

Modelling the Drivers of Urban Densification to Evaluate Built-up Areas Extension: A Data-Modelling Solution Towards Zero Net Land Take

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Abstract. The impact of urbanization is determined by the amount of land taken and the intensity with which it is used, such as soil sealing and population density. Land take can be referred to the loss of agricultural, forest, and other semi-natural and natural land to urban and other artificial land development. It is closely linked to urban expansion. City centers play an important role to curb such land take issues in allocating the growing population through urban densification. In order to assess how built-up, environmental, and socio-economic factors impacts zero net land take, this paper aims at using Multinomial regression model (MLR) to evaluate the built-up densification. This model is built, calibrated, and validated for the area of Brussels Capital region and its peripheral Brabant's using cadastral data. Three 100 × 100 m built-up maps are created for 2000, 2010 and 2020 where the map for 1990–2000 were used for calibration and was further validated using 2000–2010 maps. The causative factors are calibrated using MLR and validated using ROC curve and goodness of fit. The results show that areas at closer periphery of the city center with high densities have high probability for allocating further growth as they provide a broad range of facilities and local services along with an established connectivity infrastructure. This can be observed as a pragmatic solution for the policy makers and urban planners to achieve the intended policy of "zero net land take".

Keywords: Urban densification · Multinomial logistic regression · Zero land take

1 Introduction

In the recent few years, there has been an exponential growth in the demand of developed land worldwide [1, 7]. The prime reason for this demand is due to the urban lifestyle that require more space per capita for residential use, and the increased competition between municipalities to attract new developments for economic gain [14]. From the standpoint of sustainability, these demands affect the preservation of growth potential for future generations, thus enhancing problems related to urbanization [8]. While urbanization

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causes economic growth and increase in real estate pricing, the underlying problem of urbanization lies within housing shortages to accommodate a growing population [3]. This increase in housing density can influence land take and other related problem such as soil quality, land degradation and citizen's social experience [5].

Land take is defined as "the loss of agricultural, forest, and other semi-natural and natural land to urban and other man-made land development" [6]. The concept behind the EU "No net land take 2050" relates land take as the balance between taken and recultivated lands. The rate of rise in land take is substantially quicker than the rate of increase in population [10]. Land take is influenced by a variety of factors, including demography, socio-economic development, and environmental factors (Fig. 1).

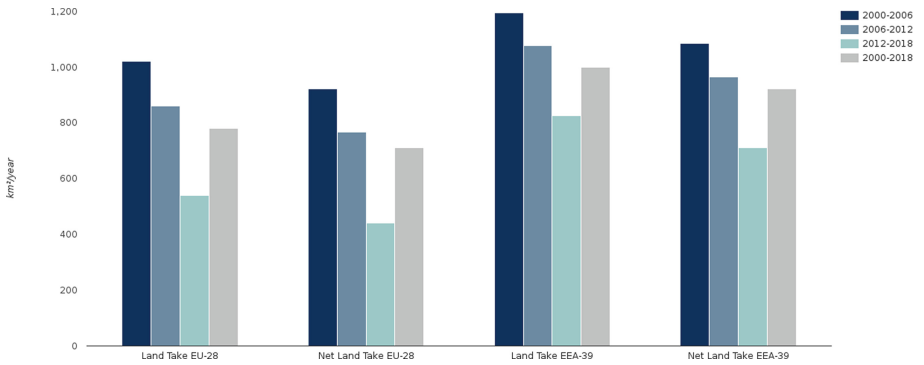

Fig. 1. Area of land take and net land take for all Corine Land Cover observation periods between 2000–2018 for the EU-28 and EEA-39 regions (Source: EEA, Europa)

In Europe, cities are becoming less dense, thus facing slower urban redevelopment and regeneration. In addition, land take can be related to urban sprawl either in the form of low density or dispersed development [13]. Land take also occurs outside of urban and peri-urban areas, thus developing high fragmentation [16]. A better understanding of underlying mechanisms of land take can be associated with urban densification [15] to aide in the EU28 "No net land take 2050" program.

The objective of this paper is to evaluate the drivers of urban densification can be viewed as a strategy for increasing the efficiency of utilizing natural resources while also bringing out a more efficient use of the city core. A multinomial logistic regression (MNL) was employed to explore the relationship between land take and densification.

