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Modélisation, simulation et analyse des dynamiques spatiales des zones humides urbaines par automate cellulaire : une étude de cas à la ville de Bogota, Colombie

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Modélisation, simulation et analyse des dynamiques spatiales des zones humides urbaines par automate cellulaire : une étude de cas à la ville de Bogota, Colombie

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Résumé

Les zones humides sont écosystèmes reconnus de vitale importance pour la conservation de la biodiversité et pour un développement soutenable. En Colombie, 26 % du territoire continental national est couvert de ces écosystèmes. Le complexe de zones humides urbaines de Bogota, en fait partie, avec 15 écosystèmes, dont la Convention Ramsar reconnaît 11. Ils sont uniques et jouent un rôle important dans l'approvisionnement des services écosystèmes à la zone urbaine. Cependant, ces écosystèmes urbains font face à de nombreux défis en raison de leur emplacement. Les causes et les conséquences de leur transformation sont très complexes. En appliquant des approches des systèmes complexes, sa dynamique de changement peut être étudiée. Les automates cellulaires sont l'une des techniques largement utilisées dans la modélisation de la dynamique spatiotemporelle des changements de l'usage et de l'occupation des sols. Cette étude propose l'analyse et la simulation des zones humides urbaines en appliquant une approche hybride par un modèle couplé de chaîne de Markov, de réseaux de neurones artificiels et d'automates cellulaires, afin d'estimer leurs changements d'étendue pour les années 2016, 2022, 2028 et 2034 dans la ville de Bogota, en Colombie. Pour extraire le changement d'occupation et d'utilisation du sol, trois images analogues des années 1998, 2004 et 2010 ont été a utilisées. Les résultats ont montré une diminution de 0,30 % de la couverture des zones humides en douze ans. De plus, les résultats suggèrent que la couverture des zones humides représentera 1,97 % de la zone d'étude totale en 2034, représentant une probabilité de diminution de 14 % en 24 ans. D'ailleurs, en appliquant l'analyse d'intensité, il a été constaté que le gain de cultures et de pâturages cible la perte de zones humides. Bien dont ces écosystèmes soient protégés et d'utilisation restreinte, leur patron de réduction se poursuivra en 2034. La pertinence de ce projet réside dans sa contribution potentielle au processus décisionnel au sein de la ville et en tant qu'instrument de gestion des ressources naturelles. En outre, les résultats de cette étude pourraient aider à atteindre l'objectif de développement durable 6 « Eau propre et assainissement » et l'atténuation du changement climatique.

Mots-clés : zones humides urbaines, systèmes complexes, automate cellulaire, réseaux de neurones artificiels, modélisation spatiotemporelle, changements de l'usage et de l'occupation des sols.

Abstract

Wetlands are ecosystems recognized as being of vital importance for the conservation of biodiversity and for sustainable development. In Colombia, 26% of the national continental territory is covered by these ecosystems. The complex of urban wetlands of Bogota is one of them, with 15 ecosystems, of which the Ramsar Convention recognizes 11. They are unique and play an important role in providing ecosystem services to the urban area. However, these urban ecosystems face many challenges due to their location. The causes and consequences of their transformation are very complex. By applying complex systems approaches, the dynamics of change can be studied. Cellular automata is one of the widely used techniques in modeling the spatiotemporal dynamics of land use and land cover changes. This study proposes the analysis and simulation of urban wetlands by applying a hybrid approach through a coupled model of the Markov chain, artificial neural networks, and cellular automata, in order to estimate the extent of changes for the years 2016, 2022, 2028, and 2034 in the city of Bogota, Colombia. To extract the change in land cover and land use, three analogous images from the years 1998, 2004, and 2010 were used. The results showed a 0.30% decrease in wetland coverage in twelve years. Furthermore, the results suggest that wetland cover will be 1.97% of the total study area in 2034, representing a 14% probability of a decrease in 24 years. Moreover, by applying the intensity analysis, it was found that the gain of crop and pastureland targets the loss of wetlands. Although these ecosystems are protected and of limited use, their pattern of reduction will continue in 2034. The relevance of this project lies in its potential contribution to decision-making within the city and as a natural resource management tool. In addition, the results of this study could help achieve Sustainable Development Goal 6 "Clean Water and Sanitation" and climate change mitigation.

Keywords: urban wetlands, complex systems, cellular automata, artificial neural network, spatiotemporal modeling, land use land cover changes.

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AC : automate cellulaire

AD : allocation disagreement

AI : aggregation index

ANN : artificial neural network

AUC : area under the curve

CA : cellular automata

CLUE : Conversion of Land Use and its Effects

CM : chaîne de Markov

COHESION : patch cohesion index

CONTAG : patch cohesion index

FLUS : Future Land Use Simulation

FoM : figure of merit

GIS : Geographic Information Systems

IA : Intelligence Artificielle

IDECA : Infraestructura de Datos Espaciales para el Distrito Capital

Klocation : Kappa location

Kno : Kappa for no ability

Kstandard :Kappa standard

LPI : largest patch index

LUCC : land use land cover change

m.a.s.l. : meters above sea level

MBA : modèles basés sur l'individu ou sur l'agent

MN : mean patch area

NP : number of patches

OA : overall accuracy

PA : producer's accuracy

PAFRAC : perimeter area fractal dimension

QD : quantity disagreement

RF : random forest

RNA : réseaux de neurones artificiels

ROC : receiver operating curve

SA : sensitivity analysis

SHAPE_AM : area weighted mean shape index

SIG : Systèmes d'Information Géographique

SVM : support vector machine

TE : total edge

WMS : Web Map Service

À mes grands-parents pour m'avoir appris à être indépendante et persévérante. « En fin de compte, la seule chose qu'ils ne peuvent pas t'enlever, c'est la connaissance. »

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Chapitre 1 - Introduction et fondements

1.1 Introduction

> La Savana de Bogota est une plaine entourée de montagnes dans la Cordillère orientale de Colombie (Amérique du Sud), qui a toujours été considérée comme le fond plat d'un ancien lac. Même les Indiens Chibcha, qui vivaient sur la Savana avant l'arrivée des Espagnols, ont une légende, selon laquelle la Savana était autrefois un lac. Cette légende raconte également que le héros Bochica, un Chibcha à la peau blanche, a ouvert un chemin vers les eaux de la Savana, qui se sont écoulées par la sortie actuelle de la cascade de Tequendama (van der Hammen et Gonzalez, 1960).

La relation entre l'homme et l'eau existe depuis des temps très anciens. À Bogota, en Colombie, des traces du système hydraulique des champs de culture surélevés ou camellones datant de l'époque préhispanique en témoignent (Rodríguez Gallo, 2019). Les rivières, les lagunes et les zones humides de l'époque constituaient un habitat favorable aux oiseaux, aux petits mammifères, aux mollusques et aux poissons d'eau douce, ainsi qu'aux activités agricoles, ressources dont les Muiscas tiraient parti comme source d'alimentation et d'activité économique. Cependant, depuis la colonisation, la synergie entre la communauté et son environnement s'est transformée, imposant non seulement de nouvelles façons de voir l'environnement, mais entraînant également l'altération du paysage. Au cours du siècle dernier, la dégradation de l'environnement s'est accélérée à Bogota. Une détérioration causée par la croissance démographique et le manque de conscience de leur environnement. Une détérioration causée par le manque de planification et la non-application de la législation visant à protéger les ressources naturelles, ainsi que par l'absence d'une vision claire des problèmes environnementaux et d'une analyse des causes, des relations et des effets à long terme (van der Hammen, 1998).

Le développement urbain de Bogota a généré un panorama critique pour les zones humides. L'intérêt de ces écosystèmes est fondé sur les services écosystémiques qu'ils génèrent, notamment la régulation des cycles de l'eau, la réduction de l'effet d'îlot de chaleur urbain, et le maintien de la biodiversité. Différentes études ont été développées autour de ces écosystèmes. L'une des plus importantes est l'étude réalisée par le scientifique Thomas van der Hammen, qui a conclu que les collines orientales, les zones humides et le fleuve Bogota devaient être bien identifiés et reliés biologiquement, formant ainsi une zone de réserve environnementale stratégique dans la ville (Van der Hammen, 2003). En outre, des études basées sur des méthodes géomatiques ont été réalisées afin d'identifier certaines des zones humides qui ont changé structurellement (Mayorga, 2016). Néanmoins, les interactions et les relations complexes des composantes environnementales qui déterminent la formation et la régulation de ces écosystèmes nécessitent l'application d'approches techniques pour détecter et analyser ses changements à travers les échelles spatiales dans les paysages urbains complexes. Les modèles de changement des terres utilisant des automates cellulaires (AC) sont de plus en plus utilisés pour explores la dynamique du changement des terres et sont considérés comme une base pour les décisions de politique publique visant à promouvoir la protection et la gestion de ces écosystèmes (Peng et al., 2020).

1.1.1 Questions de recherche

Les zones humides sont des solutions éprouvées fondées sur la nature pour la biodiversité, la santé et la lutte contre le changement climatique. Mais ils restent notre écosystème le plus menacé de la planète. Les écosystèmes urbains de Bogota ne font pas exception. Même si la politique des zones humides du district de la capitale colombienne a été établie en 2005 (Alcaldia Mayor de Bogota, 2005), ces écosystèmes ont continué d'être sujet à la dégradation anthropique. Alors, le rétrécissement continu des zones humides malgré l'existence de réglementations pour leur conservation rend impératif de poursuivre l'étude de ces écosystèmes en tant que système complexe composé des éléments sociaux et écologiques étroitement couplés. Cela nous conduit à répondre :

- Quelle est la dynamique de changement des zones humides de Bogota ?
- Quelle couverture déclenche la perte de couverture des zones humides ?
- Est-ce que l'application du modèle computationnelle qui applique la théorie des systèmes complexes peut être utile pour la mairie comme instrument de gestion des ressources naturelles ?

1.1.2 Objectifs de la recherche

Pour répondre aux questions précédentes, l'objectif général de cette recherche est d'étudier et de comprendre la dynamique de changement des zones humides urbaines de Bogota à travers de l'application d'un modèle dynamique qui permet de simuler les probabilités de changement d'étendue ou d'utilisation de ces zones. Le modèle hybride de chaîne Markov, les réseaux de neurones artificiels (RNA) et l'automate cellulaire, peut aider à décrire, à examiner, et à projeter comment les facteurs moteurs entraînent des changements dans la configuration des zones humides.

D'une part, il a fallu comprendre les caractéristiques et la dynamique des zones humides de Bogota. Dû à fait que ces écosystèmes s'agitent de systèmes complexes, il est important reconnaitre les éléments qui font partie du système, et ses interactions. Partant, il a fallu bien analyser les changements spatio-temporels et la configuration du paysage des zones humides quantitativement (K. Xu et al., 2010), à partir du traitement et interprétation des images satellites ou analogiques disponibles.

D'autre part, l'intégration de la chaîne Markov, du réseau de neurones artificiels, et l'automate cellulaire proposent une approche très robuste pour simuler les dynamiques des zones humides. La combinaison de ces techniques a rendu le modèle plus faisable pour simuler des changements complexes et à long terme dans l'utilisation des terres (Liang, Liu, Li, Zhao, et al., 2018b). Quant à l'automate cellulaire, il est pertinent pour modéliser et obtenir des probabilités des phénomènes spatiaux dynamiques (Green et Sadedin, 2005). Cette approche a été largement utilisée dans le domaine particulier de la géographie pour modéliser des dynamiques spatiales, telles que les changements de l'utilisation de la couverture du sol (Batty et Torrens, 2005; Liu et al., 2017; Tiné et al., 2019). Ce qui précède nous a conduits à établir les objectifs suivants :

- Évaluer les changements spatio-temporels du complexe de zones humides urbaines de Bogota, et identifier les facteurs qui ont conduit à ce changement dans le temps.
- Mettre en œuvre un modèle hybride afin de simuler les changements spatio-temporels des écosystèmes au cours des 20 prochaines années.

La dynamique spatiale et temporelle complexe observée dans les zones humides urbaines ont fait que les chercheurs utilisent des modèles computationnels pour les étudier et mieux les comprendre. La recherche proposée vise à simuler et étudier les changements dans les zones humides urbaines de Bogota, en Colombie depuis l'an 1998. Ce mémoire se divise en quatre chapitres. Le premier consiste en une revue de littérature qui présente des concepts clés qui couvrent la recherche à propos de la science de la couverture et de l'utilisation des sols, la théorie de la complexité, et les approches employées dans l'évaluation des changements des zones humides. Le deuxième et troisième chapitre présente deux articles scientifiques. Le premier article scientifique est une revue des méthodes qui ont été utilisées pour évaluer les performances des modèles, dans lesquels la zone d'étude a été utilisée comme étude de cas. Et le deuxième consiste en l'application d'un modèle basé sur une approche de modélisation de systèmes complexes, afin d'estimer changements d'étendue dans les zones humides pour les années 2016, 2022, 2028 et 2034 dans la ville de Bogota, en Colombie. Finalement, un quatrième chapitre présente les conclusions générales de cette recherche.

1.2 Fondements

Cette section vise à couvrir la revue de littérature dans laquelle est présenté une série des concepts clés pour la recherche proposée. Premièrement, la science du changement de la couverture et l'utilisation de la terre (LUCC en anglais) sera abordée. Ici sont décrits différents facteurs importants qui interviennent dans l'étude des dynamiques et changement de l'utilisation du sol. Ensuite, les approches qui ont été employées pour évaluer les changements des zones humides dans différents lieux du monde sont présentées. Suivi des principes de la théorie de la complexité, les techniques des systèmes complexes et statistiques utilisés pour modéliser et simuler les dynamiques et changements de l'utilisation du sol. Et finalement, les métriques employées dans la validation de modèles de changement de la couverture terrestre.

1.2.1 Dynamique du paysage

La dynamique du paysage fait référence à un processus d'évolution du paysage, retraçant la relation entre l'humanité et l'environnement naturel. En fait, son étude est liée à l'utilisation des terres et au changement de la couverture terrestre. Les études de dynamique du paysage intégrant les interactions homme-environnement et liées aux problèmes environnementaux sont devenues de plus en plus importantes. À savoir, la description et l'analyse de l'évolution du paysage à travers l'espace et le temps sont un élément fondamental de l'enquête géographique et de la recherche paysagère (Houet et al., 2010).

La dynamique naturelle du paysage est modifiée par divers facteurs moteurs du changement. Tels que la croissance démographique, les politiques économiques, et les facteurs moteurs locaux tels que les précipitations, la température et la fertilité des sols (X. Liu et al., 2017). En effet, la dynamique de l'utilisation des terres a été interprétée comme constituant une douzaine de processus. En particulier dans les zones tropicales, ces processus sont l'urbanisation, la conversion de terres, le changement de culture sur les terres cultivées existantes, l'utilisation intensive des terres cultivées, et l'incorporation du bétail dans les terres cultivées (Lambin et al., 2003).

1.2.2 Facteurs moteurs

Le changement d'affectation des terres est toujours causé par de multiples facteurs d'interaction provenant de différents niveaux d'organisation des systèmes couplés homme-environnement. Le mélange des forces motrices du changement d'affectation des terres varie dans le temps et dans l'espace, en fonction des conditions spécifiques de l'homme et de l'environnement. En ce qui concerne la recherche sur les facteurs du changement de la configuration des paysages des zones humides, les experts et les universitaires du monde entier conviennent généralement que l'influence des perturbations humaines est beaucoup plus élevée que l'évolution naturelle (Wu et al., 2019)**.**

L'urbanisation et le développement agricole ont été considérés comme les principales forces motrices affectant l'évolution spatio-temporelle du modèle paysager (Wu et al., 2019). Alors, le phénomène d'expansion urbaine a augmenté de façon exponentielle en raison de la croissance démographique, générant un impact environnemental considérable sur les écosystèmes entourant les établissements humains. La conversion des usages du sol des zones qui étaient auparavant des forêts, des savanes, des sols ruraux ou agricoles, vers les villes, laisses-en évidence le grand changement de l'occupation du sol et les nombreux effets sur les systèmes écologiques naturels.

Le LUCC intégré aux systèmes socio-écologiques conforme sous-systèmes qui interagit avec la couverture terrestre. Ainsi, le système d'occupation des sols est un système complexe, dynamique, qui change au fil de temps de façon non linéaire avec divers processus opérant à différentes échelles spatiales et temporelles (Wallentin et Neuwirth, 2017). Partant, les interactions à l'intérieur du système entraînent des rétroactions qui peuvent être positives ou négatives. D'une part, les politiques durables peuvent avoir des résultats positifs pour la conservation des zones. Mais, la croissance démographique sans politiques de contrôle peut entraîner une expansion urbaine sans contrôle et changer radicalement le LUCC. En revanche, les régimes de précipitations ou de températures peuvent produire une dynamique de compétence parmi les couvertures terrestres, ce qui les fait s'adapter. Ces rétroactions font émerger certaines hiérarchies dans la dynamique des couvertures.

La compétence et les interactions spatio-temporelles non linéaires entre les différents types de LUCC rendent complexe leur modélisation et simulation. Les complexités spatio-temporelles des LUCC peuvent être modélisées et simulées en intégrant différentes techniques telles que la télédétection, les Systèmes d'Information Géographique (SIG) (Li et Gar-On Yeh, 2010), et les techniques de systèmes complexes. Les SIG sont particulièrement utiles pour intégrer et superposer plusieurs ensembles de données d'utilisation du sol en tant qu'unité spatiale individuelle, qui peut faire l'objet d'une analyse spatiale pour l'évaluation et la détermination de la couverture et des modèles d'utilisation des terres. Néanmoins, les SIG maintiennent une vision intrinsèquement statique du monde et ne parviennent pas à capturer la dynamique du système réel (Dragićević, 2010). Les approches de systèmes complexes comme le « bottom-up » Automata Cellulaire (AC), et les techniques d'Intelligence Artificielle (IA) sont de plus en plus utilisées pour modéliser les systèmes environnementaux (Tiné et al., 2019).

Les sous-sections qui suivent donnent un aperçu des différentes approches de la modélisation des zones humides.

1.2.3 Modélisation des zones humides

Depuis les années 2000, la préoccupation pour les zones humides urbaines a gagné du terrain dans la recherche. Donc, les chercheurs ont commencé à analyser les changements dans le patron de paysage de zones humides urbaines et les mécanismes moteurs (Durand, 2007; Grayson et al., 1999; Hasse et Lathrop, 2003; Kuchay et al., 2014; Mondal et al., 2017; Potter et al., 2004; Wang et al., 2008). Cela a eu pour but améliorer la compréhension de l'évolution historique du processus, des causes et des changements récents de ces écosystèmes. Des travaux de terrain, des données de télédétection, des SIG et des techniques de systèmes complexes entre d'autres techniques ont été utilisés pour évaluer les changements dans ces écosystèmes.

Approches de télédétection et SIG

Les données résultantes de l'interprétation de photos aériennes intégrées avec les SIG ont été des premières techniques pour étudier les phénomènes de changement des zones humides (Williams et Lyon, 1997). Les données collectées à des résolutions plus fines, couplées avec des outils d'analyse d'images basés sur des objets, offrent la possibilité de développer des modèles qui représentent mieux les diverses caractéristiques des environnements bâtis et naturels (National Research Council, 2014).

À Wuhan, Kai Xu et al. (2010) ont analysé quantitativement l'évolution spatio-temporelle et la configuration du paysage, en référence aux indices de l'écologie du paysage de diversité, de fragmentation, de dominance, de forme et de dimension. Aussi, Jiang et al. (2012) ont analysé le patron des variations temporelles et spatiales des zones humides urbaines à Beijing entre les années 1986-2007. En utilisant d'arbres de décision, techniques de télédétection, et analyse de corrélation canonique, les auteurs ont classifié les zones humides urbaines, et ils ont trouvé les facteurs déterminants de changement de ces zones.

À partir des outils SIG est possible l'obtention d'une matrice dérivée d'une tabulation croisée qui aide à montrer les transferts interclasses de l'état entre les zones humides. En fait, la matrice de transition est utile pour aider à identifier les effets de succession et les distinguer sur le niveau d'eau. De plus, les SIG fournissent une méthode efficace de mesure des changements de terres humides historiques de classe basés sur des images aériennes ou satellites archivées (Williams et Lyon, 1997).

Pour déterminer les altérations que subissent aux zones humides urbaines de Bogota, la surveillance par l'utilisation de capteurs à distance et la comparaison entre les images générées, en effectuant une identification et une classification préalable de la couverture, a permis de détecter les causes particulières de ces événements et d'analyser au contraire les effets qui se sont produits au fil du temps (Fuentes Nieto et López Velandia, 2020).

Les analyses multitemporelles des images aériennes et des images satellites ont aidé à identifier les changements d'étendue des couvertures. Aux zones humides du sud-ouest de la ville comme La Vaca, Techo et Burro les pertes en étendue ont été dues au fort impact et pression foncière des urbanisations, constructions et décharges (Bernal Jaramillo, 2006). Dans d'autres comme le Tibanica la conversion totale de la couverture des lacs, en végétation aquatique a été le principal problème de la diminution du miroir d'eau (Garzón Gutiérrez, 2016).

Les études de télédétection ont permis d'avoir un diagnostic général de l'état des écosystèmes, et également de proposer des alternatives pour la récupération et la gestion des zones humides (Mayorga, 2016; Morales, 2018; Rivas Padrón et Sanabria Narváez, 2017; Rodriguez Espinosa, 2015; Rojas Barahona, 2018). En somme, les outils de télédétection ont été clés pour l'obtention d'information au panorama de prise de décisions, et l'atténuation de la perte de ces écosystèmes.

Approches de systèmes complexes

Les systèmes complexes sont généralement étudiés à l'aide des approches de modélisation informatique. De manière générale, les techniques de modélisation employées en géographie sont les modèles basés sur l'individu ou sur l'agent (MBA), et les automates cellulaires (AC).

Modèle basé sur l'agent

Les MBA consistent en un ensemble d'agents, un environnement, et un ensemble des règles. Les règles permettent que les agents interagissent dans l'environnement. Les agents sont la représentation simplifie des objets du monde réel. Ils adaptent leur comportement aux états actuels d'eux-mêmes, des autres agents et de leur environnement. Les individus sont programmés pour réagir de certaines manières (Green et Sadedin, 2005).

Le MBA est focalisé dans la modélisation du comportement des agents et, en même temps, dans l'observation et compréhension du comportement du système constitué par les agents (Grimm et Railsback, 2012). Cette approche en conjoint avec les SIG, ils ont été utilisés pour plusieurs applications. Par exemple, la modélisation du déplacement des animaux (Anderson et al., 2017; Tang et Bennett, 2010), les interactions entre les êtres humains et l'environnement (Gotts et al., 2019), les sciences sociales (Pooyandeh et Marceau, 2013), et la dispersion des maladies contagieuses (Perez et Dragicevic, 2009).

Automate cellulaire

Les automates cellulaires sont des représentations mathématiques des systèmes complexes. Le concept d'automate cellulaire a émergé dans le contexte historique de la Seconde Guerre mondiale (Langlois, 2010). Alan Turing a établi les bases de l'ordinateur moderne et Von Neumann a créé l'automate cellulaire et la Théorie du jeu. Aussi, il a travaillé dans les premiers designs des ordinateurs. Von Neumann a créé un système cellulaire très complexe pour cette époque-là. Donc, jusqu'aux ans 1970 John Conway a développé un automate cellulaire plus simple très connu « Jeu de la vie ».

Un des modèles les plus connus est le modèle de conversion de l'utilisation des terres et ses effets (CLUE en anglais). Il intègre l'automate cellulaire, et il a été développé pour estimer le changement d'utilisation des terres en utilisant des relations empiriquement identifiées entre l'utilisation des terres et ses facteurs déterminants en combinaison avec la modélisation dynamique en matière régionale au continental. De plus, l'automate cellulaire a été appliqué pour simuler le changement de zones humides dans la région de Sanjiang Plain en Chine entre les années 2000-2006 (Yu et al., 2010). Peng et al. (2020) ont utilisé des cartes d'occupation des sols, des données environnementales, et le modèle CLUE-S (pour petites extensions régionales) pour simuler la distribution spatiale des zones humides en Chine de 2000 à 2015. En Inde, Mozumder et Tripathi (2014) ont utilisé le système dynamique, la chaîne de Markov, et réseaux de neurones artificiels pour prédire les impacts futurs de l'expansion urbaine et agricole sur la zone humide de Deepor Beel. Aussi, des techniques d'intelligence artificielle comme la forêt d'arbres décisionnels, et la machine à vecteurs de support ont été employées pour l'évaluation des risques de conversion des zones humides d'East Calcutta, en Inde.

