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Contribution of Machine learning and GIS to the analysis of urban planning in flood-prone areas of Tebessa city. algeria.

Doctor : TALBI SARRA *

**Temporary professor , Faculty of architecture, Laboratory of applied civil engineering (LGCA), University Echahid chikh Larbi Tbessi of Tebessa, Algeria. Email :* talbisarra999@gmail.com .

Abstract

Today, more than ever before, our cities are exposed to many issues and phenomena that are inevitable natural or human disasters that threaten their stability. According to rapid urbanization, many of these cities extend at the expense of flood-prone areas that cause human and economic losses and make them beyond any control. According to the National Social and Economic Council, the city of Tebessa is one of the most flood-prone cities in Algeria, which made this city suffer every time from flooding issues caused by flood-prone areas.

On the one hand, the interaction between humans and the built and natural environment at the visual and sensory level is known as urban planning, which describes physical features as a framework for how to optimize the urban fabric in order to ensure the sustainability of the built environment, and on the other hand, urban planning is one of the most important components of the urban fabric and one of the factors that exacerbate the issue of flooding, especially in flood-prone areas. One of the tools used in this regard is the Geographic Information System (GIS), a system that analyzes, generates, manages and maps all types of data, and provides a basis for drawing, analyzing and using machine learning, helping users and decision makers to understand relationships, geographic context and patterns.

In this regard, our goal in this research project mainly talks about using machine learning and GIS to analyze the urban planning of flood-prone areas to understand their characteristics in the city of Tebessa.

Keywords : Flood-prone areas, Tebessa city, Machine learning, GIS, urban planning.

Résumé

Aujourd'hui plus que jamais, nos villes sont exposées à de nombreux problèmes et phénomènes qui constituent des catastrophes naturelles ou humaines inévitables menaçant leur stabilité. En raison de l'urbanisation rapide, nombre de ces villes s'étendent au détriment des zones inondables, ce qui entraîne des pertes humaines et économiques et les rend incontrôlables. Selon le Conseil national économique et social, la ville de Tébessa est l'une des villes les plus exposées aux inondations en Algérie, ce qui fait qu'elle souffre à chaque fois de problèmes d'inondation causés par les zones inondables.

D'une part, l'interaction entre les humains et l'environnement bâti et naturel au niveau visuel et sensoriel est connue sous le nom d'urbanisme, qui décrit les caractéristiques physiques comme un cadre permettant d'optimiser le tissu urbain afin d'assurer la durabilité de l'environnement bâti. D'autre part, l'urbanisme est l'un des éléments les plus importants du tissu urbain et l'un des facteurs qui exacerbent le problème des inondations, en particulier dans les zones inondables. L'un des outils utilisés à cet égard est le système d'information géographique (SIG), un système qui analyse, génère, gère et cartographie tous types de données, et fournit une base pour dessiner, analyser et utiliser l'apprentissage automatique, aidant les utilisateurs et les décideurs à comprendre les relations, le contexte géographique et les modèles.

À cet égard, notre objectif dans ce projet de recherche consiste principalement à utiliser l'apprentissage automatique et le SIG pour analyser l'urbanisme des zones inondables.

Mots clés : Zones inondables, ville de Tébessa, apprentissage automatique, SIG, urbanisme.

Introduction

The 20th century saw a spike in climate change that increased the frequency of major floods (Solomon et al., 2007); flash floods have become particularly dangerous for human life and economic damage, especially along roads, rail lines, and urban areas. Moreover, floods can increase the dangers to public health by introducing viruses and promoting microbial development (Taylor et al., 2011). Urban flooding's socio-economic effects have gotten worse as a result of altered rainfall patterns brought on by global warming (Rahmati & Pourghasemi, 2017); this has an impact on how affected cities will develop in the future (Guhathakurta et al., 2011). Rapid urbanization combined with human activities that change the shape of Wadis channels makes some areas more vulnerable to flooding (Yousefi et al., 2018). Preventing floods is better than reducing the resulting losses since floods usually start suddenly and intensify quickly over a few hours (Regmi et al., 2014).

