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Mobile Augmented Reality Application to Evaluate the River Flooding Impact in Coimbra

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Abstract: The downtown area of the city of Coimbra, Portugal, is at low altitude and has historically suffered floods that have caused serious economic losses. The present research proposes a mobile augmented reality (MAR) application aimed at visualising the effect of possible scenarios of flooding in an area of higher risk in the city. A realistic 3D model of the city was created, using data extracted with BLosm and processed through Blender, followed by its integration into Unity with Vuforia for AR visualisation. The methodology encompasses the extraction and simplification of 3D models, mapping real-world coordinates in Unity, analysing several datasets, obtaining a model through regression and implementing a workflow to manage interactions between various Unity objects. The MAR application enables users to visualise potential flood impacts on buildings, utilising colour-coded indicators to represent different levels of water contact. The system's efficacy was evaluated by simulating various use-case scenarios, demonstrating the application's capability to provide real-time, interactive flood risk assessments. The results underline the potential of integrating AR and machine learning for enhancing urban flood management and prevention.

Keywords: mobile augmented reality; flooding visualisation; regression analysis; Coimbra

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1. Introduction

The intensification of extreme precipitation, flood events and extreme variability are expected in future weather [1]. These flooding events pose multifaceted challenges, affecting critical infrastructure and exerting economic strains on different regions. Cities and governments have already been analysing urban water infrastructure and technologies to become more resilient in facing possible extreme events [2]. In this context, the imperative to comprehend, anticipate, visualise and mitigate flood risks through innovative technological interventions becomes evident. Augmented reality (AR), that is, the superposition of the reality and 3D computer-generated contents, emerges as a powerful tool for enhancing flood visualisation, risk assessment and decision-making processes.

AR for prevention and flood risk management (FRM) is important, as it aids in proactively identifying potential flood-prone areas, allowing authorities to take pre-emptive measures to safeguard vulnerable regions and communities. Augmented reality and its integration into flood visualisation have garnered considerable attention in various research studies, aiming to understand and communicate information about flood risks. Even its simple usage as a projection on an AR-sandbox or a projection of 3D computer-generated content on a screen with an image target for the tracking can lead to a better user experience for both educational and professional cases.

In the realm of mobile AR (MAR) technology, the convergence of inundation maps, FRM methodologies and innovative AR platforms have paved the way for sophisticated visualisations. Studies have revealed the potential of MAR applications in delivering

real-time, context-aware flood information through smartphones and AR devices that require low-price entries into the market. Notably, advancements in wearable technologies, such as ANTSs (Augmented Navigation and Tracking Systems), have facilitated real-world implementations beyond the laboratory setup. Fiducial markers and markerless technologies like Vuforia have enabled precise 3D positioning and tracking that are crucial in AR-based applications, museum installations and interactive landscape designs.

The research methodologies encompass a wide spectrum, from utilising Bishop Project methodologies for triangulation in model space to employing sophisticated numerical flood models like Iber+ and AR-sandbox hybrid simulations. These approaches emphasise the fusion of physical and numerical modelling to simulate flood dynamics, visualise inundations and project potential scenarios with high precision and interactivity. The preference for numerical models in flood risk management lies in their adaptability, accuracy and efficiency in addressing various scenarios. Numerical models also permit the use of the Bathtub model. This model assumes that areas with elevations below a predicted flood level will be inundated. The methodology involves comparing the elevation data of each cell in a digital elevation model (DEM) against a projected sea level rise. Cells with elevations lower than the predicted sea level are considered prone to flooding.Moreover, the exploration extends to the challenges faced by AR and VR technologies, such as potential health-related impacts on users [3], legal issues in mixed reality, and the need for robust simulation algorithms in complex landscapes.

Coimbra is a mid-sized city in the centre of Portugal, which started to evolve between the Mondego river and a small hill. Past research has already proposed AR solutions for the visualisation of a part of the city of Coimbra [4], although not for flood visualisation. The present work extends such past research and consists of the conception of an MAR application to display the impacted buildings in case of a flood of the Mondego river in Coimbra using a static image target for AR tracking. Machine learning (ML) and analyses of historical weather data and river water height are used together to predict and find, through regression and correlation, a model, to be used to change the river water plane using a function of the monthly average rain precipitation. This model is then incorporated into the final project to build a user-friendly application that allows users to adjust variables through a User Interface (UI) that changes the Mondego river's water height and displays the impact in an AR scene. This application is oriented toward the mainstream user, being suitable for use in the educational domain and museum expositions, among other possible uses.

2. Case Study of the City of Coimbra

Coimbra is a city that receives variable amounts of rain, which has historically led to occasional floods. The river front in Coimbra is populated by parks, cafes, restaurants, public infrastructures and residences. Flooding from the overflow of the Mondego river has an impact on the social, economical and environmental system. It is important to know and visualise which buildings are impacted in case of different possible floods to prevent and invest in solutions for avoiding damages. Many buildings that are far away from the river are still within the first two metres from the reference point of the overflow of the river [5]. Table 1 shows the historical flood events in the city. As the table shows, the risk of flood is real. The construction of a dam upstream and dykes along the river has contributed to a better management of the flow and the minimisation of losses. Nonetheless, incidents still happen, and as recently as 2019, there were broken dykes that caused the evacuation of two thousand people and resulted in significant economic losses.

The analysis of the rain through time in Coimbra helps to identify and notice the risk of floods. This has been conducted for each unit of time (hour, day and month) over 24 years. An import remark is that the rain precipitation values are low due to Coimbra having, on average, several days without rain.

Table 1. Main historical flood events in Coimbra [5] between 1331 and 2019.

Year	Precise Date	Main Consequences
1331	N/A	Coimbra city isolated
1520	Mar	Coimbra city isolated
1656	Feb	Coimbra city isolated
1708	Feb 17	Coimbra city isolated
1739	Dec 3–6	Indeterminate casualties
1764	Jan 19	Coimbra city isolated
1788	Feb 23	Indeterminate casualties
1804	Jan	Coimbra city isolated
1821	Jan	Coimbra city isolated
1843	Mar 27	Coimbra city isolated
1850	Jan 18	12 casualties
1852	Nov	Coimbra city isolated
1857	Dec 18	Coimbra city isolated and without flood
1860	Dec 27–28	8 casualties
1872	Jan 26–27	Max. peak flow of 5317 m^3/s
1876	Jan 23	Coimbra city isolated
1878	Dec 18	Coimbra city isolated
1900	Feb 12	Coimbra city isolated
1915	Jan 19	Coimbra city isolated
1924	Mar 25	Coimbra city isolated
1949	Jan 29	Max. peak flow of 4147 m^3/s
1955	Jan 19	Significant economic losses
1962	Jan 1	Significant economic losses
1977	Jan 14	Significant economic losses
2001	Jan 27–28	Rupture of dykes and isolated villages
2016	Feb 13–14	Significant economic losses
2019	Dec 21	Rupture of dykes, evacuation of 2 k residents

Figure 1 shows the hourly precipitation average. Most of the rain precipitation occurrences appear to have between 10 h and 18 h. Figure 2 shows the monthly average amount of rain. Most of the flood records happened from November to March [5]. The plot below shows the months that average most of the rain precipitation. From June to September, a dip occurs, reducing the likelihood of rain precipitation as a cause of flooding incidents for these months.