Les exemples ci-dessus démontrent la vaste utilisation des modèles AC pour simuler les changements des zones humides dans différentes régions. En fait, ces études ont accouplé différentes approches de modélisation. À savoir, l'intégration de plusieurs techniques de modélisation a augmenté exponentiellement dans les deux décades dernières, et a rapporté une précision supérieure (Arsanjani et al., 2013; Brailsford et al., 2019; Yang et al., 2016). Alors, les approches de modélisation hybride combinent différentes structures conceptuelles, des théories, et observations empiriques dans une représentation du système. Aussi, ils permettent choisir la procédure adéquate pour la modélisation en fonction des besoins pratiques de la modélisation (National Research Council, 2014). Néanmoins, les complexités dynamiques des zones humides urbaines de Bogota n'ont pas été étudiées par approximations de systèmes complexes.

La révision de la littérature constate qu'il existe limitations quant à études qui montrent un diagnostic général des dynamiques de changements de couverture du complexe de zones humides de Bogota, et qui simulent leurs dynamiques au cours des prochaines années. Les approches de modélisation par la théorie de systèmes complexes sont utiles à la fois pour obtenir des informations sur les relations entre les forces de perturbation et les patrons émergents dans les zones humides, et pour comprendre les effets des facteurs anthropiques et politiques dans le changement spatial de ces écosystèmes.

Bien que les approches de modélisation par la théorie de systèmes complexes aient été employées dans l'étude d'aménagement urbain de Bogota et de ses environs (Guzman et al., 2020), il n'y a pas de rapports dans la littérature scientifique traitant les problèmes des zones humides urbaines.

Il y a donc un besoin d'études qui permettent d'étudier et de comprendre leur dynamique de changement, en liaison avec les facteurs de perturbation. L'utilisation des terres et l'occupation des sols sont importantes dans l'étude des dynamiques de la couverture du sol. Pour cette raison, il est essentiel que les méthodes à employer soient capables d'estimer leur demande, et de même obtenir la prédiction de la couverture à futur. Les approches de modélisation de systèmes complexes telles que les automates cellulaires (AC) combinés à des modèles statistiques, comme la chaîne Markov (CM), et techniques d'apprentissage automatique permettent projeter à futur la distribution des zones humides. Les résultats de cette recherche seront présentés dans les chapitres 2 et 3 sous la forme des articles scientifiques.

Chapitre 2 – Premier article scientifique

Présentation de l’article

Yenny Cuellar & Liliana Perez (2023). Assessing the accuracy of sensitivity analysis: an application for a cellular automata model of Bogota’s urban wetland changes, Geocarto International, 38:1, https://doi.org/10.1080/10106049.2023.2186491.

Ce premier article s’agit d’un manuscrit rédigé en anglais qui a été publié dans la revue scientifique *Geocarto International*. Cet article donne un aperçu des différentes composantes qui doivent être prises en compte pour évaluer la sensibilité des modèles automates cellulaires dans la simulation de l’évolution spatio-temporelle du paysage des zones humides.

Accord des coauteurs

Cet article a été co-écrit par Yenny Cuellar, première auteure, et Liliana Perez, deuxième auteure. Yenny Cuellar a été responsable des simulations, des analyses, de l’interprétation des résultats, de produire les figures, et de l’écriture du manuscrit. Liliana Perez a supervisé le projet, a corrigé et aidé dans la structuration de l’article. Les deux auteurs ont contribué à la rédaction du document final.

En tant que co-auteur, j’autorise Yenny Cuellar à présenter l’article *Assessing the accuracy of sensitivity analysis: an application for a cellular automata model of Bogota’s urban wetland change* dans son mémoire de maîtrise.

Liliana Perez

Co-auteur

Assessing the accuracy of sensitivity analysis: an application for a cellular automata model of Bogota's urban wetland change

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Abstract

This study analyzes the outcomes of Cellular Automata (CA) with different neighborhood sizes and spatial resolution configurations on the performance of the Future Land Use Simulation (FLUS) model. The analysis is executed using three analogic images to extract the land use/land cover in Bogota, Colombia, for three years: 1998, 2004, and 2010. The FLUS model has an Artificial Neuronal Network model, which was used for calculating the relationships between the land uses and the associated drivers and to estimate the probability of occurrence of each land use. Whenever a CA is used to model and simulate, sensitivity analysis (SA) becomes a crucial step in CA modeling to understand better the influence of parameters' changes in the simulation outcomes. Therefore, the SA is conducted by varying the neighborhood sizes between 3 × 3, 5 × 5, and 7 × 7 for 5 and 30 meters. In addition, cross-classification maps, Area Under the Curve (AUC) of the Total Operating Characteristic, landscape metrics, the figure of merit, Fuzzy Kappa, and disagreement metrics were calculated to assess how well the model performed. High AUC values and low disagreement results show that, in general, the model performed well, and the accuracy of the outputs improves with a 3 × 3 neighborhood size and 5 meters spatial resolution. This study provides a broad assessment approach to the different methods that must be considered to evaluate the sensitivity of CA models in the simulation of urban wetlands' spatial-temporal evolution.

Keywords: urban wetlands, Cellular Automata (CA), sensitivity analysis, land use/land cover change, FLUS model.

2.1 Introduction

Land use and land cover changes (LUCC) are complex and dynamic, with non-linear fluctuations over time and various processes operating at different spatial and temporal scales (Vliet Wallentin & Neuwirth, 2017). As a result, land change models using Cellular Automata (CA) are increasingly used to explore their dynamics and are considered as a foundation for public policy decisions. As a consequence, they should be submitted to a Sensitivity Analysis (SA) for exploring "what if" scenarios. In CA models, one can represent the spatial complexity and dynamics of LUCC by selecting various configurations of its essential elements, such as the neighborhood size and spatial resolution.

Studies on SA have shown that the variation in the model output can be apportioned to different sources of variations and that models' outputs depend upon the information fed into them (Crosetto et al., 2000). Among different parameters tested in a SA, the literature reports different neighborhood sizes, types, and spatial resolution configurations in land-change models. Kocabas & Dragicevic (2006) conducted a SA by systematically varying the neighborhood size and type. Shafizadeh-Moghadam et al. (2017) evaluated the effects of varying spatial neighborhood sizes on the predictive performance of the Land Transformation CA Model. Varga et al. (2019) executed a SA to see how the size of the spatial filter in a CA model influences the outputs in a CA-Markov land change model applied in Hungary. Wang et al. (2021) explored different smoothed transition rules and neighborhood sizes to understand how they impact the outputs in an urban growth simulation.

Along the process of a SA, the assessment of the results phase becomes essential. Researchers have used different approaches to evaluate how well the models perform due to the variation of different model parameters. Many scientific articles have described the implementation of qualitative and quantitative methods. Kocabas & Dragicevic (2006) proposed assessing SA using a cross-classification map, Kappa index with coincidence matrices, and different spatial metrics. Shafizadeh-Moghadam et al. (2017) followed the metrics figured of merit (FoM), producer's accuracy (PA), and overall accuracy (OA) indices. Wang et al. (2021) used five indicators: OA, Kappa coefficient, FoM, PA, and user's accuracy (UA). Feng et al. (2022) applied cell-to-cell comparison techniques such as OA, PA, and UA in studying urban growth dynamics. When applying the previous methods, the sensitivity evaluation of the models showed that the neighborhood configuration affects the simulation quality. When applied in land-change models, smaller neighborhoods result in more accurate simulations.

Some researchers evaluated the model's results by applying metrics that provided more profound insights. For example, the area under the curve (AUC) of the Total Operating Characteristic (TOC) curves is used to determine the accuracy of the models in the study of Kantakumar et al. (2020). Also, other articles like Tong & Feng (2019) suggest methods for evaluating model sensitivity, including the TOC. In addition, Pontius & Millones (2011) proposed the use of two parameters: quantity disagreement (QD) and allocation disagreement (AD), which have been adopted to carry out the accuracy assessment of diverse simulation models of complex systems (Gaudreau et al., 2016; Islam et al., 2018; Tiné et al., 2019). These metrics are highly recommended in the literature thanks to their power to analyze the model in terms of error location and error quantity, offering more insights about what path to take to improve the simulation outcomes.

Since the SA and its assessment are fundamental during the calibration process of the model, it is necessary to apply and adopt a collection of evaluation methods in the pre-calibration stage of the model-building process. In research as in Kocabas & Dragicevic (2006), it is well documented a detailed and systematic SA assessment of a proposed CA model. Nevertheless, since the date of their publication, new techniques for evaluating SA in CA models have advanced; thus, it has become crucial to expand the documentation thus far. To do it, we have made a comprehensive literature review and chosen the analysis techniques more used and recommended within the most recent years to perform a CA model evaluation.

This study has as a foremost objective to explore a collection of well stablished and new SA methods that have emerged in the recent literature for the sensitivity analysis and calibration assessment when varying different parameters of a CA model. For this purpose, we applied the Future Land Use Simulation (FLUS) model (X. Liu et al., 2017) to document and understand the impact of the variation of different CA parameters on the simulation outcomes. The SA was conducted by varying the neighborhood sizes between 3 × 3, 5 × 5, and 7 × 7, and the spatial resolution of the model inputs with 5- and 30-meters pixel sizes. We used methods such as FoM, disagreement metrics, cross-classification maps, landscape metrics, TOC, and fuzzy index to validate the SA results. The SA procedures are implemented in a study area located in Colombia. The following sections present the study area and data for applying the CA-FLUS model. Then, we describe the methodology used, beginning with the SA description, the particularities of the model applied, and the approach used to assess the SA. Subsequently, we present the qualitative and quantitative analysis of the results and a discussion. Finally, we provide the conclusions and implications of this study.

2.2 Material and Methods

2.2.1 Study Area and Data

Bogota, the capital of Colombia, is geographically located in the Eastern Cordillera, along the northern part of the Andes (Figure 2.1). The city accounts for a complex of 15 urban wetlands recognized by the city's Environment Secretariat, from which only 11 are under protection by the Ramsar Convention, an correspond to a total area of 6,67 km^2 (Ramsar Convention Secretariat, 2019). The motivation for choosing Bogota as a case study is due to the importance of this fragile ecosystem for the capital city (Secretaria Distrital de Ambiente. Misión Humedales de Bogotá, 2021), and its role in the city's approach to climate change adaptation (Instituto Humboldt Colombia, 2018). The past and current urban dynamics and a lack of knowledge and understanding Bogota's urban wetland dynamics has driven a dramatic reduction in their extent (Observatorio Ambiental de Bogotá, 2020). The study area is centered around the influence zones of the wetlands, taking only these administrative localities.

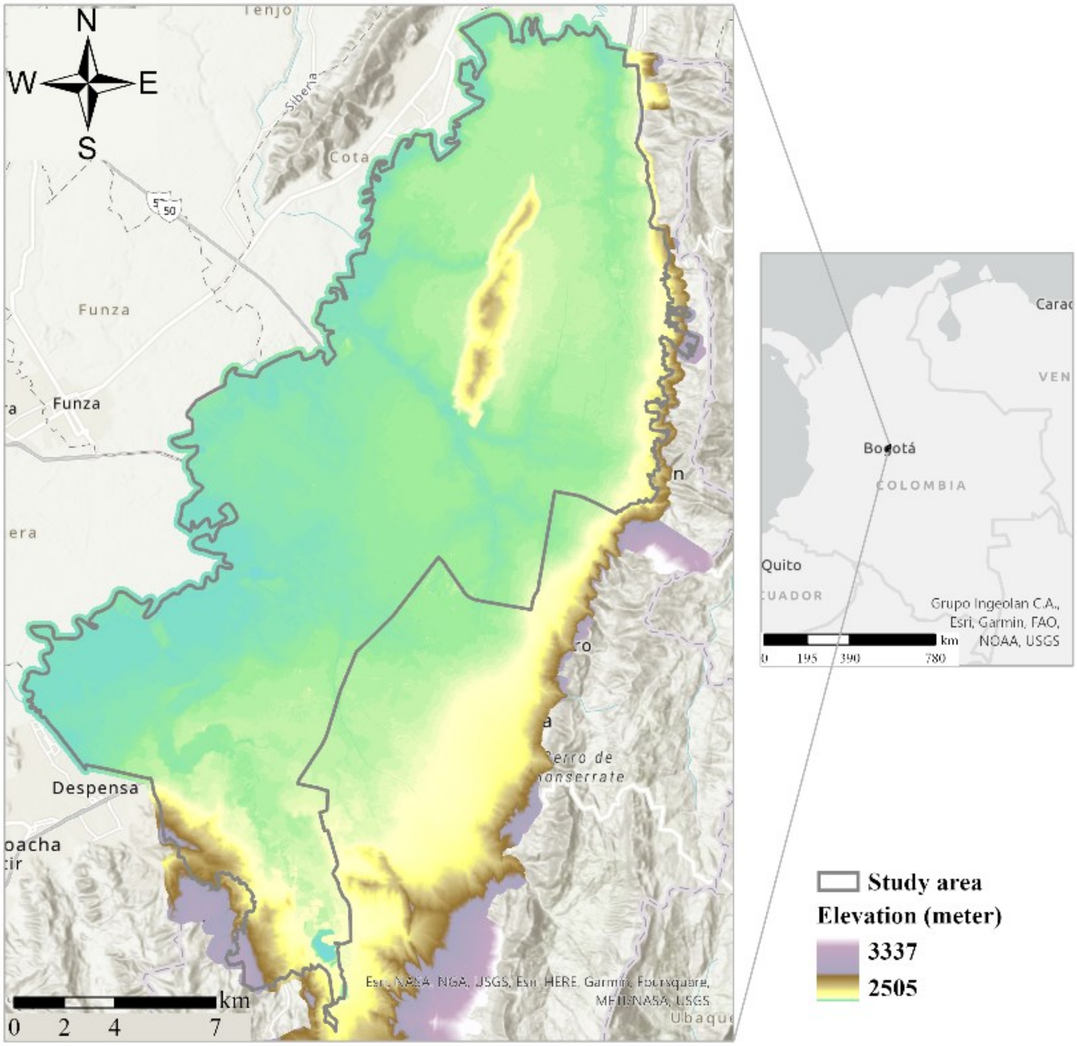

Figure 2.1. - Study area of Bogota, Colombia.

Urban wetlands are the target of many different elements of disturbance (Jiang et al., 2012) since they are susceptible to different climatic and human variables, which change depending on the geographic zone; we selected the driving factors based on a literature review, local expert knowledge, and data availability (Shaohui & Zhongping, 2013; Tian et al., 2021). Table 2.1 presents the spatial datasets used for this study, including historical land use patterns, terrain conditions (elevation, geomorphology), positional data (distance to road network), climatic factors (temperature and precipitation), population and household density, and cadastral information.

The rasterized land-use maps were derived from the interpretation of three satellite images, one analog, and two numerical, corresponding to 1998, 2004, and 2010. Table 2.2 shows the area of each land use class for each year.

The distance to the arterial road network was calculated using the ArcGIS Euclidean distance tool (ESRI, 2020). The restricted areas data are the protected zones established in the city's Land Use Plan (Secretaria Distrital de Ambiente, 2019). All the spatial datasets were rasterized, resampled to the same spatial resolutions of 5 and 30 meters (Figure 2.2), and normalized to eliminate quantitative and dimensional differences.

Table 2.1. - Data resources.

Data	Year	Type	Original resolution	Data resource
Images	1998, 2004, 2010	WMS resource	0.46 m	
Distance to the arterial road network		Vector	1_1000	https://www.ideca.gov.co/recursos
DEM	2014	raster	5 m	
Urban geomorphology	2016	Vector	1:1000	
Restricted Areas		Vector	1:1000	
Population	2004, 2010	Document	Administrative	http://www.bogota.gov.co/
Cadastral information	1998, 2004, 2010	Vector	1:1000	https://serviciosgis.catastrobogota.gov.co/
Annual Mean Temperature		Vector	1:1500	https://datosabiertos.bogota.gov.co/
Annual Precipitation		Vector	1:1500	
Annual Mean Precipitation		Vector	1:1500	

Table 2.2. Area (ha) of each land use class.

Land use class	1998	2004	2010
Constructions	21 849.4	22 544.7	22 995.3
Crops and pastures	6 709.9	5 996.9	5 499.3
Quarries	254.1	243.9	244.3
Urban Green Spaces	1 592.1	1 659.5	1 758.7
Water	136.8	136.8	137.9
Wetlands	810.2	770.7	717.0

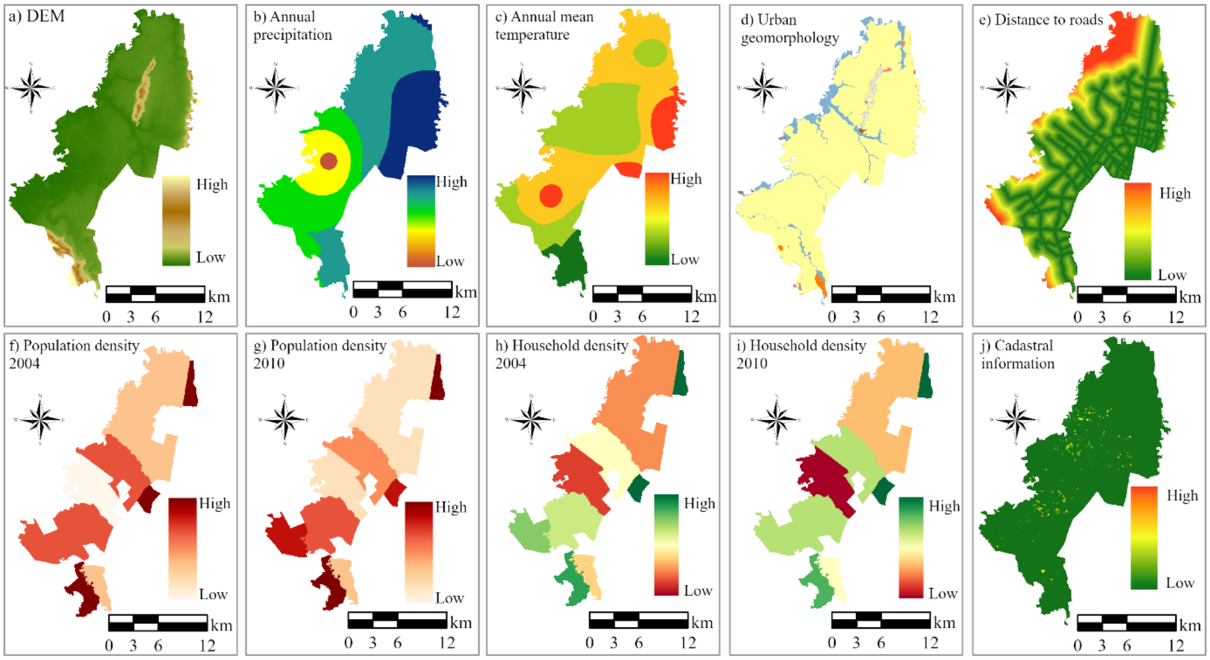

Figure 2.2. Driving factors - a detailed map of urban geomorphology together with the legend is attached as Appendix (see Figure II. 1).

2.2.2 Methodology

The methodology to perform the SA and its assessment consist of two steps, which are presented in Figure 2.3. The first step is simulating future land use changes using the FLUS model and carrying out the SA by varying the spatial resolution of the dataset from 5 to 30 meters and the neighborhood size between 3 × 3, 5 × 5, and 7 × 7. The second step is assessing the SA results using different qualitative and quantitative methods such as cross-classification maps, FoM, PA, OA, quantity and allocation disagreement, cross-classification maps, different landscape metrics, the TOC, and the fuzzy index.

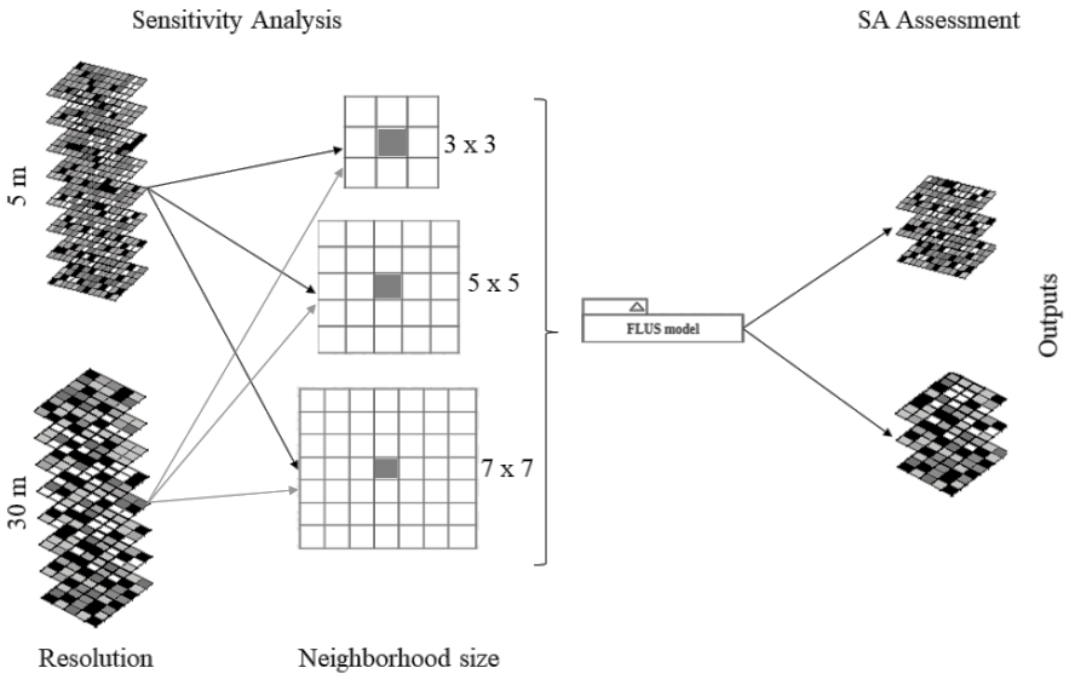

Figure 2.3. - Schematic diagram of the methodology.

FLUS model

The FLUS model has been applied successfully in other studies of urban dynamics (Liang, Liu, Li, Chen, et al., 2018; Zhang et al., 2021). Its implementation of a proportionate fitness selection gives the model a higher precision for obtaining consistent results compared to the reference data. It simulates land-use change under human and natural pressure using a spatial simulation process based on a CA model. Firstly, it uses an artificial neural network (ANN) to obtain the appropriate probabilities of the land-use classes from historical land-use data and the driving factors. The rules for the CA are drawn from those probabilities of occurrence. Then, its adaptive inertia and competition mechanisms allow the model to process the complex land-use interactions and competition locally, which can deal with the uncertainty and complexity of the change between the land-use classes under the effect of the driving factors (X. Liu et al., 2017).

Additionally, the FLUS model uses the Moore neighborhood to represent the neighborhood space. A total of 6 simulations were made to analyze the effects of neighborhood size and spatial resolution on the FLUS model results. The FLUS model has a Markov Chain module in which users can forecast future land-use demands by determining the transition probability of change from one category to another in a time interval. Nevertheless, we use the observed changes during the study period to feed the model and obtain the six outputs with different initial configurations.

Comprising the ANN of three-layer types: an input layer, a hidden layer, and an output layer, in the FLUS model, each neuron in the input layer corresponds to an input variable, land-use data, and driving variables. Likewise, each neuron in the output layer corresponds to a specific land-use type. Table 2.1 shows the variables selected as the influencing factors. For a detailed description of the FLUS model, see Liu et al. (2017).

Sensitivity Analysis

A SA aims to understand how the variation in the model output can be apportioned to different sources of model parameter variations and how the given model depends upon the information fed into it (Crosetto et al., 2000). SA is a required step of modeling practice because it determines the model credence and aid in assessing uncertainties in the model results (Kocabas & Dragicevic, 2006). Many techniques for SA have been proposed, including linear regression, measures of importance, Monte Carlo analysis, and correlation measures (Crosetto et al., 2000). There are two types of SA techniques. On the one hand, the univariate SA examines the model result concerning the variation of only one parameter at a time while the other parameters remain constant. On the other hand, the multivariate SA systematically varies multiple input parameters and determines the impacts on the analyzed outcome (Kocabas & Dragicevic, 2006).

Further, SA can also be a tool for pre-calibration analysis (Crosetto et al., 2000). Generic procedures to perform SA on spatial models have been done. For example, Crooks et al. (2008) investigated the influence of the size of neighborhoods and the influence of geographical features in a residential segregation model tuned to London data. The analysis showed that the geometry of an area could act as a physical barrier to segregation. Shafizadeh-Moghadam et al. (2017) evaluated the effects of CA with different neighborhood sizes on the predictive performance of a Land Transformation Model.

