PREDICTING SPATIO-TEMPORAL URBAN GROWTH IN TABUK, SAUDI ARABIA USING A CELLULAR AUTOMATA-MARKOV MODEL

[1]EMAN ALBALAWI, [2]ASHRAF DEWAN, [3]ROBERT CORNER

[1,2,3]Department of Spatial Sciences, Science and Engineering, Curtin University, Australia
[1]Department of Geography, Umm Al-Qura University, Makkah, Saudi Arabia
E-mail: [1]eman.albalawi@postgrad.curtin.edu.au, [2]a.dewan@curtin.edu.au, [3]r.corner@curtin.edu.au

Abstract - Assessing land-use change can provide essential information to aid land management and planning. The city of Tabuk, Saudi Arabia is under increasing pressure from urban growth due to increase in population and a booming economy. To predict areas of likely future urban expansion for Tabuk city, urban data were extracted from satellite imagery for 1985, 1995, 2005 and 2015. The Cellular Automata – Markov model was used to create a model based on historical land use and land cover (LULC) data for factors affecting urban growth, including biophysical and proximate data. Urban growth in 2005 and 2015 was predicted and compared to observed data to assess prediction accuracy. Results for 2005 and 2015 indicated prediction capability of the model for to have a total agreement for predicted and reference data were 89 and 98 %, respectively. The predicted land use pattern of the study area for the years 2025 and 2035 was examined, and the future urban transition predicted an increase in urban area of about 137 km^2. Results predicted a clear encroachment on agricultural areas, with an expected loss of 10%. If the current trends continue, the urban growth will have adverse impacts on arid ecosystem function. New policies are, therefore, required for urban sustainability. This study provides beneficial information that could aid urban planners and policymakers for more appropriate plans in Tabuk in the pursuit of Saudi Arabia's 2030 vision for sustainable urban and economic development.

Keywords - Arid environment; Prediction, Remote sensing; Tabuk, Cellular Automata-Markov.

I. INTRODUCTION

A major factor of land use change for many cities is an areal expansion of urbanization caused by rapid population growth and increased economic activity [1]. Better living standards and employment opportunities attract people to the city which increases production and demand for resources [2]-[3]. Rapid population growth is more common in developing countries and is especially problematic for environmentally fragile semi-arid/arid regions [4]-[5] such as those found in Saudi Arabia. Unplanned urban growth and emergence of random and unplanned houses increased urban waste, plus air and water pollution [6-11] can lead to major environmental problems such as land degradation and irreversible desertification. Saudi Arabia as a fast-developing country represents a desert environment that is very fragile and highly affected by human activities [12]. Economic evolution due to the oil boom of the 1970s together with rapid growth of urban population in Saudi Arabia has caused remarkable urban expansion. The total population for Saudi Arabia in 2016 was 32.28 million with annual population growth rate of 2.5 % since 2000 [13]. There is a tendency for Saudi Arabia's population to move to urban cities because of high employment opportunity, improved level of education, and better urban services compared to rural areas [14].

Spatiotemporal land use information can help developing countries understand land change process, causes and implications for environmental damage, and to develop more sustainable policies for better land use management [15]-[16]. Geospatial techniques such as satellite data, spatial modeling, combined with ancillary data in a geographical information system (GIS), are valuable tools for detecting, monitoring, and predicting future changes in land use [17]-[18]. Models used to indicate potential impacts on natural resources and implemented for land use prediction include Agent-Based Model (ABM), Markov chain Analysis model (MCA), Cellular Automata (CA), Conversion of Land Use and its Effects (CLUE), or integrated models [19-22] which include qualitative and quantitative approaches at different levels of complexity [23-26]. A detailed review of land-use change models can be found in Briassoulis [27].

Cellular Automata-Markov (CA_MARKOV) model is an integration model and a powerful tool in spatio-temporal dynamic modeling with the ability to model complex systems and is compatible with most spatial datasets [28]-[29]. Reliable and realistic models depend on driving forces used for urban change predicting and modeling [30]. Biophysical and socioeconomic factors are the main factors considered when modeling and predicting future urban growth [31]. Proximate causes and neighborhood variables are also important when modelling urban growth. The factors selection is dependent on data availability and objectives of the study. In developing countries, however, consistency and quality of available data are the main challenges. Eastman and Toledano [32] stated that CA_MARKOV model works well when limited historical data is available. Use of the CA_MARKOV model is also beneficial in countries where LULC change occurred at a high and fast rate [33].

Saudi Arabia is currently working towards a '2030 Vision' to reduce dependency on oil and create economic diversity by investing in tourism and industrial sectors [34, 35].

The Tabuk region will factor highly in the '2030 Vision'. Tabuk is close to the Egyptian and Jordanian borders (in north-west Saudi Arabia) and will be the site for the Neom project; the first independent, smart city powered solely by wind and solar energy. Connecting Saudi Arabia and Egypt with the King Salman Bridge project will be an important global hub for world trade [36].

Both projects are expected to encourage trade between African and Asian continents, increase the number pilgrims, raise the tourism sector, attract global/national investments, contribute to country's GDP, boost future economic growth and overall development of the Tabuk. However, such projects place added pressure on already limited natural resources, e.g. non-rechargeable groundwater [34, 36, 37].

Tabuk City has the second highest urban population with 71% of total regional population [38]. Increased population is mostly from national immigration, and a military base in Tabuk city with military personnel distributed unevenly across the city [39]. Urban growth and increased population have led to dramatic changes in LULC [40].

Unplanned houses, flash floods due to poor drainage, excess use of fossil groundwater, and increased desertification were noted in Tabuk [41-43]. Considering these issues, modeling the potential impacts of future growth can aid decision makers in managing urban infrastructure and regulating natural resources (such as water) to minimize unsustainable urban development. Development projects in Tabuk will attract more people looking for an opportunity for a better lifestyle, investment and urban development and economic benefits [3].

In pursuit of Saudi Arabia's 2030 urban and economic development, demand for considered land management for Tabuk to minimize negative environmental impacts is required. This paper aims to assess the capability of an integration of Cellular Automata and Markov's chain models for modeling urban growth in Tabuk city. Specific questions to be answered are:

- Can available driving factors be used to accurately predict patterns of future urban expansion? And
- where are the most likely areas urban growth will take place for years 2015-2025 and 2015-2035?