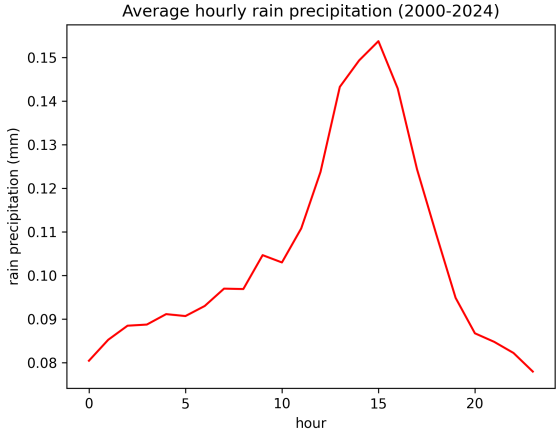


Figure 1. Hourly average of all hours in the day (2000–2024).

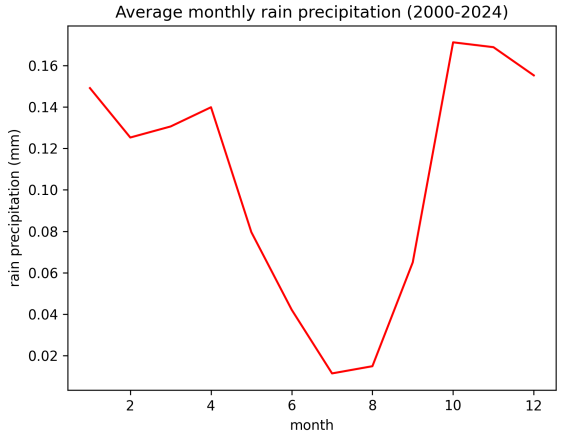


Figure 2. Monthly average of all months in the year (2000–2024).

3. State of the Art on Visualisation and Modelling of River Flooding

A literature review was performed using Scopus, Science Direct and the search engine Google Scholar. Different keywords relevant to the work, such as "mobile augmented reality", "flooding visualisation", "machine learning and flood prediction models" were tried. This section explains, for each paper found and deemed relevant, the problem, the materials and methodology employed, the solution proposed and the contributions to the scientific community. Only publications after 2015 were reviewed to ensure relevance to the most recent technologies and solutions. The reviewed studies were synthesised and categorised based on their primary focus areas.

3.1. Flooding Visualisation

Haynes Paul et al. [6] explained how they used mobile augmented reality to enable users to track the location that is impacted by floods and populate this location with a 3D building geometry for visualisation. The software aspect involved the integration of various components into a cohesive and user-friendly MAR application adaptable to changes. The key tools employed in this phase included Vuforia, WeSenseIT REST server API, and a dataset formatted in JSON. The algorithmic aspect focused on the augmented reality section. Two major concepts used were triangulation, which consisted of using three rays in a model space, and tracking corner for virtual building facades. The authors elucidated the challenges faced with the baseline Vuforia (without additional packages) in outdoor scenarios. They explained that the reliability of the application began at up to 6 m and detailed that the deformation of the image made it difficult for buildings that were close, because their virtual geometries were not really fixed, as well as for the buildings that were far. The visualisation of water height within the application was considered plausible for real-world scenarios and was tested for Fishlake, Doncaster, UK. The paper reported a positive reception among the expert team members, particularly in the context of emergency applications.

I. Alihan H. et al. [7] used a building framework to simulate and visualise flooding in 3D using position-based fluids for real-time flood visualisation and analysis. The framework created contains the geographical information and several parameters for the simulation, such as friction coefficients, storm drain information, precipitation and soil absorption. They stated that historical information is an important parameter for flood modelling and analysis. They developed a software called "City Maker", which consisted of a system design to extract 3D urban OSM data and used a custom visualisation pipeline that provided a ready-made simulation environment. They demonstrated the usability of position-based fluids to simulate and visualise flooding events, and also showed that using environmental data through SRTM elevation with a 30 m resolution was enough to

perform a realistic representation of a study area in river flooding simulations, particularly for the test case of the digital model of Corpus Christi, TX, USA.

Marto Anabela et al. [8] created an MAR application named DinofelisAR to view a Forum from the Roman Era superimposed over its current ruins. Vuforia was used as the authors stated that they obtained slightly better results for an augmented reality application running outdoors. They also showed that most of the participants, 90 visitors, tested their application and affirmed to feeling more involved when using the MAR application in their visit. One participant who had never known about nor tried AR technology before agreed that AR technology was easy to use.

Panou Chris et al. [9] proved two important points for an MAR application: (1) the availability and technological advances of modern smartphones allow for the development of reliable AR experiences that enhance the understanding of historical datasets, and (2) the gamification of their cultural heritage application is gaining increasing value as it engages visitors. AR can also emphasise the interaction with historical datasets and can be complemented by new forms of visualisation and interaction.

Tomkins Adam and Eckart Lange [10] used AR and proved that interaction with 3D cartographic visualisation can enable real-time multi-user exercises in flood visualisation. Li Wenkai et al. [11] reviewed existing solutions concerning AR in engineering analysis and simulation. They stated that AR visualisation can enhance perception and understanding of the dataset, as it overcomes limitations from VR systems by providing a simple and immediate user interface to a digitally augmented environment. AR also allows users to interact with real objects in addition to virtual contents in an augmented scene, like a mobile phone screen, thereby enhancing user experience.

Bakhtiari Vahid et al. [12] conducted a comprehensive overview of stakeholder analysis and categorised cutting-edge technologies into five groups. They noticed a limited exploration on review research about how stakeholders can actively contribute to the advancement and improvement of visualisation tools such as AR, VR, DT (digital twin) and MR (Mixed Reality). They emphasised the importance of efficient communication and collaboration among stakeholders, as these processes are crucial for addressing the complexities of urban flood risk management. They stated that stakeholders can play in the development and enhancement of these tools.

Zhang Guoyong et al. [13] used an AR visualisation method based on a 3D-printed terrain model and explored techniques such as adaptive processing of flood data and hybrid virtual flood and terrain models. Their statistical results indicated that the methodology is useful for understanding the flood hazard and in providing a more intuitive and realistic visual experience at 60 frames per second. They obtained a better result compared to the traditional AR flood visualisation method.

