URBAN EXPANSION SCENARIOS BASED ON ARTIFICIAL NEURAL NETWORK (CASE OF ERDENET CITY, MONGOLIA)

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ABSTRACT: Due to accelerated urbanization since the 1950's, most of the Mongolian population, or about 68%, live in urban areas. The systematic understanding of urban expansion is a crucial clue for urban planning and sustainable land development. Therefore, in this paper, we used the Markov chain model and an Artificial neural network to simulate and predict current and future urban areas expansion in Erdenet city (third largest urban area of Mongolia and fourth copper mining industry in the world) vicinity. Clark Lab's (Clark University) IDRISI software's Land change modeler module had been used for the urban expansion prediction. The Land change modeler module was developed by the Multilayer perceptron neural network with the Markov chain model. Multilayer perceptron neural network allows the integration of factors to interpret land change, while the Markov chain model with cellular automata restructuring of them spatially.
This model has been used in our country for the first time in the case of Erdenet city. The main aims of the study are (i) land use and land cover change detection; (ii) simulation of urban expansion in different scenarios; (iii) provision of reference information for urban planning and land development.
Urban expansion predicted 2046's trend based on a historical expansion of Erdenet city between 1996, 2006 and 2016, which were prepared according to input model requirements. Low and medium resolution satellite images are allowed cities and regions to regularly monitor their spatial and temporal dimensions and land-use changes. Landsat imageries (Landsat TM 5, Landsat ETM 7 and Landsat OLI 8) of 1996, 2006 and 2016 were used to derive land use map.
In the urbanization process, many socioeconomic and physical factors and their current situation have a significant impact. Digital elevation model, slope, distance to road, population growth rate, distance to economic centers, suitable lands, road network, possible area for urban transition were used as an explanatory factor map of urban land-use change.
The model proposes three spatial alternatives for the future expansion of Erdenet city. These include spontaneous scenario, environment-protecting scenario, and resources-saving scenario. The impacts of variations are different, but for the entire period, urban expansion rates are likely to increase. The land use transition into urban areas has similar changes in environmental protection and resources-saving scenarios, while spontaneous expansion is significantly different from others. By spontaneous scenarios of 2046, open space and the unused areas will be gradually reduced by built-up areas. The land-use change in the north-east and northwest area is estimated to have the largest increase in comparison with other locations.
The spatial pattern of the modeled scenarios will provide the stakeholders and planners with information on where and how will go urban expansion process by 2046 and will give important information for future development projects. Simulation performance of the Markov chain model with an Artificial neural network model can be used improving the understanding of the urban expansion processes while also allowing for better planning of Erdenet city, as well as for other rapidly developing regions of Mongolia.

1. INTRODUCTION

As a result of rapid population growth, land-use changes occur, and the environment is degrading. (Wu *et al*., 2006; Guan *et al*., 2011). Urban land-use changes are complex phenomenon, and they are interconnected with many factors and depend on politics, economy, society, cultural factors and many others (Barredo *et al*., 2003; 2004). In developing countries, land-use change is characterized by urban expansion and the slum on settlement areas (Arsanjani *et al*., 2011). Due to the land is being converted into commercial, residential, and industrial purposes, urban expansion is

taking place (Ettema, 2007; Al-Shalabi *et al*., 2013; Arnous, 2013) at preurban areas. It is necessary to improve the data and appropriate models needed to increase land efficiency at the urban planning policy (Dadhich & Hanaoka 2011; Othman *et al*., 2013). However, there is a need for a substantial amount of information to effectively monitor and control the land-use changes. The mapping, modelling, and analysis of land-use changes can be done through advanced GIS and remote sensing (Araya & Cabral 2010; Youssef, 2011; Wakode *et al*., 2014). Therefore, remote sensing technology allows for land-use and land cover information to be updated and that land-use changes can be spatialy and efficiently analyzed and modeled (Dadhich & Hanaoka 2011; Wakode *et al*., 2014; Youssef, 2011; Biro *et al*., 2014).
The monitoring of changes in land use requires the predictability of urban modelling. In order to improve the representation of the dynamic process, the different modifications of the Markov chain model (MCM) (Tang et al., 2007), multi-criteria analysis (Myagmartseren et al., 2017; Gantumur et al., 2017), statistical model (Landis, 2001), and ANN (Almeida *et al*., 2008; Li & Yeh, 2002; Wang & Mountrakis, 2011; Yeh & Li, 2003 Thapa & Murayama, 2009) develops predictive models. Most of these models predict changes in the surface, based on biophysical and socioeconomic factors affecting previous and adjacent neighboring regions and territories. The dynamic process consists of several non-linear interactions between geographical locations, land use, transportation, population, economy, and long-term policies. These non-linear links can be solved by modelling Artificial neural networks (ANN) (Yeh and Li, 2003; Almeida *et al*., 2008; Khoi & Murayama, 2011).

