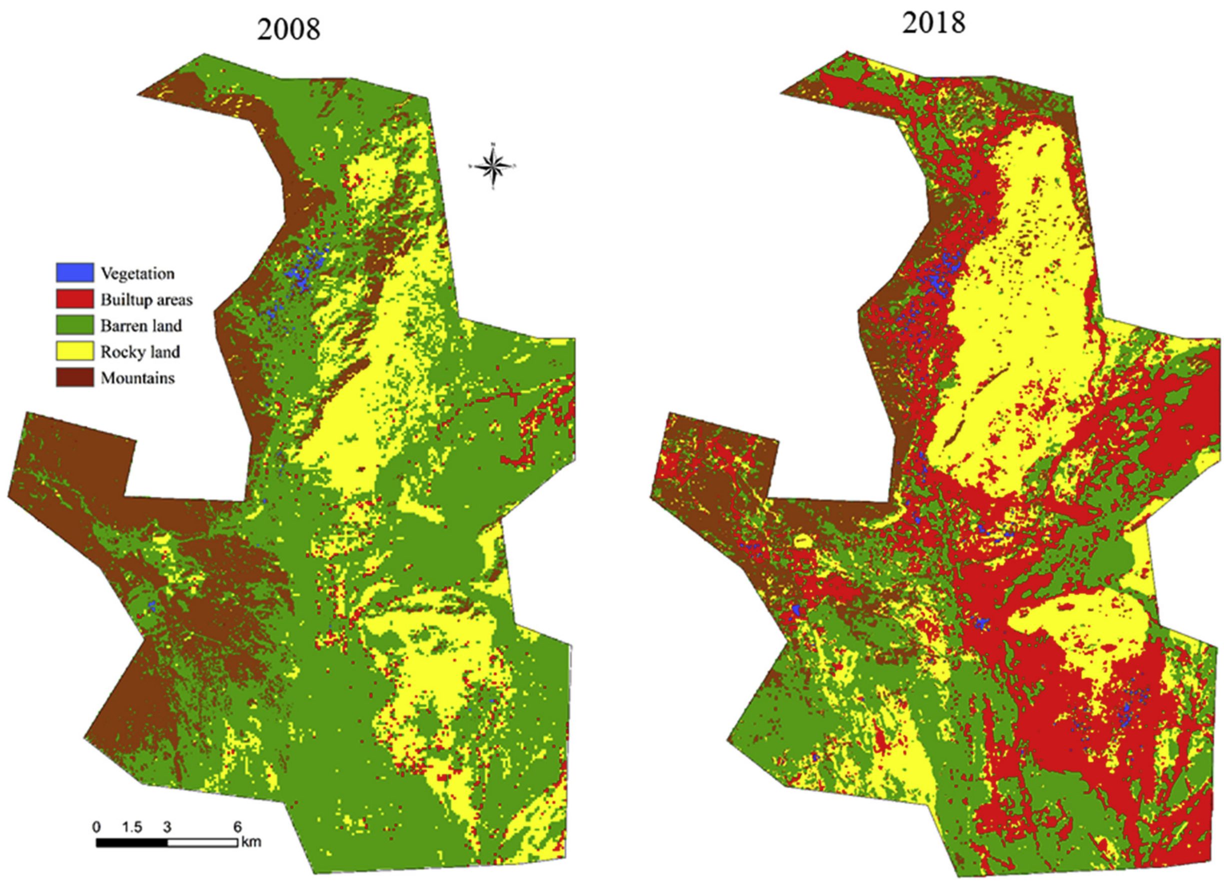

Fig. 8. The actual changes of LULC classes for the years 2008 and 2018.

urban environment (El Asmar and Taki, 2014; Luber and McGeehin, 2008; Wu et al., 2013). In essence, the terrain conditions which surrounds urban areas across Nizwa city significantly determine the direction and magnitude of future urban growth. The direction of expansion follows narrow strips of gentle slopes, where most buildable lands are located within dry valleys. However, the construction costs and natural risks increase as the slope increases, for example, urban clusters that are located on higher slopes are often more susceptible to the risk of flash floods. A new pattern of urban expansion can be clearly seen across rocky outcrops lands, where isolated clusters of buildings lack green space. This was identified easily across the west-east direction, particularly through the Farg-Izki highway. Since the required space for mountainous built-up to grow is not available, such a pattern may interrupt any sustainable planning in mountainous cities, particularly related to the equilibrium of urban ecology.