3.2. Prediction Modelling

Ali Y. et al. [14] pursued the objective of estimating vertical uncertainties of different DEMs on inundation simulations and examined the effect of different inundation models on quantifying flood risk and prevention. The study area was London and they justified it by specifying that London has 300,000 proprieties estimated to be near the tidal flood risk area. The bathtub method for the inundation simulation was used and it was assumed that an area with an elevation less than a projected flood level would be flooded. Flooding areas are determined through a simple calculation procedure in a GIS environment and the bathtub method can be filled with and without hydrological connectivity. They concluded that the adapted bathtub was a useful alternative to hydrodynamic models considering computational requirements and data availability. They also explained how a small difference in the vertical accuracy of a DEM has a strong effect on the quantitative assessment of a sea-level-rise inundation simulation.

Jerónimo P. et al. [15] used and prototyped the installation of a hybrid physical–numerical flood model facility in an augmented reality environment. The installation consisted of an AR-sandbox module that can be used for educational purposes and

prevention-risk-use cases. Emphasis was placed on addressing the "inherent conflict" when using numerical and physical models. They demonstrated that numerical models are nowadays more advanced and less complex than physical models. As precise and more complex as physical models are, their installation cost makes them an expensive solution for simple and non-complex flood simulations. The paper shows several existing prototypes and installations of interactive displays of topographic models created in the past: TerraVision, SANTI and MIT's SandScape. In physical models, testing alternatives in real time by changing a small part of the physical reality (objects in the test zone such as buildings, cars and voluntary obstructions) makes replication more complex. In a hybrid model, the real world (physical model) consists of a sandbox that is mapped through a Kinect sensor and recreated in a virtual environment. The numerical model is then applied and the simulation calculated is then projected onto the sandbox for visualisation, making it straightforward and practical for the end user, especially for educational applications. The paper concludes and notices that employing an explicit-in-time finite model solver results in a high-fidelity, physically based mathematical model.

Eseosa Halima I. et al. [16] worked on the prediction of areas susceptible to floods and inundations in Nigeria, based on historical flooding records from 1985 to 2020. The authors stated that they used 15 variables like topographic, climatic and land use information. They also trained two machine learning models, an Artificial Neural Network (ANN) and Logistic Regression (LR), to develop and generate a susceptibility flood map. The methodology employed consisted of creating a geospatial database containing the conditioning variables and historical flood occurrences, building and validating the machine learning, and produced as an output a flood susceptibility map. As a result of the comparison between the two models, the ANN was better than the LR (76.4% and 62.5%). The authors concluded by stating that the use of machine learning can effectively map and predict flood-prone areas and can be used in policy and plan prevention.

Munawar Hafiz Suliman et al. [17] emphasised in a review of remote sensing technologies used for flood predictions that floods are uncertain as they depend on several climatic and environmental factors, and so, are difficult to predict. They stated that the improvement in the adoption of the latest technology is a must for disaster prediction and forecasting. They proposed a framework that uses a deep learning neural network to generate reports to predict future flood events by learning from big data collected from various sources such as historic flood events, social media posts and Google and satellite images.

3.3. Critical Analysis of ML and DL Applications in Flood Modelling

Fazlul K. et al. [18] reviewed several recent published studies on classical ML and deep learning (DL) applications for flood modelling. They explained how the ML/DL models suffer from the lack of using expert knowledge in modelling flood events. They explained how the traditional fixed-grid 2D model is not always sufficient to reproduce river conveyance. They explained how the model's grid is not aligned with the riverbanks, and in many cases, the lowest points in the river are not adequately represented in the model. They stated that the grid size must be small enough to actually model the hydraulic effects producing the hydraulic gradient through the floodway for sharp bends and narrow channels.

One solution that solves the problem that small and big grids have is to use flexible mesh models as they allow for complicated floodway geometries to be modelled with precision without losing efficiency. The review then detailed the use of machine learning for two important tasks: classification and regression. The authors presented a study that used 70% of the data for the training models and 30% for validation, and also used DEMs of resolution sizes ranging from 12.5 to 30 m from ALOS PALSAR. They concluded by explaining that the major limitations of ML/DL models are their generalisation, the fact that they are oriented in a specific case and not uniform for approaches like river basins. They also showed the lack of benchmark data to evaluate model performance as a limiting factor for developing efficient ML/DL models for flood inundation simulation/prevention.

3.4. Summary

Table 2 lists and compares some of the most important works identified in the state of the art, comparing the subject of study, the methods used and the results obtained. As the table shows, there are relevant works from 2016 to 2023. The topic has received attention in different cities of the world, which is a recognition of the importance of the technology for policy and decision makers. Some studies use real-time sensor reading, while others are scenario simulators. Regarding the technologies used, while the older applications relied more on mathematical models, the most recent ones tend to favour the integration of machine learning approaches.

Table 2. Review summary table.

Authors	Year	Subject	Methodology	Result
Haynes Paul, Hehl-Lange Sigrid, and Lange Eckart [6]	2018	MAR application to see impact of flood in open environments	Vuforia with NTF + WeSenseIT + Testing with Doncsaster City Council (UK)	Visualisation of water height is good + use of app for real use cases has been judged plausible by limited number of experts
Jerónimo P., Luis H., Luis C., Manuel R., Viviana B., and Francisco-Alberto V. [15]	2020	Installation of a hybrid physical–numerical flood model in an AR environment	Use of a real sandbox + Kinect + Iber + Processing	Use of a simple finite model obtains good result + installation mainly oriented to educational purposes
Tomkins Adam and Lange Eckart [10]	2019	Interactive landscape design and flood visualisation in augmented reality	Fiducial tracking + Terrain visualisation, Flood visualisation and Terrain modification pipeline + Multi-user interaction	Interactive and collaborative 3D cartographic visualisations enable real-time multi-user exercises in landscape intervention design and flood visualisation
Marto Anabela and Gonçalves Alexandrino [8]	2019	Mobile AR: user evaluation in a cultural heritage context	MAR application to view a Forum from the Roman Era superimposed over its current ruins	Vuforia is slightly better outdoor + participants found AR easy to use and feel more involved when using the MAR application in their visit
Panou Chris, Ragia Lemonia, Dimelli Despoina and Mania Katerina [9]	2018	An architecture for mobile outdoor augmented reality for cultural heritage	Software architecture of a complete mobile tourist guide for cultural heritage sites	Outdoor MAR provides novel experiences to a wide audience + gamification engages visitors and allows for better interaction
Li Wenkai, Nee A., and Ong S. [11]	2017	A state-of-the-art review of augmented reality in engineering analysis and simulation	A review on several solutions and methodologies for AR application in engineering analysis and simulation	AR allows users to interact with real objects in addition to virtual contents in the augmented scene + AR provides solutions for limitations found in VR
Ali Y., Ram A., Steven K., Masumi Y., Fredrik L. and C. S. B. G. [14]	2016	Estimating the vertical uncertainties of different DEMs' effect on inundation simulations + examining the effect of different flood models on quantifying flood risk	Use of bathtub model + Simulation with hydrologically connected neighbour for filling a DEM cell	The adapted bathtub can be a useful alternative to hydrodynamic models considering computational requirements and data availability
Eseosa Halima I., Hiroaki S., and Hiroki T. [16]	2022	Prediction of flood and inundations in a susceptible area in Nigeria based on historical flooding records from 1985 to 2020	Creation of geospatial database containing variables and historical flood occurrences + Building ML + Validation + Produce a flood susceptibility map	ANN is better than LR (76.4% and 62.5%) + have to use a lot of parameters for producing good flood susceptibility map
I. Alihan H., Scott A. K., and Michael J. S. [7]	2020	Building a framework to simulate and visualise flooding in 3D using position-based fluids for real-time flood visualisation and analysis	Use of historical information + Extraction of OSM + Use of Lagrangian for flood modelling	Demonstration of the usability of position-based fluids to simulate and visualize flooding events.
Bakhtiari V., Piadeh F., Chen A. S. and Behzadian K. [12]	2024	Stakeholder analysis in the application of cutting-edge digital visualisation technologies for urban flood risk management: A critical review	Critical review of cutting-edge flood visualisation	Existing gap in research considering policy-makers, researchers and insurance providers + stakeholders involved majorly in inundation simulation and evacuation routing
Munawar H. S., Hammad A. W. A. and Waller S. T. [17]	2022	Remote sensing methods for flood prediction: A review	Review of the adoption of remote sensing methods for predicting floods	Rapid surge of studies implementing AI techniques coupled with remote sensing techniques for flood predictions
Zhang G., Gong J., Yi Li, Sun J., Xu B., Zhang D., Zhou J., Guo L., Shen S. and Yin B. [13]	2020	An efficient flood dynamic visualization approach based on 3D printing and augmented reality	Flood AR visualization method based on a 3D-printed terrain model + Techniques such as adaptive processing of flood data, hybridisation of virtual flood and terrain models	Useful for providing a more intuitive and realistic visual experience + better result compared to traditional AR flood visualization method
Fazlul K., Mohammed Ali A., David A., Lachlan T., and Lars P. [18]	2023	Review of several recent published studies on ML and DL application for flood modelling	Explains several methodologies from the studies and compares it	Repartition for dataset in ML is 70% testing and 30% validation + the limitation of ML/DL models is generalisation + lack of benchmark data to evaluate model performances