Due to variable seasonal precipitation patterns, Tebessa City has experienced multiple flood events in recent years in various regions (ANGIRE, 2019); areas with poor drainage, dense populations, agricultural lands, and complex hydrographic networks like Wadis—which form a complex system within the city's urban perimeter—are especially susceptible to flooding (Sanitation and Environmental Protection Department (DAPE), 2013). The risk of flooding has increased in these locations due to the convergence of runoff from rainstorm events (HADJLA, 2016). Flood dangers have also increased as a result of Chaabas being turned into wastewater collectors for the city, creating a single sewage system that combines wastewater and rainfall (Water Ressources Departement, 2018). Therefore, reducing flood damages through watershed flood risk modeling is essential for efficient environmental and water management (Siahkamari et al., 2018).

Flood-prone regions have been identified and evaluated using a variety of techniques, such as remote sensing and Geographic Information System (GIS) technology, which have provided fresh insights into flood investigations because of their capacity to manage multi-temporal datasets (Lhomme et al., 2010). The development, administration, and integration of flood occurrence databases and their contributing elements are made easier by GIS technologies (Bates et al., 2010). Notwithstanding the potential advantages of using geospatial databases for flood modeling, their intricacy and volume of data frequently prevent research-level institutions from using them, which prevents stakeholders and local communities from adopting them more widely (Miller et al., 2004).

Flood susceptibility mapping utilizing artificial intelligence (AI) and machine learning models (ML) has become more popular and accepted with the development of GIS techniques, offering trustworthy flood evaluations (Azareh et al., 2021). By analyzing large datasets to find complex patterns and connections, machine learning (ML), a crucial component of modern information technology, has proved helpful in determining the hazards of flash floods (Regmi et al., 2014). However, certain approaches are required for the evaluation and validation of ML and AI models (Hu et al., 2020).

This research therefore seeks to fill this gap by integrating GIS and machine learning techniques to analyze flood-prone in Tebessa, Algeria. The study aims to identify their spatial characteristics, assess their exposure to flooding, and provide decision-makers with spatially explicit tools to support more resilient and sustainable urban planning.

Methodology and material

This research follows a multi-stage methodological framework combining Geographic Information Systems (GIS) and machine learning techniques to analyze flood-prone public spaces in the city of Tebessa, Algeria. The approach is divided into four main phases: data collection, data processing, predictive modeling, and spatial analysis (Figure 01).

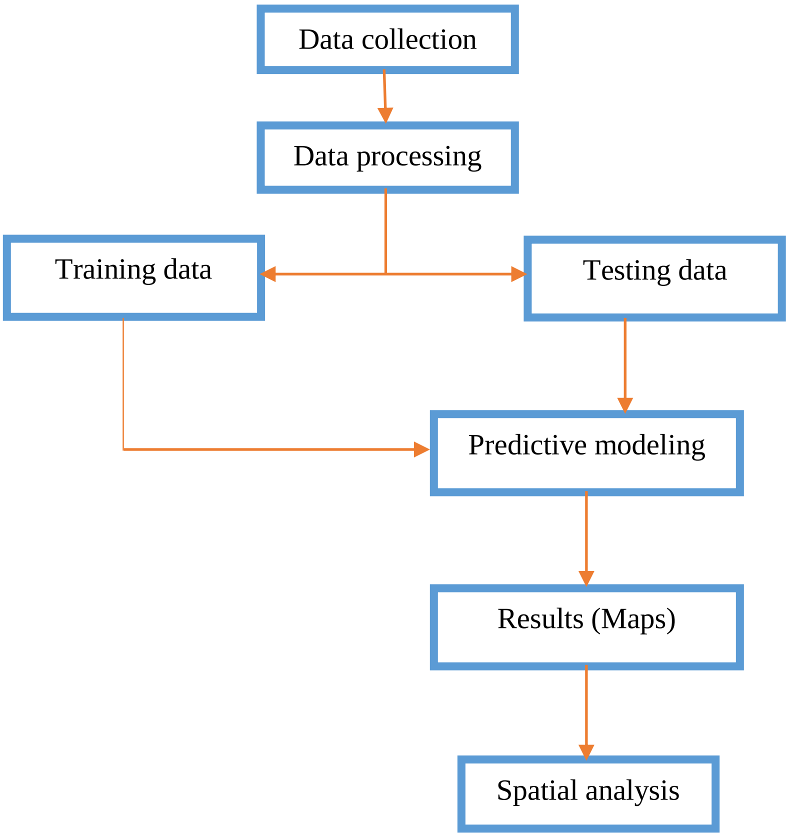

Figure 01 : Illustrates the methodological flowchart of this study.