2. METHOD

Erdenet city is one of the main economic pillars of Mongolia and primarily was founded for the fourth largest copper mine industry in the world. Erdenet city is located in the northern part of the country with the arid climate conditions of the forest-steppe region.
The main aims of the study are (i) land use and land cover change detection; (ii) simulation of urban expansion in different scenarios; (iii) provision of reference information for urban planning and land development.
During the last 30 years, the population of Erdenet city has increased greatly, with the rapid expansion of the city and land use change. Land cover/ use images taken from the satellite have become important for understanding the effects of natural resources uses over time. Using geographic information systems (GIS) and remote sensing technologies is a great help to research data and support on different policy levels. Within the framework of this study, Erdenet city's 1996, 2006 and 2016 land use maps were processed based on remote sensing information. Landsat imageries (Landsat TM 5, Landsat ETM 7 and Landsat OLI 8) of 1996, 2006 and 2016 were used to derive land use map.
For the classification of Landsat image, a supervised classification method was used. At the end of the classification, we identified the land use and land cover of 13 classes: forest, mixed land use, slum area, residential, industrial, water, mining, administrative and business, airport, cropland, railway, road, and open space.
The land use map of 1996, 2006 and 2016's was classified and the land-use change was detected in the MCM. The MCM is used to modelling the land use and land cover changes, sizes, and trends (Muller & Middleton 1994; López *et al*., 2001; Weng, 2002; Jianping *et al*., 2005; Coppedge *et al*., 2007; Dadhich & Hanaoka, 2011; Sang *et al*., 2011). MCM for land-use changes can be shifted from probable transition to a different situation over time (Coppedge *et al*., 2007). Also, the probability of transition can be used to predict future land use and urban expansion patterns (Muller & Middleton, 1994; Dadhich & Hanaoka *et al*., 2011). Based on the land use map of 1996, 2006 and 2016, an analysis of the land use and land cover changes in Erdenet city were determined by using the MCM from 1996 to 2006 and 2006 to 2016. Transition probability and transition matrix for land-use change were taken in 10 years (Formula 1).

$$S(t+1) = P_{ij} * S(t) \text{ and} \rightarrow$$

$$\text{and} \rightarrow P_{(ij)} = \begin{pmatrix} P_{11} & P_{12} & P_{1n} \\ P_{21} & P_{22} & P_{2n} \\ P_{n1} & P_{n2} & P_{nn} \end{pmatrix} \text{and } (0 \le P_{ij} < 1 \text{ ба } \sum_{j+1}^{N} P_{ij} = 1, (i,j = 1,2,\ldots\ldots n)) \quad (1)$$

Where S_t is the state of land use in initial time t; S_{t+1} is the state of land use in next time t+1; P_{ij} is the transition probability matrix in a state.

Clark Lab's (Clark University) IDRISI software's Land change modeler module had been used for the urban expansion prediction. The Land change modeler module was developed by the Multilayer perceptron neural network (MLPNN) with the MCM (Eastman, 2009).
ANN model for land-use change has never been used in our country and it was first introduced in the case of Erdenet city. Therefore, owing to lack of practice we are adopted ANN method of previous study. The ANN method of the study had been adopted from Thapa and Murayama (2009) for the urban expansion of the Kathmandu valley of Nepal.
The ANN is a mathematical model based on biological neural networks. It is a Multilayer perceptron (MLP) associated with the nervous system (a pixel/cell of raster image) and is processed through the neural networks using the backpropagation algorithm. The neural network usually consists of one input layer, one output layer, one or more

hidden layers. The consecutive layers of these units will connect each raster cell (neuron) to the next network. The connection is responsible for transmitting the information through the network, and it is determined by the weight that can be either positive or negative by default (Almeida *et al*., 2008; Yeh & Li, 2003). During the model performance, each sample (for example, a pixel related to raster layer) is weighted in the input layer and the receptor cells summarize all cells from the previous level. In general, the inputs of a node are weighed as follows:

$$Net_j = \sum_{j-1}^{m} w_{ij} O_j \rightarrow O_j = F(net_j) \quad (2)$$

Where W is the weight between points i and j, and Oj is the output signal from the node. F function is usually a non-linear sigmoid function and it is used for the integer sum.