4. Materials and Methods

4.1. Hardware

An Android phone with a rear-facing camera was used to run the final application. For the current work, a Samsung Galaxy A12 mobile phone was used.

The application required an image target specifically designed for AR calibration. This target could be modified in Unity to adapt to different scenarios, and it could be "anything" chosen by the user. When it was in the field of view, the application activated the AR model.

The final application required two Android permissions. The camera use permission was necessary, as the application works with AR. The GPS use permission was used to show the real-time location of the users in Coimbra—but it was not mandatory—so that users outside the city could still utilise the application to view impacted infrastructures.

4.2. Data

4.2.1. Geospatial Data

Mid-quality/High-quality 3D model data for the city of Coimbra obtained through BLosm plugin were used to create the real scaled model of the city of Coimbra. The area of Coimbra used in the application is a rectangular region of 4.8 × 5.4 km^2, rather than the actual real border of the region of the municipality. This region was chosen to be manageable for a mobile application while still being sufficiently large for studying impacted buildings along the river front.

The model extracted from BLosm was a real-sized scale model, with a terrain resolution of up to 30 m, with buildings from OSM. Most of the buildings were present, and a small part of them were missing as OSM is community-oriented in relation to implementing and adding real buildings' geometries.

Concerning the dataset from CLMS, a selected area was chosen to acquire the dataset of the Mondego river height, as seen in Figure 3.

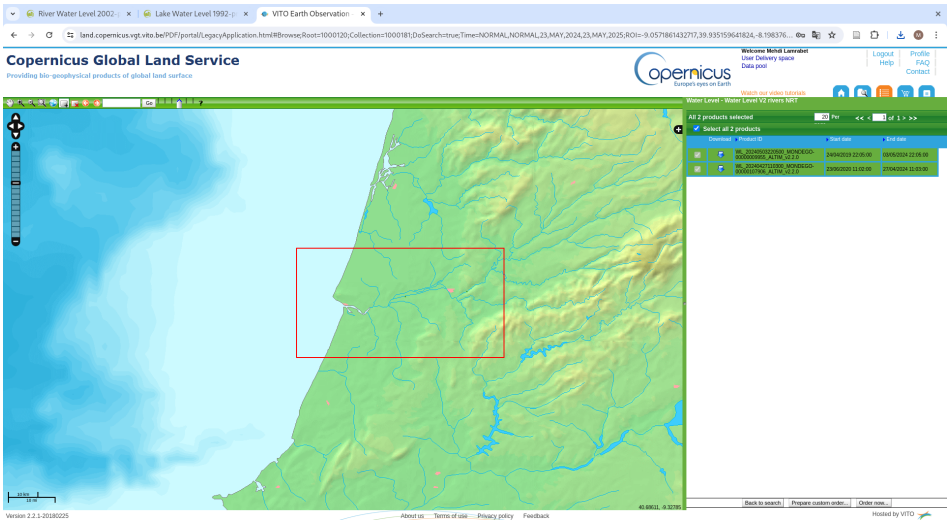


Figure 3. Platform to acquire the dataset from CLMS. The city of Coimbra is within the red box.

Two dataset points for this area were found for the Mondego river. They were plotted with their location with an OSM map in QGIS, as seen in Figure 4. The higher altitude point is closer to the Coimbra city centre, and therefore, it was chosen for hydrological connectivity. The other point is at a lower altitude and closer to the ocean.

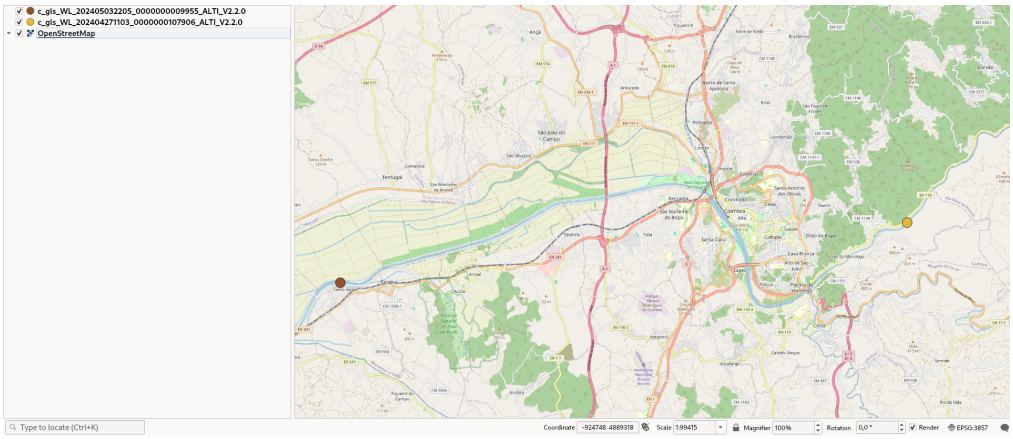


Figure 4. Screenshot of a QGIS plotting of location of dataset points.