II. DATA AND METHODOLOGY

A. Study Area, data and image processing

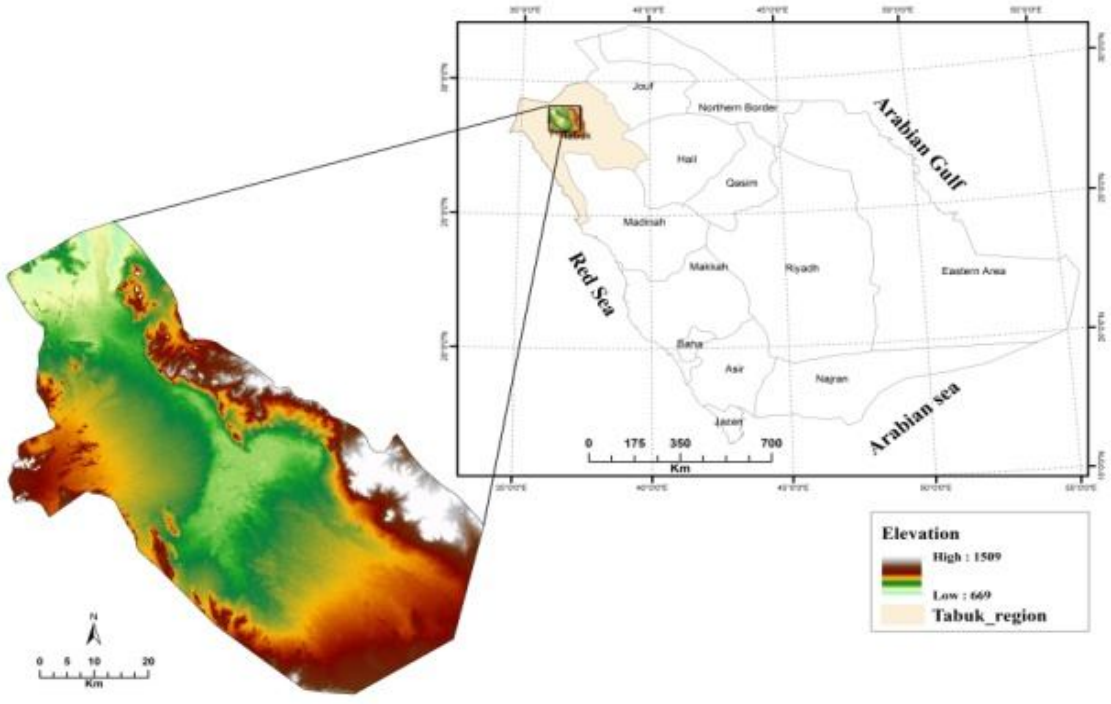


Figure 1 Location of the study area

The study area has an extent of 4212 km^2 within Tabuk, approximate in north-western region of Saudi Arabia (Fig 1). Tabuk is located at an altitude of 600-800 m above mean sea level. The province is considered arid with an annual rainfall of 40 mm, occurring between November and January with snowfalls every 2-3 years. Landsat Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+) and Operational Land Imager (OLI) (path 173 and row 40) for 1985, 1995, 2005 and 2015 were downloaded from EarthExplore. Images were geometrically corrected and rectified to Universal Transverse Mercator (UTM) coordinate system. To correct Landsat imageries for atmospheric scattering, dark object subtraction method (DOS) was used. The LULC maps generated using Object-Based Image Analysis (OBIA) classification with the overall accuracies of 94%, 94%, 96%, and 93%, respectively. Four types of LULC were defined are 'barren land,' 'urban areas,' 'agricultural land,' and 'water.' As the focus of this paper was on urban growth, the dataset of LULC was again reclassified as urban and non-urban areas. Digital Elevation Model (DEM) with 12.5 m size cell was obtained online from Alaska Satellite Facility site (https://www.asf.alaska.edu). The 2015 road dataset in vector format was made available by the General Commission for Survey (GCS). Road shapefiles for 1995 and 2005 were prepared and measured using digitization tool in ArcGIS with the help of Topographical maps and high-resolution images.

B. Markov Chain Analysis

The Markov chain Analysis (MCA) is a stochastic model which develops a transition probability matrix for each pixel from the past and current state to the next state [44]. A pair of land use maps records the probability that each land use class will change to other class between two different dates. Classified maps for 1985-1995, 1995-2005 and 2005–2015 were used to compute transition probabilities. The calibration time intervals used was ten years. The background areas were assigned to a value of 0.0, and the proportional error was 0.6 based on the overall accuracy of the classified maps. The Markov Chain Model generated transition probabilities, transition area matrices and a set of conditional probability images [45]. The MCA model is practical for describing and quantifying land use change and doesn't consider spatial characteristics or the patterns of land use for predicting future change [46]-[47]-[48]. Spatial characteristics were added to the urban land use modeling using the Cellular Automata model [45].

C. Factors specification and preparation for modeling urban growth

Determine the driving forces/factors to predict urban expansion is the essential step for developing the model [21]. Prior to Cellular Automata modeling, suitability maps were created using factors expected to affect urban growth. Five factors were considered based on data availability including biophysical and proximity factors. Biophysical factors are Digital Elevation Model (DEM) and slope. The slope was calculated (as a percentage) from DEM data. Proximity factors are the distance from an urban well, distance from roads, and distance from urban areas. The Euclidian distance tool was used to calculate proximity factors. Several steps were required before potential transition maps (suitability maps) creation. Fuzzy Membership Function was applied to calculate biophysical and proximity factors. Fuzzy module evaluates the possibility that each pixel belongs to a fuzzy class [45]. The selection of the Fuzzy Function was based on visual analysis. For example, where urban area was overlaid with the DEM layer. The DEM values were chosen from 0 to 800, where values > 800 are assessed as not suitable for urban growth, and lower values are assessed as more suitable). A similar assumption was applied to slope layer, distance from roads, distance urban and urban well distance (Table 1). Each land use dataset was then standardized as the final step in this function (ranging from 0 to 255), where a high value of 255 is more suitable for urban growth and 0 is least suitable.

Table 1 Fuzzy parameters for factors driving urban growth

Factors	Function shape	Function type	Control points
Distance to urban well	Monotonically decreasing	J-shaped	0-250
Distance to road	Monotonically decreasing	J-shaped	0-50
Distance to urban area	Monotonically decreasing	Linear	0-100
DEM	Monotonically increasing	Sigmoidal	0-800
SLOPE	Monotonically increasing	Sigmoidal	0-40

Analytic Hierarchy Process (AHP) weight derivation was used to compute relative weights based on factor importance for urban growth. The weights are developed by providing a series of pairwise comparisons of the relative importance of factors to the suitability of pixels for the activity being evaluated. These pairwise comparisons are then analyzed to produce a set of weights that sum to 1 [45].