3. RESULT

In this study Landsat imageries (Landsat TM 5, Landsat ETM 7 and Landsat OLI 8) of 1996, 2006 and 2016 have been used to mapping land use and land cover. Compared to the expansion of built-up areas between 1996 and 2016, the city's open space and vicinity's cropland areas have been rapidly diminished. Built-up land use as the main demand for socio-economic growth has increased by 2317 hectares and it is expected to increase further. However, expansion of the urban area is expanded by the slum district area, which is gradually increasing as well as high and medium-rise built-up area is expected to growth.

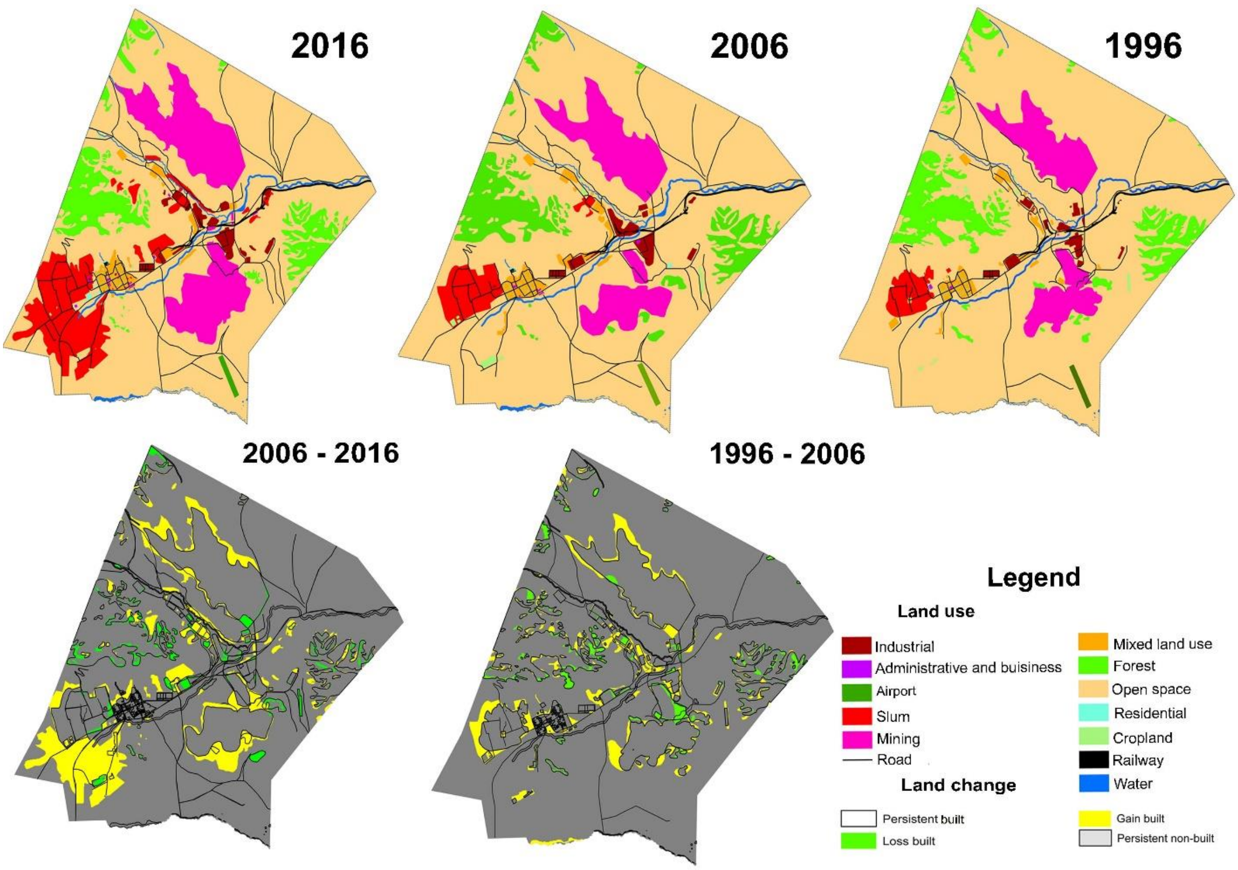

Figure 1. Land use and land use changes of the Erdenet city.
The illustration had been adopted from Thapa and Murayama (2009), Source: Landsat images (http://landsat.usgs.org/landsat-data-access) had been processed by authors

Selecting the best fit between the empirical data and the reality of variables describing the expansion of the urban area is an important part of the artificial neural network. After calculating the transition state of existing land, different interpreting variables have been defined to regulate changes in the study area (Figure 2). These eight maps were based on land changes from 1996 to 2006 and from 2006 to 2016. Two maps of land-use changes (1996-2006, 2006-2016) and eight describing variables were used to create the predicted land use map of 2026, 2036 and 2046. ANN develops a multi-layer function that predicts the transition potential, based on values in any location for eight interpretative variables. MLPNN has reached 81.2% at an accuracy level of 10.000 replications, which exceeded the accepted accuracy. The land use map of 2016 has been modeled and the results are used to verify the model compared with the existing Erdenet city's Land Department onsite surveyed land use map of 2016. Modelling is considered if the validation is less than 75%, the model should be reprocessed (Lillesand & Kiefer, 1994). When overlapped the modeled land use map of 2016 with the existing onsite map, the Kappa index was 81.2%, with is satisfactory accurate.