4.2.2. Meteorological Data

Meteorological data from Open-Meteo were utilised to gather rainfall information for Coimbra from 2000 to 2024, from https://open-meteo.com/en/docs/historical-weather-api (accessed on 28 October 2024). The "Copernicus Land Global Service" (CLMS) portfolio from https://land.copernicus.eu/en/products/water-bodies/water-level-rivers-near-real-time-v2.0 (accessed on 28 October 2024) was selected for the Mondego river water height. Access to the CLMS platform required an account, through which data could be collected by selecting the specific region.

The "Historical weather API" dataset contains hourly measured weather attributes and data since 1940. A subset of 24 years, from 2000 up to 2024, was chosen. An even smaller subset, used to correlate with the river height dataset, was selected, with a range from 2020 up to 2024. The features that were gathered are as follows:

- Rain precipitation in mm;
- Evapotranspiration in mm;
- Temperature in °C.

4.3. Software

The software tools used in this project included QGIS 3.34 open source software for Windows (https://qgis.org/, accessed on 28 October 2024) for GIS data processing and preparation, OpenStreetMap (https://www.openstreetmap.org/, accessed on 28 October 2024) (OSM) data for detailed city mapping, Blender 4.2.3 for Windows (https://www.blender.org/, accessed on 28 October 2024) for generating the 3D model of the city, and Unity 6 game engine (https://unity.com/, accessed on 28 October 2024) with Vuforia 10.7 (https://developer.vuforia.com, accessed on 28 October 2024) for MAR application development.

Vuforia was chosen as the alternative for the mobile augmented reality development. It was selected due to its ability to function "out of the box" with fewer sensor requirements compared to other services, thereby increasing compatibility with a broader range of mobile devices equipped with a rear-facing camera and an accelerometer. Additionally, Vuforia's adaptability to both fixed cameras (non-mobile phone devices) and moving targets proved advantageous for hardware flexibility.

The machine learning models were developed, trained and tested in Python 3.8.10 (https://www.python.org/, accessed on 28 October 2024), using the required SciPy 1.14.0 (https://scipy.org/, accessed on 28 October 2024) libraries.

4.4. System Architecture

An overview of the experimental setup architecture is shown in Figure 5. The figure shows the general workflow and links between each component of the project. Gear wheels represent the libraries that provide most of the solutions used.

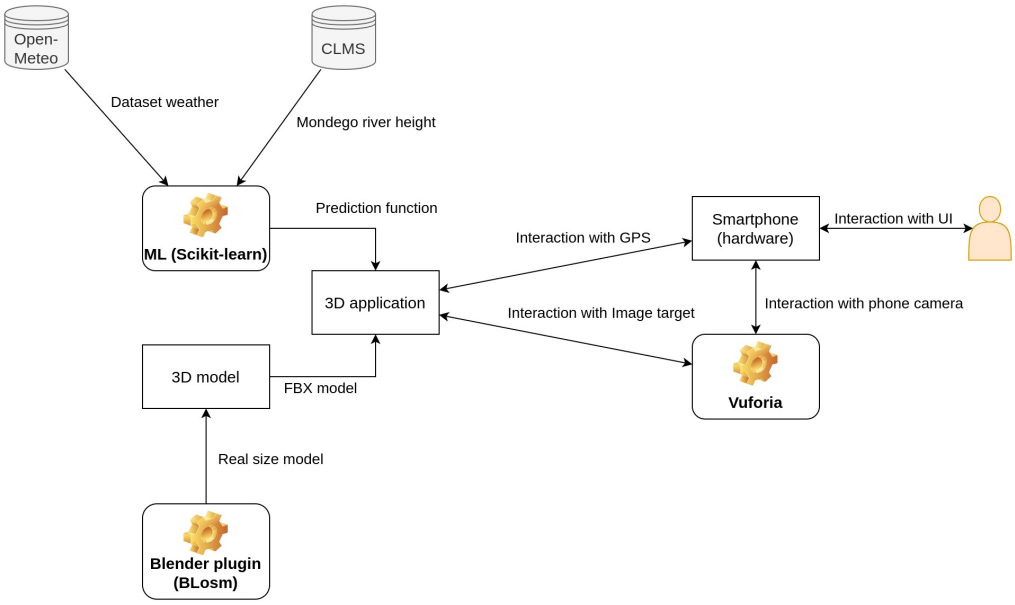


Figure 5. General workflow and links between each component of the project. Gear wheels represent the libraries that provide most of the solutions used.

For the 3D model, correction, processing and 3D application, a custom methodology and experiment were conducted. The ML component used the dataset to learn and generate predictive models, which were then combined with the 3D real-sized model in the 3D application. This application communicated with Vuforia to process the 3D models in the scene. Interaction between the user and the application was performed by a user-friendly interface, allowing interaction with the water plane. Although GPS interaction was included, it was not mandatory to the final project, as it could be disabled and did not conflict with the usability of the main application. The final application with a video demonstration could be found in a GitHub repository: https://github.com/MehdiLamISIB/CoimbraFloodPrevention (accessed on 28 October 2024).

4.5. Configuration and Pre-Optimisation

The necessary data for the 3D real-sized model of the city of Coimbra were obtained using a Blender plugin called BLosm, which extracts data from OpenStreetMap. This plugin utilises predefined rules to generate 3D structures such as buildings, areas and roads from OSM data, assigning appropriate colours to each component with respect to predefined rules from OSM as available in this link: https://wiki.openstreetmap.org/wiki/Simple_3D_Buildings (accessed on 28 October 2024). BLosm added a new panel in Blender, allowing users to select the desired area and specify options for extracting specific elements. Figure 6 shows a screenshot taken from Blender.

Following the data extraction with BLosm, modifications were made in Blender, such as converting curved roads to mesh objects and reduce the triangle count by using modifiers called “Decimates”. These modifiers attempted to reduce the triangle count by preserving the geometrical shape. The buildings extracted were initially grouped as one mesh object. A function was applied to separate each building into its own object, leading to an increase in the number of buildings/objects to approximately 16,000 or more. This significantly increased memory and CPU usage in Unity, as each building had its own components and properties. To mitigate this issue, all the buildings that were not impacted by the flooding, based on their height location and a maximum realistic water height for the flooding, were grouped into a single object, reducing the number of individual parts up to 2000. Blender’s scripting capability was necessary to achieve this. This realistic flooding height was chosen as the lowest possible to include most of the buildings. For instance, a flooding with a height of 10 m is almost impossible for a flooding that comes from a river overflow.