1. Study Area Definition

Tebessa, situated on the eastern border of Algeria adjoining Tunisia, covers a land area of 184 square kilometers and boasts a population of 249,583 according to the 2022 statistics from the Direction of Programming and Budget Monitoring - Wilaya of Tebessa (URBA-BA, 2018).

Geographically, the area is made up of plains, such the MERDJAH Plain, and southern mountains, including ANWAL and DOKKANE. It runs from east to west across the city and has an average elevation of around 800 meters above sea level. Evaluations of slopes and elevations are part of the study of topographic characteristics at the level of the urban perimeter (URBA-BA, 2018).

It is characterized by two bioclimatic stages (a north that is very cold in winter and very hot in summer, and a south that is cold in winter and temperate in summer).

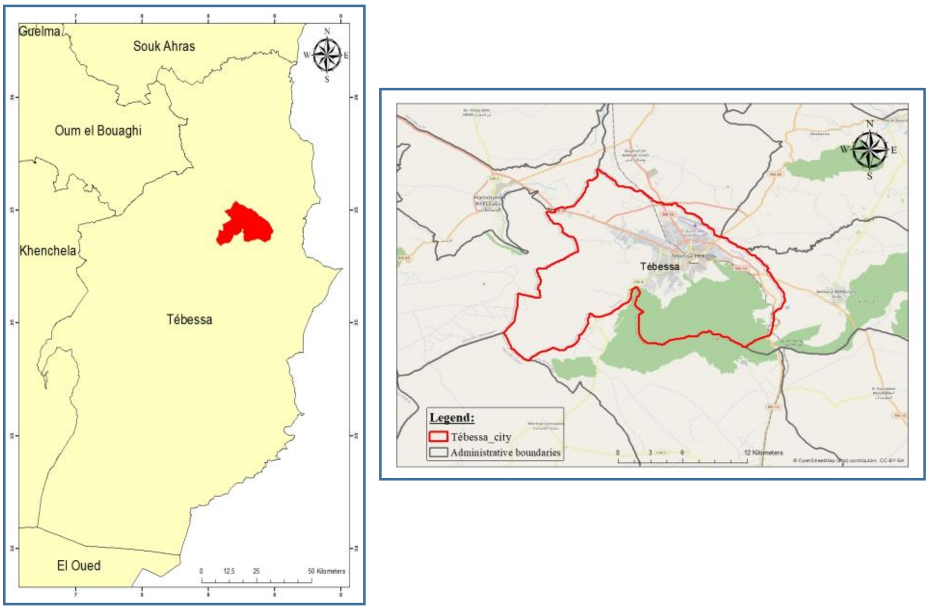

Figure 02: showcases the administrative location of Tebessa City.

2. Data Collection

The data collection phase is a fundamental step in this research, as it provides the necessary inputs for GIS analysis and machine learning modeling. Therefore, spatial data were collected from freely available sources, such as Landsat and Sentinel satellite imagery, as well as historical flood records issued by civil protection authorities (Table 01) (Intensive flooding and a remarkable geographical extent.), to predict future disaster risks in flood analysis (Rahmati & Pourghasemi, 2017). Field surveys and field observations were also used to validate the data, whenever possible, to verify the accuracy of satellite-derived information and ensure the reliability of datasets.

Table 01: Significant past flood events (Initial Flood Risk Assessment).

Year	Months / Dates	Number of interventions	Damages	Number of victims
2015	August, September, October.	81 Operations	Housing and some public facilities	1 dead and 26 survivors.
2018	May, August, September, October.	325 Operations	Housing and some public facilities.	02 dead and 10 injured.

Source: The direction of Civil Protection of the Wilaya of Tebessa, 2023.