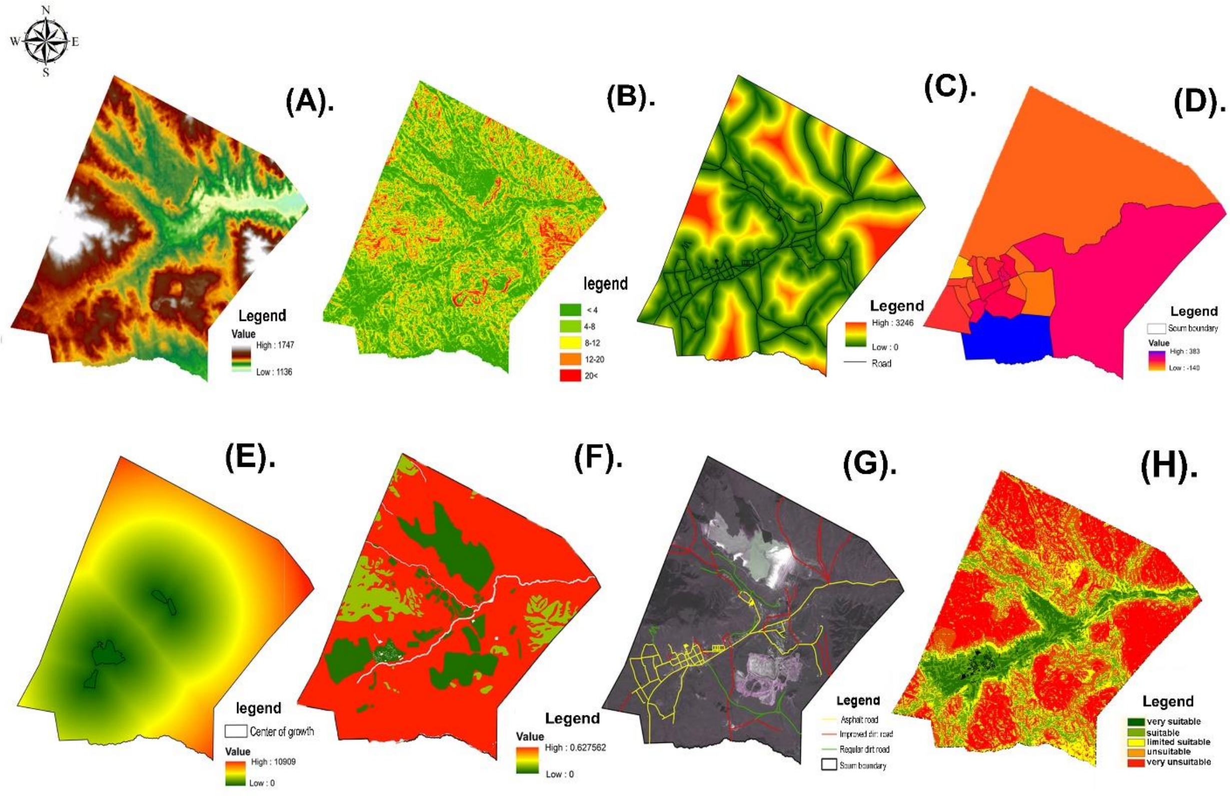

Figure 2. Variables describing the distribution of urban expansion:
(A) Digital elevation model (DEM); Slope (B); Distance from the road (C); The annual population growth rate (D); The distance from the growth center (E); Potential areas of transition(F); Road (G) and Suitable land (H).
Source: GDEM 30 m http://asterweb.jpl.nasa.gov/gdem.asp; Cadastral map and time series land use planning data of Land Administration Department of the Erdenet City.

The study proposes three scenarios (Thapa and Murayama, 2009) for future spatial alternatives in Erdenet city. These include: Spontaneous scenario (SS), Environment-protecting scenario (EPS), Resources-saving scenario (RSS) (Thapa and Murayama, 2009).

The SS is based on the historical trend of land change and allows unlimited expansion of the urban area without any interaction and restrictions further. The EPS considers environmental issues in the distribution of urban expansion. Like as developing cities, Erdenet city faces grave environmental and ecological challenges. This challenge represents rapid population growth and socio-economic development. Urban expansion with insufficient land management and infrastructure, inappropriate expansion of slum districts, waste of mining industry, air, water, and soil pollution have a significant impact on the environment. Therefore, from the city master plan's spatial measurements included in EPS, which will optimize spatial expansion. To process this scenario, the map of constraints was developed using the land use map of 2016, GDEM 30 m, environmental protection zone areas from the master plan of the city. Whereas included biodiversity habitat protection zones, forest regeneration strip, river and riparian buffer, special protected areas, railway buffer, and places more than 25 degrees steep slopes. It is important to save an environmental and economic resource and to develop sustainable future like as an RSS, for it the protected areas defined in the environmental protection documents to alter urbanization are comprised. It is difficult to determine the boundaries of elevated and steep slopes in each patch of land use. The height and slope values are 2000 m and 30 degrees or more are included in the scenario as a constraint. Also, restriction zones haltering urbanization and natural resource reservation zones from the master plan of the city had been included.

The impacts of land-use change of three scenarios are different, but for the entire period, urban expansion rates are likely to increase. Land use transition into urban areas has similar changes in environmental protection and resources-saving scenarios, while spontaneous expansion is significantly different from others. By spontaneous scenarios of

2046, open space and unused area will be gradually reduced by built-up areas (Figure 3). The land-use change in the north-east and northwest area is estimated to have the largest expansion in comparison with other locations.