The rapid consumption of space and natural resources in the Omani mountainous cities due to ongoing urbanisation is not only a major challenge of sustainable development, but also a burden for future strategic plans of 2020 and 2040. Evidently, the expansion of urban areas need to be equipped with sufficient basic infrastructure, mainly transportation, water, energy and other social amenities. Similar studies conducted elsewhere in developing countries (Thies et al., 2014; Shahraki et al., 2011; Singh et al., 2015) have reported that built-up areas have dramatically increased in the last two decades and will continue increasing in the next years. However, the rapid urban growth in the mountainous cities of Oman has significantly influenced vegetation cover and will shrink open spaces as well as cause environmental damage. Various negative consequences of losing green spaces and bare soil can be identified, such as poor quality of the environment, threats to the ecological biodiversity and wildlife, pollution and decreasing air quality, higher chronic morbidity and urban heat islands impact (Luber and McGeehin, 2008). Hence, policy makers and planners in Oman need to consider the projected spatial extent and distribution patterns of LULC categories with respect to negative impacts, particularly housing characteristics, urban sprawl, infrastructure and utilities, vegetation coverage, and green spaces.

Overall, the present study provides new insights into simulating LULC dynamics of mountainous urban areas. To the best of our knowledge, research on spatial analysis and LULC prediction in Oman generally is very rare. Consequently, these findings contribute new

Table 8
The actual and simulated LULC changes in hectares.

	2028		2038		2028-2038	2028-2038 changes*
	Area (ha)	% of total area	Area (ha)	% of total area	Area (ha)	% changes
Vegetation	15.88	0.0362224	10.08	0.021639	−5.8	−36.52
Builtup	14985.31	34.18161	22480.28	48.25887	7494.97	50.02
Bare land	11079.93	25.273407	6758.7	14.50904	−4321.23	−39.00
Rocky land	11607.07	26.475818	11279.41	24.21374	−327.66	−11.96
Mountains	6152.08	14.032943	6054.22	12.99672	−97.86	−24.01