According to the previous studies of (HADJLA, 2016), The flood risk analysis framework for Tebessa City generally considers four factors (Figure 03):

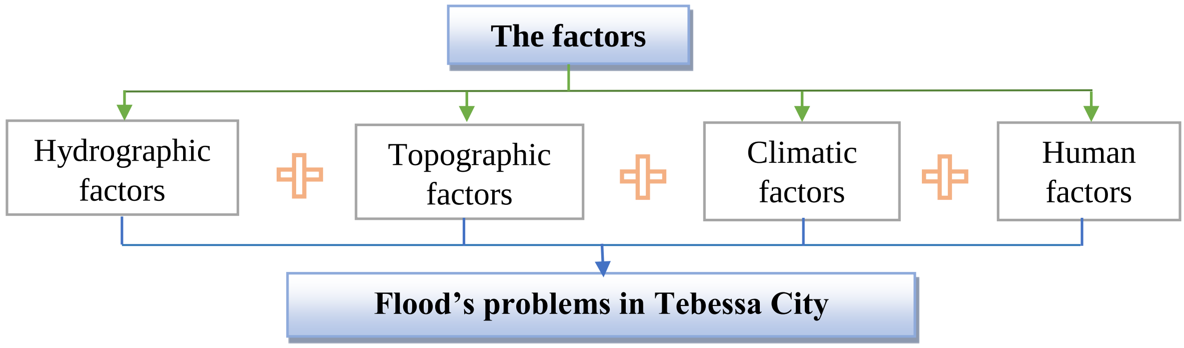

Figure 03: Factors of the occurrence of floods in the city of Tebessa (HADJLA, 2016).

- *Topographic factors*:
  are represented in the steep slopes located in the south of the city, with weak slopes in the north, and in general, the flatness is the dominant feature of the place of the city.
- *Hydrographic factors*:
  are represented in the dense water network that penetrates the city and consists of the 07 Wadis mentioned above.
- *Climatic factors*:
  are represented by the semi-dry climate and semi-cold winters, which are often heavy and irregular rains, in addition to the type of climate and the nature of the soil reflected on the vegetation cover, and these factors combined effect and exacerbate the problem of floods in the city.
- *Human factors:*
  are factors related to overpopulation, the process of legal urbanization, and human intervention, positive or negative, on the field: Fast urbanization; Lack of proper city setup related to networks or setup related to watercourse rectification…

3. Data Processing

At this stage the data was cleaned and aligned as follows (Table 02 and Figure 04):

Table 02: Data processing steps.

Steps		
Data Cleaning and Harmonization		• Projection unification to WGS 84 UTM Zone 32N. • Removal of duplicate and inconsistent attribute entries. • Cloud masking in satellite imagery using the QA band.
Land Use/Land Cover Classification		• Supervised classification using the Random Forest algorithm to identify impervious surfaces, vegetation, water bodies, and open spaces. • Accuracy assessment through confusion matrix using field survey points and Google Earth imagery.
GIS-Based Spatial Analysis	**Flood-Prone Area Delineation**	• Hydrological modeling using DEM to derive slope, flow direction, and flow accumulation. • Identification of potential flood zones via the HEC-HMS and HEC-RAS models integrated in ArcGIS.
	Public Space Overlay	• Intersection of public/open space layers with flood-prone zones to extract affected areas. • Spatial statistics (area, perimeter, proximity to drainage) for each public space polygon.