To evaluate the suitability of these factors Multi-Criteria Evaluation (MCE) methods were used. The MCE is a decision support tool which can limit the alternatives under consideration to specify suitable locations for urban growth [45]. To create a constraint map for the given years (1995, 2005 and 2015), image calculator tool was used to create an image containing the value of zero (where development is excluded) and value of one (where development is permitted). Weighted linear combination (WLC) within the MCE method was

selected to operate both extracted weights of urban growth factors and constraints maps as the final stage before the Cellular automata model performed. The MCE method was operated only for the urban area land use class. The group of urban suitability images of 2005, 2015, and 2025 was generated, considering effects and factors to focus on urban growth. For other land covers (barren land, agricultural area, and water) suitability criteria were based on the current spatial distribution for each land cover. Each land cover was assigned a weight; 1 for suitable sites and 0 for non-suitable sites to obtain the suitability map of each land cover.

D. Implementing the Cellular Automata-Markov model

The Cellular Automata can calculate the probability for each cell independently to estimate the spatial distribution of land use at a future date [29]. In this study, an integrated Cellular automata-Markov Model combined spatial characteristics with urban land use modeling for predicting change in Tabuk city. The Cellular Automata-Markov model (CA_MARKOV) is a commonly used tool for urban growth modeling, and land-use change prediction [28]-[29]. The CA_MARKOV model consists of three elements: multi-temporal maps, a transition function, and simulated future land use change maps. The dataset results were given as input to CA_MARKOV model. There are four elements within the CA model: cell space, cell states, the neighborhood of the cell, transition rules and time steps [29]. To test the performance of the model, urban growth of 2005 and 2015 with a span of 10 years was modeled. Predicted maps were then compared to observed 2005 and 2015 urban maps. The urban area of 1995 was used as the basis for the 2005 prediction. Markov transition areas file which created from the Markov chain model of 1985-1995 was used with transition suitability data for 1995. The predicted land use maps were then integrated during a Multi-Objective Land Allocation (MOLA) procedure. A 5 × 5 contiguity filter was chosen for the cellular automata to ensure that the change was not random—urban land use change likely to occur to an existing pixel that is near to existing urban areas. Previous studies have revealed that a 5 × 5 contiguity filter resulted in a more accurate prediction [49]-[5]-[50]-[47]. A similar process was applied to predict urban growth in 2015.

E. Validation of CA_MARKOV model and Predicting 2025 and 2035 urban growth

Reference and predicted urban area maps for 2005 and 2015 were modeled and compared statistically using the quantity and allocation disagreement method by Pontius [51]. The model measures the agreement between two categorical data predicted maps and reference map using seven components of agreement and disagreement. The model also calculates Kappa Index of Agreement (KIA) and three more useful variations on the KIA including Kappa for no information (Kno), Kappa for grid-cell level location ($Klocation$), and Kappa for stratum-level location ($KlocationStrata$). A detailed description of each expression is provided by Pontius and Suedmeyer [52]. Pontius [51]-[53] provides the theoretical concepts for the validation of a land-use change model. A mask image of the study area was used to limit the analysis and focus on the study area boundary. Based on successful validation with high agreements, the CA_MARKOV model is suitable for the future prediction of 2025 and 2035. The 2015 observed map was then used as a base map. The transition probability matrix for 2005-2015 and suitability maps were used to predict urban growth in 2025. The same process was applied to predict future urban growth from 2015 to 2035 using the 2025 map as a base map.

III. RESULTS

A. Urban land use change and transition probabilities matrices

The spatio-temporal urban growth patterns for Tabuk City were analyzed from 1985-2015 (Table 2 & Fig. 2). From 1985-1995, urban areas increased around 40 km^2, indicating a doubled growth in the ten-year interval. In the 1995-2005 period, urban areas increased about 57 km^2, covering 5.6 % of the study area. During 2005-2015, urban area increased from 145 km^2 to 315.08 km^2 with an increase of 17 % in urban area. From 1985 to 2015, urban area increased significantly by c. 267 km^2, covering 28 % of the study area (Table 2). The spatial pattern of urban changes to 2015 showed that Tabuk City is expanding toward the northwest and west directions (Fig. 2). During the study periods, transition maps show a considerable conversion of barren and agricultural lands classes to urban area class (Fig. 2). The result showed that a clear encroachment of urban areas on the agricultural land, it's more noticeable in the Northeast direction of Tabuk City.

Table 2 Area statistics of urban areas, 1985- 2015

Urban Area	Year			
	1985	1995	2005	2015
Km^2	48.29	88.15	145.02	315.08
%	1.14	2.09	3.44	7.47
Urban changed	Year			
	1985-1995	1995-2005	2005-2015	1985-2015
Km^2	+ 39.86	+56.86	+170.06	266.79
%	3.9	5.6	17	28

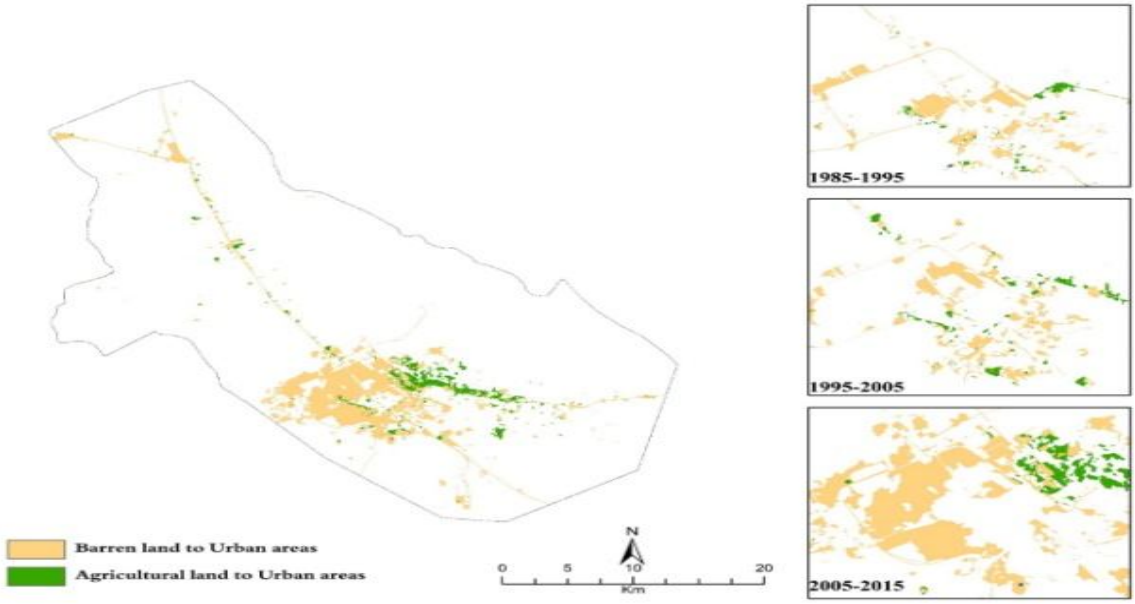


Figure 2: Transition map from land use/land cover classes to urban area from 1985 to 2015, with the spatial trend of urban land use change