2 Materials and Methods

2.1 Study Area

The selected study area (Fig. 2) comprises of Capital region of Brussels, Vlaams Brabant and Walloon Brabant. This area has been selected for its high geographical and political importance. It covers an area of 3376 km^2 which is 11% of total area of Belgium. To present an idea of the study area, Brussels Capital region is a highly clustered area with

population of 2,109,631 which has grown almost by 0.78% within a span of five years. On the other hand, the area of Walloon Brabant comprises of a small cluster of urban cores with mostly peri urban landscapes. According to EEA report on Urban sprawls, Belgium is one of the two greatest hubs of urban sprawl with a weighted urban proliferation index greater than 6 (Urban permeation unit) UPU/m^2 [6]. This is because of the mixed landscape of dense urban core towards the north especially in Flanders and highly fragmented rural area in the south in Wallonia. Thus, urban sprawl limits the scope for more sustainable land use as it follows a ribbon and scattered pattern both in Flanders and Wallonia. In this context, densification policies are important to limit the increasing land take off and strategi the urban sprawl in an effective and sustainable way [5].

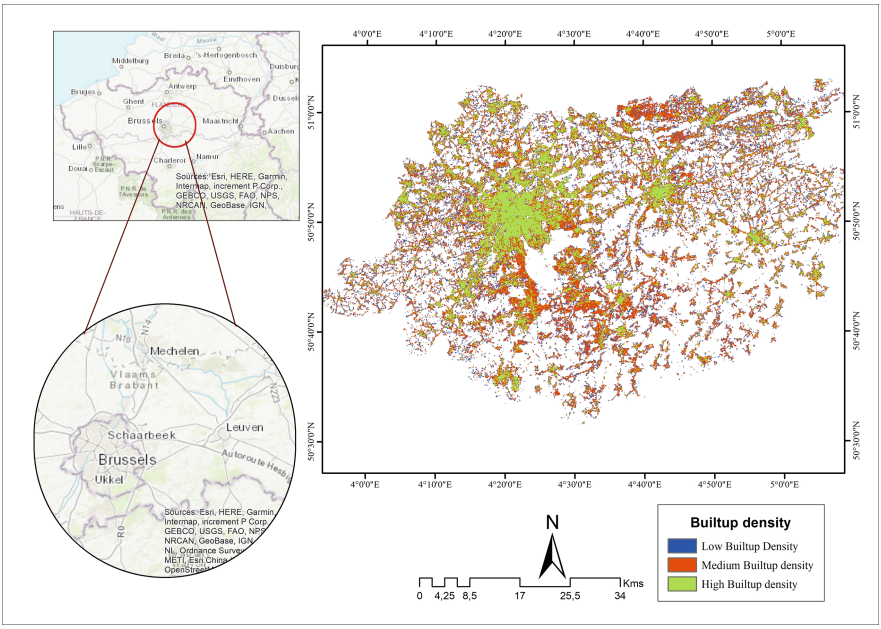

Fig. 2. Study area

2.2 Framework of Multinomial Logistic Regression (MLR) Model

A MLR model have been employed to analyze the impact of the controlling factors that impact the urban expansion and densification of our study area. While working with MLR model the two most important aspects considered were 1. The dependent variable ($\boldsymbol{Y}$) 2. The independent variables ($\boldsymbol{X}$). Initially the dependent variables were considered as categorial having a natural ordering between them (low-high). However, the chi square test statistic is <0.001 which establish that the supposition of natural ordering of the dependent variable remain unsatisfied. Therefore, a MLR model has been implied considering that the dependent variable as multi-nominal. The general formula of MLR model is

$$\mathrm{Log}(k_n) = \alpha_{k_1} + \beta_{\mathrm{k}_{11}} X_1 + \beta_{k_{12}} X_2 + \ldots + \beta_{\mathrm{k}_{1v}} X_v$$

where $log(k_n)$ is the natural logarithm of class k_n, X is a set of explanatory variables (X_1, X_2.....X_v), α_{kn} is the intercept term for class k_n, and β is the slopes for classes.