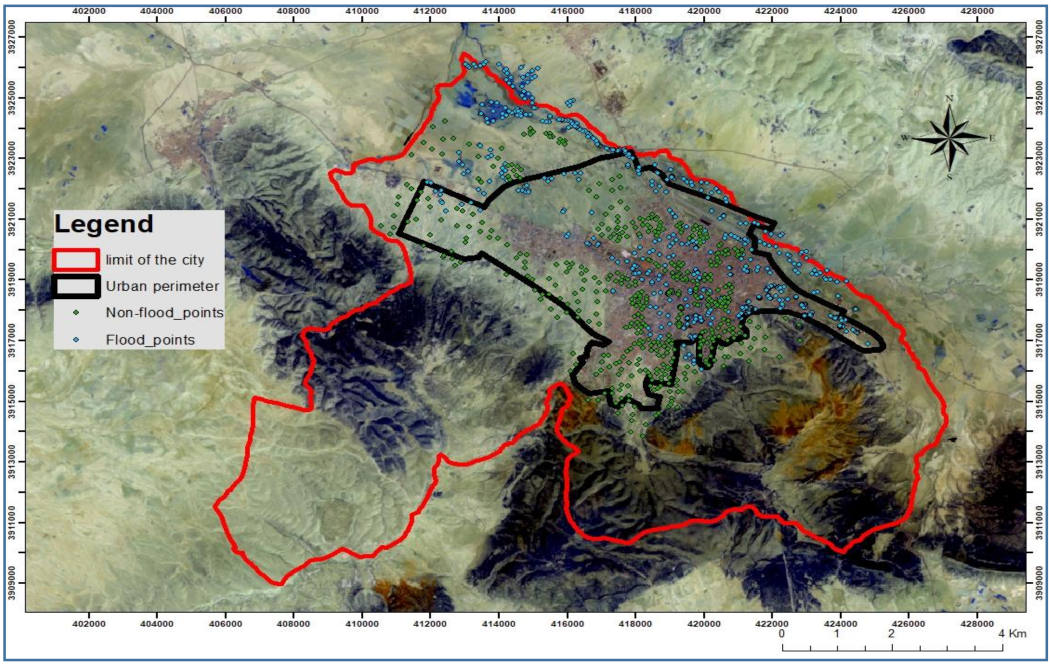

Figure 04: the location of flooded and Non-Flooded points in Tebessa city.

5. Machine Learning Modeling

The stages of the machine learning are presented in three main table 03: (1) Input features (2) Model selection and training (3) Model evaluation. A detailed description of these steps is as below (Table 03):

Table 03: Machine learning modeling stages.

Steps	
Input Features	• Elevation, slope, distance to watercourses, land cover type, imperviousness index, and drainage density.
Model Selection and Training	• Comparative evaluation of three models: Random Forest (RF), Gradient Boosting (GB), and Support Vector Machine (SVM). • Dataset split into 70% training and 30% testing sets.
Model Evaluation	• Performance metrics: Accuracy, Precision, Recall, F1-score, and Area Under Curve (AUC). • Feature importance ranking to identify the most influential variables in flood susceptibility of public spaces.

Results

The results presented in this study highlight areas at risk from flooding in the city of Tebessa, with the aim of identifying and predicting vulnerable spaces to flooding. For analysis, Geographic Information Systems (GIS) were used to integrate and visualize spatial data such as land use, elevation, drainage networks, and the distribution of urban spaces (Figure 05). In parallel, machine learning algorithms were applied to identify areas at risk from flooding and predict the likelihood of flooding in specific locations based on historical flood events, rainfall data, and topographical features. By combining these methods, the study not only highlights vulnerable urban areas but also provides valuable insights into how urban spaces, essential for mobility, recreation, and social interaction, are affected by flood risks.

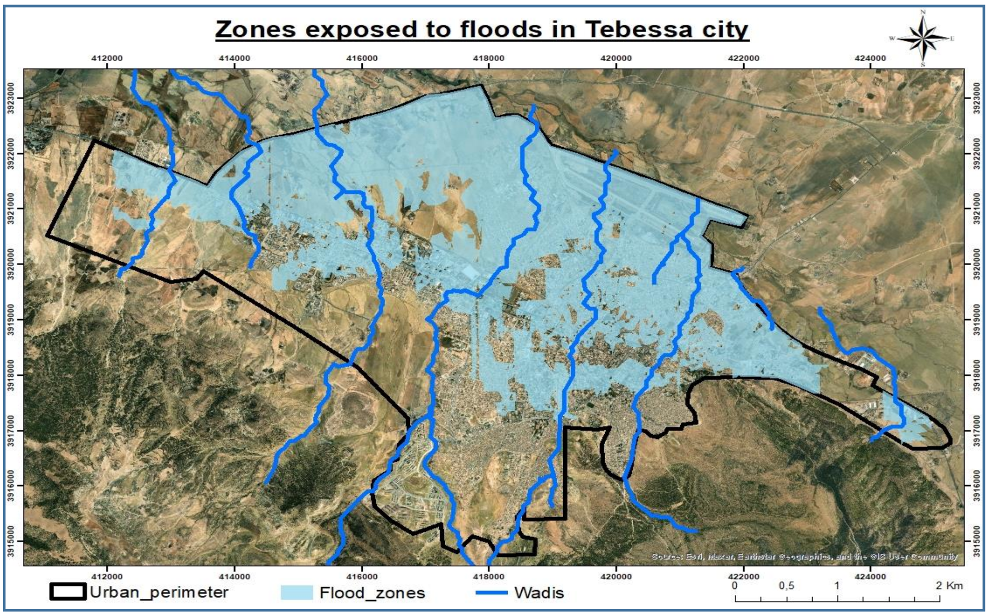

Figure 05: zones exposed to floods in Tebessa city.