Similarly, Wang et al. 2021 examined the effects of cell size on the performance of the transition rules of a CA model. SA techniques are usually applied to produce simulated outcomes that imitate the patterns observed in the real world. However, the sensitivity procedure in this paper explores the influence of two input parameters, i.e., neighborhood size and spatial resolution, on the model output. We run six simulations using three different neighborhood sizes in combination with 5 m and 30 m spatial resolutions.

Sensitivity Analysis assessment approach

Assessing the outcomes of a SA is crucial in spatial modeling applications (Kocabas & Dragicevic, 2006). As such, this study aimed to evaluate the CA-FLUS model performance by undertaking a SA and a series accuracy assessment approach to understand the model's sensibility to the variation of different parameters. We used many metrics suggested in the literature for a consistent SA evaluation. The assessment conception for the study uses univariate Sensitivity Analysis in which input factors are assumed independent. The presented SA assessment approach put together the qualitative and quantitative methods of cross-classification map, different landscape metrics, FoM, PA, OA, the AUC of the TOC curves, the Fuzzy Kappa index, and the disagreement metrics. The SA was achieved by varying the neighborhood size and the spatial resolution of the model inputs. We compared the model outcomes with real land-use data using different metrics. Table 2.3 provides descriptions of these metrics.

Table 2.3. Metrics used for SA assessment

Approaches	Formula	Description
Figure of merit (FoM)	$FoM = \frac{B}{A+B+C+D}$	The FoM is the intersection of observed and simulated changes divided by the addition of observed and predicted changes[(a)].
Producer accuracy (PA)	$PA = \frac{n_{ii}}{n_{+k}}$	PA indicates the proportion of pixels that the model simulates well as change[(a)].
Overall accuracy (OA)	$OA = \sum_{i=1}^{k} \frac{n_{ii}}{n}$	OA provides the general agreement between the reference map and the simulated one[(a)].
Area under the curve for the Total operating characteristic (TOC)	$AUC = \int_0^1 TPR\ d(FPR)$	TOC metric indicates how well the model is forecasting change[(b)].
Fuzzy Kappa statistic	$K = \frac{P-E}{1-E}$	It is used to demonstrate the overall agreement between what is observed and what is simulated[(c)].
Quantity disagreement (QD)	$Q = \frac{\sum_{g=1}^{J} q_g}{2}$	Measures the disagreement between the number of cells in each category without considering the spatial location[(d)].

Allocation disagreement (AD)	$A = \frac{\sum_{g=1}^{J} a_g}{2}$	Evaluates the amount of disagreement between the reference map and the simulation map regarding the spatial location of the cells in each category[(d)].

[a](Varga et al. 2019), [b](Azari et al. 2022), [c](Hagen-Zanker 2009), [d](Pontius & Millones, 2011)

For the visual comparison of the CA model outcomes, we used the cross-classification maps. First, we assessed the categorical data errors with the confusion matrix by comparing outcome maps with the reference land-use maps (Crosetto et al., 2000). Within a confusion matrix, the true positives-true negative represents the correct number of pixels simulated, and the false positives-false negatives represent the errors of the simulated maps. The FoM is a well-known metric used for model validation via three-map comparison: reference beginning of the validation interval, simulation, and reference at the end of the validation interval (Varga et al., 2019). It goes from zero to one, meaning zero is no intersection between simulation and reference change, while one means perfect intersection between simulation and reference change. In Table 2.3, A is the proportion of error cells due to the observed change – predicted as persistence, B is the proportion of correct cells due to observed change – predicted as change, C is the proportion of error cells due to observed change modelling – predicted as a wrong gaining category, D is the proportion of error cells due to observed persistence – predicted as change and E denotes the area of correct cells due to observed persistence – predicted as persistence (R. Pontius et al., 2008).

The TOC is another analysis to evaluate the performance of land use models (Pontius Jr & Si, 2014). It is used to analyze the agreement between the output of a model with the reference map. The TOC shows misses, hits, false alarms, and correct rejections. As in the Receiving operating curve (ROC), the AUC of the TOC offers a metric to summarise the performance. The AUC has values on a scale from 0 to 1, where values between 0.90-1 means excellent, 0.80-0.90 indicates good, 0.70-0.8 signifies fair, and 0.60-0.70 poor accuracy level (Saha et al., 2021). In Table 2.3, *TPR* is the true positive rate or sensitivity that measures the fraction of the initial positives pixels which have been predicted correctly, and *FPR* is the false positive rate that indicates the fraction of the negatives pixels that have been selected as positive incorrectly (Fawcett, 2006). A more detailed explanation of the TOC curve, used in land-change modeling, can be found in (Pontius Jr & Si, 2014).

The Fuzzy Kappa statistic agrees with two categorical raster maps (Hagen-Zanker, 2009). It considers transition/change (T. Xu et al., 2019). Its values range from zero to one, where zero indicates no similarity and one identical similarity between the two maps. For the Fuzzy Kappa statistic in Table 2.3, P is the mean agreement, and E is the expected agreement. Additionally, another two measures proposed by Pontius & Millones (2011) were applied: Quantity Disagreement (QD) and Allocation Disagreement (AD). Those indices are calculated through a contingency table for categorical variables, and their values vary from zero to one, where zero shows perfect agreement, and one indicates perfect disagreement. In Table 2.3, $\sum_{=1}^{J} q_g$ is the summatory of the global quantity disagreements of g classes in the reference and comparison maps. Similarly, $\sum_{g=1}^{J} a_g$ computes the allocation disagreement for all categories g is the summatory of the overall quantity disagreements of g categories in both reference and comparison maps. Similar to AD, $\sum_{g=1}^{J} a_g$ computes the allocation disagreement for all categories g (R. G. Pontius & Millones, 2011b).

We calculated different landscape metrics to compare the structure and pattern of land-use classes simulated by the FLUS model. Landscape metrics are regarded as essential ecological planning tools and can aid urban land planners and managers in measuring the arrangement of landscape elements in time and space (Y. Li et al., 2010). Therefore, the landscape metrics were calculated and examined across class (each patch type in the given mosaic) and at a landscape level (the landscape mosaic all considered together).

Class metrics calculate the aggregate properties of the patches that belong to a single class. *Total area* (CA) is an indicator of landscape composition that reveals how much of the landscape is comprised of a particular patch type (McGarigal & Marks, 1994). *The largest patch index* (LPI) quantifies the rate of the total landscape area defined by the largest patch. *The mean patch area* (MN) is the sum across all patches of the corresponding patch type divided by the number of patches of the same class. *Perimeter-area fractal dimension* (PAFRAC) cast shape complexity across various spatial scales. *A number of patches* (NP) of a particular patch type are the total number of fragmented patches that belong to a specific land-use class. *The aggregation index* (AI) expresses the global agglomeration of the landscape. *The total edge* (TE) is the total length of the patch class. *Area-Weighted Mean Shape Index* (SHAPE_AM) weights patches conformable to their size. The landscape metrics also measure the aggregate properties of the complete patch mosaic

(McGarigal & Marks, 1994). *The patch cohesion index* (COHESION) measures the connectivity physical of each patch type. *Contagion* (CONTAG) measures patch-type combinations of units of different patch types and the spatial distribution of a patch type.

Software tools

The FLUS modeling tool was downloaded from https://www.geosimulation.cn/FLUS.html. Different tools were used to implement all the assessment techniques to evaluate the SA results. The OA was directly calculated from the FLUS model. The FoM and the PA were calculated from the confusion matrices. The cross-classification maps, quantity, and allocation disagreement were all run using TerrSet (Eastman, 2020). The fuzzy kappa index was calculated with the Map Comparison Kit (MCK) (Visser & Nijs, 2006). The AUC for the TOC curve was calculated using packages "raster" (Hijmans, 2022) and "TOC" (Pontius Jr & Si, 2014) of the statistical software R (R Core Team, 2020). Finally, the landscape metrics were computed in FRAGSTATS 4.2 (McGarigal & Marks, 1994), and maps were produced with ArcGIS Pro 2.3 (ESRI, 2020).

2.3 Results

The FLUS model was run to simulate 6-year land-cover changes in the case of urban wetland changes in Bogota, initiated in 2004 (T_0). The simulation time frame was selected to validate the results against the available land-use map corresponding to 2010. As a result, six simulation maps were generated with the wetland class as the target land use of the study. These correspond to a small area to the total space of the study area. Therefore, to correctly evaluate the SA outputs, we emphasized the wetlands cover assessment. This section presents the results obtained by varying the neighborhood size at different spatial resolutions and analyzing the results using the SA assessment approach.

Figure 2.4 and Figure 2.5 illustrate the outcomes of cross-classification maps for 5 m and 30 m resolution. The first two rows present the resulting maps for neighborhood sizes 3 x 3, 5 x 5, and 7 x 7 of different areas of the study zone. The third row presents the cross-classification maps obtained to compare the simulations produced for the following combinations of neighborhood sizes: 3 x 3 vs. 5 x 5, 3 x 3 vs. 7 x 7, and 5 x 5 vs. 7 x 7.

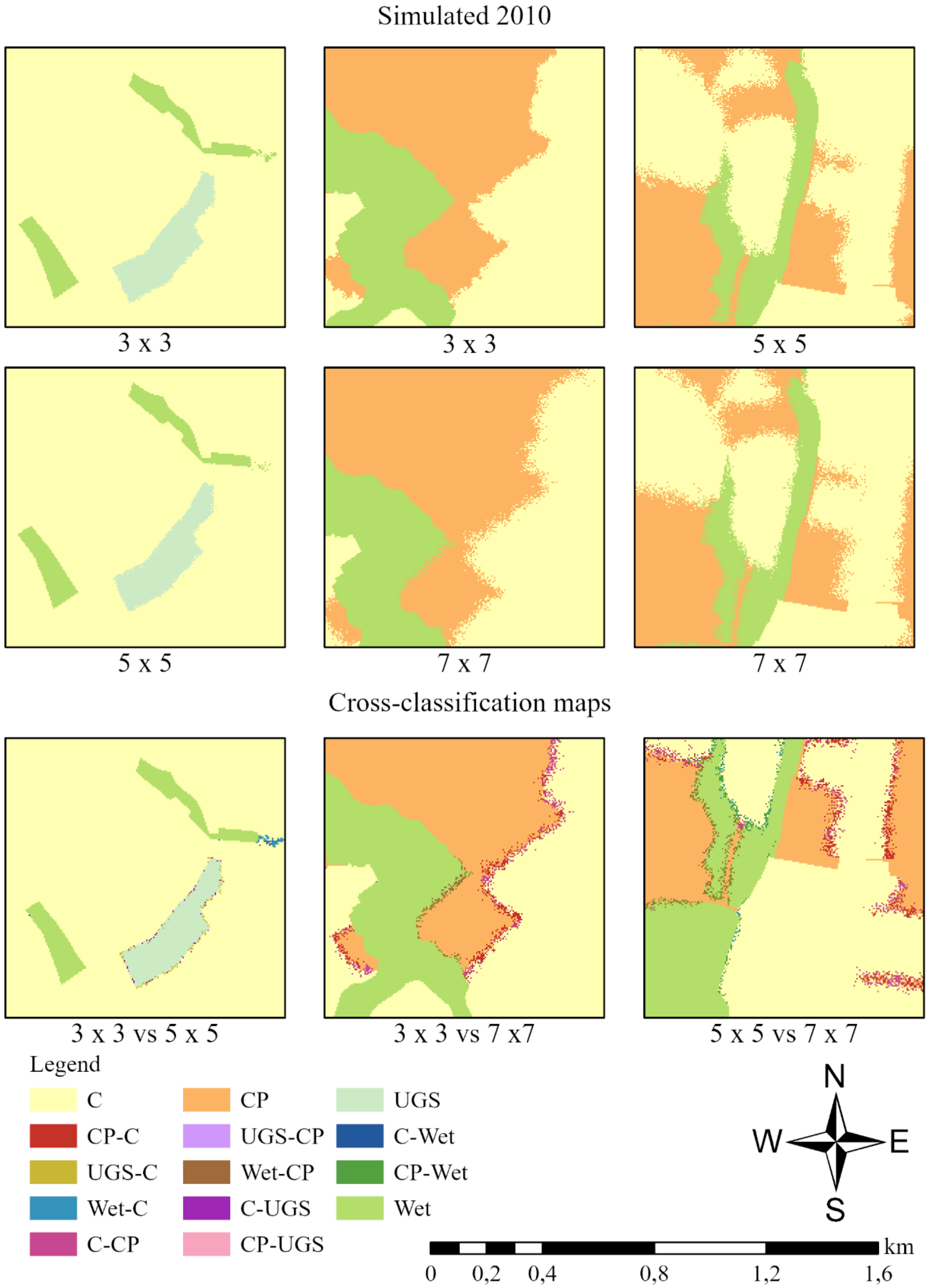

Figure 2.4. - Results from the SA assessment through cross-map method for 5 m spatial resolution. C (constructions), CP (crops and pastures), W(water), UGS(urban green spaces), Wet (wetlands).

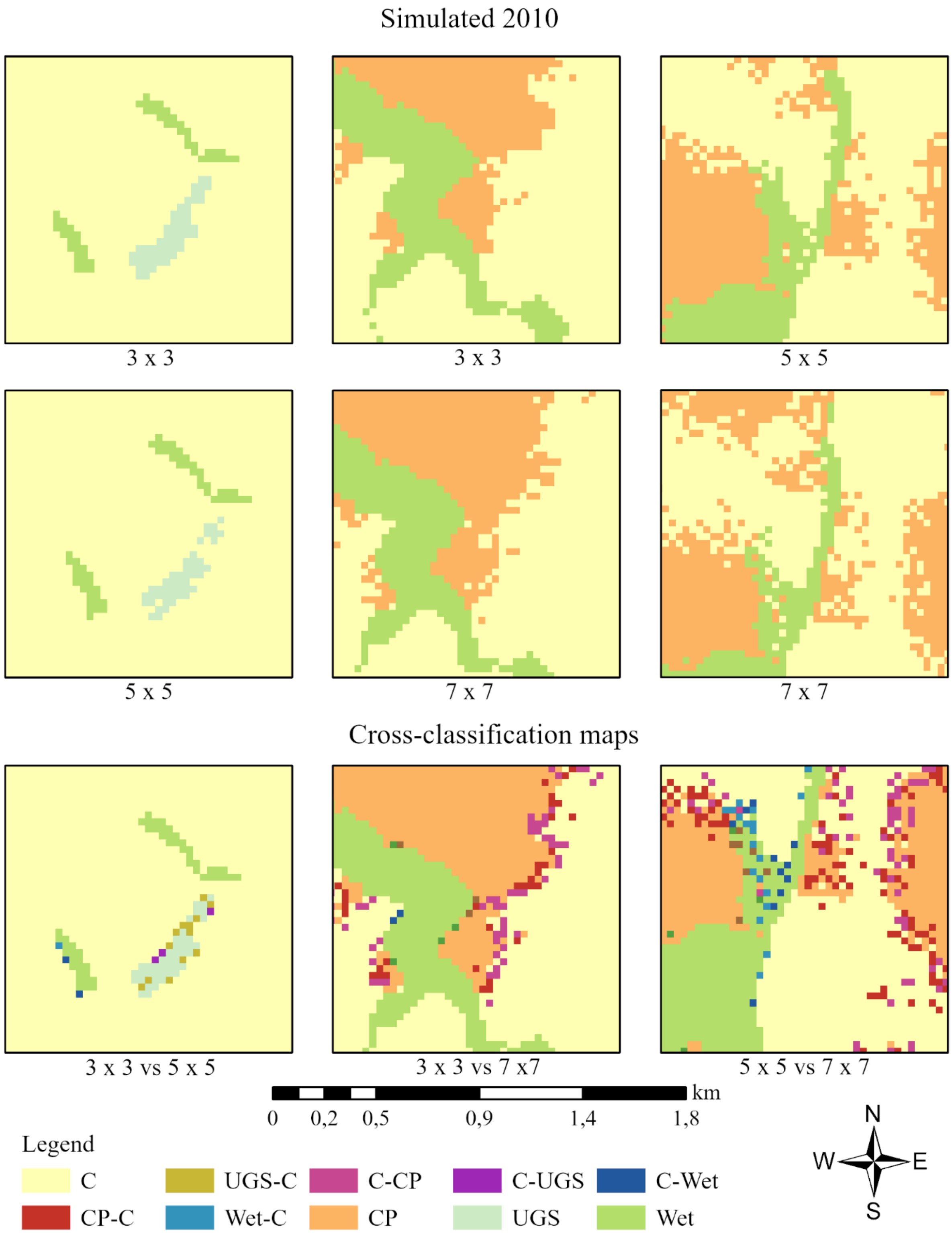

Figure 2.5. - Results from the SA assessment through the cross-map method for 30 m spatial resolution. C (constructions), CP (crops and pastures), W(water), UGS(urban green spaces), Wet (wetlands).

With the decrease of spatial resolution, the differences between the results from different neighborhood sizes become visually apparent for neighborhood size. However, as the difference between the neighborhood sizes is small, we need to establish which configuration is the best based on the visual evaluation. Then, this one was funded by the overall accuracy values (Table 2.4) of the cross-classification maps.

Table 2.4. – Overall accuracy for cross-classification maps with wetlands mask.

Spatial resolution	Reference-Neighborhood size	Overall accuracy	Spatial resolution	Reference-Neighborhood size	Overall accuracy
	3 x 3 vs 5 x 5	0,9893		3 x 3 vs 5 x 5	0,9701
5 m	3 x 3 vs 7 x 7	0,9874	30 m	3 x 3 vs 7 x 7	0,9661
	5 x 5 vs 7 x 7	0,9871		5 x 5 vs 7 x 7	0,9639

The assessment results employing landscape metrics show that the FLUS model outcomes are sensitive to the changes in neighborhood sizes for different spatial resolutions. Table 2.5 summarizes the class metrics results for all neighborhood sizes in 5 m and 30 m spatial resolutions.

Table 2.5. - Landscape metrics for neighborhood sizes 3 x 3, 5 x 5, 7 x 7 for 5 m and 30 m spatial resolution.

Neighborhood size	Number of patches (NP)	Largest patch index (LPI)[%]	Total edge (TE) [m]	Mean patch area (MN) [m2]	Area-Weighted Mean Shape Index (SHAPE_AM)	Perimeter-area fractal dimension (PAFRAC)	Aggregation index (AI) [%]
5m							
Wetlands							
Reference	27	0,66	117 311,533	26,54	3,18	1,45	98,02
3x3	121	0,63	137 602,474	6,04	3,36	1,24	97,71
5x5	334	0,63	160 272,939	2,19	3,74	1,27	97,32
7x7	470	0,63	180 588,875	1,55	4,04	1,31	96,97
30m							
Wetlands							
Reference	29	0,66	109 020	24,71	3,08	1,38	88,84
3x3	40	0,63	115 350	18,28	3,29	1,38	88,28
5x5	42	0,63	118 830	17,41	3,36	1,39	87,92
7x7	54	0,63	123 900	13,54	3,44	1,40	87,40

In addition, we calculated two more landscape metrics, the Patch cohesion index (COHESION) and Contagion (CONTAG). The COHESION value for the reference map (5 m) and the simulated map with a 3 x 3 neighborhood size were 99.95. Similarly, the COHESION value was 99.69 and 99.68 for the reference map and 5x5 neighborhood size simulation map with 30 m spatial resolution, respectively. CONTAG value for 5 m spatial resolution was 75.4 for the reference map and 74.23 for the 7 x 7 neighborhood size. For 30 m spatial resolution, the COHESION value for the reference map was 71.98 and 71.45 for 3 x 3 neighborhood size.

Table 2.6 shows the results for the OA, PA, and FoM. Values of disagreement and agreement for the wetland land use class are presented in Table II.1. For clarity in our results, the confusion matrices are in the appendix from Table II.1 to Table II.7.

Table 2.6. - SA assessment of the outcomes indicated by the OA, PA, and FoM for wetlands land-cover.

Neighborhood size 5 m spatial resolution	PA**	OA*	FoM**	Neighborhood size 30 m spatial resolution	PA**	OA*	FoM**
3x3	0.864104	0.9401	0.1082	3x3	0.8714	0.935115	0.1173
5x5	0.864104	0.9401	0.1107	5x5	0.86	0.934225	0.1267
7x7	0.864101	0.9398	0.1132	7x7	0.8608	0.931885	0.1363

*for the whole map **for the wetland land use class.

The AUC wetland values were estimated according to the TOC curves. In the appendix, Figure II.2 shows the TOC curves. Figure 2.6 depicts Figure II.2 in detail, showing the first eight thresholds.

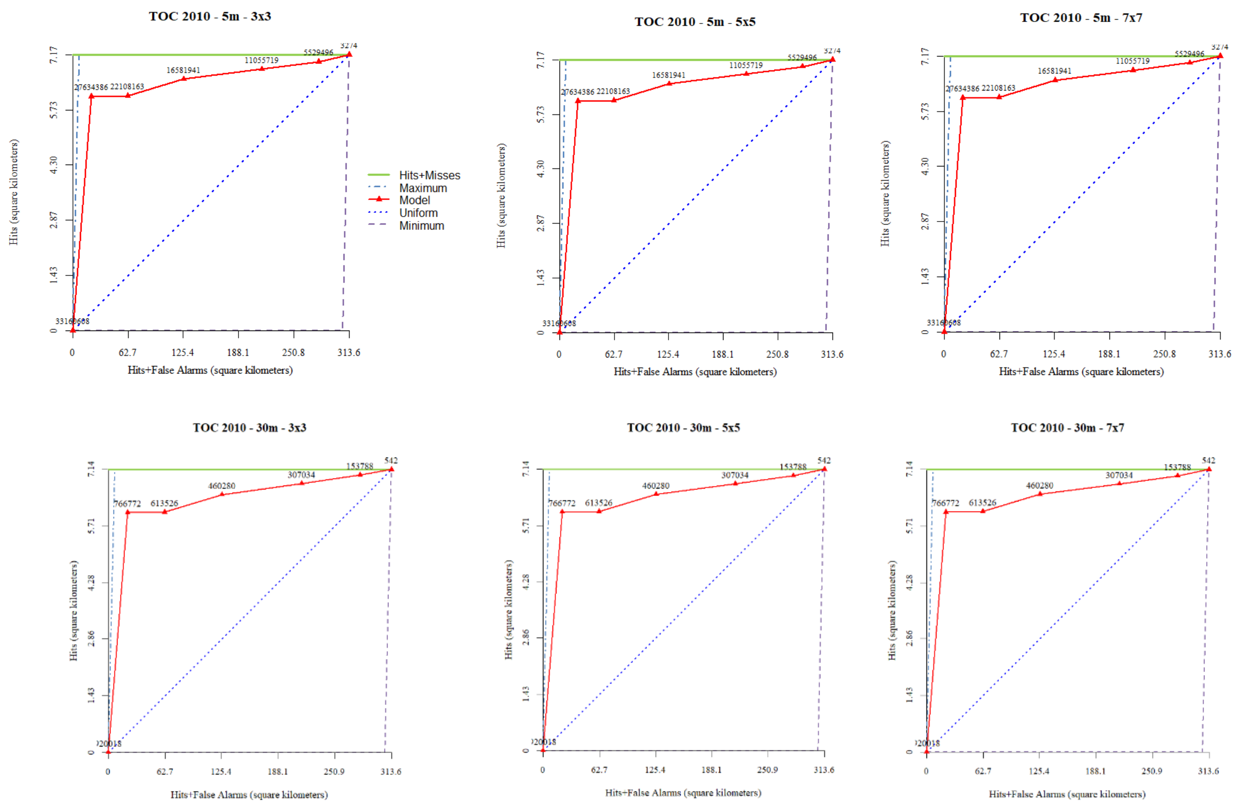

Figure 2.6. AUC of the TOC - zoom of Figure II.1 with thresholds.

Fuzzy Kappa values showed an agreement between the simulation maps and the reference map between 0.41 and 0.90. For the wetlands category, the Fuzzy Kappa presented an agreement of 0.904 in 7 x 7 neighborhood size for 30 m spatial resolution. Assessment outcomes applying Fuzzy Kappa are shown in Figure 2.7. Another essential assessment approach was calculated bias QD and AD. Figure 2.8 shows the two components of disagreement for the three neighborhood sizes at 5 m and 30 m spatial resolution to the general extent. The two components of disagreement are piled to display how they amount to total disagreement. Specifically, the outcomes in 3 x 3 neighborhood size have 5.47% and 5.80% total disagreement for both spatial resolutions 5 m and 30 m, respectively.