2.3 Dependent Variable

The Cadastral Data (CAD) by Belgian Land registry has been used as the dependent variable for the model. Cadastral data provides information of parcels and plots and is widely used for fiscal purposes. CAD data is mainly a vector data consisting of spatial information about plots and parcels of a geographical area. Each building has its own set of attributes, the most crucial of which is the "construction year" for our purposes. Three raster maps, also called built-up maps in this context were created using the construction year for 2000, 2010 and 2020. These maps were rasterized into 2 * 2 m cell for obtaining a fine resolution raster image. Due to high computational time of 2 * 2 m cell, the images were further aggregated at 100 * 100 m raster. This cell size has been chosen as it is the best combination of aggregation and sensitivity analysis of Moran's I [11] are commonly used for Landuse modelling at regional level [12].

Each class contains the density values of 2 * 2 m cell. A threshold of 25 m^2 in aggregated raster was determined to consider a cell as built-up. Each aggregated cell value $<$ 25 m^2 were considered as non-built up because this threshold corresponds to an average residential building in Belgium [17].The aggregated raster was classified based on density values into four classes (Table 1) using geometric interval classification method which is useful for highly skewed data which are do not follow a normal distribution [2].

Table 1. Built-up density classes range in number of 2 × 2 cells (% of 100 × 100 cell area)

Class	Minimum	Maximum
Class-0 (non builtup)	0	24 (1)
Class-1 (low builtup density)	25	117 (5)
Class-2 (medium builtup density)	118	541 (22)
Class-3 (high builtup density)	542	2500 (100)

A built-up transition matrix has been represented for the four density classes over the two modelled period. Table 2 suggests that transition from low to medium density areas are mostly predominant across both the year, which shows that there is a tendency of significant urban sprawl present in majority of new development. This can lead to proliferation in land take resulting in urban fragmentation. On the other hand, transition from low to medium is peripheral in nature, which is why the transition from class 0 to class 1, 2 and 3 is considered as expansion while transition from class 1–2 and class 2–3 is considered as densification.

Table 2. Class-to-class changes (% of total changes)

2000–2010	Class-0	Class-1	Class-2	Class-3
Class-0	401504 (99.25%)	–	–	–
Class-1	1478(0.37%)	27418 (91.36%)	–	–
Class-2	1149(0.28%)	2424 (8.08%)	63257 (94.95%)	–
Class-3	416(0.10%)	170 (0.57%)	3363 (5.05%)	30261
2010–2020	Class-0	Class-1	Class-2	Class-3
Class-0	399288 (99.45%)	–	–	–
Class-1	1030 (0.26%)	27197 (94.12%)	–	–
Class-2	860 (0.21%)	1551 (5.37%)	64095 (95.91%)	–
Class-3	326 (0.08%)	148 (0.51%)	2735 (4.09%)	34210

2.4 Drivers Controlling Built up Extension: Independent Variable

Primarily thirty-six (36) literatures have been considered out of many for selecting the drivers that impact the urban built up extension largely on combination of major factors: a) Relevant literatures with most common factors controlling changes under European context, b) Combination of various drivers with high impact on built up development under different territorial scenarios. However, to avoid multicollinearity a VIF (Variance Inflation factor) test has been conducted (Fig. 3) as otherwise the model exhibit bias result making it statistically irrelevant.

Hereto a total of eighteen (18) drivers has been selected under four categories of (i) accessibility factors, (ii) geophysical factors, (iii) environmental, and (iv) socio-economic factors. Accessibility was measured by Euclidian distance from Highways,