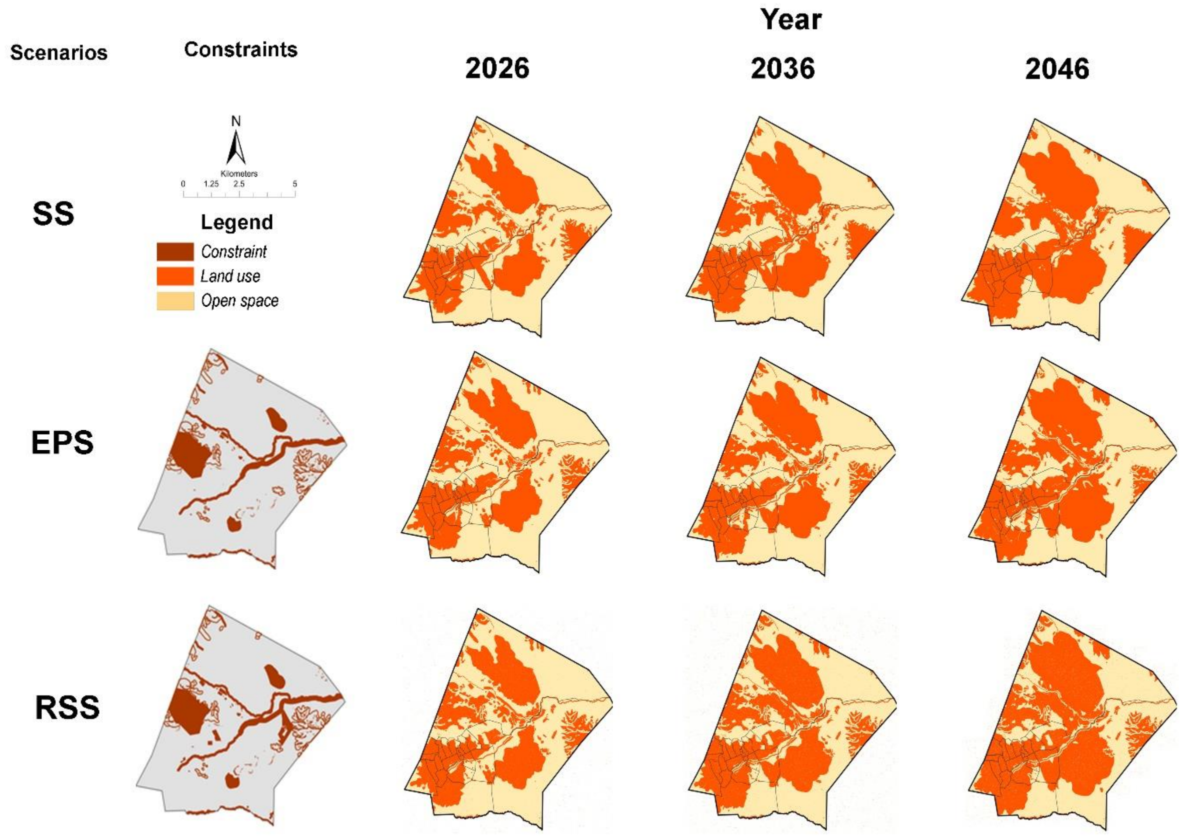

Figure 3. Future spatial trends of the Erdenet city.
The illustration had been adopted from Thapa and Murayama (2009)

Although, the rate of urbanization will increase at all predicted times, in each type of urban land use more and less controversial to an agriculture, environment and open space. Residential land-use transition in suburban areas have similar none changes in EPS and RSS, while in the spontaneous expansion it is rapidly enlarged in all three-time period (table 1). Also, the mining waste area is significantly increasing both in EPS and RSS.

Table 1. The future trend of land use (ha)

Land use type	2026			2036			2046		
	RSS	EPS	SS	RSS	EPS	SS	RSS	EPS	SS
Open space	16785	16732	16319	14328	15136	15074	14328	13538	13372
Slum district	3512	3574	3657	4785	4625	4507	4785	5681	5495
Mixed use	505	463	446	508.73	414.63	435	508	362	423
Forest	2340	2095	2052	2484	1991	1903	2484	1887	1754
Water	356	351	357	348	356	357	348	356	357
Cropland	10	8.3	7.2	10.2	6.4	4.3	10	5	1.2
Mining	4419	4381	4425	5151	5081	5170	5151	5779	5914
Industrial	507	509	521	505	510	641	504	510	762
Residential	36	36	50	36	36	64	36	36	78

4. CONCLUSION

Modelling urban land use change and optimization of future expansion has been the main goal of urban planners for many years. In order to understand past development processes and future growth trends, this study has been tested the urban expansion model, based on ANN and predicted future land use spatial distribution of the Erdenet city. The ANN is suitable for modelling the complex and nonlinear variables of the urban land-use changes. ANN model for land-use change study was first introduced in Mongolia and due to lack of practice, the method of the study had been adopted from Thapa and Murayama (2009). Three scenarios (SS, EPS and RSS) have been developed to predicting the spatial expansion trend of the Erdenet city. Hopefully, these land use changes predictions and proposed alternatives will be the baseline information of Erdenet city development policy, environmental protection long-term strategy, and urban plans. The model has the advantage of providing planners with important information about future land use and distribution: where and how to develop urban development. The model variation scenarios will provide the stakeholder's decision support options of the urban expansion process by 2046 and will give important information for spatially enabled decision making. Accuracy assessment and model performance of MCM with ANN model has successful performance result and can be further used in other urban areas of Mongolia.

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