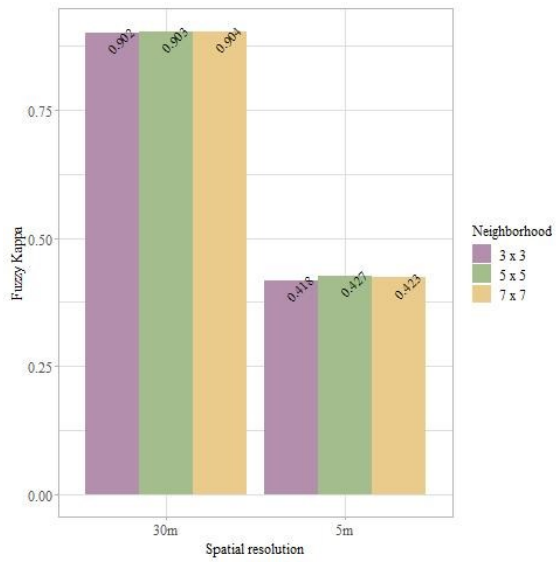

Figure 2.7. Graph of fuzzy Kappa index and similarity above each bar for wetlands land-cover.

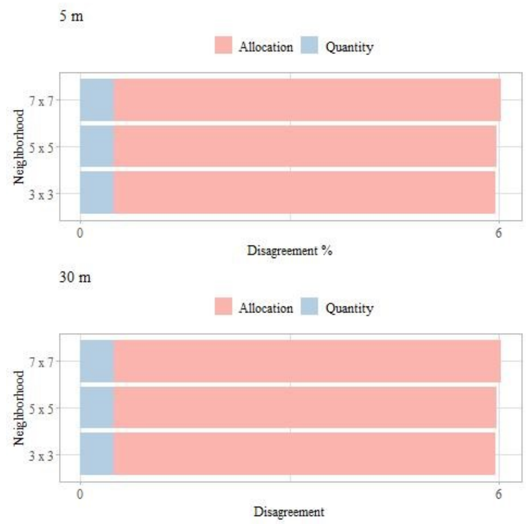

Figure 2.8. Quantity disagreement, allocation disagreement.

2.4 Discussion

We proposed a systematic application of a wide of quantitative and qualitative techniques in evaluating CA response to the variation of its parameters. The results of SA reveal interesting information about the model's performance. First, the cross-maps depict areas where there are spatial differences. By increasing the size of the neighborhood, for both 5 m and 30 m spatial resolution, the contrast between the outcomes tends to be more evident visually. Then, cross-tabulation maps show spatial differences in model results when spatial resolution decreases. The overall accuracy values for the cross-classification maps (Table 2.4) decrease not only with the increase in neighborhood sizes but also with the increment of the spatial resolution. Nevertheless, the low differences between those values suggest that using different neighborhood sizes can result in similar simulation outcomes. In other words, cross-tabulation results comparing the neighborhood sizes at all spatial resolutions suggest moderate agreement.

Also, when the landscape metrics values are compared, the outcomes evidence that model results produce different landscape metrics. For example, the MN values decrease with increasing neighborhood size but increase with decreasing spatial resolution. By contrast, the PAFRAC, NP, TE, and SHAPE_AM values increase with increasing neighborhood size. For example, for the wetlands, land-use MN decreases from 6.04 to 1.55 for 5 m spatial resolution, and 30 m decreased from 18.28 to 13.54. Conversely, NP increased from 121 to 470 for 5 m.

Moreover, the model also seems sensitive to spatial resolution changes. NP and TE values decrease when the spatial resolution decrease. As a result, the land-use patterns are affected by changes in spatial resolution. Notably, for wetlands, land-use NP decreases from 121 to 40 with small neighborhoods from 5m to 30 m spatial resolution, and TE values decrease from 137602.47 m to 115350 m. However, the largest patch index values present little variations for different neighborhood sizes and spatial resolutions.

In the same way, the aggregation index values do not vary a lot between the neighborhood sizes, but it decreases when decreasing spatial resolution. COHESION and CONTAG values hint that outcome maps are similar to the reference maps, having a closer similarity when using a 3 x 3 neighborhood size with 5 m spatial resolution. Furthermore, the landscape metrics shown in Table 2.5 expose that outcome in a 3 x 3 neighborhood size with 30 m spatial resolution simulate better the target class (wetlands). Roodposhti et al. (2020) obtained similar results, suggesting that neighborhood rules are more important than neighborhood size when comparing different settings and analyzing the results with landscape metrics.

The OA, PA, and FoM indicators revealed that the model could perform well with varying neighborhood sizes. The model simulated at least 86% of the observed changed cells for 5 m resolution and over 94% of the unchanged cells. For the 30 m resolution combination, around 87% of the observed changed cells were correctly predicted, and over 93% of the unchanged cell. Despite at 30 m resolution combination having better accuracy results, the accuracy gain seems minor. Table 2.6 shows that FoM values change a lot between the resolutions. Although the FoM values are not highly accurate, they are acceptable because of the observed net change. R. Pontius et al. (2008) found a positive relationship between the FoM and the observed net change. As in this study, the simulation period is short (2004-2010), then the FoM values for the target category are accepted. The application of the previous metrics in the process of sensitivity evaluation of the CA showed similar accuracy outcomes when varying the neighborhood sizes as in the research of Shafizadeh-Moghadam et al. (2017), where the different neighborhood sizes (3x3, 5x5, 7x7, 9x9) produced somewhat similar results, although the 7x7 neighborhood size had a better performance.

Analysing the TOC curves, we notice that the configuration model of 30 m resolution with 3x3 neighbourhood size has the highest AUC, indicating a better performance than the other model configurations. For all simulations, TOC curves clasp the left side of the parallelogram because the wetlands in the reference map exist at the first-ranked values of each index in the output maps. In addition, the TOC curves for the indices touch the top bound of the parallelogram because some of the wetland's absences are at the latter-ranked values. The thresholds shown in Figure 2.6 depict that the most significant number of hits derives from the simulation with 5 m resolution with a 7x7 neighbourhood. As the AUC of the TOC quantifies the relationship of the thresholds in general, we found that the AUC values were more significant than 0.95. Such good results indicate that the model performs well in the wetlands. Furthermore, AUC values increase when the neighborhood size and spatial resolution increase.

Figure 2.7 shows that the model can simulate well the land-use classes. Even though, of these outcomes, the 5 m spatial resolution simulated maps have the lowest Fuzzy Kappa values. By contrast, the wetlands category presented a high agreement in 7 x 7 neighborhood size for 30 m spatial resolution. The model is, therefore, sensitive to changes in spatial resolution. In addition, the quantity disagreement represents less than 6% of the global disagreement for both resolutions. Despite AD values being larger than QD, we consider these values acceptable because future research aims to obtain the probability of the net quantity of wetland changes.

Applying a wide range of techniques in assessing SA helped us better understand how the FLUS model responds to the resolution and neighborhood variations. However, the 3 x 3 neighborhood size with a 5 m spatial resolution model was more realistic than the other neighborhood sizes, and spatial resolutions were applied. Previous studies obtained similar results (Díaz-Pacheco et al., 2018; Kocabas & Dragicevic, 2006; Roodposhti et al., 2020). CA models have been used to study LUCC to explore their complex dynamics at different spatial and temporal scales. Since this approach allowed us to represent the spatial complexity and its dynamics by choosing different configurations of its essential elements, such as the neighborhood size and spatial resolution, its implementation may help to minimize model errors and uncertainties, helping the modeler to find optimal combinations of its components, understanding how these variations influence the CA outcomes which will help to make better decisions in the land use management and urban planning process.

2.5 Conclusions

In this study, taking the land-use change process of Bogota from 1998 to 2010 as an example, we explored different assessment approaches for evaluating SA in the CA-FLUS model. A systematic method to assess SA in CA models was shown to represent real-world patterns as accurate as possible. SA validation was accomplished through the comparison of multiple quantitative and qualitative metrics. Calculating metrics such as the QD and AD helped us choose which path to take to improve the model's prediction. Moreover, the landscape metrics applied allowed us to successfully determine the initial parameters configuration of the model, in order to better simulate the connectivity and patchiness of the wetlands. Despite the results demonstrating that the CA model outcomes are sensitive to neighborhood size and spatial resolution changes, all the initial configurations are generally acceptable to reproduce the land use change patterns in the study area. Strengths of this study include applying a wide range of evaluation metrics that help to better parameterize the model based on the objective of the model. Similarly, we were able to show that TOC, disagreement measures, and landscape metrics are sufficient to thoroughly evaluate the model performance since they reveal behaviors that quantitative measures such as FoM or PA and OA do not.

Concerning the limitations of this study, it is important to underline that they mainly come from the nature of the input data. For example, the data pre-processing step, such as the transformation from vector-to-raster and raster resampling, could have influenced the simulation outcomes; Díaz-Pacheco et al. (2018) have explored this type of limitation in further detail. It is also suggested to adopt other recent analyses proposed in the literature, such as the Intensity Analysis (Varga et al., 2019), which allow the assessment of the transition matrices. It considers the intensity of each category's gross loss and gross gain concerning the temporal change overall. For future studies, we suggest the adoption of multiple approaches instead of just one or two to evaluate a model sensitivity and assess a model calibration. Methodological studies like this can facilitate the implementation of CA models by improving their calibration, goodness-of-fit and the validation stages.

Chapitre 3 – Deuxième article scientifique

Présentation de l'article

Ce deuxième article s'agit d'un manuscrit rédigé en anglais qui est en deuxième révision dans la revue scientifique *Scientific Reports*. Cet article porte sur la dynamique du changement spatio–temporelle des zones humides urbaines de Bogota, en Colombie.

Accord des coauteurs

Cet article a été co-écrit par Yenny Cuellar, première auteure, et Liliana Perez, deuxième auteure. Yenny Cuellar a été responsable des simulations, des analyses, de l'interprétation des résultats, de produire les figures, et de l'écriture du manuscrit. Liliana Perez a supervisé le projet, a corrigé et aidé dans la structuration de l'article. Les deux auteurs ont contribué à la rédaction du document final.

En tant que coauteur, j'autorise Yenny Cuellar à présenter l'article *Multitemporal Modeling and Simulation of the Complex Dynamics in Urban Wetlands – The case of Bogota, Colombia* dans son mémoire de maîtrise.

Liliana Perez

Co-auteur

Multitemporal Modeling and Simulation of the Complex Dynamics in Urban Wetlands – The case of Bogota, Colombia

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Abstract

Urban wetlands are essential to the longstanding health and well-being of cities. Acknowledged as rich in biodiversity and highly productive ecosystems, they provide ecosystem services represented in aspects such as air purification, urban climate regulation, physical and mental health, recreation, and contemplation, among a wide variety of other goods and services on which the quality of life of the inhabitants of large cities such as Bogota depends largely. We used Cellular Automata to model and simulate urban wetland changes in Bogota, Colombia. The study applied the coupled Markov-Future Land Use Simulation (FLUS) model to simulate and analyze Land Use/Land Cover (LULC) change over 20 years. First, we used an orthomosaic (1998) and two WorldView-2 satellite images (2004 and 2010), to detect land cover changes. Then, using the Artificial Neural Network FLUS module, we calculated the relationships between land classes and associated drivers and estimated the probability of occurrence of each land class. Finally, we applied Intensity Analysis to examine the observed and projected LULC change (1998-2034). Results indicate that gains in areas of crops and pastures are at the expense of wetlands. In addition, simulation outputs show that wetlands will likely represent less than 2% of the total study area in 2034, representing a 14% decrease in 24 years. The importance of this project lies in its potential contribution to the decision-making process within the city and as an instrument of natural resource management. Additionally, the results of this study could contribute to the United Nations Sustainable Development Goal 6, “Clean water and sanitation," and climate change mitigation.

Keywords: urban wetland area estimation, Land Use/Land Cover (LULC) Change, Cellular Automata, Artificial Neural Network (ANN), Intensity Analysis, FLUS model.

3.1 Introduction

Founded in and around cities or their suburbs (Ramsar, 2018), urban wetlands are unique and play an indispensable role in the well-being of the urban area. They offer multiple ecosystem services such as water supply, water purification, diminishing the urban heat island effect, providing habitat to critical plant and animal species, flood regulation, and recreational opportunities (Dooley & Stelk, 2021; Millenium Ecosystem Assessment, 2005). However, those ecosystems face threats, such as sewage pollution, changed water regimes, reduced hydrological functions, habitat and biodiversity loss or climate change, and loss due to land-use change (Alikhani et al., 2021). Moreover, in previous decades, individuals and societies have disregarded the value of wetlands (Das & Mehrotra, 2021), filling them with municipal and construction waste material and seeing them as a source of insecurity. For example, in Bogota, the area of wetlands in the 1940s was 50 000 hectares, but today it stands at only 901 hectares (Durand, 2007; Secretaria de Ambiente, 2022; Van der Hammen, 2003).

In 1950, 70% of the world's population lived in rural areas, but it was until 2007 that the urban population surpassed this number (United Nations, 2019). Ever since, the urban population has continued growing, and United Nations estimates it will increase to 68% by 2050 (United Nations, 2019). Urban growth is increasing environmental pressure, especially in and around urban centers (Sandoval, 2013). Latin America and the Caribbean are amongst the most urbanized regions in the world, where nearly 81% of the inhabitants live in cities (United Nations, 2018). In Colombia, during the 60s and 70s of the 20th century, urban growth was fueled mainly by migration from the countryside to the city due to violence (United Nations Population Fund (UNFPA) & Universidad Externado de Colombia, 2007). Since the late 1950s, the city of Bogota has experienced substantial growth and spread westward, reaching today the Bogota River. As development and urban growth increase, protected wetlands - that once were in the peripheral or rural areas - are absorbed by the city, losing their environmental and ecological qualities (Sandoval, 2013). Thus, preserving and protecting these ecosystems is crucial because of their inherent role in monitoring global change and guiding human adaptation to a changing world (United Nations, 2019).

To retain and restore urban wetlands, studies on the changes in urban wetlands have gained momentum since the 2000s, and researchers have analyzed mainly historical changes in their landscape patterns and ecological functions. Fieldwork, remotely sensed data, Geographic

Information Systems (GIS), and complexity science modeling approaches have been applied to evaluate changes in these ecosystems (Das & Mehrotra, 2021; Durand, 2007; González Angarita et al., 2022; Grayson et al., 1999; Hasse & Lathrop, 2003; Kai Xu et al., 2010; Mondal et al., 2017; Potter et al., 2004; Yu, Huan; He, Zhengwei; Pan, 2010). The complex interactions and relationships among the environmental components that drive wetland formation and regulation require methodological approaches to detect and analyze wetland changes across spatial and temporal scales in complex urban landscapes. Land Use Land Cover (LULC) change models using Cellular Automata (CA) are increasingly used to explore land change dynamics. They are considered a basis for public policy decisions to promote protecting and manage ecosystems (Peng et al., 2020).

Researchers have used computational models to understand better the spatial and temporal dynamics observed in urban wetlands. X. Wang et al. (2008) used landscape indices and the Markov model to evaluate the relationship between changes in wetland landscapes and urban construction in Wuhan, China. Peng et al. (2020) developed a model of spatial allocation by pairing Random Forest (RF) regression and the Conversion of Land Use and its Effects (CLUE-s) model to simulate the spatial dynamics of the urban wetlands in the Wuhan Agglomeration. Ghosh & Das (2020) assessed the East Kolkata Wetland shift peril using RF and Support Vector Machine (SVM). Saha et al. (2021) mapped the floodplain wetlands of the Atreyee river basin of India and Bangladesh. They estimated their area up to 2039 using Artificial Neural Networks and Cellular automata (ANN-CA) techniques. To sum up, researchers have implemented spatiotemporal models to help decision-makers protect the wetland landscape.

There is a broad spectrum of studies on LULC changes in Bogota City. Cabrera-Amaya et al. (2017) did a floristic characterization of the vegetation in the Jaboque wetland and determined the changes in the vegetation cover between 2004 and 2016. Morales (2018) conducted a multi-temporal analysis in the Santa Maria del Lago wetland in 1952, 1990, and 2014. Garzón Gutiérrez (2016) assessed the environmental conditions of the Juan Amarillo wetland using and comparing multi-temporal remote sensing data. Bernal Jaramillo (2006) studied the physical degradation of the La Vaca, Techo, and El Burro wetlands to establish landscape guidelines for their management. In summary, previous studies have aimed to study Bogota's wetlands' physical, historical, and compositional changes to draw the attention of citizens and competent entities to restore, conserve and protect them. However, to our knowledge, no studies have investigated future trends of wetland changes in Bogota.

The main goal of this research is to implement a computational model to simulate and study the changes in the urban wetlands of Bogota, Colombia. To accomplish our main objective, we: 1) interpreted one analog (1998) and two numerical images digitized (2004 and 2010) to extract LULC and estimated the changes and tendencies in the wetlands during the frame time; 2) obtained the probability maps for each land class from the application of ANN to simulate wetland changes; 3) applied a hybrid land cover model, using the LULC probability maps, the Markov Chain, and the FLUS-CA model (X. Liu et al., 2017); and 4) employed the Intensity Analysis framework (Aldwaik & Pontius, 2012; Varga et al., 2019) to validate the model and analyze the results.

The following section presents the study area and data for implementing the CA-FLUS model. Next, we describe the methodology, beginning with the particularities of the modeling approach and continuing with the techniques used to evaluate the observed and projected LULC changes. Then we present the results and discuss the analysis. Finally, we depicted the conclusions and implications.

3.2 Material and Methods

3.2.1 Study Area

Located in the Eastern Cordillera, in the northern part of the Andes, the capital city of Colombia accounts for an altitude between 2650 and 3750 m asl (meters above sea level). The temperature of the city varies between 7°C-14.5°C. The rainfall is bimodal, with alternating periods of 2 to 3 months of rain with rainfall of 163 mm (April-June and September-November) and two dry periods with 20 mm (January-February and July-August) (IDIGER. Subdirección de análisis de riesgos y efectos del cambio climático, 2019). The urban area occupies approximately 379 km² and has a particular river network. It is next to the Eastern Hills, near the paramos of Chingaza and Sumapaz. The population reaches 7,181,469 (DANE, 2018). The Bogota wetlands, located west of the city, are part of the historic area of marshy transition with the city center. Bogota's urban wetland complex has 15 ecosystems recognized by the city's Environment Secretariat, but the Ramsar Convention recognizes only 11 with an area of 6.67 km² (Ramsar Convention Secretariat, 2019).

Figure 3.1 shows the location of fifteen wetlands. We took only the administrative localities that have a direct impact and are around the influenced area of the ecosystems.

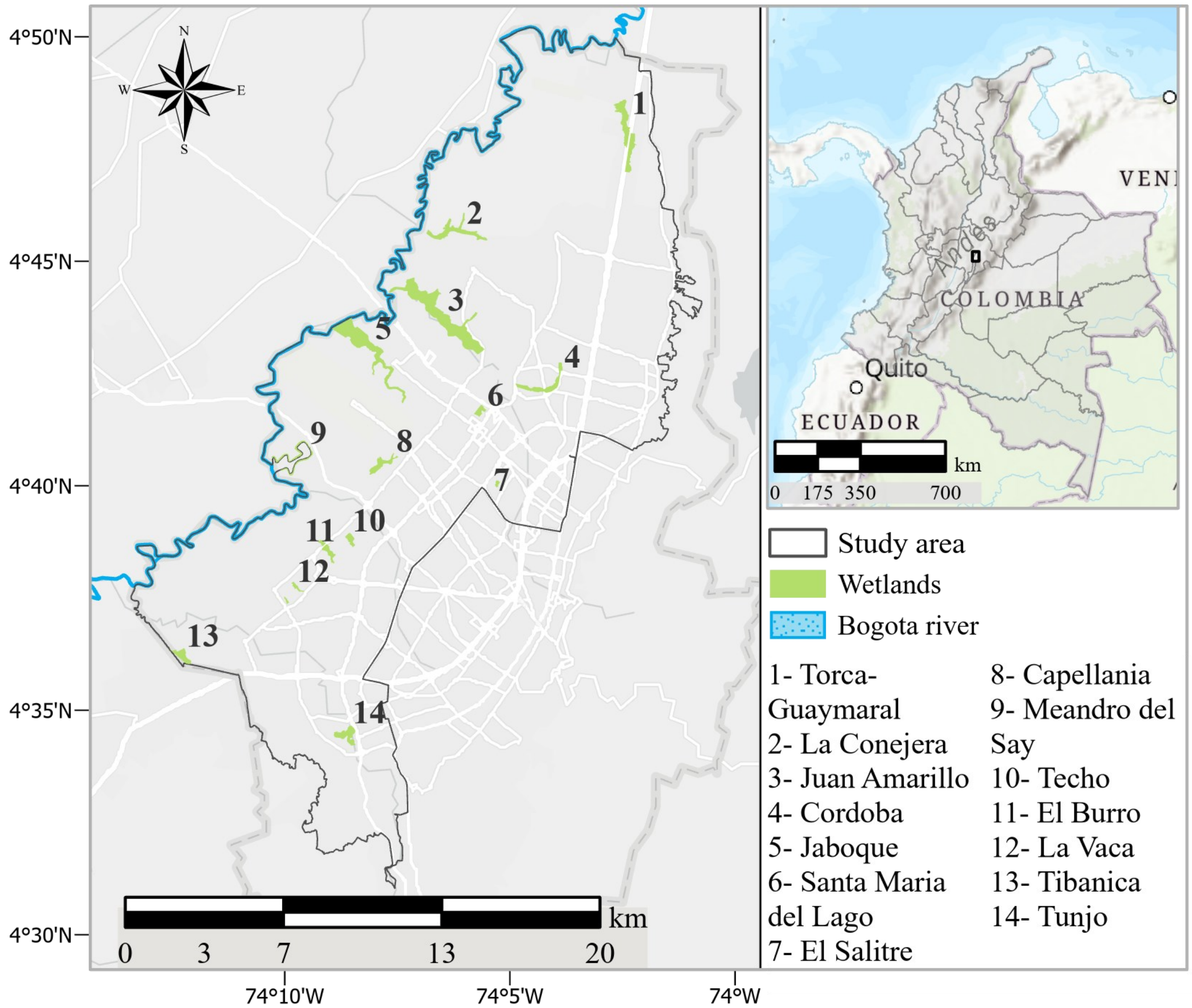

Figure 3.1. - The study area of Bogota, Colombia.

3.2.2 Data sources

Three images were selected from the Spatial Data Infrastructure of Bogota (IDECA), based on their temporality and resolution. The chosen remotely sensed products were: a) for the year 1998 an orthomosaic, created from orthorectified aerial photographs, and b) for the years 2004 and 2010 WorldView-2 satellite images. Subsequently we performed an on-screen digitization of the images by using visual image interpretation elements and obtained the LULC maps. Then, parting from the definition of wetlands, "areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish or salt, including areas of marine water the depth of which at low tide does not exceed six metres (Ramsar Convention Secretariat, 2016)", we selected six land classes: constructions, urban green spaces, crops and pastures, quarries, water, and wetlands.

Many variables affect urban wetlands (Jiang et al., 2012). Therefore, we selected the driving factors and local knowledge based on a literature review (Jiang et al., 2012; Shaohui & Zhongping, 2013; Tian et al., 2021; Wu et al., 2019). The driving factors identified were the distance to roads, the Digital Elevation Model (DEM), population density, household density, cadastral information, and climatic variables such as precipitation and temperature. Table 3.1 lists the spatial datasets used to simulate LULC in Bogota. We calculated the distance to the arterial road network using the Euclidean distance tool of ArcGIS Pro version 2.6.0 (ESRI, 2020). The restricted area data represent the protected area system established in the city's Land Use Plan (Secretaria Distrital de Ambiente, 2019). All the spatial datasets were rasterized and resampled to a five-meter pixel size. The driving factors were normalized to improve model accuracy to eliminate dimensional and quantitative differences (Figure 3.2).

Table 3.1 - Data resources.