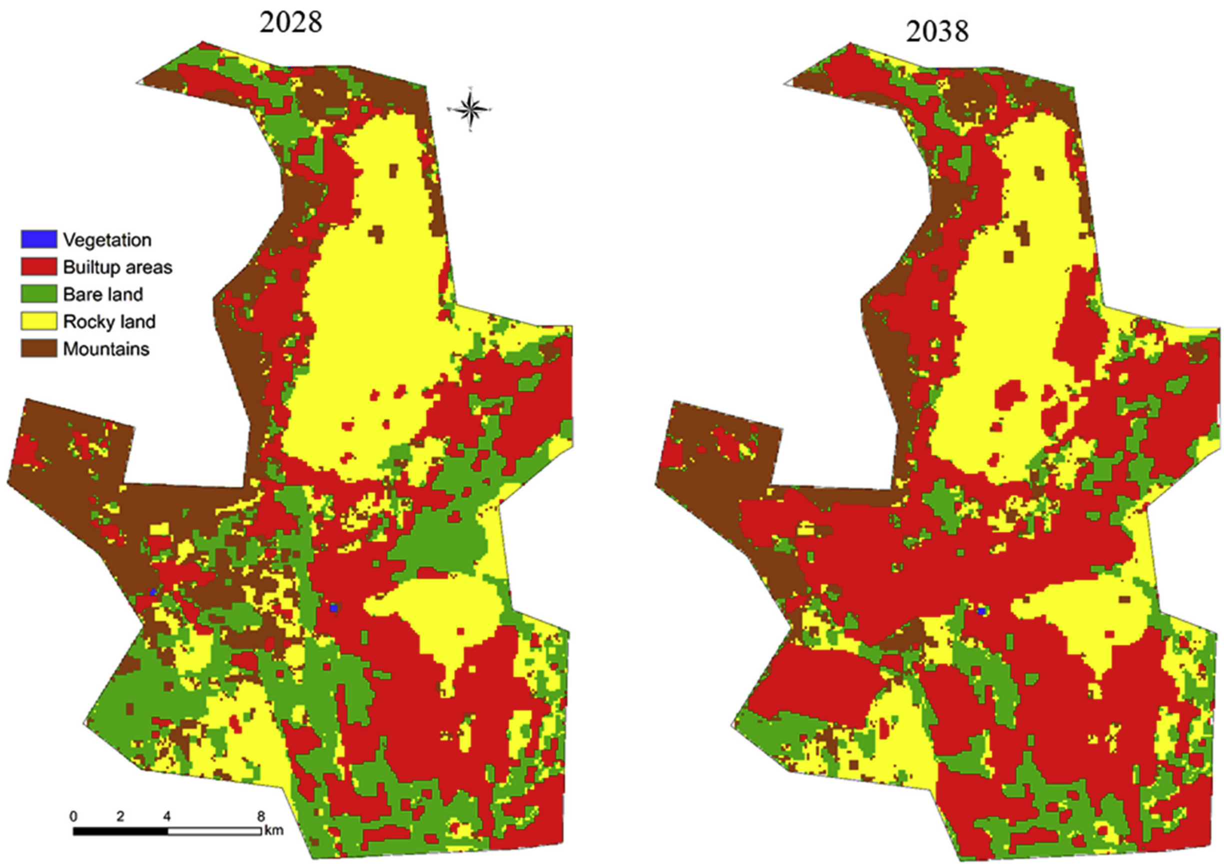

Fig. 9. The simulated changes of LULC classes for the years 2028 and 2038.

understanding and have several key implications for research on urban planning of mountainous cities in Oman as well as in neighbouring countries. Using advanced GIS and image processing metric techniques to identify areas that are susceptible to urbanisation is invaluable for the national strategy of future urban planning. In addition, the output of the simulations in this research could serve not only as spatial guidelines for monitoring future trends of LULC dynamics, but also to address threats and deterioration of urban sustainability in mountainous cities. Image spatial resolution remains a key factor which directly influences spatial metrics, landscape details and analysis output (Herold et al., 2003). In this research, integrated remote sensing and GIS techniques were able to identify the land change patterns quantitatively. Nevertheless, further studies may utilise finer resolution images and incorporate ancillary data to capture the underlying processes behind the observed land changes to enrich understanding of intra-urban variations of LULC dynamics across mountainous urban areas.

6. Conclusion

During the last decade, Omani cities have experienced unprecedented urban expansion due to socioeconomic transformation, mega projects and consistent immigration to urban areas. Accordingly, there is growing pressure on major urban agglomerations, placing intense demand on vacant lands for housing development. Geospatial simulation is an important technique to model and forecast urban growth and its consequences on future planning and sustainable development. In this research, the integration of remote sensing and advanced GIS techniques with the CA-Markov model successfully simulated urban growth and LULC changes in Nizwa city. The model was validated with 2018 observed data and showed satisfactory reliability. The findings indicated that the spatial patterns of urbanisation in the study area were influenced by terrain, topography, and transportation network. In addition, the major urban expansion occurred across vegetation areas, substantially along open spaces and bare lands.

In the mountainous cities of Oman such as Nizwa, the urbanisation can lead to a sprawl pattern because of rugged terrains, higher slopes, hilltops and unsuitable topographies. The settlements often are surrounded by mountain ranges, thus flat lands close to existing urban centres are dramatically shrunk by the urban sprawl. The negative impact of urban sprawl, such as destroying vegetation and urban ecosystem, should be avoided. Planners and policy makers must consider the high risks of landslides, flash floods and difficulties of spatial accessibilities to basic and public services. Consequently, effective management policies should be adopted for tackling the urban sprawl expansions and the shrinking of green spaces and vacant lands, for example, providing residents with land for housing should be regulated based on spatial guidelines adopting planned locations that pose little development challenges.

To the best of our knowledge, research regarding spatial modelling of mountainous cities in Oman is very rare. This analysis employed advanced GIS techniques, spatial modelling and utilisation of satellite images in the simulations of LULC changes to successfully predict the future of urban growth. The modelling process gave promisingly accurate and reliable results for examining possible future urban changes, allowing urban landscape patterns and growth directions to be identified and predicted. These results can provide a great opportunity for addressing the future challenges of the urban mountainous environment, its sustainability and growth scenarios. The simulated results of this study can be employed to assess urban planning policies in the mountainous cities of Oman and the surrounding regions. Likewise, the produced results of this research can serve as an indispensable guideline for local governors and planners to manage the spatiotemporal directions of urban expansion and their future ramifications.

Author statement

Shawky Mansour: Conceptualization, developed the study design, and drafted the manuscript, **Mohamed Al Belushi;** undertook most of the data collection, Writing- Original draft preparation. **Talal Al-Awadhi:** Data collection, visualization and reviewed the manuscript, and. All authors read and approved the final manuscript.

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