The relationship between population density and urban growth in Tabuk from 1985 to 2015 was highly correlated (Fig. 3). From 1985, the population size increased corresponding to the high rate of population migration in Tabuk City. In 2005, the trend of the urban area was on the rise due to the high demand for land and space to accommodate increased population, health, services and education facilities.

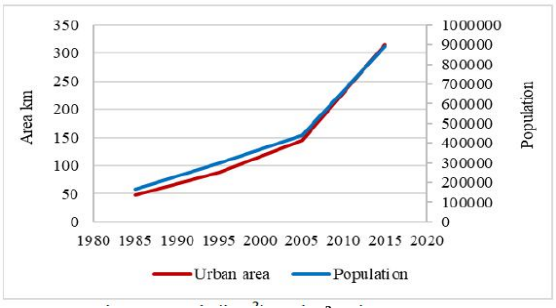


Figure 3 Urban growth (km^2) and population

Transition probabilities obtained using the Markov chain Analysis for 1995-2005, 2005-2015 and 2015-2025 are shown in Table 3. Transition probabilities between 1995-2005 show that the highest-class transition with a 0.1380 probability of changing to urban is converted from water class. The agricultural areas had the second highest probability of conversion to an urban area (a probability of 0.0447). Urban area class remains high in its status with a 0.7856 probability. The transition probabilities during 2005–2015 showed that the agricultural land class had the highest probability of conversion to urban area class compared to other classes (0.0572). Similarly, a probability of 0.8370 for urban class remains in the current urban state. While barren class converted to urban class continues to increase from 0.0111 to 0.0150 between 1995–2005 and 2005–2015, respectively. The lowest probability of 0 is associated with water class to urban class during this period. For the period of 2015–2025, the transition probability indicate that the pattern is expected to continue, with a conversion probability of 0.0595 and 0.0455 from agricultural and barren classes to urban respectively. The highest class with a 0.8436 probability for urban to remain in the current urban status. The second highest probability of change to urban (0.2795) come from water class in this period.

Table 3 Markov transition probabilities matrices of 1995-2025

Year	Probability of changing				
	2005				
1995	Class	Barren land	**Urban areas**	Agricultural land	Water
	Barren land	0.9450	**0.0111**	0.0438	0.0001
	Urban areas	0.1618	**0.7856**	0.0527	0.0000
	Agricultural land	0.5390	**0.0447**	0.4163	0.0000
	Water	0.8091	**0.1380**	0.0529	0.0000
	2015				
2005	Class	Barren land	**Urban areas**	Agricultural land	Water
	Barren land	0.8888	**0.0150**	0.0963	0.0000
	Urban areas	0.1504	**0.8370**	0.0126	0.0000
	Agricultural land	0.2730	**0.0572**	0.6695	0.0003
	Water	0.1509	**0.0000**	0.2000	0.6491

	2025 (Expected)				
2015	Class	Barren land	**Urban areas**	Agricultural land	Water
	Barren land	0.8946	**0.0455**	0.0599	0.0000
	Urban areas	0.0998	**0.8436**	0.0566	0.0000
	Agricultural land	0.2658	**0.0595**	0.6748	0.0000
	Water	0.1477	**0.2795**	0.1795	0.3932

B. Model validation and predicted urban growth for 2025 and 2035

To validate the CA_MARKOV model, actual and predicted urban areas (km^2) for 2005 and 2015 were compared (Figs 4 & 5). There is little variation between predicted and actual urban areas. For example, urban area in the actual map for 2005 represented as 3.44 % of the total study area and the corresponding predicted urban class was 3.20 %.

In 2015, also, a high similarity between actual and the predicted urban area representing 7.47 and 7.43 % of the total study area, respectively (Fig. 4). The 2005 and 2015 predicted and actual maps showed highly similar (Fig. 5).

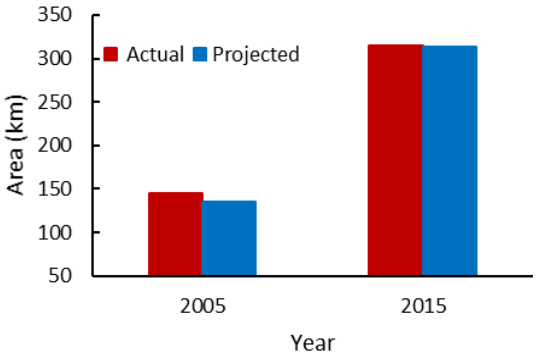


Figure 4 Comparison between actual and predicted urban areas (km^2) for 2005 and 2015

The summary of agreement and disagreement components between the predicted maps and corresponding reference maps for 2005 and 2015 is presented in Table 4.

Table 4 Summary of validation of Agreement/disagreement for 2005 and 2015

Year	2005	2015
Agreement Chance	0.5000	0.5000
Agreement Quantity	0.4263	0.3620
Agreement Strata	0.0659	0.1348
Agreement Grid cell	0.0000	0.0000
Disagree Grid cell	0.0000	0.0000
Disagree Strata	0.0000	0.0027
Disagree Quantity	0.0078	0.0005

The results show a strong agreement between the predicted and reference map. For example, the agreement between the predicted maps and reference maps due to chance were 0.5000 for both years. Similarly, the agreement quantity was 0.4263 in 2005 and 0.3620 in 2015. In contrast, the allocation disagreement for 2005 and 2015 were 0.0000 and quantity disagreements were close to zero (Table 4).