Data	Year	Format	Resolution	Source and description
Orthomosaic	1998	WMS	0.5 m	
WorldView-2 Satellite Imagery	2004, 2010	WMS	0.46 m	
Distance to the arterial road network		Vector	1:1000	Open data portal of the city of Bogota https://www.ideca.gov.co
DEM	2014	Raster	5 m	
Urban geomorphology	2016	Vector	1:1000	
Restricted Areas		Vector	1:1000	
Population	2004, 2010	xlsx	Localities*	http://www.bogota.gov.co
Cadastral information	1998, 2004, 2010	Vector	1:1000	https://serviciosgis.catastrobogota.gov.co
Annual Mean Temperature		Vector	1:1500	https://datosabiertos.bogota.gov.co
Annual Precipitation		Vector	1:1500	

*Local administrative division of the City of Bogota

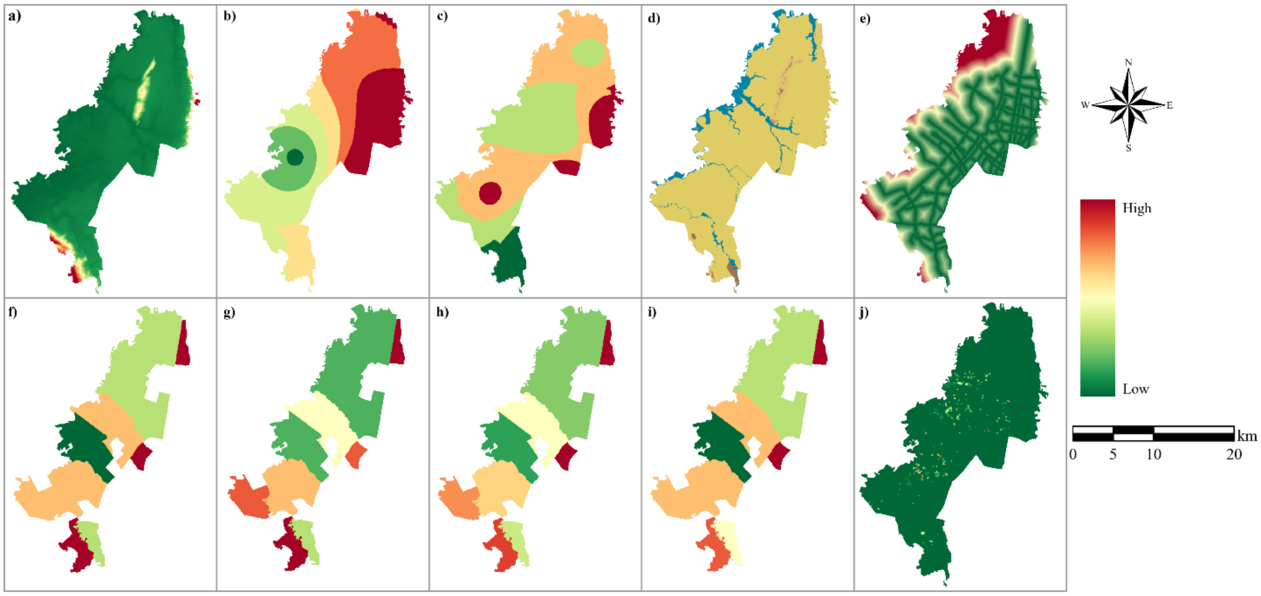

Figure 3.2 - Driving factors used to simulate land use change – a) Digital Elevation Model, b) Annual Precipitation, c) Mean annual temperature, d) Urban geomorphology, e) Distance to roads, f) Population density for the year 2004, g) Population density for the year 2010, h) Household density for the year 2004, i) Household density for the year 2010, j) Cadastral information. A detailed map of urban geomorphology and the legend are attached as Supplementary Fig. III.1.

3.2.3 Methodology

We applied three methodical approaches to simulate LULC change: Markov Chain (MC), Artificial Neural Networks (ANN), and the Future Land Use Simulation (FLUS) model used successfully in the simulation of complex LULC in past research (Liang et al., 2020; Liang, Liu, Li, Chen, et al., 2018; Liang, Liu, Li, Zhao, et al., 2018; X. Liu et al., 2017).

Land use demand projection using Markov Chain

We use the MC model as the "top-down” land-use demand forecasting module of the FLUS model (Liang, Liu, Li, Zhao, et al., 2018). The MC model is a method for projecting future land-use demands by determining the transition probability of change from one category to another in a time interval and employed in other simulation studies (Arsanjani et al., 2013; Mondal et al., 2017; Xu et al., 2019). In this research, we implemented MC in three time periods, i.e., 2010-2016, 2016-2022, and 2022-2028.

FLUS model

The FLUS model simulates land-use change under the effect of human existence and nature by applying a spatial simulation process based on a CA model. To set relationships between historical land-use data and the driving factors of change, it implements an ANN. The value of the probabilities of occurrence on each pixel guides the allocation of changes in land-use distribution. Then, its self-adaptive inertia and competition mechanism allow the model to develop complex local land-use interactions and competition, effectively dealing with the uncertainty and complexity of the transformation of various land-use types under different influences (X. Liu et al., 2017). In addition, the FLUS model uses the Moore neighborhood to represent the neighborhood space. This study tested the model's sensitivity using three neighborhood dimensions 3x3, 5x5, and 7x7. See X. Liu et al. (2017) for a detailed model description.

Artificial Neural Network

Researchers use Machine learning techniques like ANN to approximate the nonlinear and complex relationships between LULC patterns and their driving variables (Lin et al., 2011; Xu et al., 2019). Used as data mining tools to extract land-use class transition rules for CA (Yang et al., 2016), the ANN includes several neurons that work in parallel to transform the input data into output categories (Morales, 2018) - consisting of three-layer types: an input layer, a hidden layer, and an output layer. In the ANN, each neuron in the input layer conforms to the land-use maps and the driving factors. Each neuron in the output layer conforms to a distinct land type representing the probability of occurrence of each land type concerning the influencing factors. We employed the random sampling technique to extract 70% of the data as samples to ensure the same sampling points for all kinds of land. Normalized processing is carried out on the data samples and then imported into the ANN model to obtain the suitability probability of each category.

3.2.4 Model implementation

Figure 3.3 shows the steps we followed to simulate land-cover change. Firstly, we performed a change analysis to identify the most crucial land-cover class transitions in the first-time interval. We used the LULC maps from 1998 and 2004 for carrying out the change analysis.

Secondly, we utilized the MC to obtain the unknown land demand in simulated intervals. Initially, land demand was calculated based on the reference map for the year 2010. Then, subsequent time intervals were calculated based on the previous time interval. So, for example, to obtain the land demand for 2016, the transition matrix was calculated for the years 2004-2010.

Thirdly, the ANN was constructed of 10 neurons (Table 3.1) in the input layer (the driving factors) and six neurons in the output layer (corresponding to the land types). 70% of the total pixels across the study area were randomly selected as the training dataset (X. Liu et al., 2017). Before training the network, the sampling data is normalized to [0 1]; to do it, the FLUS model uses the sigmoid function as the model transfer function to ensure the estimated probability values' range is [0 1] (X. Liu et al., 2017).

The FLUS model was run to simulate 30-year land-cover changes on the study case of urban wetland changes in Bogota, initiated in 2004. The simulation timeframe was selected to validate the results against the available LULC map corresponding to 2010. A total of five simulated maps were calculated, and an emphasis of our analysis assessment was centered around the urban wetlands category.

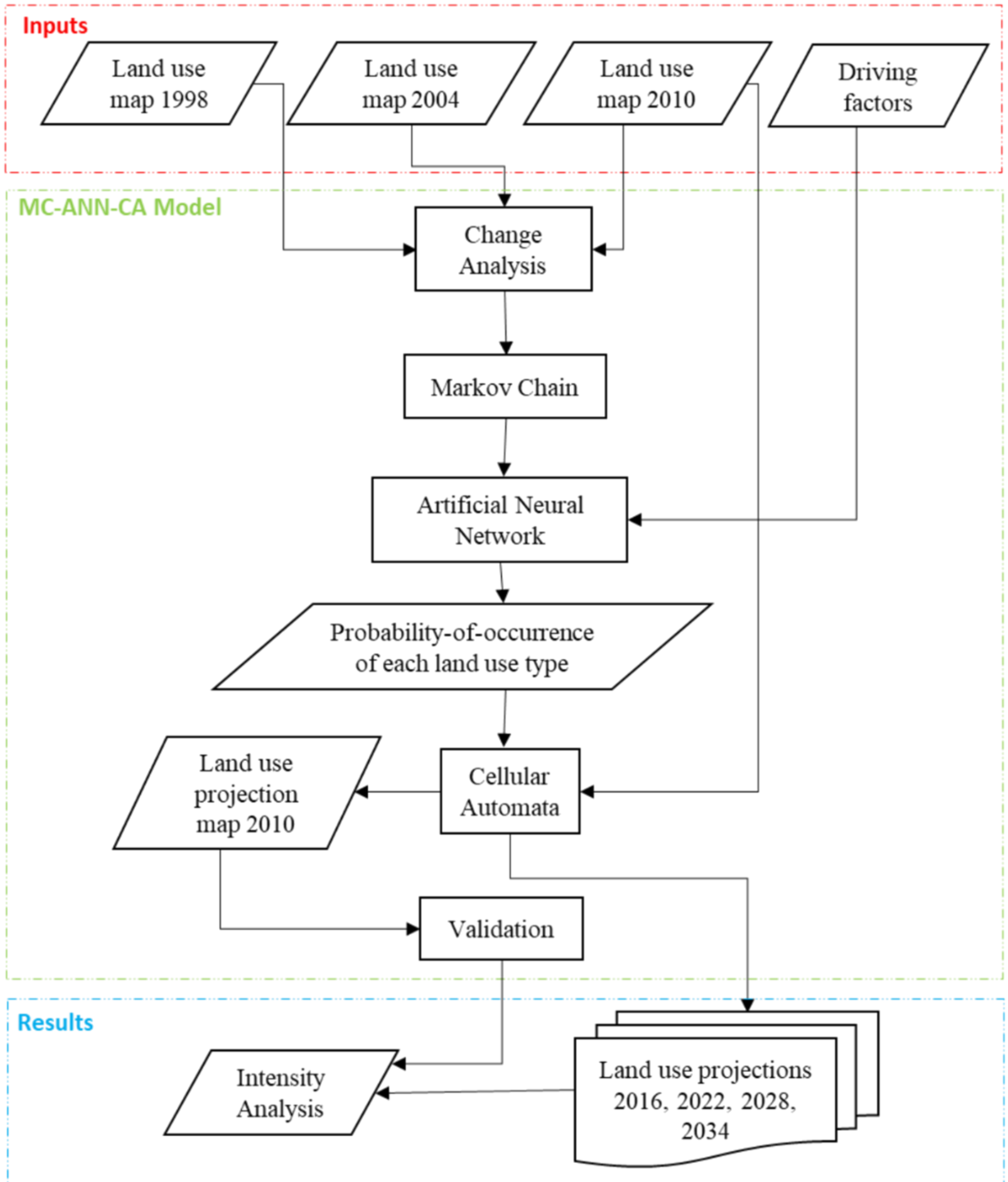

Figure 3.3. - Schematic diagram of the methodology.

The following stage used the CA module to carry out LULC map projections. A 3 x 3, 5 x 5, and 7 x 7 Moore neighborhoods were used for the simulation. The CA module was implemented in two phases: calibration/validation and simulation. We calibrated and validated the model from 1998 to 2010 and performed the simulation from 2016 to 2034. First, we calibrated the model using the observed maps of 1998 and 2004. Then, to obtain the projection for the year 2010, we used the observed 2004 LULC map. Next, we validated the model by comparing the reference 2010 land-cover map with the 2010 projected map (see the "Model validation" section). Then, we simulated LULC maps for 2016, 2022, 2028, and 2034, starting from the observed 2010 LULC map. Finally, we performed the validation and analysis results by applying the Intensity Analysis.

3.2.5 Model validation – Intensity Analysis

In this research, we used the Intensity Analysis technique to quantitatively examine the simulation performance of the FLUS model in the interval, category, and transition levels. Aldwaik & Pontius (2012) thoroughly detailed the procedure and equations of Intensity Analysis. At the interval level, the total size of the change and the annual rate of change is calculated for each time interval (i.e., for the pair of maps defining each time interval). This level of analysis allows us to identify intervals with slow and fast rates of annual change. At the category level, the size of gross gains and losses and the intensity of gross gains and losses are calculated for each land class. This level of analysis identifies dormant and active land types in a specific time interval. Finally, the size and intensity of land-type transitions are calculated at the transition level. For each land type with gains or losses, this level of analysis identifies other land types that are notable targets of transition and notably avoided in transitions.

We first validated the results from the ANN model. Then we validated the model by comparing the 2004-2010 reference LULC change with the projected 2004-2010 projected map. Finally, we compared the 1998-2010 observed LULC change with the projected 2016-2034 LULC change in terms of the interval, category, and transition intensities.

ANN validation

We used the Area Under the Curve (AUC) of the Total Operating Characteristic (TOC) index to quantify the ANN model performance. The TOC calculates how the ranks of an index variable (probability-of-occurrence maps) classify between the presence and absence in a binary reference variable (observed values of LUCC) (Pontius Jr & Si, 2014). The TOC shows misses, hits, false alarms, and correct rejections. As in the Receiving operating curve (ROC), the AUC of the TOC offers a metric to summarise the performance. The AUC is used as an indicator for overall prediction accuracy. Generally, AUC values go from 0 to 1, where values between 0.60-0.70 mean poor accuracy level, 0.70-0.80 indicates fair, 0.80-0.90 signifies good, and 0.90-1 means excellent (Saha et al., 2021).

Land-cover projection validation

Since the neighborhood effect parameter in the Cellular Automata (CA) model is essential during model calibration, we applied a Sensitivity Analysis (SA) process by varying the neighborhood with 3 x 3, 5 x 5, and 7 x 7 sizes. We calculated the Figure of Merit (FoM) to assess the SA. FoM is a rate where the simulated and reference change intersection is represented in the numerator, while the union of simulated and reference change is at the denominator (Varga et al., 2019). Then, we followed the Intensity Analysis framework proposed by Aldwaik & Pontius (2012). We evaluated the performance of the modeled LULC map by comparing the reference change versus the predicted change in the study area. A simulation of LULC changes from 2004 to 2010 was run to test the model, and we contrast the result with the observed change from the 2004 to 2010 LULC maps. Lastly, we compared the 1998-2010 reference LULC (Aldwaik & Pontius, 2012) change with the simulated 2016-2034 land-use change regarding its interval, category, and transition level.

3.2.6 Software tools

We downloaded the FLUS model from https://www.geosimulation.cn/FLUS.html. Then, we carried out the analysis using various software packages. First, we calculated the cross-tabulation matrices using TerrSet (Eastman, 2020). Second, we use the statistical software RStudio 2022.07.0 (R Core Team, 2020) to obtain the AUC for the TOC curve using the packages "raster (Hijmans, 2022) " and "TOC" and the "lulcc" package to compute the FoM (Moulds, 2019). Third, we applied Intensity Analysis employing the free software from http://www.clarku.edu/~rpontius/ and the package “intensity analysis (Pontius & Khallaghi, 2019)” for RStudio 2022.07.0 (R Core Team, 2020). Finally, we made the maps with ArcGIS Pro 2.6 (ESRI, 2020).

3.3 Results

3.3.1 Land Use and Land Cover Change (LUCC)

Past LULC was calculated three maps that included six classes, as follows: constructions, crops and pastures, quarries, urban green spaces, water, and wetlands (Figure 3.4). Table 3.2 shows the results from comparing the three maps. Among the six land classes, the classes of urban green spaces, constructions, and water presented an increase in area. In contrast, the classes of crops and pastures, wetlands, and quarries decreased, with the crops and pastures showing the most significant decrease by 1211 ha less.

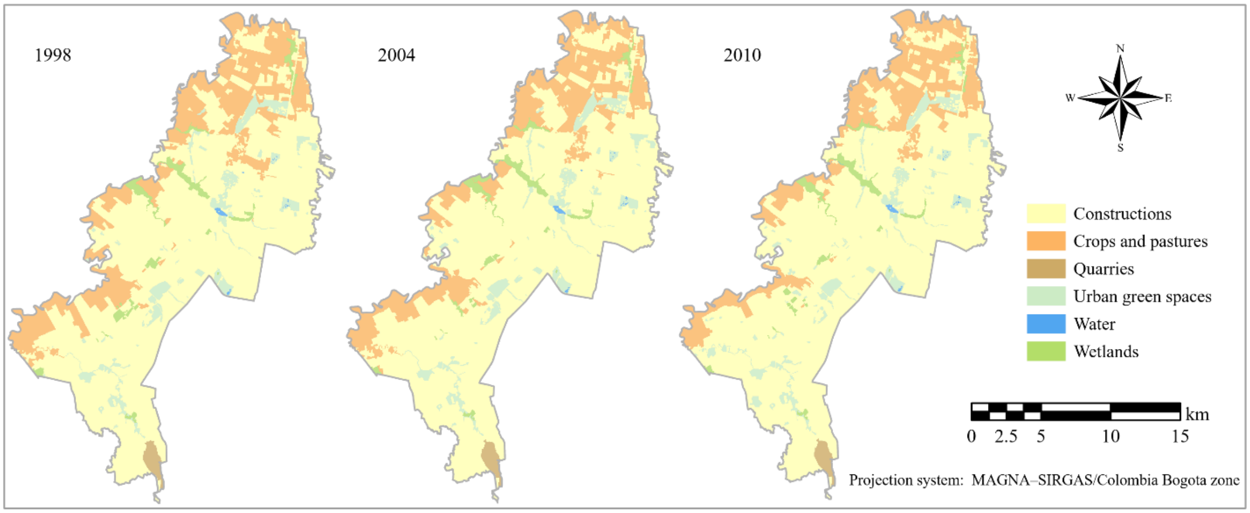

Figure 3.4 - Maps of six land categories in 1998, 2004, and 2010.

Wetlands represented 2.58% of the total study area in 1998, 2.46% in 2004, and 2.29% in 2010, decreasing in 12 years by 0.3% of the study area. So then, the wetlands reduction from 1998 to 2004 represented a 4.87% loss in wetlands class area and 1.51% in 2010. These results show the continuous decrease of the wetland cover over the years. On the contrary, the area covered by constructions, representing the largest class in the study area, increased by 3.65% from 1998 to 2010, going from 69.7% in 1998 to 72% in 2004 and 73.3% in 2010.

Table 3.2. - Area (ha) per land class and relative area increment or decrement in 2010 compared with 1998.

	1998	2004	2010	Increment/Decrement (%)
Constructions	21 849,4	22 544,7	22 995,3	5,2
Crops and pastures	6 709,9	5 996,9	5 499,3	–18
Quarries	254,1	243,9	244,3	–3,9
Urban Green Spaces	1 592,1	1 659,5	1 758,7	10,5
Water	136,8	136,8	137,9	0,8
Wetlands	810,2	770,7	717,0	–11,5

3.3.2 Validation results

ANN performance

We calibrated the FLUS model using LULC maps and driving factors and employed the model to obtain the projected maps for 2016, 2022, 2028, and 2034. Applying the ANN module, we generated the land transition probability map for each land type (see Supplementary Fig. III.2).

Those maps illustrate the chance of each cell transitioning to each of this study's six land types. Figure 3.5 shows the TOC curves of the six land types. The AUC values of each land class were computed according to the TOC curves. Validation of the ANN model showed the AUC to be above 0.7 in all land classes, with values ranging from 0.72 to 0.98 and a mean value of 0.85.

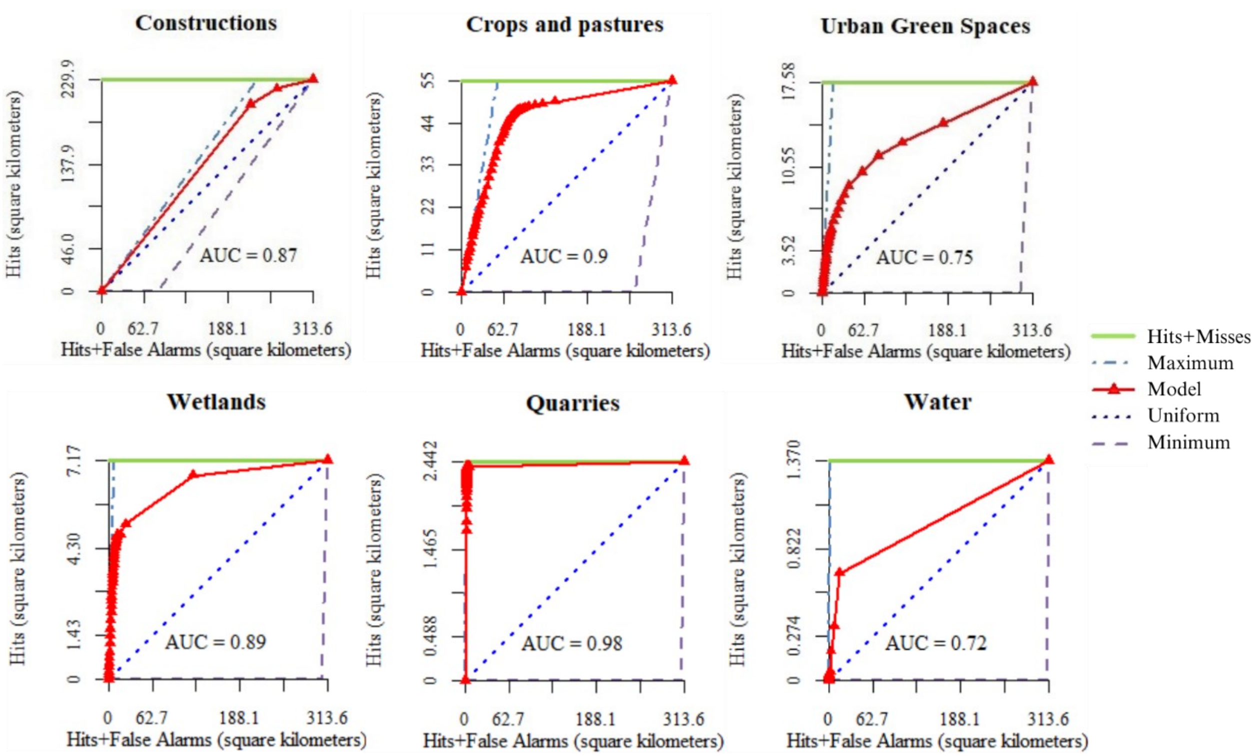

Figure 3.5 - TOC curves and AUC values to validate the ANN.

Land-cover projection validation

At the interval level, results show that land change is quite fast for the first reference interval, 1998-2004, while land change is relatively slow for the second reference interval, 2004-2010. Table 3.3 shows LULC transitions in percentages during calibration and validation time intervals. During the 1998-2004 reference period, the overall reference change was 1617 ha. The overall reference change during 2004-2010 was 1480 ha, while during the 2004-2010 simulation, the overall change was 716 ha.

Table 3.3. – Land-use transition, each row is the start time and each column the end time. For each transition, the top number gives 1998-2004 reference, the middle number gives 2004-2010 reference, and the bottom number gives 2004-2010 simulation.

Category	Constructions	Crops and pastures	Quarries	Urban Green Spaces	Water	Wetlands	Total (%)	Loss (%)
Constructions	68,51	0,80	0	0,25	0	0,09	69,66	1,15
	70,66	0,78	0	0,36	0	0,08	71,87	1,22
	71,78	0,04	0	0,09	0	0	71,91	0,13
Crops and pastures	2,82	18,18	0	0,18	0	0,27	21,44	3,26
	2,08	16,54	0	0,40	0	0,15	19,17	2,63
	1,88	17,14	0	0,11	0	0	19,13	1,99
Quarries	0,03	0	0,78	0	0	0	0,81	0,03
	0	0	0,78	0	0	0	0,78	0
	0,02	0	0,76	0	0	0	0,78	0,02
Urban Green Spaces	0,21	0	0	4,85	0	0	5,08	0,23
	0,44	0	0	4,83	0	0,01	5,29	0,46
	0,02	0	0	5,27	0	0	5,29	0,02
Water	0	0	0	0	0,43	0	0,43	0
	0	0	0	0	0,43	0	0,43	0
	0	0	0	0	0,43	0	0,43	0
Wetlands	0,30	0,17	0	0,01	0	2,09	2,58	0,49
	0,13	0,26	0	0,02	0	2,04	2,46	0,41
	0,09	0,04	0	0	0,00	2,33	2,46	0,13
Total (%)	71,87	19,17	0,78	5,29	0,43	2,46	100	5,16
	73,31	17,58	0,78	5,61	0,44	2,29	100	4,72
	73,78	17,22	0,76	5,47	0,43	2,33	100	2,28
Gain (%)	3,37	0,99	0,00	0,44	0	0,36	*5,16*	
	2,65	1,04	0	0,77	0	0,24	*4,72*	
	2,01	0,08	0	0,20	0	0	*2,28*	
Net change (%)	2,22	2,27	0,03	0,21	0	0,13		
	1,44	1,59	0	0,32	0	0,17		
	1,87	1,91	0,02	0,18	0	0,13		

We applied the SA to see how the size of the neighborhood influences the results. First, the simulation map showed that the change was allocated around the edges of zones of certain land types, as seen in Supplementary Fig. III.3. In contrast, the change in the reference maps is rarely allocated on those edges. Next, we calculated the FoM to evaluate SA results. FoM values were 7.08% for 3 x 3 neighborhood size, 7.14% for 5 x 5, and 7.09% for 7 x 7. A wide variety of metrics were implemented to evaluate the SA of the model, and we found that the accuracy of the outputs model improves with a 3 x 3 neighborhood size and 5 m spatial resolution. For a detailed explanation of SA results, see Cuellar & Perez (2023).