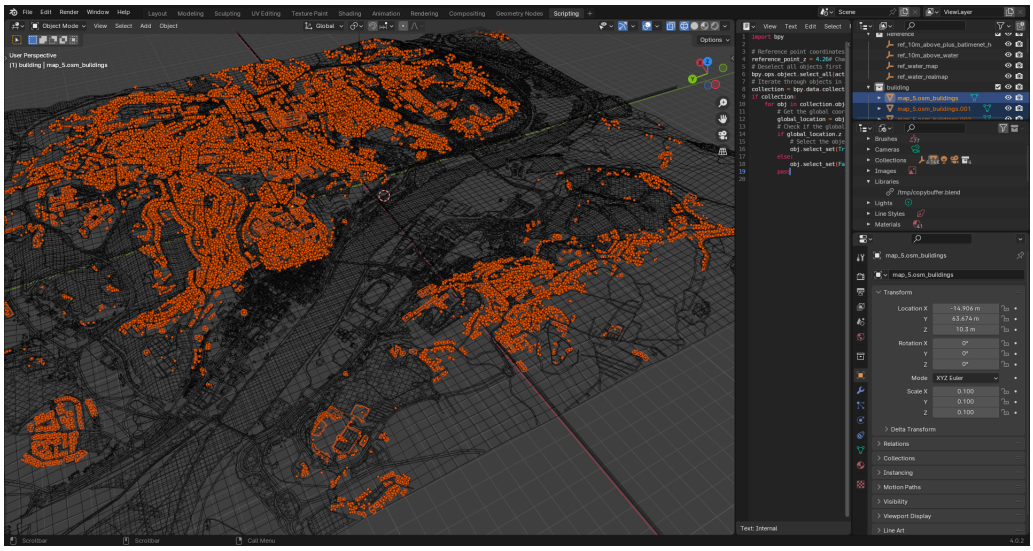


Figure 6. Selected area after running the script (Blender).

An instance of a Vuforia AR camera and image target GameObject is sufficient to run a prototype application in Unity. After importing the image target from the database created through the Vuforia platform, it can be selected and displayed in the scene as a real-world reference. This image target reference is used to adapt the 3D objects in the editor, providing some insights into the proportions for the final application.

4.6. AR Configuration and Setup

The AR configuration employed for this project was set by default in Unity. An instance of a Vuforia AR camera and image target is enough for running a prototype application. Vuforia allows us to use an image target added in the Vuforia personal database. After importing the file in the Unity project, the image target can be selected and shown in the scene to have a real-world reference. This helps us to adapt the 3D objects in the editor to have some insight about the proportions in the final application. The setup is to display the map with the water plane, letting the user interact with a user interface. The idea is the same as an exhibition in a museum, providing the freedom for the user to explore the map at every position and so enhancing the experience.

4.7. Mapping of the Real Coordinates in the 3D Scene

The rectangle method was used to show the real coordinates on the AR map. It consists of having the two corners of the real-sized model from Unity, the left down and the right up. It can be compared with the two coordinates (latitude and longitude) from BLosm that are necessary to be selected in Blender for the 3D model extraction.

By knowing the corners in Unity and their real-world coordinates, the process first determines the real position of the mobile device. These coordinates can then be transformed into x and y positions, as the map is relatively small and can be approximated as a flat plane. The conversion between the real geographical point and the Unity coordinates' point is achieved with a linear proportion.

Once the conversion coefficient is obtained, the operation involves calculating the difference between the location point and the low reference point (lower-left corner), multiplying this difference by the coefficient, and finally adding the lower-left corner position in Unity.

4.8. Impacted Buildings

Each of the buildings that have their own property are grouped in an empty Unity GameObject called "Buildings affected" to easily apply the change to each of them.

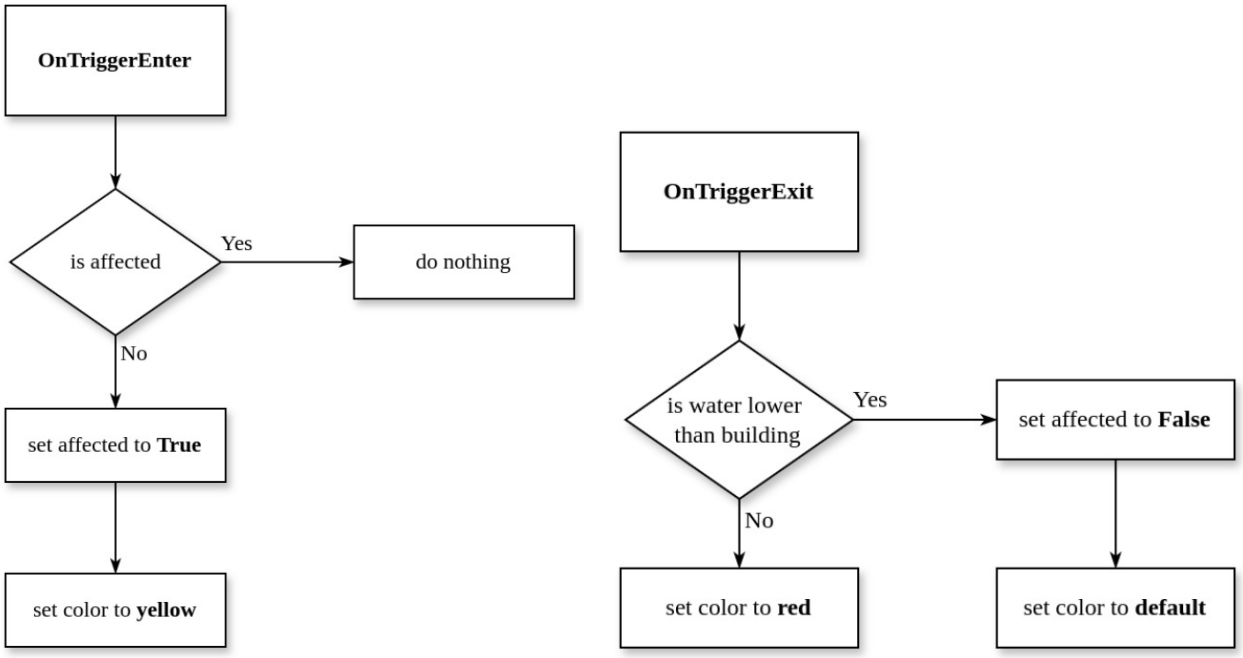
To detect the contact between the water plane and each building, the collider pipeline from Unity was used. The buildings are static objects and it is the water plane that moves. The trigger "collided pipeline" was used, as it detects collision without causing them. It allows the water plane to pass through the buildings.

The first process is to add a mesh collider and set it to convex. It allows Unity to automatically apply a collider based on the geometries. The object that contains this mesh then needs to turn on the collider component's elements called "trigger". A Rigidbody needs to be added to make the trigger work and is added to the water plane as it is the object that moves and passes through the object.

The change in colour makes it easier for the user to see which buildings are impacted by the water height. In Unity, two callback functions, OnTriggerEnter and OnTriggerExit, are utilised to detect collisions. These callbacks determine if the colliding object is a building, using "tags" as identifiers.

In the conditional diagram in Figure 7, these two functions are called individually and the use of the variable "affected" avoids some unnecessary repetition by playing with them. The height comparison is performed between the building's centroid and the water plane's centroid using Unity Transform. Three colours, C_d, C_y, and C_r, are used to display the status of a building, defined as follows:

- C_d (default colour): indicates no contact with water.
- C_y (yellow colour): indicates that the building is in contact with water.
- C_r (red colour): indicates that the building is below water.