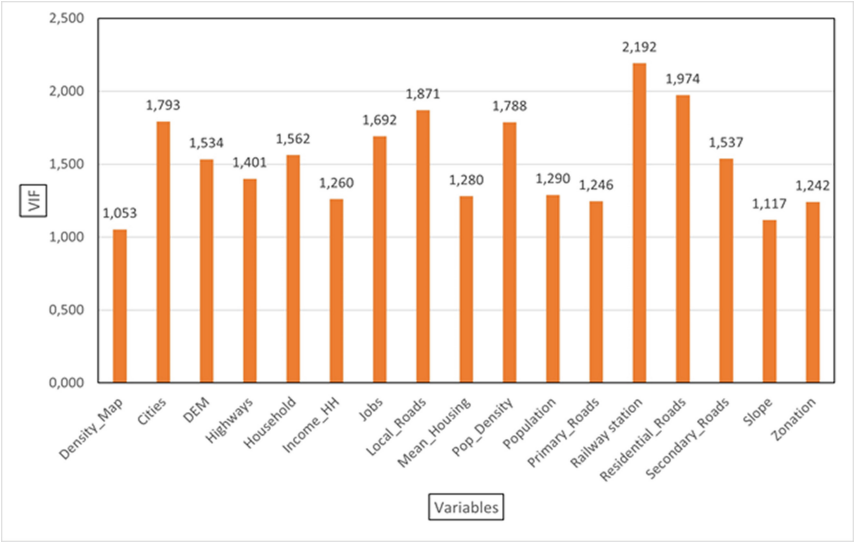

Fig. 3. Variance Inflation factors for all the driving factors

Primary roads, secondary roads, residential and local roads which were obtained from open street maps. Euclidian distance from cities considers the two major urban cores of Brussels and Leuven along with few minor cities. Another important driver that has been considered was distance to railway stations. The locations of the railways station were obtained from Open Street maps.

Digital Elevation Model (DEM) was provided by Belgian National Institute and was used to calculate the slope in percentages. Euclidean distances were also calculated for parks, natural reserves which will facilitate us to understand the role of environment in impacting Built up land take extensions. Statistical data was obtained from Statbel in delimited text format and mapped to raster images with a resolution of 100 × 100 m. These included number of jobs, Income household, Mean number of housings, total number of populations (Table 3).

Table 3. List of selected driving factors

Factor	Name	Type	Unit	Source
X_1	Elevation (DEM)	Continuous	Meter	Belgian National Geographic institute
X_2	Slope	Continuous	Percent Rise	Own calculation based on DEM
X_3	Dist. to highways	Continuous	Meter	OpenStreet maps
X_4	Dist. to primary roads	Continuous	Meter	OpenStreet maps
X_5	Dist. to secondary roads	Continuous	Meter	OpenStreet maps
X_6	Dist. to residential roads	Continuous	Meter	OpenStreet maps
X_7	Dist. to local roads	Continuous	Meter	OpenStreet maps
X_8	Dist. to cities	Continuous	Meter	OpenStreet maps
X_9	Dist. to parks	Continuous	Meter	OpenStreet maps
X_{10}	Dist. to reserves	Continuous	Meter	OpenStreet maps
X_{11}	Dist. to station	Continuous	Meter	OpenStreet maps
X_{12}	Household	Continuous	Number	Statbel
X_{13}	Income household	Continuous	Number	Statbel
X_{14}	Jobs	Continuous	Number	Statbel
X_{15}	Mean housing	Continuous	Number	Statbel
X_{16}	Population density	Continuous	Number	Statbel
X_{17}	Population	Continuous	Number	Statbel
X_{18}	Zoning	Categorical	Binary	SPW (Walloon Brabant), Geopunt (Flemish Brabant), perspective Brussels (Brussels Capital Region

2.5 Validation of MNL Model

Receiver operating characteristic (ROC) curve was used to validate the model performance. It compares the probability values produced from MNLto a reference values of urban cells in each class. Plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) yielded the ROC curve (FPR). The ROC values are 0.5 (totally random) and 1 (perfect fit).

3 Result and Discussion

The impact of different drivers on expansion and densification process have been presented through Table 4 and 5, respectively. The odds ratio (OR) which equals exponential B has been derived from the model to show the relative measurement of contribution of each driver. An OR >1 shows a positive impact of development with an increasing probability, whereas OR <1 designates towards a negative impact.

Land development is more difficult due to elevation and slope. There is a negative relationship between slope and elevation for low and medium density expansion. As in densification process, the slopes OR value <1 signifies that built up areas in rugged terrains are more dispersed than in flatter areas. In both periods, Distance to natural amenities, parks and reserves shows a positive impact on densification as well as expansion. This is in line with the findings of [18] suggesting that natural amenities can encourage highly dispersed settlements, thus affecting global net land take through spatial segregation.

Transportation infrastructure can be seen as a form of land take as it not only takes up space but also support housing and commercial activities. All significant drivers related to road class has an OR <1 thus suggesting that probability of urban development is higher for locations such as highways, roads, stations, and urban centers. Distance to highways and secondary roads negatively contributes to all densification process. Other distance related factor, i.e., distance to residential roads contributed positively to the densification of medium to high density areas in 2010–2020, thus deeming towards higher land take.