In Supplementary Figure III.4, we presented the results from the Intensity Analysis at the category level for each time interval. The dashed line in each graph illustrates the uniform intensity of annual change. The analysis showed a deceleration of the overall change from the first-time interval (1998-2004) to the second-time interval (2004-2010), with the simulation deceleration being more intense than the reference downtrend. Figure IIIand III.4c show that the 2004-2010 simulation loss intensities are less than the 1998-2004 reference loss intensities. Additionally, Supplementary Figures III.4a and III.4b depict that the reference patterns are not stationary from the calibration interval (1998-2004) to the validation interval (2004-2010). Notably, the reference wetland category gains more during the calibration interval than during the validation interval.

Consequently, this category's intensity in the simulation does not match the reference from 2004-2010. Comparing Supplementary Figure III.4b and III.4c reveals more information about model performance in the validation time interval (2004-2010). While Reference change shows gains and losses in categories, in the simulation, categories either gain or lose. In other words, in the simulation, the relative difference between the gain and loss of each category is significant, except for the water category, which shows very little change. It is also noteworthy that in reference data of calibration and validation time intervals, the most extensive loss is in wetlands, and the second largest is in crops and pastures. In contrast, the most significant loss in simulation is in crops and pastures, and the second largest is in wetlands. Supplementary Figure III.5 presents the transition-level results for wetlands, crops and pastures, urban green spaces, and constructions.

a) **b)** **c)**

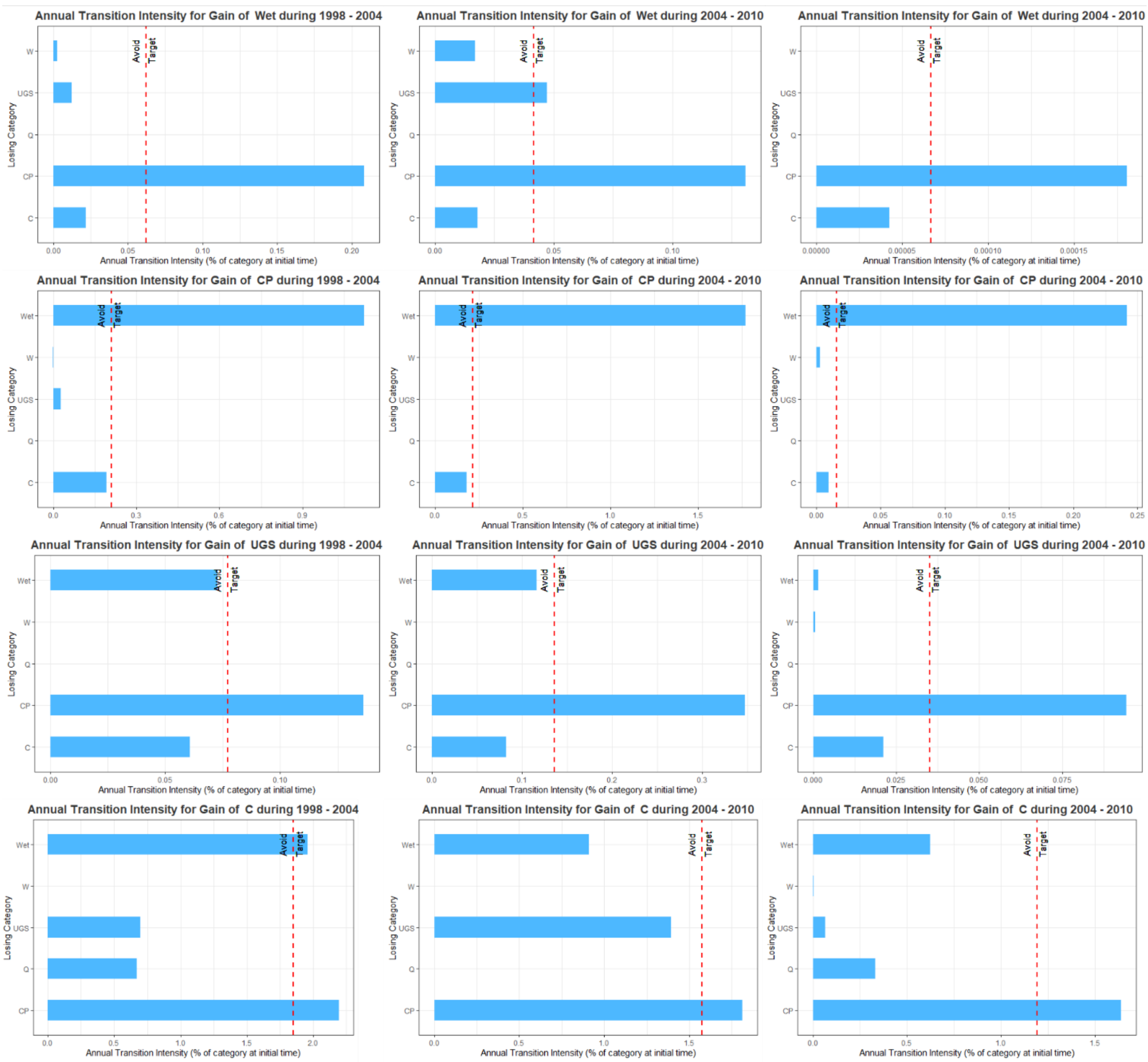

Figure . Comparing the calibration and validation time intervals shows how the model almost extrapolated change intensities from the 1998-2004 reference calibration interval to the 2004-2010 simulation validation interval. The gain of wetlands targeted crops and pastures loss during all the intervals. However, unlike reference change in the validation interval, it did not target urban green space loss in the simulation. The construction gain targeted crops and pastures in all intervals and targeted wetland loss during the calibration interval. In contrast, gains of urban green spaces, crops, and pastures from all other categories are stationary across the three intervals.

3.3.3 Land-use change intensity

Interval level change

The annual change intensity for all land classes is 0.16% between 1998 and 2034; this decreases from the historical (1998-2010) to the future (2010-2034), 0.63% and 0.25%, respectively. However, the rate of change in the study area was not uniform. For example, the annual change intensity in 1998-2010 was *fast*, whereas the projected intensity in 2010-2034 was *slow*.

Category level change

The wetlands, constructions, crops and pastures, and urban green spaces categories had more significant changes than other land categories (Figure 3.6). In 1998-2010, gains in construction land class were principally in the west of the study area, while losses were mainly in the north. In contrast, the gains and losses in 2010-2034 are distributed across the study region. Historical (1998-2010) and projected (2010-2034) gains in crops and pastures were mainly in the north, though the projected gains are much less than the historical gains. In comparison, losses in this category were distributed in the west from north to south from 1998-2010. The 2010-2034 losses are concentrated in the north, with some other losses near the western border of the study area. Finally, the 1998-2010 gains for wetlands are settled mainly in the northwest area, while losses are in the center and south. This category's projected gains are negligible, and projected losses are distributed in the center and north of the study area.

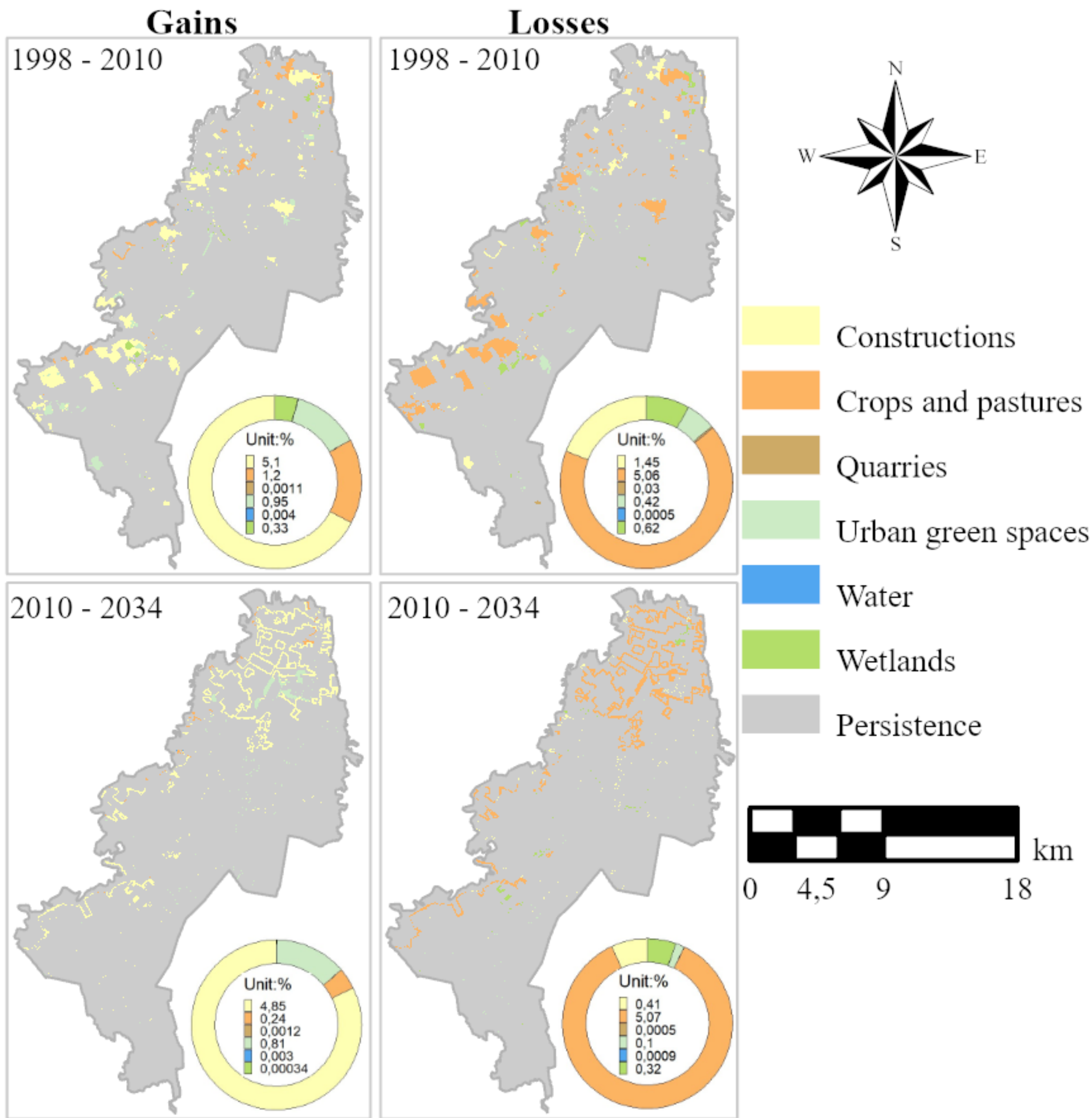

Figure 3.6. - Percentage of gains and losses of each land class in 1998-2010 and 2010-2034.

In 1998-2010, the constructions, crops, and pastures experienced the most significant coverage change compared to the other land categories. The same behavior was projected in 2010-2034 (Figure 3.7). Furthermore, in Figure 3.7a, constructions exhibited a noticeable gain during both periods. In contrast, losses were primarily noticeable in crops and pastures. Although the gain and loss of wetlands are small in both intervals, their annual loss intensity is much higher than that of constructions and higher than crops and pastures in 1998-2010. In the projected period (2010-2034), wetlands loss intensity is much higher than construction gains and loss intensities (Figure 3.7b). For crops and pastures, its annual gain intensity was *dormant* over both time ranges (Figure

3.7b), but its loss intensity was higher than that of the wetlands in 2010-2034. The urban green spaces category was the most *active* during both intervals regarding annual gain intensity. Wetlands' gain intensity was *active* during 1998-2010 and negligible in 2010-2034, but its loss intensity was *active* in both periods.

Figure 3.7c shows crops and pastures, and constructions had the most considerable differences in both time intervals. Their *quantity* component is larger than the other two intensity components. Both are more intensive than *quantity* in 1998-2010, but crops and pastures are more intense than *quantity* in 2010-2034. Urban green spaces and wetlands do not have a minor *quantity* component, but they were the only ones with a *quantity* component less intensive than the *quantity overall* in 1998-2010. In contrast, in the projected period, the *quantity* component is minor for wetlands in size but more intensive for wetlands than for the other categories. Urban green spaces and wetlands have the most *significant exchange* component, and both are more intensive than *exchange overall in 1998-2010.* In 1998-2010, the only categories that had shift were wetlands, urban green spaces, and water, and all are more intensive than *shift overall.* Whereas in 2010-2034, constructions, crops and pastures, and water are the only categories that have a *shift,* just constructions and water are more intensive than *shift overall.* The overall quantity line in Figure 3.8d indicates that *quantity* is 55% of the difference in all six categories. *Exchange* accounts for 43% of the difference overall, and *shift* accounted for 1% in 1998-2010. In contrast, in the projected interval, those intensity components are 87% in *quantity*, 9% in e*xchange*, and 4% in the s*hift.*

Figure 3.7 - Category Level Intensity Analysis. Rows a) Land change size gains and losses, b) land change intensity, c-d) change size and intensity by components. Wetlands (Wet), urban green spaces (UGS), crops and pastures (CP), quarries (Q), water (Wa), and constructions (C).

Transition level change

Figure 3.8 shows the results of the transition-level Intensity Analysis for the most significant gains: wetlands, crops and pastures, constructions, and urban green spaces. Although during the time intervals of 1998 to 2010 and 2010-2034, the transition intensities from crops and pastures to constructions and wetlands are more substantial than that from the remaining categories, from those results, it can be observed that the gain of constructions and wetlands comes more from the loss of crops and pastures. The transition intensities from wetlands, crops, and pastures to urban green spaces differ over the two periods. In 1998-2010, the gain of urban green spaces *avoid*ed the loss of wetlands but *targeted* the loss of crops and pastures, while it *target*ed losses in both categories during 2010-2034. The gain of crops and pastures *targets* the loss of wetlands in both time intervals and *avoids* the loss of constructions.

Additionally, the gain of crops and pastures, constructions, and wetlands is stationary through time to how those categories *avoid* or *target* the non-crops and pastures, non-constructions, and non-wetlands categories. However, the gain of urban green spaces is not stationary over time. For example, the gain of urban green spaces *targeted* only crops and pastures during 1998-2010, but during the projected period, it also *targets* wetlands areas.

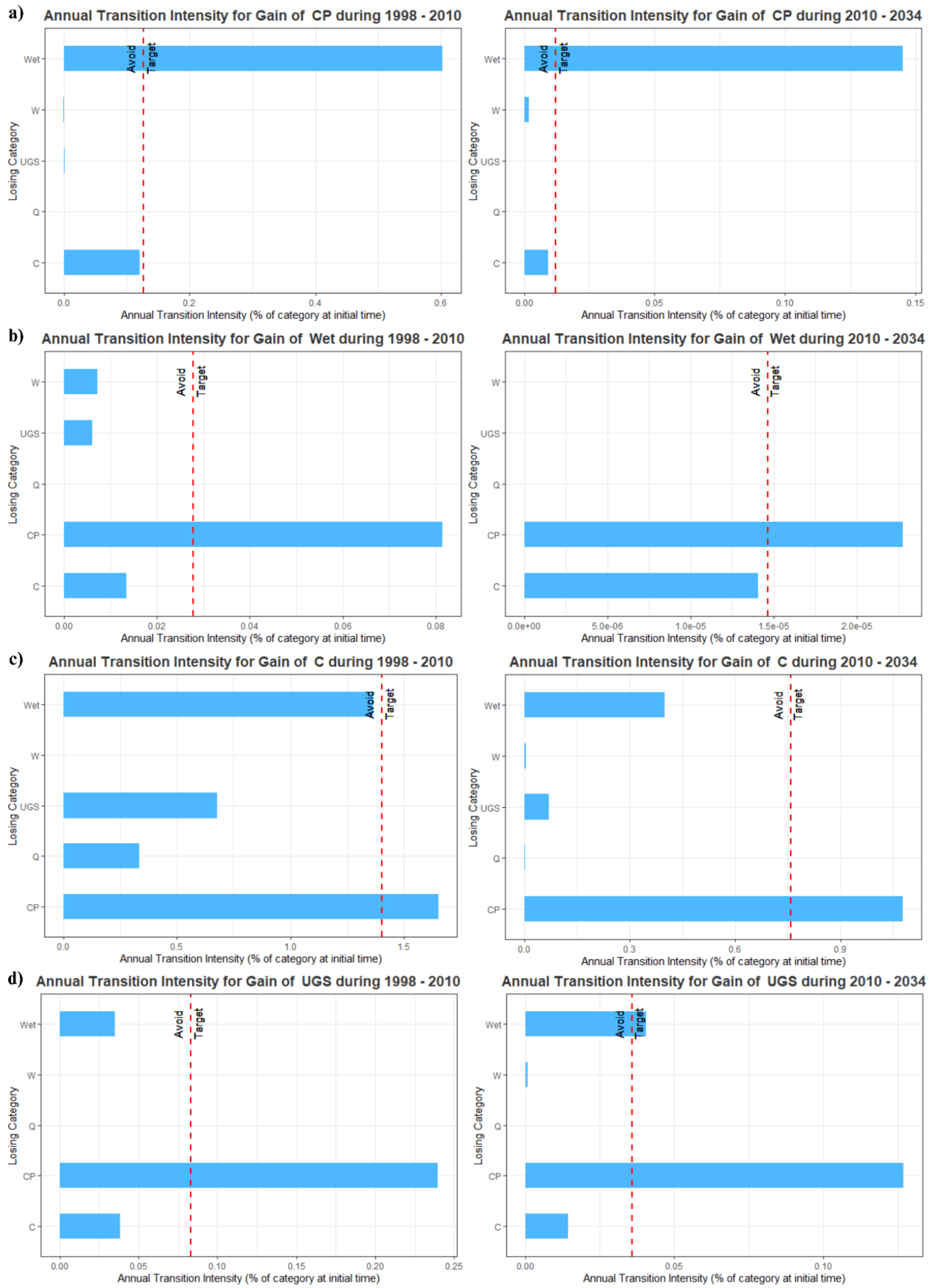

Figure 3.8 - Transition intensity from losing a) crops and pastures, b) wetlands, c) constructions, d) urban green spaces, and land classes during 1998-2010 and 2010-2034. Wetlands (Wet), urban green spaces (UGS), crops and pastures (CP), quarries (Q), water (Wa), and constructions (C).

3.3.4 Future simulated land use change in quantity

Figure 3.9 shows the projected LULC maps. The cultivated land was mainly in the north and west of the study area bordering the Bogota River. Its coverage declined from 21.4% in 1998 to 12.71% in 2034. The wetlands land was principally found in areas connected with watercourses, declining from 2.6% in 1998 to 1.97% in 2034. The urban green spaces were located throughout the study area, and their coverage increased from 5% in 1998 to 6.3% in 2034. The constructions represented a vast extent in the study area, and their coverage grew from 70% in 1998 to 78% in 2034.

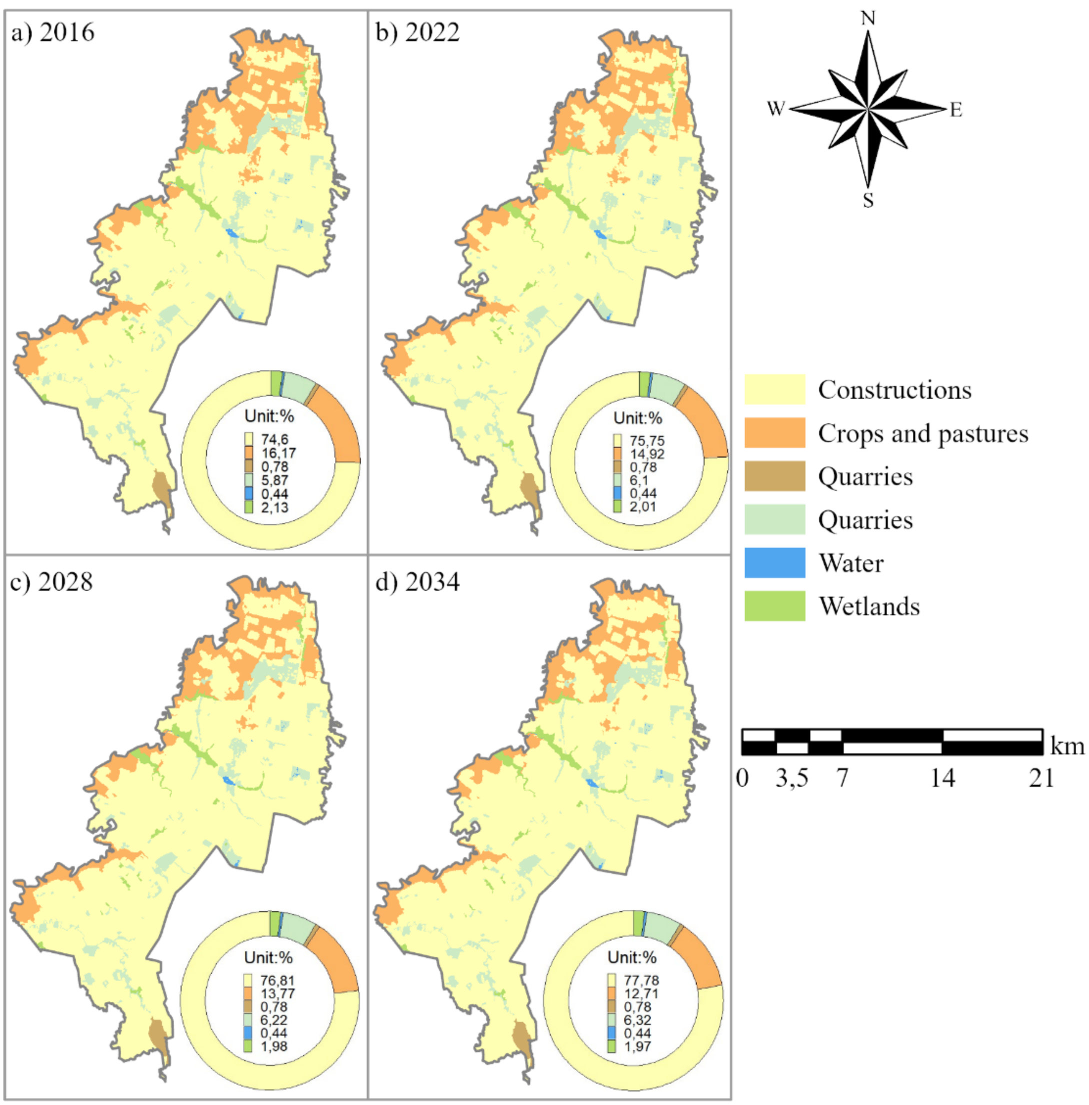

Figure 3.9. - Percentage (concerning the total area) of projected LULC in a) 2016, b) 2022, c) 2028, and d) 2034.

Constructions, crops and pastures, and urban green spaces categories of land are the three LULCs that dominate the study area and comprise about 96% of the total (Table 3.4). During 1998-2010, there were net changes of 3.86% for the crops and pastures, for the constructions and green spaces 4.18%, for water and wetlands 0.30%, while for water and quarries, it was near-zero. Land change assessed at the general landscape level showed that construction was the leading land-gaining category after urban green spaces. Crops and pastures cover was the main losing category. The gains in construction and urban green spaces were 1600 ha and 297 ha, respectively. Constructions lost approximately 454 ha, but crops and pastures lost the most with 1587 ha, nearly the same that the constructions category gained. Wetlands gained 102 ha and lost approximately 195 ha, with a net change of almost 93 ha. Likewise, the simulation results showed a similar pattern for all the land covers throughout the study area. The output map for the year 2034 shows a decrease of almost 0.33% in wetlands coverage concerning the extension in 1998, which translates into 101 ha.

Meanwhile, constructions and green spaces cover continue their pattern with a net gain of 5.15%, that is 1614 ha. On the other hand, the construction class continues to record the highest losses with 1589 ha less. In other words, based on the reference data, by 2034, the total area of constructions and urban green spaces will be equivalent to 26358 ha, for wetlands almost 616 ha, and 3982 ha for crops and pastures.

Table 3.4. – Land-use transitions in 1998-2034 based on the comparison between the reference land-use in 1998 and the projected land-use in 2034. Each row is the start time and each column the end time. For each transition, the top number gives 1998-2010 reference, and the bottom number gives 2010-2034 simulation.