(**a**) OnTriggerEnter flowchart. (**b**) OnTriggerExit flowchart.

Figure 7. Conditional diagram of each trigger collision callback.

B_i is the status of the building i and h_w is the water height. The status can be determined by the following conditions:

$$B_i = \begin{cases} C_d & \text{if } h_i > h_w \\ C_y & \text{if } h_i = h_w \\ C_r & \text{if } h_i < h_w \end{cases}$$

where h_i is the height of building i.

The change in colour C_i is linked by these conditions, providing a visual indication of the buildings impacted by the water height h_w.

4.9. Dataset Format and Sample

The historical dataset from open-meteo had attribute choices, start date and end date, as found in https://open-meteo.com/en/docs/historical-weather-api (accessed on 28 October 2024). The file obtained was a CSV file that had this structure and was modified.

The CLMS dataset is a json file. The attribute section called "data" had the information used to obtain the water height, uncertainty and the date when this information was measured, obtained at https://land.copernicus.eu/en/products/water-bodies/water-level-rivers-near-real-time-v2.0 (accessed on 28 October 2024). The "properties" attribute was voluntarily emptied, as it contained information that had not been used.

New attributes/features were also created to analyse the trend of the rain through time so as to find patterns through time.

To accommodate with the CLMS portfolio dataset, the average of the hourly rain precipitation from the Historical Weather API was averaged to one sample per month.

4.10. Evaluation of the Prediction Model

The evaluation of the predicted method was performed through the use of the SciPy Scikit-learn library. The dataset was first selected and then trained with 30% allocated to the test dataset. The result was a regression line model that obtained the height of the water from the Mondego river in metres, measured by rain precipitation in millimetres.

After the analysis and coherence of the model, the coefficient and intercept obtained are used with a GameObject and a class in Unity3D that can be modified through the editor. A slider is used by the user to change the rain precipitation, the regression line model is then applied, and the water plane moves according to the chosen precipitation rain value.

5. Results

This section presents the results of the linear regression model for predicting water levels in the function of precipitation, as well as the 3D model developed.

5.1. Correlation Between Attributes in the Historical Weather Dataset (2020–2024) and CLMS Portfolio

Figure 8 indicates the correlation between each attribute. The sampling period is monthly, the total data points are 51 raw points for the water river height and 51 monthly average points for each weather attribute. The attribute that has the highest correlation with the river water height is the rain precipitation at 0.56, and there is a correlation of 0.88 between the temperature and the evaporation.

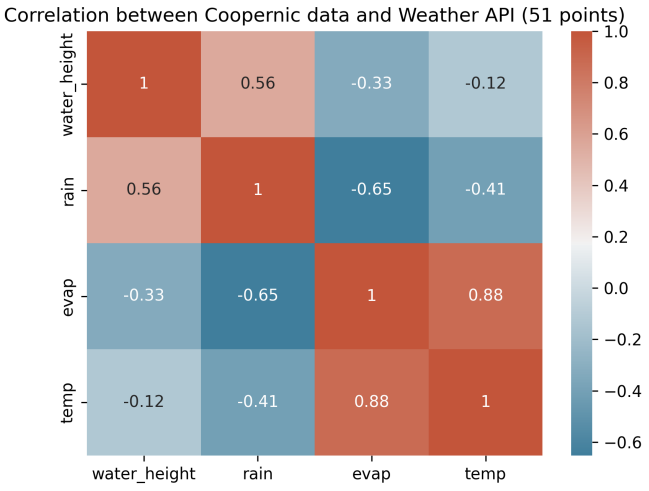


Figure 8. Heat map of the correlation matrix for all variables.

Figure 9 shows the scatter plot of water river height and the rain at the same year and month, along with the regression line calculated. The correlation between the two variables is stronger in low rain precipitation and initial water height. The divergence and spread of values are higher after the value of 0.15 mm of monthly average rain. Some outstanding points may be caused by water management at a dam that is located upstream in the river (Aguieira dam). This dam manages water retention according to the needs for electricity production along the year.

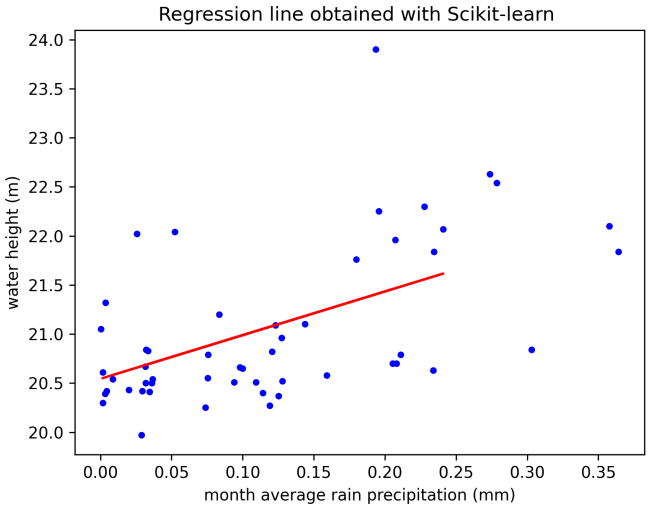


Figure 9. Correlation between monthly average rain and river water height.

Table 3 shows the results and errors obtained for the regression model. The intercept value is linked to the initial water river height, compared to the sea level reference. The coefficient is high due to the limitation of using the monthly average rain precipitation. The errors between data points and prediction using the regression line are on average less than 2%, which shows that the regression is a good approximation for estimating water level in the function of precipitation level.

Table 3. Regression line results and errors.

Name	Value	Unit
coefficient	4.450	m
intercept	20.54	m
MSE	0.147	m
MAE	0.304	m
MAPE	1.457	%

5.2. Mobile Application and User Interface

Figure 10 shows the user input menu, where rain and time can be configured. Figure 11 shows a scenario where buildings affected by floods are listed and marked in yellow colour on the map. The river water height can be obtained by moving a slider representing the value of the monthly average rain precipitation.

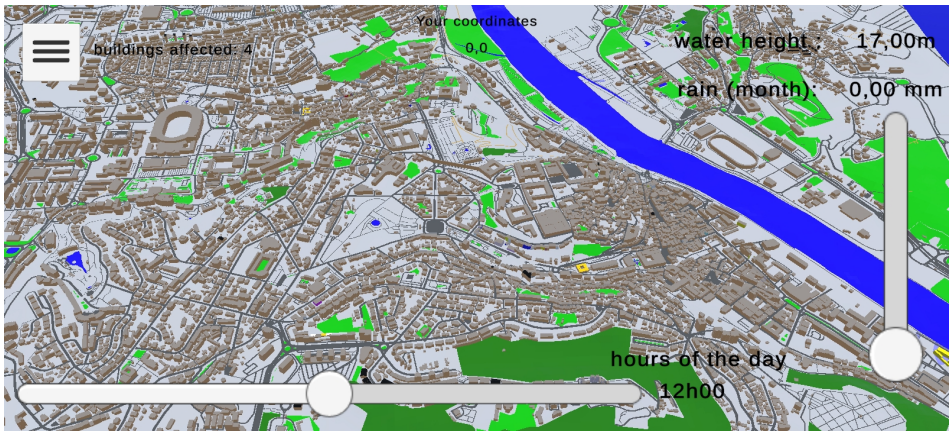


Figure 10. Screenshot of the application User Interface.