The findings aim to support urban planners and decision-makers in adopting effective flood risk management strategies and ensuring safer and more resilient urban development in Tebessa city .

Discussion

The results of this study confirm that the city of Tebessa is highly vulnerable to flooding (Figure 06), particularly in its urban spaces, which play a critical role in the urban fabric. This finding is consistent with previous research conducted in other flood-prone urban areas, where the expansion of built-up land into natural floodplains has intensified the exposure of open and public spaces to flood risks (Douglas et al., 2008; Liao, 2012) . Similar to studies in Mediterranean and North African cities, our analysis shows that limited drainage infrastructure and rapid urbanization exacerbate flooding impacts on key urban areas (Ajjur & Mogheir, 2020).

However, in contrast to some research that focuses primarily on residential and industrial zones as the most affected by flooding (Jha et al., 2012), this study emphasizes the particular vulnerability of urban spaces—streets, plazas, and parks—as essential social and cultural nodes (Figure 07). This broader perspective expands the debate by demonstrating how floods not only cause material damage but also disrupt mobility, daily activities, and community interactions, confirming insights from recent works on the social dimensions of urban flooding (Amoako & Frimpong Boamah, 2015).

Methodologically, the combined use of GIS and machine learning in this study provides a more predictive and spatially explicit assessment than traditional hydrological modeling approaches. While earlier GIS-based studies mapped flood risk zones largely through topographic and hydrological overlays (Sanyal & Lu, 2004), the integration of machine learning here allowed for the identification of non-linear relationships between rainfall patterns, land use, and vulnerability of specific urban spaces. This approach aligns with emerging studies that highlight the capacity of artificial intelligence to improve flood risk mapping and decision support systems (Mosavi et al., 2018).

Taken together, this comparative analysis illustrates that Tebessa's challenges mirror global urban flood vulnerabilities but also highlight context-specific dimensions. The emphasis on urban spaces as both highly exposed and socially critical differentiates this study from prior research and offers a novel contribution to urban resilience planning in flood-prone contexts.