Category	Constructions	Crops and pastures	Quarries	Urban Green Spaces	Water	Wetlands	Total (%)	Loss (%)
Constructions	68,21	1,01	0	0,32	0	0,11	69,66	1,45
	72,93	0,16	0	0,25	0	0	73,35	0,41
Crops and pastures	4,23	16,38	0	0,62	0	0,21	21,44	**5,06**
	4,53	12,47	0	0,53	0	0	17,54	5,07
Quarries	0,03	0	0,78	0	0	0	0,81	0,03
	0	0	0,78	0	0	0	0,78	0
Urban Green Spaces	0,41	0	0	4,66	0	0	5,08	0,42
	0,10	0	0	5,51	0	0	5,61	0,10
Water	0	0	0	0	0,43	0	0,43	0
	0	0	0	0	0,44	0	0,44	0
Wetlands	0,42	0,19	0	0,01	0	1,96	2,58	**0,62**
	0,22	0,08	0	0,02	0	1,97	2,29	0,32
Total (%)	73,31	17,58	0,78	5,61	0,44	2,29	100	7,58
	77,78	12,71	0,78	6,32	0,44	1,97	100	5,90
Gain (%)	**5,10**	1,20	0	0,95	0	**0,33**	*7,58*	
	4,85	0,24	0	0,81	0	0,0003	*5,90*	
Net change (%)	3,65	3,86	0,03	0,53	0	0,30		
	4,44	4,83	0	0,71	0	0,32		

3.3.5 Future wetland changes in Bogota

In this research, we utilized the FLUS model to obtain the projection of the spatial distribution of Bogota's wetlands. To explore their spatiotemporal changes, we calculated their areas from 1998 to 2034 (Figure 3.10). The reference pattern indicated an increase in the northeastern wetlands, except for Torca-Guaymaral, Jaboque, and Cordoba, which had a decreasing pattern. In addition, the wetlands located in the southwest indicated a decreasing reference pattern, except for La Vaca, which had an increasing pattern. Finally, El Salitre and Santa Maria del Lago wetlands maintained a similar pattern during the reference period. Therefore, the simulation maps founded on the spatial dynamics during the historical time 1998-2010 displayed a similar pattern in the study area. The simulated map for the year 2034 shows an increase in 3% of the wetlands located in the northwest, except for Torca-Guaymaral, Jaboque, and Cordoba, with a 52%, 11%, and 34% decrease, respectively. Also, it shows a reduction in 54% of the southwestern wetlands, except for La Vaca, with a 6% decrease. To sum up, by 2034, the total wetlands area is projected to be 611 ha, losing almost 25% of its surface compared to 1998.

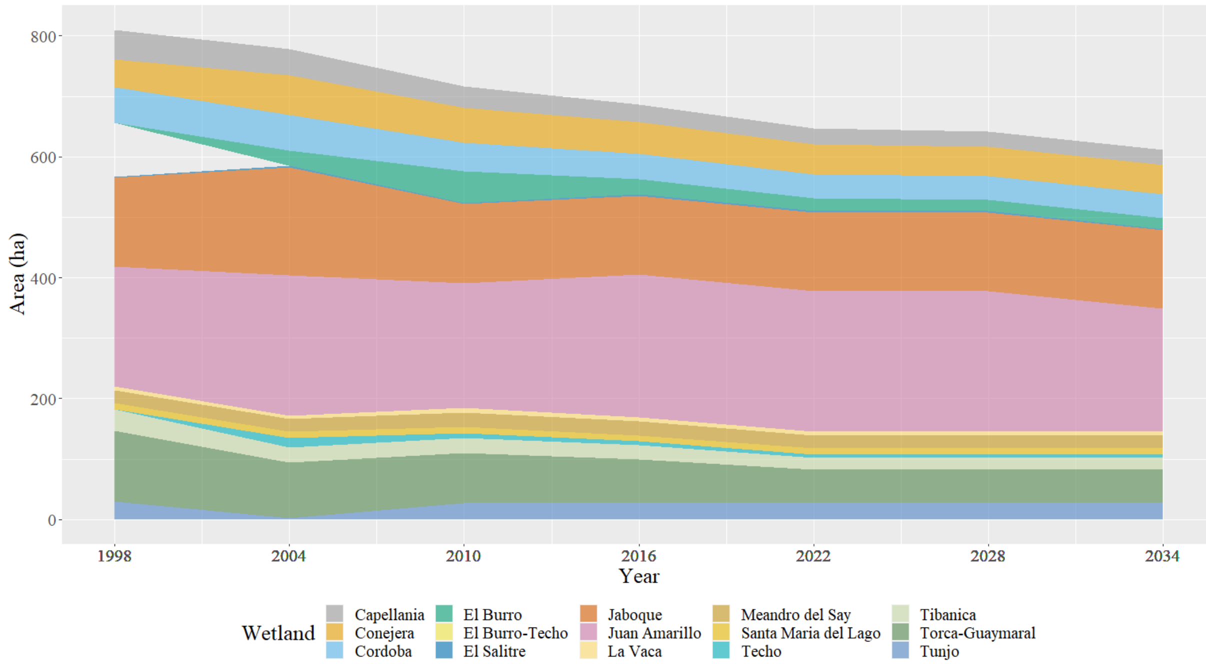

Figure 3.10. - Wetland areas from 1998 to 2034.

3.4 Discussion

Urban wetlands provide numerous ecosystem services, such as reducing urban heat island effects, providing bird shelter and passive recreation areas, and enhancing water quality (Millenium Ecosystem Assessment, 2005). However, urban wetlands remain highly vulnerable to human intrusion. The main drivers of the degradation of urban wetlands are population increase, uncontrolled urban development, water pollution, land use change, drained water, water regime change, and loss of biodiversity (Alikhani et al., 2021). Worldwide, and especially in the 21st century, the natural habitat and landscape layout have been drastically modified. Changes in LULC have been the subject of multiple investigations over the past two decades (Lambin et al., 2003; Y. Liu et al., 2014; Mahiny & Clarke, 2012; Yang et al., 2016). Using spatiotemporal data, we analyzed LULC changes in the area of influence of the Bogota wetlands from 1998 to 2010. From the LULC maps and the physical and socioeconomic determinants, we obtained the probabilities of occurrence of each LULC using the ANN of the FLUS model. In addition, we obtained LUCC projections for 2016, 2022, 2028, and 2034 using the hybrid ANN-Markov-CA FLUS model.

We computed the AUC values of each land class according to the RTC curves to evaluate the ANN. Then, the TOC compared the simulated map with the reference map in 2010. For all LULC types, the AUC was above 0.7, indicating a high degree of agreement between the maps. Figure 3.5 shows that the spatial uniformity between the reference and simulated map for wetlands is significantly increased by 89%. Then, the AUC values indicated that the adjustment of the probability of occurrence of the individual LULC, obtained from the training of the ANN, can be well explained by the selected driving factors.

During the validation, sensitivity analysis showed that all neighborhood configurations caused the simulated changes to occur near the sides of the patches (see Supplementary Fig. III.3). SA results show that different neighborhood sizes cause the gain of a ground cover to be around patches of existing ground cover, as it turned out to be in previous research such as that of Varga et al. (2019). The FoM components indicated that the simulation change only corresponds partially to the reference change in any neighborhood size. Misses were greater than false alarms, which means that reference change from 2004-2010 was more significant than that simulated by the model. Additionally, the Intensity Analysis's validation at the interval level displayed that the FLUS model adequately simulated the decline of global change from the calibration period (1998-2004) to the validation period (2004-2010). At the category level (see Supplementary Fig. III.4), it showed that the model simulated the active or dormant form of loss or gain of each LULC with almost the same state of the LULCs during the calibration interval, except for the constructions that during the calibration period was dormant and became active in the validation period. At the transition level, the results showed that the simulated gain of crops and pastures targeted wetlands, a stationary pattern during time according to the reference data. Also, the transition level showed that the simulated increase of constructions targeted wetlands decreased during the calibration interval; however, during the validation interval, the expansion in constructions just targeted crops and pastures (see Supplementary Fig. III.5). So, the pattern for construction was not stationary.

Validation analysis showed that the study area has a vast dormant category phenomenon. Constructions land class accounts for most of the extent domain in the historical period (Table 3.3); it is dormant regarding gains and losses (Supplementary Fig.III.4). Also, results showed that losses in each LULC are mainly caused by the gain in constructions (Supplementary Fig. III.5). Nevertheless, gains in crops and pastures land class were the leading cause of wetlands land class loss (see Table 3.3 and Supplementary Fig. III.5). Then, the large extent of construction land use performs an essential role in the total change because the reference change is 5.16% of the entire study area, and nearly 4.5% involves transitions with construction (see Table 3.3). A similar phenomenon was reported in the Indonesian forest, where the large forest size played an essential role in the gains and losses behavior of the bare and grass categories (Pontius et al., 2013).

We employed the Intensity Analysis approach to analyze the LULC change in 2010-2034 in terms of its interval, category, and transition level, focusing on the wetlands' category. Mainly construction class increased primarily in the historic interval and likely will continuously increase by 2034. The pattern of urban expansion is evident towards the western part of the city, areas occupied mainly by agricultural activities but which, with the establishment of new (primarily illegal) neighborhoods further south in Bogota, progressively converted its LULC from crops and pastures to constructions. Similar patterns were found by Czerny & Czerny (2016). This phenomenon was portrayed in the intensity analysis at the transition to the construction level (see Figure 3.8). The intensity analysis showed that crops and pastures category coverage has been and will be the most affected globally by other coverages and constructions that go hand in hand with the creation of new green areas and wetland coverage. Rashid & Aneaus (2020) found that agricultural areas decline mostly by built-up areas in the urban wetland in Kashmir Himalaya, India. Although the dynamics of LULC change from crops to constructions/green areas are mainly due to recent human settlements, the role of wetlands needs to be analyzed in more detail.

Simulation maps based on the spatial dynamics during the historic time 1998-2010 displayed a similar pattern for wetlands cover. On the one hand, wetlands in the northwest had a reference pattern of expansion, except for Torca-Guaymaral, Jaboque, and Cordoba, which had a decreasing pattern. On the other hand, the wetlands located in the southwest indicated a decreasing reference pattern, except for La Vaca, which had an increasing pattern. In contrast, El Salitre and Santa Maria del Lago wetlands keep the same pattern during the reference period.

For La Conejera, we found that the increase in wetlands leads to a loss of green areas and crops, while it is a projected loss in construction. Likewise, more wetland area is projected to be lost due to crop expansion. These results are consistent with the last report of the District Secretary for Environment (Secretaria Distrital de Ambiente, 2021d), where there was evidence of an increase in crops by private farms located in the northern sector of the wetland. Juan Amarillo wetlands also had a pattern of expansion, which triggered a loss in crops and pastures land in the reference time but will target loss in construction. In addition, the presence of livestock in the wetland may be linked to its use as a livestock grazing area, a problem that has been the subject of attention in improving the ecosystem (Secretaria Distrital de Ambiente, 2021c). A similar behavior was evidenced in the Meandro del Say wetland, in which gains in wetland areas target the loss of crop areas, and gains in green areas target loss in the wetland surface. This behavior could be explained due to one of the stressors currently facing the wetland since large soccer fields in much of the wetland's interior belong to the El Say farm, where a soccer team trains (Secretaria Distrital de Ambiente, 2021e). Chang et al., 2021) found similar results in China under a scenario of protected farmland where the wetland area decreased rapidly compared with other land classes.

Regarding the wetlands that are projected to lose surface area, let us start with Torca-Guaymaral. A loss is projected due to the gain in crop cover. Although, its loss was also targeted by gains in construction in the historic period. Recent reports indicate agricultural activities in the wetland's ecological corridor (Secretaria Distrital de Ambiente, 2021g). On the part of the Jaboque wetland, in the past, its pattern was one of loss due to the gain of cultivated area. However, although the loss of its surface area is projected (Figure 3.10), its intensity of loss is insignificant since the intensity analysis did not show an active loss of its cover due to the gain of another category. Despite the projections in this wetland, the model could not capture the spatiotemporal dynamics because the current stressors of the wetland do not match the results, given that the southern part of the wetland has been primarily affected by the creation of orchards (Secretaria Distrital de Ambiente, 2022). In the Cordoba wetland, the observed dynamic was the loss of the wetland area due to the gain in construction land in both periods studied. Despite being one of the wetlands where citizen participation has been crucial to its recovery in the mid-2000s (Ruíz et al., 2011), illegal occupation of the wetland space has caused impacts on the ecosystem because it has been used for improper activities that disrupt the habitat (Secretaria Distrital de Ambiente, 2021b). This pattern is projected to continue impacting its conservation.

Regarding the wetlands in the southern part of the study area, Capellania had the same loss pattern due to the gain in construction land class. Constructions cover has been and will continue to be an essential component in the fragmentation of the wetland since, for example, the Avenida la Esperanza passes through the wetland, dividing it into a northern and southern sector. In addition, the Avenida Longitudinal de Oriente is expected to pass through the wetland (Secretaria Distrital de Ambiente, 2021a). Towards the middle of the 1950s, the wetlands of the locality of Kennedy;

La Vaca, El Burro, and Techo counted about 98 ha (Mayorga, 2016). In the 1998 map, it is noted how these ecosystems began to be impacted by urbanization, transforming them into what is now known as the three ecosystems. Of this significant wetland, in 2010, it had lost at least 33% of its 1998 extension, and it is projected that its degradation will continue with a loss of up to 73% in 2034. In the southern zone of Bogota, the predominant characteristic of wetland conversion was due to the gain of building cover. These results are supported by research that shows that informal urbanization activity in sectors such as Kennedy gained strength in the locality to satisfy housing demands in the 1970s (Mayorga, 2016). The problem of illegal settlements is not a matter of the past; the recent report of the District Secretary for the Environment reports new constructions in the non-legalized neighborhood of Lagos de Castilla (Secretaria Distrital de Ambiente, 2021f).

The information presented in this article focuses on the dynamics of change that have occurred in the urban wetlands of Bogota and puts into perspective how these patterns may continue to be replicated in the coming years. Adopt Intensity Analysis as a method of analyzing the results, which considers the intensity of each category's gross loss and gross gain concerning the temporal change overall; let us highlight exciting phenomena. First, it is evident that despite establishing a public policy on wetlands approximately twenty years ago, the results show that these ecosystems have continued to be affected by poor urban planning in the city. Sizo et al. (2015) obtained similar outcomes where the future conditions of urban wetlands in Saskatoon did not improve because of the lack of the historical trend of wetland loss and the conservation strategy. Contrary to popular belief, the results yielded interesting information regarding the stressors in each wetland studied. We found that these ecosystems have changed their nature to serve as shelter for the population and have been affected by using crops or pastures. At a global level, another remarkable aspect is the predominant loss of crops and pastures historically located towards the area surrounding the Bogota River. We show that crops and pasture areas have been reduced due to the conversion to build sites jointly with green spaces.

Alongside the main findings of this study, it is important to mention its limitations. The first aspect to mention should be the level of error and/or uncertainty that can be introduced due to the nature of the input datasets and the manipulation they undergo; transformation, such as the vector to raster conversion and raster resampling, could influence simulation outcomes (Díaz-Pacheco et al., 2018). First, our land maps were converted from a vector to raster format, with a 5 m spatial resolution, given that in the sensitivity analysis, the results obtained at this resolution were more in agreement with the reference data. Second, simulating long-term land cover changes is complex due to the influence of diverse climatic, demographic, socioeconomic, and physical factors. In our study, we selected ten factors. However, we should have included future climate data, which, under the climate change perspective, will significantly benefit our understanding of the future dynamics of urban wetlands under climate change scenarios (Salimi et al., 2021). Third, data limitations made it impossible to conduct a study over a more extended period, and other recently declared wetland ecosystems, such as La Isla, Hyntiba-Escritorio, and Tingua Azul, were not included. We call on geographic information holders to facilitate open data with more unrestricted access. Fourth, the methodology adopted did not include vertical urban densification (Y. Liu et al., 2021). However, as many aspects of human welfare, for example, ecosystem services offered by these natural resources, are associated with housing density (Chen et al., 2020), future research should include this variable to determine whether vertical densification changes impact wetland ecosystem services, especially its habitat quality.

3.5 Conclusions

Wetlands' LULC reduction patterns from 1998 to 2010 will likely continue by 2034 despite being protected areas with restricted use. The greatest threat to wetlands was a human disturbance by construction activity or conversion to crop or livestock areas. It is assumed that it will continue to be so in the predicted time frame. However, the characteristics of wetland decrease in the reference and projected period differ. From 1998 to 2010, the northwestern urban wetlands decreased more due to crop conversion, while the wetlands in the south were more threatened by the expansion of building areas. Even though the Capital district's wetlands policy was established in 2005, the city's urban wetlands have continued to be subject to anthropogenic degradation. Then, the existing norms about their conservation and protection should be revised to ensure integrated management of that urban ecosystems.

It is time to become aware, to restore the value of these ancestral ecosystems, and to move from a preservationist vision to a conservationist one, where we protect, recover, and conserve the wetlands that provide so many benefits to the community and that will help us mitigate climate change.

Chapitre 4 – Discussion et conclusion générale

Cette recherche avait pour objective ultime d’étudier la dynamique de changement des zones humides urbaines de Bogota en appliquant un modèle hybride qui permettrait d’estimer les changements d’étendue de ces écosystèmes urbains. Après une revue de la littérature existante sur les zones humides urbaines de Bogota, il a été conclu qu’il y avait des limites au niveau de la recherche qui permettrait d’avoir un aperçu général des changements de surface que toutes les zones humides ont subis, et de plus il n’y a pas de travaux qui étudient ces écosystèmes et leur environnement dans toute leur complexité. Afin de combler cette lacune dans la littérature, et d’étudier ces écosystèmes à partir d’une autre perspective, ce projet a proposé d’employer des techniques mixtes utilisant la chaîne de Markov, l’intelligence artificielle et les automates cellulaires.

La dynamique des changements d’utilisation et de couverture des sols dans la zone d’étude a montré que les zones humides qui ont perdu le plus de surface étaient celles situées au sud-ouest de la ville. Cette observation est concordante avec la recherche de González Angarita et al. (2022) qui ont montré que l’activité d’urbanisation informelle dans des secteurs comme celui de Kennedy et Bosa a augmenté de manière significative en raison des effets de la migration des zones rurales vers la capitale, et que implantations illégales étaient situées dans les zones hydrauliques des milieux humides et des aires de gestion et de préservation de l’environnement.

L’application de l’analyse d’intensité nous a permis de découvrir des dynamiques qui n’auraient pas été possibles avec les méthodes d’analyse traditionnelles. Par exemple, bien que la dynamique du changement de l’étendue des zones humides soit négligeable par rapport à la zone d’étude totale, on a constaté que l’intensité du changement est beaucoup plus importante que celle de la couverture des constructions et des pâturages. De plus, cela nous a permis de voir qu’historiquement la perte de la couverture des zones humides était principalement due à un changement d’utilisation des terres vers la culture, suivi par la construction.

Les analyses de sensibilité effectuées dans le second chapitre ont permis d’évaluer le modèle et choisir la taille de voisinage la plus appropriée pour l’étude. Par ailleurs, ils ont permis de faire une revue approfondie de la littérature concernant les méthodes d’évaluation existantes pour estimer la performance des modèles d’utilisation et d’occupation des sols. De cette façon, non seulement il a été possible de choisir la taille de voisinage la plus appropriée pour l'étude, mais aussi de retenir la méthode plus pertinente pour évaluer et analyser les résultats du modèle.

Le chapitre 3 s'est concentré sur la présentation de la dynamique de changement qui s'est produit dans les zones humides urbaines de Bogota de 1998 à 2010, et a mis en perspective la manière dont ces patrons vont se poursuivre dans les années à venir. Les résultats ont mis en évidence que malgré l'existence de politiques de protection, la dynamique de la dégradation de l'environnement a continué et continuera d'être affectée par les effets anthropiques.

Comme discuté dans les articles scientifiques de cette mémoire, les limitations des données se sont avérées être un défi pour les résultats du modèle. Il n'a pas été possible de mener l'étude sur une plus longue période et sur d'autres écosystèmes de zones humides récemment déclarés, tels que La Isla, Hyntiba-Escritorio et Tingua Azul. D'autre part, nous n'avons pas inclus les données climatiques futures qui, dans le contexte du changement climatique, bénéficieront grandement à notre compréhension de la dynamique future des zones humides urbaines sur les scénarios de changement climatique. Finalement, la méthodologie adoptée n'a pas inclus la densification urbaine verticale (Y. Liu et al., 2021). Les recherches futures devraient inclure cette variable afin de déterminer si la densification verticale a un impact sur les changements dans les écosystèmes des zones humides, notamment urbaines. Ces limitations sont une opportunité pour une recherche future qui devrait sûrement inclure toute la zone de Bogota, en prenant en compte ses collines orientales, toutes ses cours d'eau et ses écosystèmes naturels.

Malgré les défis, le travail présenté contribue au domaine de la géographie, car l'approche méthodologique intègre les sciences de l'information géographique, en analysant à partir d'une approche complexe la dynamique spatio-temporelle de la couverture du sol et du changement d'utilisation du sol, mettant l'accent sur les écosystèmes des zones humides urbaines dans la ville de Bogota. En particulier, la contribution a été apportée en intégrant de techniques de modélisation spatio-temporelle, comme les automates cellulaires, ainsi que des techniques d'intelligence artificielle, telles que les réseaux de neurones artificiels, et de techniques statistiques, comme la chaîne de Markov.

Compte tenu des résultats, d'ici 2034, la superficie totale des zones humides devrait être de 563 ha, avec une perte de près de 31 % de sa surface par rapport à 1998. Cette recherche vise à attirer l'attention des preneurs de décision et de la communauté en général sur la récupération, la protection et la conservation de ces écosystèmes.

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Appendice

Table II. 1 - Agreement and disagreement values for wetland land use class.

Resolution	Neighborhood	Change simulated as persistence	Correctly simulated change	Incorrectly simulated change	Persistence simulated incorrectly	Persistence simulated correctly
5 m	3 x 3	0.0035294605	0.0005201335	0.0001016665	6.562470e-04	0.01977552
	5 x 5	0.0035199717	0.0005315361	9.975273e-05	6.502666e-04	0.01978150
	7 x 7	0.0035100841	0.0005429387	0.0000982377	6.435686e-04	0.01978820
30 m	3 x 3	3.465304e-03	0.0005598461	0.0001090982	6.373633e-04	0.01983578
	5 x 5	3.419368e-03	0.0006000402	0.0001148402	6.029112e-04	0.01987023
	7 x 7	3.373432e-03	0.0006431053	0.0001177112	5.856852e-04	0.01988746

Table II. 2 - Confusion matrix-5 m resolution 3x neighborhood size.

	C	CP	Q	UGS	W	Wet
C	1781037	52939	367	13055	8	3501
CP	43684	377758	0	7023	41	3916
Q	2	0	19226	0	0	0
UGS	12777	3617	0	119491	3	396
W	1	14	0	0	10856	12
Wet	2363	5999	0	286	74	49756

Table II. 3 - Confusion matrix-5m resolution 5x neighborhood size.

	C	CP	Q	UGS	W	Wet
C	1781037	52939	367	13055	8	3501
CP	43684	377758	0	7023	41	3916
Q	2	0	19226	0	0	0
UGS	12777	3617	0	119491	3	396
W	1	14	0	0	10856	12
Wet	2363	5999	0	286	74	49756

Table II. 4 - Confusion matrix-5m resolution 7x neighborhood size

	C	CP	Q	UGS	W	Wet
C	1780874	52578	317	13459	8	3401
CP	43801	377024	0	6985	38	3966
Q	7	0	19223	0	0	0
UGS	12610	4260	0	119730	3	394
W	0	9	0	0	11133	9
Wet	2387	6211	0	309	61	49405

Table II. 5 - Confusion matrix-30m resolution 3x neighborhood size.

	C	CP	Q	UGS	W	Wet
C	49304	1472	7	457	0	89
CP	1392	10300	0	196	1	106
Q	2	0	549	0	0	0
UGS	369	177	0	3292	0	11
W	0	0	0	0	300	0
Wet	72	163	0	5	1	1397

Table II. 6 - Confusion matrix-30m resolution 5x neighborhood size.