Expansion highly corelated with zoning status., which is in line with [11]. In both the periods there is a gradual upward trend from low to medium and medium to high density areas. Land use planning are one of the most common instruments to explain land take. This suggests that zonation policies can directly affect land take, for ex strong zonation policies can result in fragmentation of non-urban area. Planning regulations favor excessive land take by means of low-density zoning which can be seen through Table 4. It suggests that during the period of 2000–2010, the expansion of low density was 23 times likely to be in the zones designated for urban use. Conversely, the effect of zoning status in densification from medium to high densities are non-significant. This can help in limiting the impervious surface of land take and thus decreasing fragmentation.

Table 4. The coefficients (β) of the MNL model for urban expansion (reference: class-0). Sample size 31000

	2000–2010			2010–2020		
	Coefficients β (odds ratio)			Coefficients β (odds ratio)		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
DEM	−0.086* (0.918)	−0.257* (0.774)	−0.207* (0.813)	−0.153* (0.858)	−0.284* (0.753)	−0.380* (0.684)
Slope	−0.020 (1.020)	−0.013* (0.987)	−0.110* (0.896)	−0.005 (0.995)	−0.060* (0.941)	−0.148* (0.862)
Dist. to highways	0.032 (1.032)	−0.041 (0.960)	−0.287* (0.751)	0.027 (1.028)	−0.010 (0.990)	−0.081 (0.992)
Dist. to primary roads	−0.010 (0.990)	−0.048* (0.953)	−0.091 (0.913)	−0.002 (0.998)	−0.021 (0.979)	0.015 (1.015)
Dist. to secondary roads	0.064* (1.066)	−0.023 (0.978)	−0.153* (0.858)	0.050* (1.051)	0.020 (1.021)	−0.277* (0.758)
Dist. to residential roads	−0.038 (0.963)	0.002 (1.002)	0.043 (1.043)	−0.069* (0.933)	−0.149* (0.862)	0.067 (1.070)
Dist. to local roads	−0.028 (0.973)	−0.018 (0.982)	−0.070 (0.932)	0.019 (1.019)	0.057* (1.058)	0.057 (1.058)
Dist. to cities	0.102* (1.107)	0.093* (1.098)	−0.021 (0.979)	0.054* (1.055)	0.066* (1.068)	0.089 (1.093)
Dist. to parks	0.000 (1.000)	−0.010 (0.990)	0.017 (1.017)	0.004 (1.004)	−0.050* (0.951)	−0.057 (0.945)
Dist. to reserves	−0.069* (1.072)	0.141* (1.152)	0.163* (1.177)	0.108* (1.114)	−0.212* (1.236)	−0.272* (1.313)
Dist. to stations	0.029 (1.029)	−0.013 (0.988)	−0.553* (0.575)	0.048* (1.049)	0.087* (1.091)	−0.313* (0.731)
Household	0.125* (1.133)	0.057* (1.058)	−0.408* (0.665)	−0.041* (0.960)	0.013* (1.013)	0.115* (1.121)
Income household	0.130* (1.139)	−0.036 (0.964)	−0.434* (0.648)	0.114* (1.121)	−0.117* (0.889)	−0.313* (0.731)
Jobs	−0.081* (0.922)	0.006 (1.006)	0.080 (1.083)	−0.041* (0.960)	0.013* (1.013)	0.115* (1.121)
Mean housing	−0.038 (0.963)	−2.042* (0.130)	−0.013 (0.987)	−0.821* (0.440)	−1,719* (0.179)	−7.201* (0.001)
Population density	−0.139 (0.871)	0.001 (1.001)	0.093* (1.098)	−0.098* (0.907)	−0.004 (0.996)	−0.026* (0.974)
Population	0.05 (1.005)	−0.123 (0.974)	−0.056 (0.945)	−0.009 (0.991)	−0.020 (0.980)	0.031 (1.032)
Zoning	3.174 (23.903)	2.639 (13.999)	3.518 (33.717)	2.344 (10.423)	2.644 (14.069)	3.174 (23.903)
ROC	**0.668**	**0.676**	**0.794**	**0.665**	**0.684**	**0.745**

* Indicate significance at $P \leq 0.05$ level

The ROC for medium to high densification process produced the best performing descriptive for the both the periods. Estimation of the potential urban expansion produced many false positives, which were estimated at ROC values 0.66–0.79. This implies that the driving factors used in this study were statistically significant for urban densification process.