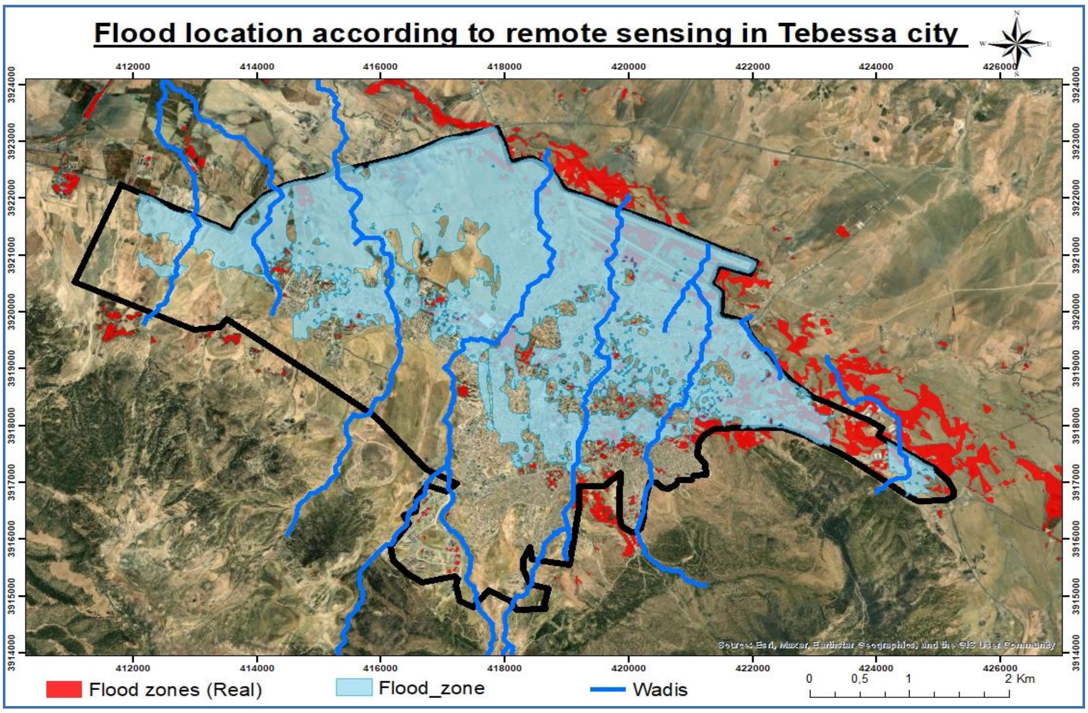

Figure 06: Flood location according to remote sensing in Tebessa city.

Figure 07: Damage to public spaces caused by floods in Tebessa.

Conclusion

The findings of this research demonstrate that the integration of Geographic Information Systems (GIS) and machine learning techniques provides a powerful framework for analyzing flood-prone areas in rapidly urbanizing cities such as Tebessa. By mapping spatial patterns of risk and predicting the vulnerability of urban spaces, the study highlights the extent to which urban expansion into floodplains exacerbates the exposure of critical urban areas. The analysis reveals that urban spaces—parks, plazas, and circulation networks—are disproportionately affected by flooding due to their location in low-lying and poorly drained areas, making them both physical hotspots of damage and social nodes of disruption. This underscores the necessity of incorporating flood risk assessments into urban planning policies, particularly in regions experiencing uncontrolled growth. Beyond its local relevance, the study illustrates how combining GIS with machine learning enables a more nuanced understanding of the relationship between urban form, hydrological processes, and human vulnerability. Ultimately, these results provide decision-makers with evidence-based insights that can inform sustainable planning, adaptive design of public spaces, and proactive flood risk management strategies aimed at enhancing urban resilience.

References

Ajjur, S. B., & Mogheir, Y. K. (2020). Flood hazard mapping using a multi-criteria decision analysis and GIS (case study Gaza Governorate, Palestine). *Arabian Journal of Geosciences*, *13*(2), 44. https://doi.org/10.1007/s12517-019-5024-6

Amoako, C., & Frimpong Boamah, E. (2015). The three-dimensional causes of flooding in Accra, Ghana. *International Journal of Urban Sustainable Development*, *7*(1), 109–129. https://doi.org/10.1080/19463138.2014.984720

ANGIRE, N. agency for integrated water resources management. (2019). *Collecte et analyse de données sur les inondations -Site de Tébessa-*.

Azareh, A., Rafiei Sardooi, E., Choubin, B., Barkhori, S., Shahdadi, A., Adamowski, J., & Shamshirband, S. (2021). Incorporating multi-criteria decision-making and fuzzy-value functions for flood susceptibility assessment. *Geocarto International*, *36*(20), 2345–2365. https://doi.org/10.1080/10106049.2019.1695958

Bates, P. D., Horritt, M. S., & Fewtrell, T. J. (2010). A simple inertial formulation of the shallow water equations for efficient two-dimensional flood inundation modelling. *Journal of Hydrology*, *387*(1–2), 33–45. https://doi.org/10.1016/j.jhydrol.2010.03.027

Douglas, I., Alam, K., Maghenda, M., Mcdonnell, Y., Mclean, L., & Campbell, J. (2008). Unjust waters: Climate change, flooding and the urban poor in Africa. *Environment and Urbanization*, *20*(1), 187–205. https://doi.org/10.1177/0956247808089156

Guhathakurta, P., Sreejith, O. P., & Menon, P. A. (2011). Impact of climate change on extreme rainfall events and flood risk in India. *Journal of Earth System Science*, *120*(3), 359–373. https://doi.org/10.1007/s12040-011-0082-5

HADJLA, A. (2016). *Urbanization and sustainable development in the city of Tebessa*.