	C	CP	Q	UGS	W	Wet
C	49387	1479	5	461	0	108
CP	1390	10362	0	206	0	112
Q	1	0	516	0	0	0
UGS	306	255	0	3099	0	11
W	0	0	0	0	297	0
Wet	63	173	0	11	1	1419

Table II. 7 - Confusion matrix-30m resolution 7x neighborhood size

	C	CP	Q	UGS	W	Wet
C	49235	1456	6	564	0	92
CP	1453	10349	0	185	0	116
Q	0	0	539	0	0	0
UGS	310	326	0	3141	0	8
W	0	0	0	0	317	0
Wet	54	168	0	6	1	1336

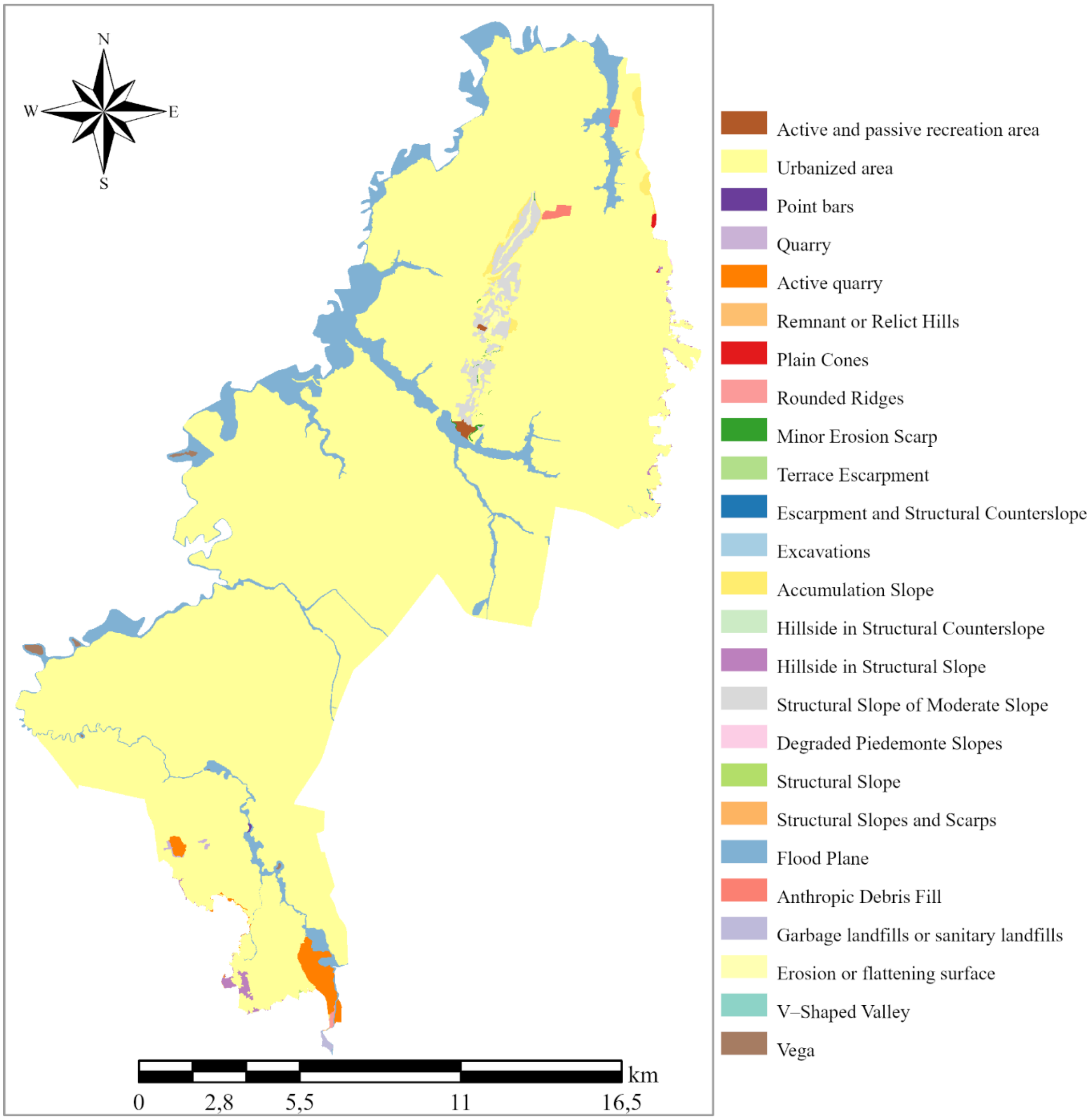

Figure II. 1. Urban geomorphology.

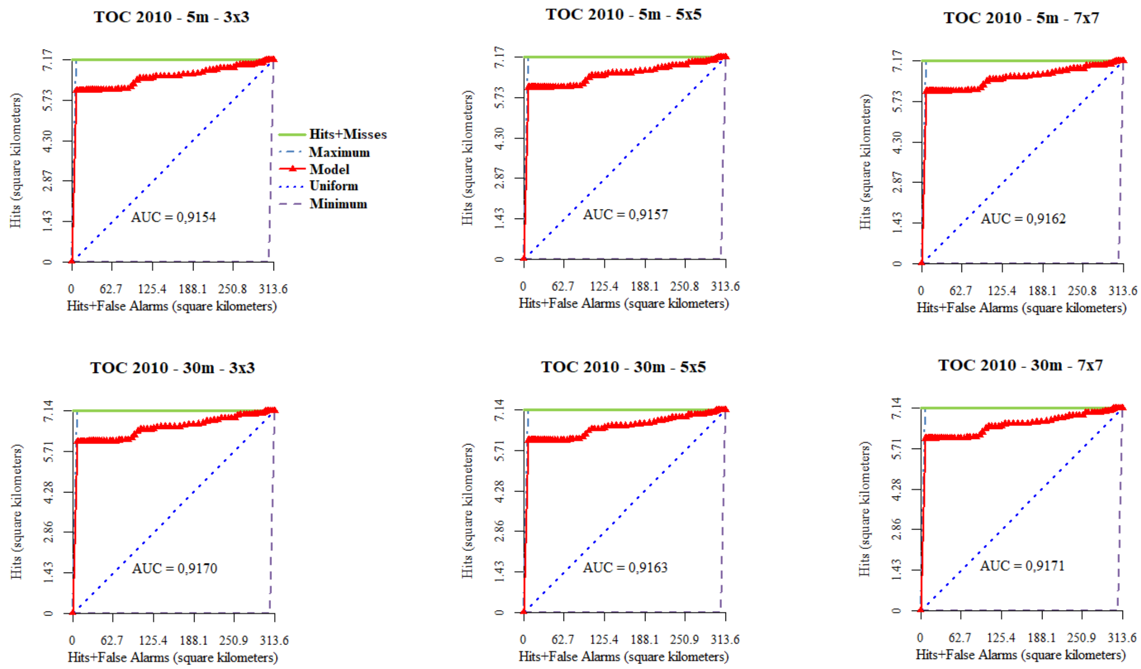

Figure II.2. - Résultats des test de sensibilité utilisant le ROC pour l'utilisation des terres des zones humides.

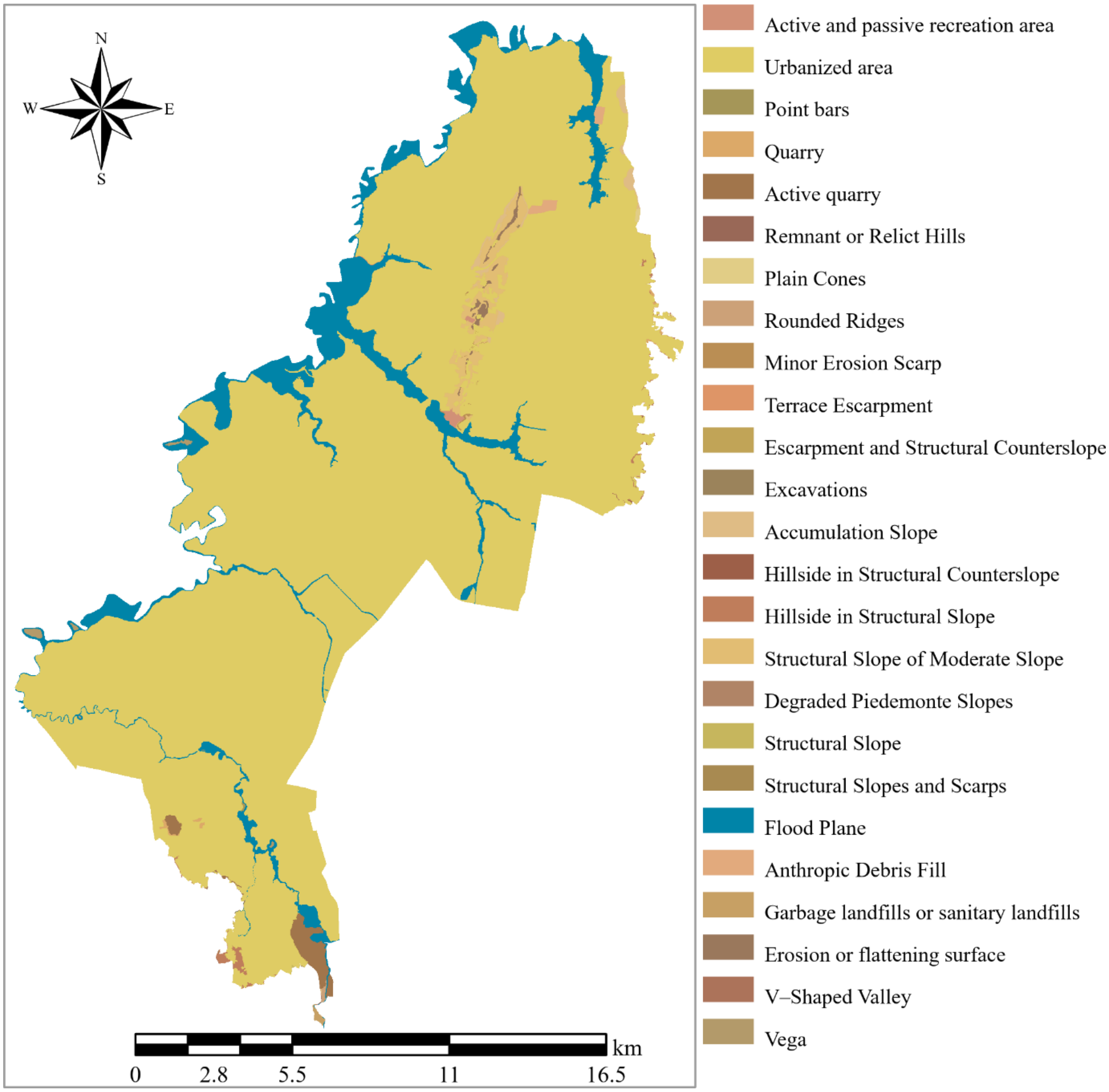

Figure III.1 Urban geomorphology.

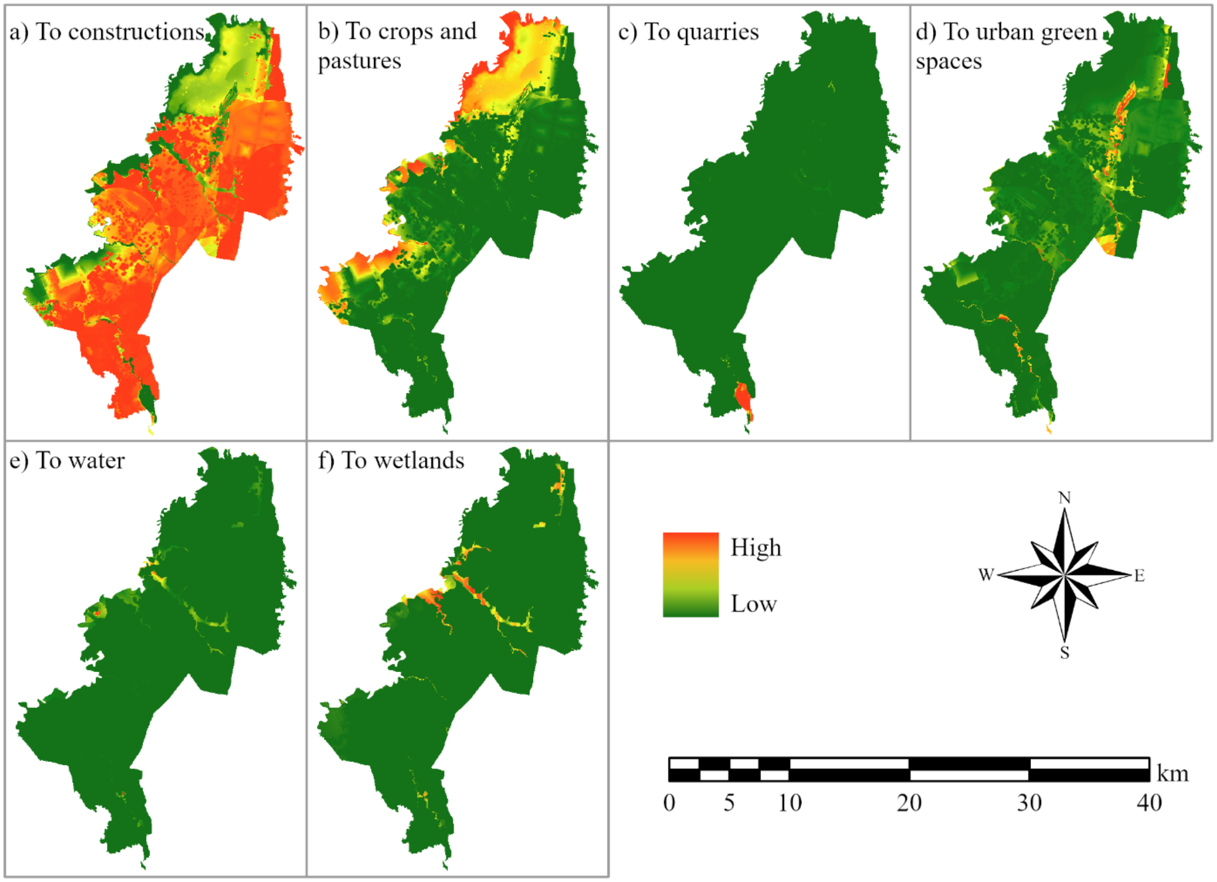

Figure III.2 - Land transition probability map for each land type.

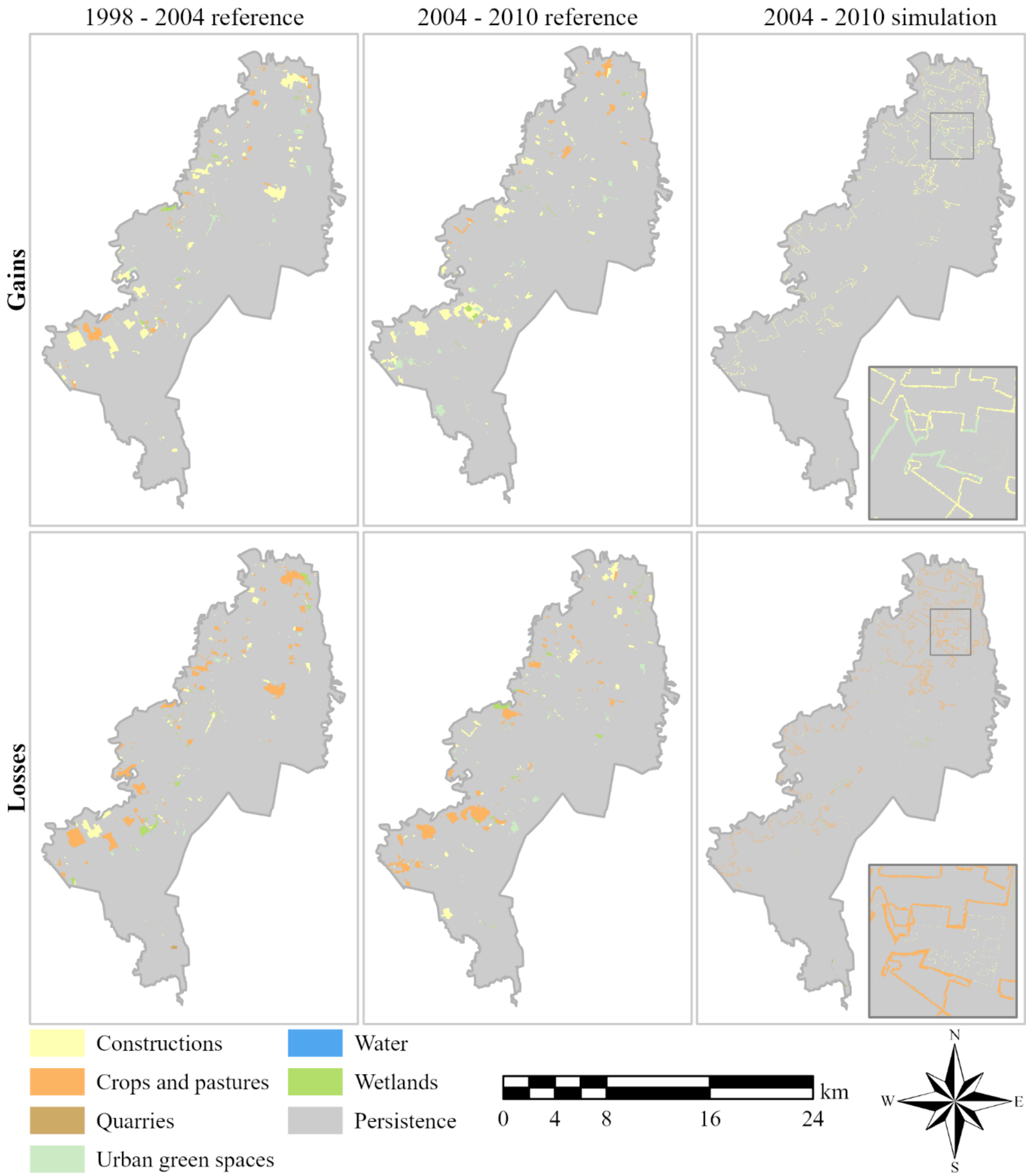

Figure III.3. - Change maps during the validation step.

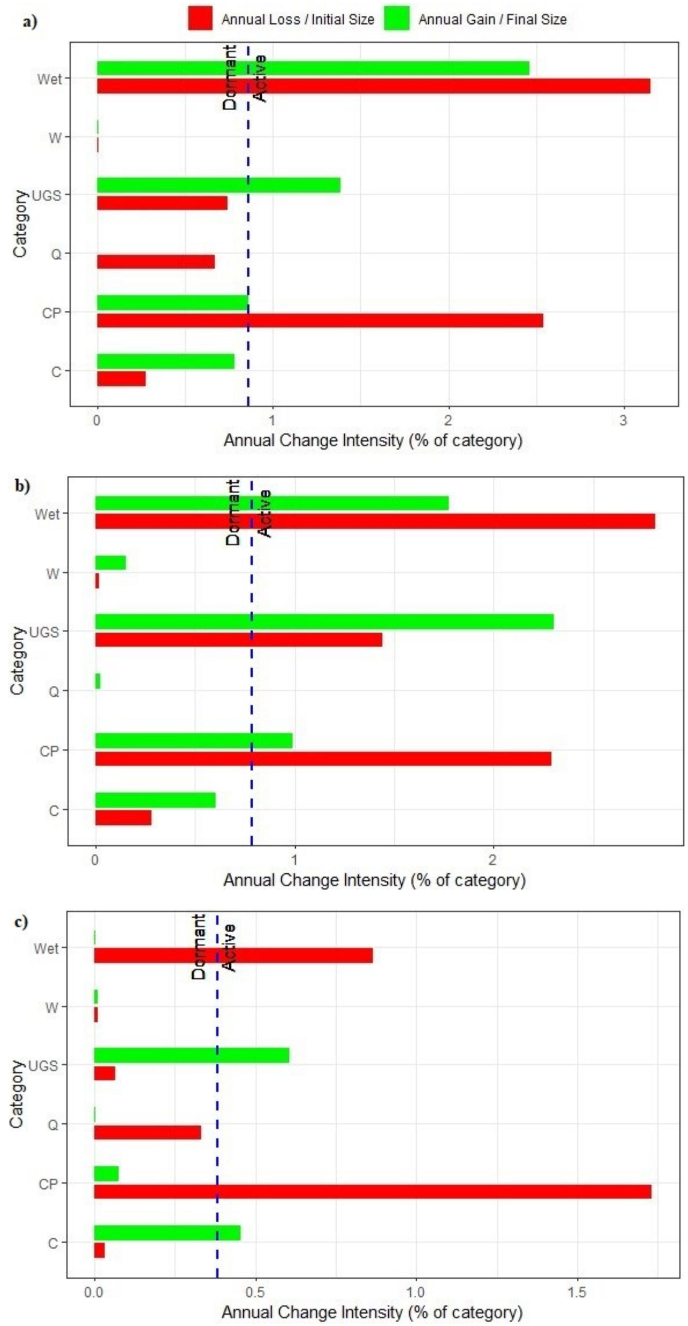

Figure III. 4. - Category intensities during a) 1998-2004 reference, b) 2004-2010 reference, and c) 2004-2010 simulation. Wetlands (Wet), urban green spaces (UGS), crops and pastures (CP), quarries (Q), water (Wa), and constructions (C).

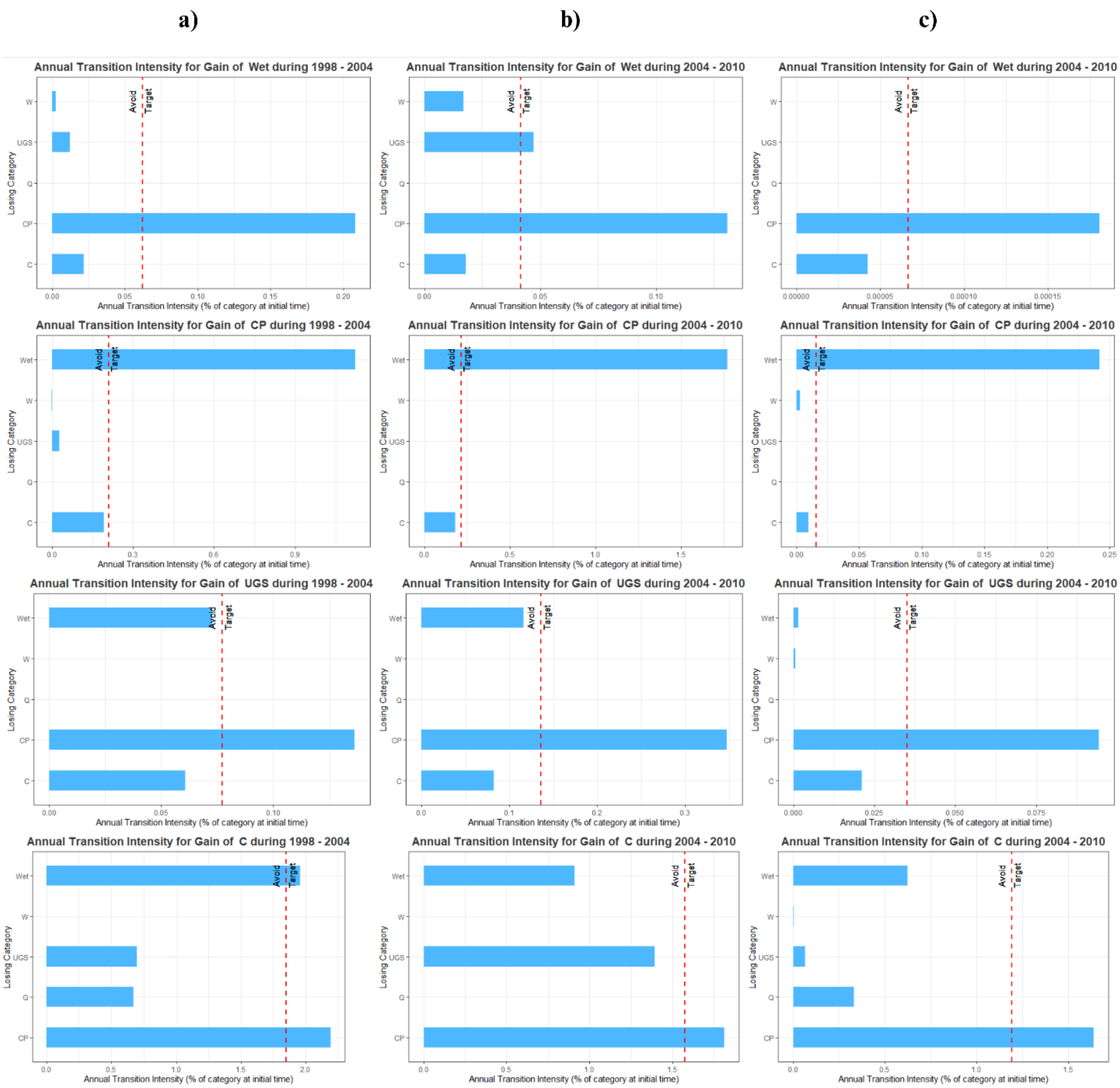

Figure III.5. - Transition intensity for the gains of wetlands (Wet), urban green spaces (UGS), crops and pastures (CP), water (W), quarries (Q), and constructions (C). Columns a) 1998-2004 reference, b) 2004-2010 reference, and c) 2004-2010 simulation.