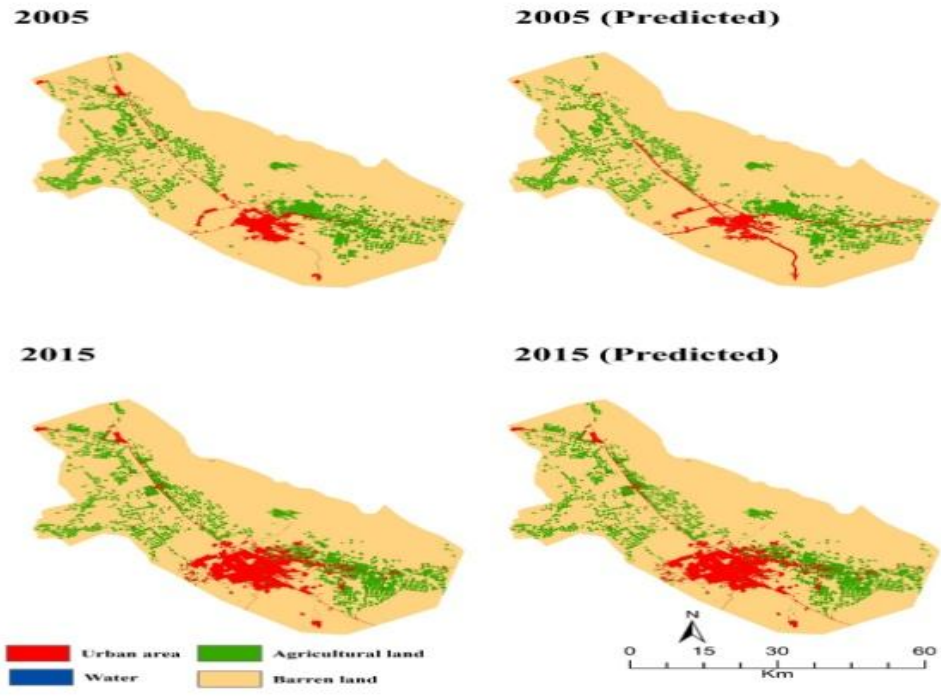


Figure 5 Comparison of predicted urban area for the years 2005 and 2015 and classified maps.

The KIA result for predicted urban area in 2005 was 0.8946, and for other variations *Kno*; *Klocation* and *KlocationStrata* were 0.9845, 1.0000, and 1.0000, respectively. The KIA for 2015 predicted urban area was 0.9770, and the statistics for location *Kno* was 0.9936, *Klocation* was 0.9802, and for the *KlocationStrata* was 1.0000. The results of predicted urban area for 2005 and 2015 showed that the CA_MARKOV model can predict accurately urban growth for 2025 and 2035 with confidence and realistic outcomes.

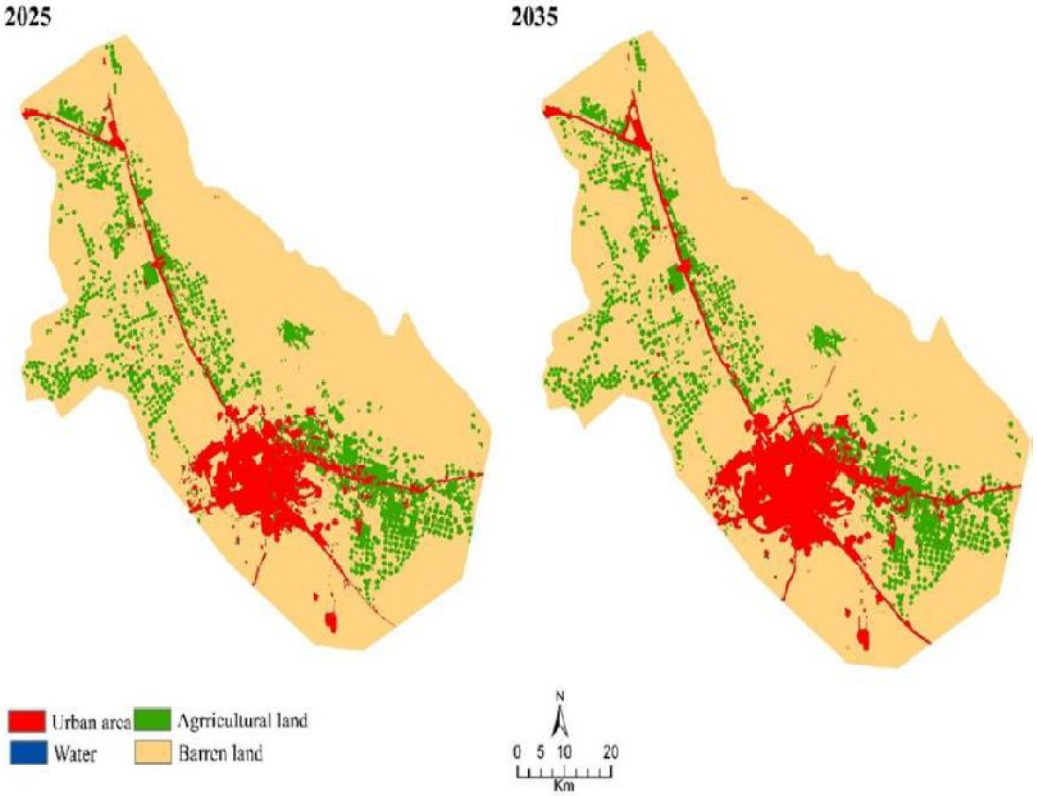


Figure 6 Predicted urban growth of Tabuk for 2025 and 2035

The CA_MARKOV- model shows the urban area will increase over the next 10 and 20 years (Fig. 6). The urban changes in Tabuk would likely to take place within and around the edge of the city that follows the previous trend of land use change. Therefore, the level of urban density increases in Tabuk City as seen in Fig. 6. In 2025, urban areas would reach to 361 km^2 of the total land in the study area, with an addition increase of 46.62 km^2 from 2015. The CA_MARKOV- model also showed that the amount of land in urban areas increases from 315 km^2 (7.47% of land area) in 2015 to 452.94 km^2 (9.12% of land area) in 2035 (Table 5).

Table 5 Predicted urban growth for 2025 and 2035, based on statistics of the CA-M model (in km^2)

Year	2025	2035	Area change	
			2015-2025	2015-2035
Urban area simulated	361.70	452.94	+ 46.62	+ 137.86
%	8.58	10.75	4.6	9.12

The future extent, trend, direction, and occupied percentage of urban growth of Tabuk city can be determined Figs 6&7 and Table (5) in the years 2025 and 2035.