Hu, J., Zheng, B., Wang, C., Zhao, C., Hou, X., Pan, Q., & Xu, Z. (2020). A survey on multi-sensor fusion based obstacle detection for intelligent ground vehicles in off-road environments. *Frontiers of*

Information Technology & Electronic Engineering, *21*(5), 675–692. https://doi.org/10.1631/FITEE.1900518

Jha, A. K., Bloch, R., & Lamond, J. (2012). *Cities and Flooding: A Guide to Integrated Urban Flood Risk Management for the 21st Century*. The World Bank. https://doi.org/10.1596/978-0-8213-8866-2

Lhomme, S., Serre, D., Diab, Y., & Laganier, R. (2010). Les réseaux techniques face aux inondations, ou comment définir des indicateurs de performance de ces réseaux pour évaluer la résilience urbaine (Urban networks and floods: How to define performance indicators to evaluate urban resiliency). *Bulletin de l'Association de géographes français*, *87*(4), 487–502. https://doi.org/10.3406/bagf.2010.8193

Liao, K.-H. (2012). A Theory on Urban Resilience to Floods—A Basis for Alternative Planning Practices. *Ecology and Society*, *17*(4), art48. https://doi.org/10.5751/ES-05231-170448

Miller, R. C., Guertin, D. P., & Heilman, P. (2004). INFORMATION TECHNOLOGY IN WATERSHED MANAGEMENT DECISION MAKING. *Journal of the American Water Resources Association*, *40*(2), 347–357. https://doi.org/10.1111/j.1752-1688.2004.tb01034.x

Mosavi, A., Ozturk, P., & Chau, K. (2018). Flood Prediction Using Machine Learning Models: Literature Review. *Water*, *10*(11), 1536. https://doi.org/10.3390/w10111536

Rahmati, O., & Pourghasemi, H. R. (2017). Identification of Critical Flood Prone Areas in Data-Scarce and Ungauged Regions: A Comparison of Three Data Mining Models. *Water Resources Management*, *31*(5), 1473–1487. https://doi.org/10.1007/s11269-017-1589-6

Regmi, A. D., Yoshida, K., Dhital, M. R., & Pradhan, B. (2014). Weathering and mineralogical variation in gneissic rocks and their effect in Sangrumba Landslide, East Nepal. *Environmental Earth Sciences*, *71*(6), 2711–2727. https://doi.org/10.1007/s12665-013-2649-8

Sanitation and Environmental Protection Department (DAPE). (2013). *Réalisation d'une étude portant sur l'élaboration d'une stratégie nationale de lutte contre les inondations*.

Sanyal, J., & Lu, X. X. (2004). Application of Remote Sensing in Flood Management with Special Reference to Monsoon Asia: A Review. *Natural Hazards*, *33*(2), 283–301. https://doi.org/10.1023/B:NHAZ.0000037035.65105.95

Siahkamari, S., Haghizadeh, A., Zeinivand, H., Tahmasebipour, N., & Rahmati, O. (2018). Spatial prediction of flood-susceptible areas using frequency ratio and maximum entropy models. *Geocarto International*, *33*(9), 927–941. https://doi.org/10.1080/10106049.2017.1316780

Solomon, S., Intergovernmental Panel on Climate Change, & Intergovernmental Panel on Climate Change (Eds.). (2007). *Climate change 2007: The physical science basis: contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Taylor, J., Lai, K. man, Davies, M., Clifton, D., Ridley, I., & Biddulph, P. (2011). Flood management: Prediction of microbial contamination in large-scale floods in urban environments. *Environment International*, *37*(5), 1019–1029. https://doi.org/10.1016/j.envint.2011.03.015

URBA-BA, D. d'urbanisme d'architecture et de construction-W. de T. (2018). *Rapport PDAU intercommunal Tebessa-Hammamet-Elkouif-Bekkaria-Boulhaf Dyr the final phase*.

Water Ressources Departement. (2018). *Rapport sur l'evaluation de l'etat d'execution du plan d'action de lutte contre les inondations la Wilaya de Tébessa*.

Yousefi, S., Mirzaee, S., Keesstra, S., Surian, N., Pourghasemi, H. R., Zakizadeh, H. R., & Tabibian, S. (2018). Effects of an extreme flood on river morphology (case study: Karoon River, Iran). *Geomorphology*, *304*, 30–39. https://doi.org/10.1016/j.geomorph.2017.12.034