Figure 11. UI showing some affected buildings marked in yellow color.

Figure 12 shows the user's GPS location on the 3D map. The map indicator shows a good approximation, within a few metres from the real position on the 3D AR map. It firstly approximates the position and stabilises to a convergent position if the user is not moving too far away from the initial point.



Figure 12. GPS indicator on 3D AR map.

The indication of the impacted buildings works as expected. The number of buildings affected changes when the water plane moves. The phone displacement in the scene from the AR tracking of the image target does not impact the number count as the 3D objects move together. The change in the colours is performed simultaneously and has no noticeable delay.

Concerning the tracking, when the user moves the phone slowly, the 3D objects are mapped correctly. The optimisation of each component in the final mobile application such as AR, 3D and ML has been crucial for having a good user experience without sacrificing too many frames per second (FPS), as most mainstream smartphone devices are limited to 30 FPS.

6. Discussion

6.1. Main Contributions

This work makes several significant contributions to the field of urban flood management through the innovative integration of augmented reality and machine learning grouped together.

A comprehensive and detailed 3D model of Coimbra was created using data extracted with the BLosm plugin and processed through Blender, which serves as the foundation for a mobile augmented reality application. The extraction and simplification of the 3D models, with optimised AR visualisation, results in a model which maintains accuracy to display a real-sized city model without compromising details and information about the city.

The usage of a regression line to predict the Mondego river's water height based on two different datasets, with analysis and correlation tools, shows an innovative way of obtaining a model with the current constraints, such as the lack of open data from government agencies, and with the usage of mobile devices that are low-power for a heavier model.

This application allows for the real-time visualisation of potential flood impacts on buildings, utilising colour-coded indicators to represent different levels of water contact. This colour-coded visual simplifies the interpretation of data and helps users to quickly grasp the severity of potential flooding. The efficacy of the system was demonstrated through simulations of various use-case scenarios, showing the application's capability for real-time, interactive flood risk assessments in outside and inside areas with a good tracking method, even with a small image target.

The general workflow for managing interactions between various objects and software was also a key contribution, ensuring smooth operation of the AR application combined with ML and giving a starting point to people that want to develop a flooding MAR application. Overall, the integration of AR and ML in this research offers significant advancements in urban flood management, highlighting the potential to enhance flood prevention and mitigation strategies in urban areas.

6.2. Limitations of the Mondego River Dataset

Data limitations have a huge impact on the results. The river height data that are important for the prediction of the water level height depend on institutions whose approval requests take a long time to be obtained, and the amount and formats of the data are diverse. This limitation led to our search for open-access datasets on the internet. The historical weather API has a large sample of data points that are registered hourly and contains several features in the city of Coimbra. The CLMS dataset is the only available dataset that has been found in open access that contains several data points of the Mondego river height. As these data were taken from a space, their precision is not as accurate as it would have been if precise measurements were taken from the ground with adequate sensor monitoring. Nonetheless, the error obtained when modelling water height in the function of precipitation and month shows very good results.

The use of the regression model can be performed by calculating the average of the month. The precipitation value obtained for February 2016 is 0.267 mm, so the water height result for the prediction is

$$h = coeff * x + intercept = 4.45 * 0.26 + 17 = 18.157 \quad (1)$$

Since the closest infrastructures on the river front are at 18 m and the h value is higher at an interval of 0.157 m, these infrastructures are flooded. This approximation

value approaches the real value but has a huge limitation as it predicts the flooding value afterwards or is based on estimated precipitation values. The regression model, even limited by the month output, can indicate if chances of flooding in a given month are high and which water height value is expected. The 3D model also allows us to visualise the impact in a user-friendly and intuitive way.

6.3. Sediment Removal to Prevent Flooding in Coimbra

Existing solutions to prevent flooding from the overflow of the Mondego river's water height have already been planned and financed. One solution is sediment removal from the river bed to augment its capacity. It helps to prevent the water from rising higher than the river front and minimises impacts on the infrastructures along the way. This operation is often performed in August, costs in the order of millions of euros and only works for two years, as shown in the following two links: one from the town hall, https://www.coimbra.pt/2018/01/desassoreamento-do-mondego-evita-cheias-e-permite-valorizacao-do-rio/ (accessed on 28 October 2024); and the second from a news press, https://www.publico.pt/2017/08/11/local/noticia/dois-anos-para-desassorear-albufeira-do-mondego-em-coimbra-1782109 (accessed on 28 October 2024).

This augmentation of capacity contributes to avoiding overflow and subsequently the flooding and its impact on the infrastructures in the river front. It has been proven that this solution mitigates the impacts of flooding from river overflow and is a good viable economic and environmental solution when combined with the monitoring and management of these sediments [19].

7. Conclusions

The primary objective of this project was to develop a user-friendly mobile augmented reality application to visualise buildings in the city of Coimbra affected by flooding due to the water level of the Mondego river. A second objective was to predict the water level based on precipitation. The unavailability of accessible data from government agencies led to the use of open-access datasets, which are less precise than direct measurements from the Mondego river, but still allowed us to create realistic models.

The methodology followed consisted of analysing the correlation between meteorological variables and water levels, employing a regression model for its efficacy with datasets obtained from the Historical Weather API and the Copernicus Land Monitoring Service portfolio. Optimisation of the 3D real-sized model was used to reduce memory and CPU usage, and the final mobile application provided users with a reliable approximation of impacted buildings by colour-coding them and displaying the user's real-time position within the 3D model using a GPS indicator in an AR environment facilitated by Vuforia.

This work shows that MAR is a solution that adds value to develop visualisation applications for FRM by using low-price-entry devices, existing data, software libraries and plugins. In future work, the area under analysis may be expanded and other prediction models can be explored. Real-time weather information could also be incorporated in order to add to the system the ability to predict the probability of flood in near real-time.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
API	Application programming interface
AR	Augmented reality
CLMS	Copernicus Land Monitoring Service
DEM	Digital elevation model
DL	Deep learning
DSM	Digital surface model
DT	Digital twin
FPS	Frames per second
FRM	Flood risk management
GIS	Geographic information system
GPS	Global position system
MAE	Mean absolute error
MAPE	Mean absolute percentage error
ML	Machine learning
MR	Mixed reality
MSE	Mean-squared error
OSM	Open Street Map
SPH	Smoothed particle hydrodynamics
SRTM	Shuttle radar topography mission
TWI	Topographic Wetness Index
UI	User interface
URP	Universal render pipeline

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