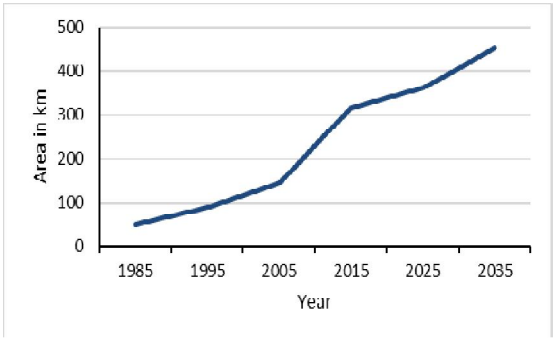


Figure 7 Trend of urban growth in Tabuk from 1985 to 2035

Urban growth is predicted to occur along roads networks in 2025 and 2035. The trend of Tabuk City would extend into north-western and a few areas into southeastern parts. An intensive growth of urban land that caused more encroaching into the agricultural area was detected in 2025 and 2035. For example, a clear encroach more on agricultural land was observed in north-east of the city (Fig. 6), showing a

decrease in the agricultural area from 577 km^2 in 2015 to 566 km^2 in 2025 and 538 km^2 in 2035.

IV. DISCUSSION

The integration of CA_MARKOV model predicts further trend and pattern of urban expansion in Tabuk City with satisfactory results. The analysis suggests that urban area will experience considerable growth that could have adverse impacts on arid ecosystem function if the current trends continue. Prior studies noted the importance of such studies in developing countries for land management and urban planning [54]-[55], the study outcomes provide a great contribution for future urban growth planning in Saudi Arabia.

The expansion of Tabuk city is relying solely on fossil groundwater that is not sustainable. Over-extraction influences, groundwater chemistry, identified in several studies [56]-[57], these which found that groundwater depletion and contamination in Tabuk are associated with rapid population growth. The study indicates an increase in urban area which could be a result of high rate of rural-urban migration and economic evolution which could lead to rapid degradation and increased desertification [58]. A considerable loss of agricultural area also observed in other cities around the world for the same reasons [59]-[60], reported that urban expansion due to migration and economic changes are coupled with a reduction in vegetation and agricultural area.

The simulation findings that current agricultural areas would be reduced to about 10% by 2035 due to urban expansion could be attributed to the relative location of urban boundaries in the vicinity of agricultural areas resulting in high transition probability from agricultural class to urban. If agriculture areas move or increase in response to urban growth, then a significant effect could be placed on arid region ecosystems. Additional pressure to feed an increased population leading to uneven and intense agricultural growth activities [61]–[62]–[11].

The trend for urban predicted growth for 2025 and 2035 likely to take place near-road network and the existing urban area is consistent with others findings, when new urban development occurred along road network and existing urban area due to ease of mobility and accessibility to work and public services within the city [63]-[64]. Further development in Tabuk City, however, will be onto fragile areas, which are prone to resource deterioration such as water shortages, desertification and groundwater depletion as these are common issues in arid regions [1]-[54].

More people would be attracted to migrate to Tabuk area due to Saudi Arabia's 2030 vision for creating a new economic region to improve economic conditions like job opportunities and the per capita income [65]. This could have an impact on existing urban infrastructures. Despite enormous efforts of the Saudi government to minimize impacts on resources and to achieve urban and economic sustainability, the challenge is still on due to the harsh environmental condition, limited natural resources, and climate change for the country [66]-[67]-[68]. Possible issues on the fragile arid environment addressed in this study due to urban expansion, emphasize the importance of urban prediction study for more appropriate strategies for urban expansion.

The CA_MARKOV model based on simple rules is beneficial model to perform a prediction process with data scarcity [32]. For example, the suitability maps created from the available factors including biophysical and proximity factors used as rules during the modeling process have achieved a strong agreement in predicted and reference maps for the years 2005 and 2015 and gained confidence for accurate future simulations for the years 2025 and 2035. However, for a better understanding of the urban complex system, biophysical, environmental and socioeconomic factors are important for assessing the dynamics of urban change and predicting future growth [69]. Further studies, which take these factors into account will need to be undertaken to provide insightful information that aid decision makers to improve current practice and to more urban sustainability.

CONCLUSION

The predicted urban land use in 2025 and 2035 indicated that the trend of expanding into fragile areas and encroaching onto agricultural land might lead to loss of agricultural land. Improved management policies are required for realistic and more sustainable urban planning in such environments to cope with the increased population from a booming economy in the pursuit of Saudi Arabia's 2030 vision.

ACKNOWLEDGMENTS

Thanks to Dr Kerri Clarke for helpful comments on the manuscript.

REFERENCES

[1] M. Carley and I. Christie, Managing sustainable development: Routledge, 2017.
[2] M. Asif, "Growth and sustainability trends in the buildings sector in the GCC region with particular reference to the KSA and UAE," Renewable and Sustainable Energy Reviews, vol. 55, pp. 1267-1273, 2016.
[3] R. A. Moussa, "King Abdullah Economic City: The Growth of New Sustainable City in Saudi Arabia," in New Cities and Community Extensions in Egypt and the Middle East, ed: Springer, 2019, pp. 51-69.
[4] M. Tewolde and P. Cabral, "Urban sprawl analysis and modeling in Asmara, Eritrea," Remote Sensing, vol. 3, pp. 2148-2165, 2011.
[5] M. W. A. Halmy, P. E. Gessler, J. A. Hicke, and B. B. Salem, "Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA," Applied Geography, vol. 63, pp. 101-112, 2015.