Table 5. The coefficients (β) of the MNL model for urban densification

	2000–2010		2010–2020	
	Coefficients β (odds ratio)		Coefficients β (odds ratio)	
	Reference: class 1 Sample Size: 22300	Reference: class 2 Sample size: 18000	Reference: class 1 Sample Size: 22300	Reference: class 2 Sample size: 18000
	Class 2	Class 3	Class 2	Class 3
DEM	−0.203* (0.816)	−0.068 (1.070)	−0.133 * (0.875)	−0.075 (0.928)
Slope	−0.086* (0.917)	0.003 (1.003)	−0.046* (0.955)	−0.065 (0.937)
Dist. to highways	−0.016 (0.537)	−0.107 (0.898)	−0.059 * (0.943)	0.015 (1.015)
Dist. to primary roads	−0.031 (0.970)	−0.002 (0.998)	0.002 (1.002)	−0.012 (0.989)
Dist. to secondary roads	−0.109 * (0.897)	−0.040 (0.960)	−0.013 (0.987)	−0.408* (0.665)
Dist. to residential roads	0.074 (1.077)	0.081 (1.085)	−0.048 (0.953)	0.327* (1.387)
Dist. to local roads	−0.041 (0.960)	−0.120 (0.887)	0.008 (1.008)	−0.001 (0.999)
Dist. to cities	−0.012 (0.988)	−0.035 (0.641)	−0.003 (1.003)	−0.065 (0.937)
Dist. to parks	−0.055 (0.947)	−0.106 (0.900)	−0.082* (0.922)	0.075 (1.078)
Dist. to reserves	−0.129 * (1.138)	−0.050 (0.952)	0.124 * (1.132)	0.053 (1.054)
Dist. to stations	−0.018 (0.982)	−0.596 * (0.551)	0.003 (1.00	−0.198 (0.821) *
Household	−0.070* (0.932)	−0.279 * (0.757)	−0.043** (0.958)	−0.169 (0.845)
Income household	−0.172* (0.842)	0.225 * (1.252)	−0.233 * (0.792)	−0.333* (1,395)

(*continued*)

Table 5. (*continued*)

	2000–2010		2010–2020	
	Coefficients β (odds ratio)		Coefficients β (odds ratio)	
	Reference: class 1 Sample Size: 22300	Reference: class 2 Sample size: 18000	Reference: class 1 Sample Size: 22300	Reference: class 2 Sample size: 18000
	Class 2	Class 3	Class 2	Class 3
Jobs	0.075* (1.078)	0.096 (1.101)	0.049* (1.050)	0.179* (1.196)
Mean housing	−2.999* (0.050)	−0.333 (0.717)	−0.899 * (0.407)	0.161 (1.174)
Population density	0.110* (1.116)	0.096 (1.101)	0.064* (1.066)	−0.056 (0.946)
Population	−0.029 (0.952) *	−0.175 (0.840)	−0.004 (1.004)	0.001 (1.000)
Zoning	0.083 (1.087)	−0.018 (0.982)	−0.038 (1.039)	−0.064 (0.938)
ROC	**0.804**	**0.728**	0.828	**0.685**

* Indicate significance at $P \leq 0.05$ level

4 Conclusion

Jaeger and Schwick in 2014 suggested limiting urban sprawl through social action by introducing targets and regulate design of the use of landscape as a common property resource as a step to move towards No land take mission by 2050 [9]. In our study, Brussels Capital region, cities of Flemish and Walloon Brabant has been the area of interest presenting a cross border scenario with multiple governance. Dense urban core like Brussels and Leuven shows significant infill development over the years, while Wallonia is mainly dominated by urban sprawl. Most of the research considers sprawl as matter of concern. On the upside, densification can be seen as a workaround to these problems at multi-class level. Belgium has a land take of 104 km^2 [6] from 2012–2018 which is comparatively lesser than its neighboring countries like France and Germany, but it is counterintuitive while taking recultivation into account which is only 18%. Our study identified that drivers like zoning, distance to roads, natural amenities and geophysical features play a significant role in expansion process. Thus, it can be recommended from the study that robust regional policies and effective planning method will complement a national policy, providing a progressive shift towards no land take strategy.

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