[6] E. K. Albalawi and L. Kumar, "Using remote sensing technology to detect, model and map desertification: a review," J Food Agric Environ, vol. 11, pp. 791-797, 2013.
[7] S. Deep and A. Saklani, "Urban sprawl modeling using cellular automata," The Egyptian Journal of Remote Sensing and Space Science, vol. 17, pp. 179-187, 2014/12/01/ 2014.
[8] C. He, B. Gao, Q. Huang, Q. Ma, and Y. Dou, "Environmental degradation in the urban areas of China: Evidence from multi-source remote sensing data," Remote sensing of environment, vol. 193, pp. 65-75, 2017.
[9] A. MacLachlan, E. Biggs, G. Roberts, and B. Boruff, "Urban growth dynamics in Perth, Western Australia: using applied remote sensing for sustainable future planning," Land, vol. 6, p. 9, 2017.
[10] B. Zheng, S. W. Myint, P. S. Thenkabail, and R. M. Aggarwal, "A support vector machine to identify irrigated crop types using time-series Landsat NDVI data," International Journal of Applied Earth Observation and Geoinformation, vol. 34, pp. 103-112, 2015/02/01/ 2015.
[11] I. R. Hegazy and M. R. Kaloop, "Monitoring urban growth and land use change detection with GIS and remote sensing techniques in Daqahlia governorate Egypt," International Journal of Sustainable Built Environment, 2015.
[12] A. M. Youssef and N. H. Maerz, "Overview of some geological hazards in the Saudi Arabia," Environmental Earth Sciences, vol. 70, pp. 3115-3130, 2013.
[13] T. W. Bank, "Population, total," World Development Indicators, Saudi Arabia, 2016.
[14] A. Abdulsalam, I. Elsegaey, R. Khraif, and A. Al-Mutairi, "Population distribution and household conditions in Saudi Arabia: reflections from the 2010 Census," SpringerPlus, vol. 3, p. 1, 2014.
[15] X. Li and A. G.-O. Yeh, "Modelling sustainable urban development by the integration of constrained cellular automata and GIS," International Journal of Geographical Information Science, vol. 14, pp. 131-152, 2000/03/13 2000.
[16] M. Batty, "Cities as complex systems: scaling, interactions, networks, dynamics and urban morphologies," 2008.
[17] T. Sohl and B. Sleeter, "15 Role of Remote Sensing for Land-Use and Land-Cover Change Modeling," 2012.
[18] C. Agarwal, G. M. Green, J. M. Grove, T. P. Evans, and C. M. Schweik, "A review and assessment of land-use change models: dynamics of space, time, and human choice," Gen. Tech. Rep. NE-297. Newton Square, PA: US Department of Agriculture, Forest Service, Northeastern Research Station. 61 p., vol. 297, 2002.
[19] M. Batty, Cities and complexity: understanding cities with cellular automata, agent-based models, and fractals: The MIT press, 2007.
[20] Clarke, S. Hoppen, and L. Gaydos, "Methods and techniques for rigorous calibration of a cellular automaton model of urban growth," in Third international conference/workshop on integrating GIS and environmental modeling, Santa Fe, New Mexico, 1996.
[21] Clarke, Hoppen, and Gaydos., "A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area," Environment and planning B: Planning and design, vol. 24, pp. 247-261, 1997.
[22] A. Veldkamp and L. Fresco, "CLUE: a conceptual model to study the conversion of land use and its effects," Ecological modelling, vol. 85, pp. 253-270, 1996.
[23] E. López, G. Bocco, M. Mendoza, and E. Duhau, "Predicting land-cover and land-use change in the urban fringe: a case in Morelia city, Mexico," Landscape and Urban Planning, vol. 55, pp. 271-285, 2001.
[24] B. Mertens and E. F. Lambin, "Land-cover-change trajectories in southern Cameroon," Annals of the association of American Geographers, vol. 90, pp. 467-494, 2000.
[25] D. C. Parker, S. M. Manson, M. A. Janssen, M. J. Hoffmann, and P. Deadman, "Multi-agent systems for the simulation of land-use and land-cover change: a review," Annals of the Association of American Geographers, vol. 93, pp. 314-337, 2003.
[26] P. H. Verburg, P. P. Schot, M. J. Dijst, and A. Veldkamp, "Land use change modelling: current practice and research priorities," GeoJournal, vol. 61, pp. 309-324, 2004.
[27] H. Briassoulis, Analysis of Land Use Change: Theoretical and Modeling Approaches: Regional Research Institute, West Virginia University, 2000.
[28] I. Santé, A. M. García, D. Miranda, and R. Crecente, "Cellular automata models for the simulation of real-world urban processes: A review and analysis," Landscape and Urban Planning, vol. 96, pp. 108-122, 2010.
[29] R. White and G. Engelen, "High-resolution integrated modelling of the spatial dynamics of urban and regional systems," Computers, Environment and Urban Systems, vol. 24, pp. 383-400, 2000/09/01/ 2000.
[30] A. Veldkamp and E. F. Lambin, "Predicting land-use change," ed: Elsevier, 2001.
[31] E. F. Lambin, B. L. Turner, H. J. Geist, S. B. Agbola, A. Angelsen, J. W. Bruce, et al., "The causes of land-use and land-cover change: moving beyond the myths," Global Environmental Change, vol. 11, pp. 261-269, 12// 2001.
[32] Eastman and J. Toledano, "A Short Presentation of CA_MARKOV," in Geomatic Approaches for Modeling Land Change Scenarios, M. T. Camacho Olmedo, M. Paegelow, J.-F. Mas, and F. Escobar, Eds., ed Cham: Springer International Publishing, 2018, pp. 481-484.
[33] S. Singh, S. Mustak, P. Srivastava, S. Szabó, and T. Islam, "Predicting Spatial and Decadal LULC Changes Through Cellular Automata Markov Chain Models Using Earth Observation Datasets and Geo-information," Environmental Processes, vol. 2, pp. 61-78, March 01 2015.
[34] M. S. Al Surf and L. A. Mostafa, "Will the Saudi's 2030 Vision Raise the Public Awareness of Sustainable Practices?," Procedia Environmental Sciences, vol. 37, pp. 514-527, 2017.
[35] M. Yamada, "Vision 2030 and the Birth of Saudi Solar Energy," Middle East Institute Policy Focus, vol. 15, p. 2016, 2016.
[36] A. A. Farag, "The Story of NEOM City: Opportunities and Challenges," in New Cities and Community Extensions in Egypt and the Middle East, ed: Springer, 2019, pp. 35-49.
[37] . Shay, "Bridge over troubled water-Egypt and Saudi Arabia to build the Red Sea Bridge," 2016.
[38] H. Abdelatti, Y. Elhadary, and A. A. Babiker, "Nature and Trend of Urban Growth in Saudi Arabia: The Case of Al-Ahsa Province–Eastern Region," Resources and Environment, vol. 7, pp. 69-80, 2017.
[39] Central Department of Statistics & Information. (2016).
[40] E. Albalawi, A. Dewan, and R. Corner, "Spatio-temporal analysis of land use and land cover changes in arid region of Saudi Arabia," International Journal of Geomate, vol. 14, pp. 73-81, 2018.
[41] Al-Ahmadi and A. Hames, "Comparison of four classification methods to extract land use and land cover from raw satellite images for some remote arid areas, kingdom of Saudi Arabia," Earth, vol. 20, pp. 167-191, 2009.
[42] K. Al-Harbi, "Monitoring of agricultural area trend in Tabuk region–Saudi Arabia using Landsat TM and SPOT data," The Egyptian Journal of Remote Sensing and Space Science, vol. 13, pp. 37-42, 2010.
[43] A. Al-Momani and M. a. Shawaqfah, "Assessment and management of flood risks at the city of Tabuk, Saudi Arabia," The Holistic Approach to Environment, vol. 3, pp. 15-31, 2013.
[44] C. Petit, T. Scudder, and E. Lambin, "Quantifying processes of land-cover change by remote sensing: Resettlement and rapid land-cover changes in south-eastern Zambia," International Journal of Remote Sensing, vol. 22, pp. 3435–3456, 2001.
[45] J. Eastman, "IDRISI Terrset Manual," Clark Labs-Clark University: Worcester, MA, USA, 2016.
[46] M. R. Muller and J. Middleton, "A Markov model of land-use change dynamics in the Niagara Region, Ontario, Canada," Landscape Ecology, vol. 9, pp. 151-157, June 01 1994.
[47] L. Sang, C. Zhang, J. Yang, D. Zhu, and W. Yun, "Simulation of land use spatial pattern of towns and villages

based on CA–Markov model," Mathematical and Computer Modelling, vol. 54, pp. 938-943, 2011.
[48] J. Liu, J. Zhan, and X. Deng, "Spatio-temporal patterns and driving forces of urban land expansion in China during the economic reform era," AMBIO: a journal of the human environment, vol. 34, pp. 450-455, 2005.
[49] Y. H. Araya and P. Cabral, "Analysis and modeling of urban land cover change in Setúbal and Sesimbra, Portugal," Remote Sensing, vol. 2, pp. 1549-1563, 2010.
[50] M. S. Mondal, N. Sharma, M. Kappas, and P. Garg, "Modeling of spatio-temporal dynamics of land use land cover-a review and assessment," 2012.
[51] Pontius, "Statistical methods to partition effects of quantity and location during comparison of categorical maps at multiple resolutions," Photogrammetric Engineering and Remote Sensing, vol. 68, pp. 1041-1050, 2002.
[52] Pontius and B. Suedmeyer, "Components of agreement between categorical maps at multiple resolutions," Remote sensing and GIS accuracy assessment, pp. 233-251, 2004.
[53] Pontius, "Quantification error versus location error in comparison of categorical maps," Photogrammetric engineering and remote sensing, vol. 66, pp. 1011-1016, 2000.
[54] Singh, Mustak, Srivastava;, Szabó;, and Islam., "Predicting spatial and decadal LULC changes through cellular automata Markov chain models using Earth observation datasets and geo-information," Environmental Processes, vol. 2, pp. 61-78, 2015.
[55] A. A. Al-sharif and B. Pradhan, "Monitoring and predicting land use change in Tripoli Metropolitan City using an integrated Markov chain and cellular automata models in GIS," Arabian Journal of Geosciences, vol. 7, pp. 4291-4301, 2014.
[56] Y. Nazzal, I. Ahmed, N. S. N. Al-Arifi, H. Ghrefat, F. K. Zaidi, M. M. El-Waheidi, et al., "A pragmatic approach to study the groundwater quality suitability for domestic and agricultural usage, Saq aquifer, northwest of Saudi Arabia," Environmental Monitoring and Assessment, vol. 186, pp. 4655-4667, August 01 2014.
[57] T. Zumlot, A. Batayneh, Y. Nazal, H. Ghrefat, S. Mogren, H. Zaman, et al., "Using multivariate statistical analyses to evaluate groundwater contamination in the northwestern part of Saudi Arabia," Environmental Earth Sciences, vol. 70, pp. 3277-3287, December 01 2013.
[58] C. Barbero-Sierra, M.-J. Marques, and M. Ruíz-Pérez, "The case of urban sprawl in Spain as an active and irreversible driving force for desertification," Journal of Arid Environments, vol. 90, pp. 95-102, 2013.
[59] B. Pandey and K. C. Seto, "Urbanization and agricultural land loss in India: Comparing satellite estimates with census data," Journal of Environmental Management, vol. 148, pp. 53-66, 2015/01/15/ 2015.
[60] R. J. Corner, A. M. Dewan, and S. Chakma, "Monitoring and prediction of land-use and land-cover (LULC) change," in Dhaka Megacity, ed: Springer, 2014, pp. 75-97.
[61] M. S. Al-Shayaa, M. B. Baig, and G. S. Straquadine, "Agricultural extension in the Kingdom of Saudi Arabia: Difficult present and demanding future," J. Anim. Plant Sci, vol. 22, pp. 239-246, 2012.
[62] C. B. d'Amour, F. Reitsma, G. Baiocchi, S. Barthel, B. Güneralp, K.-H. Erb, et al., "Future urban land expansion and implications for global croplands," Proceedings of the National Academy of Sciences, vol. 114, pp. 8939-8944, 2017.
[63] E. Vaz, J. J. Arsanjani, L. Phillips, M. Johnson, K. Deener, C. Bonanni, et al., "Predicting Urban Growth of the Greater Toronto Area-Coupling a Markov Cellular Automata with Document Meta-Analysis," Journal of Environmental Informatics, vol. 25, pp. 71-80, 2015.
[64] Y. Chen, X. Li, X. Liu, B. Ai, and S. Li, "Capturing the varying effects of driving forces over time for the simulation of urban growth by using survival analysis and cellular automata," Landscape and Urban Planning, vol. 152, pp. 59-71, 2016.
[65] W. A. Aboneama, "Creating a Unique Sustainable Rating System for Saudi Arabia to Achieve Environmental Assessment and 2030 Vision," European Journal of Sustainable Development, vol. 7, pp. 269-279, 2018.
[66] I. Y. Al-Filali and G. M. Gallarotti, "Smart development: Saudi Arabia's quest for a knowledge economy," International Studies, vol. 49, pp. 47-76, 2012.
[67] J. Cheeseman, "Food security in the face of salinity, drought, climate change, and population growth," in Halophytes for Food Security in Dry Lands, ed: Elsevier, 2016, pp. 111-123.
[68] Y. A. Aina, "Achieving smart sustainable cities with GeoICT support: The Saudi evolving smart cities," Cities, vol. 71, pp. 49-58, 2017/11/01/ 2017.
[69] D. Guan, H. Li, T. Inohae, W. Su, T. Nagaie, and K. Hokao, "Modeling urban land use change by the integration of cellular automaton and Markov model," Ecological Modelling, vol. 222, pp. 3761-3772, 2011.

★★★