A Digital Twin Urban Flood Forecasting System

Integrating a Weather Forecast Model and an Urban Flood Model

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Abstract: *Digital Twin reconstructs corresponding entities of various physical world objects in the information world, providing both dynamic and static attributes in near real-time. Static information can be obtained through traditional surveying methods, while dynamic attribute information relies on diverse sensors from the Internet of Things (IoT). Given that raw data collected by IoT sensors are often dispersed, point-based data from in-situ stations with spatial and temporal gaps, scientific models play a crucial role in integrating these disparate data into a continuous spatiotemporal data. As the physical world encompasses interdisciplinary characteristics, data from different domains require integration and estimation using scientific models that consider various factors from their respective fields. Therefore, to accurately mimic physical world through dynamics and fully establish a digital twin, it is necessary to integrate cross-disciplinary scientific models that take various IoT readings as inputs, such as meteorological, hydrological, geological observations. This approach enables real-time tracking and forecasting of changes in the physical world, providing more realistic simulation results and supporting various value-added applications. While constructing a comprehensive digital twin system is still an on-going task, a subset of this system can be built to prove the concept. Given the rapid increase in extreme precipitation events in Taiwan leading to urban flooding, this study establishes a digital twin system focusing on the urban flood forecasting. This study uses urban flood zone assessment as a case study to integrate diverse sensor data, the high-resolution numerical weather prediction model, and the urban flood model to create a digital twin for flood forecasting. By comparing forecasts with actual observations to assess accuracy, this study seeks to establish a digital twin that accurately reflects the dynamics of the physical world. Ultimately, this study will also evaluate accessible areas based on the digital twin flood forecasts and develop an urban flood navigation system to plan disaster prevention routes. This system aims to facilitate evacuation and sheltering during flood events, demonstrating the application value of digital twin technology in urban virtual-real integration.*

Keywords: digital twin, Internet of Things, weather forecast, flood simulation, disaster prevention and rescue

Introduction

Digital twin technology has recently become a major focus in technological development, with the Department of Natural Sciences and Sustainable Development, National Science and Technology Council of Taiwan highlighting "Multidimensional Spatial Information and digital twin" as a key research area. Digital twin reconstructs corresponding entities of various physical world objects in the information world, providing both dynamic and static attributes in near real-time to achieve virtual-real integration (Grieves, 2017). Static attribute information refers to data that does not frequently change, such as topographic maps and urban facilities. Dynamic attribute information refers to data that frequently changes over time, such as weather and environmental observation data. Static information can be obtained through traditional surveying methods, while dynamic attribute information relies on diverse sensors provided by the Internet of Things (IoT). However, raw data collected by IoT sensors are often dispersed, point-based data from in-situ stations with spatial and temporal gaps, scientific models play a crucial role in integrating these disparate data into a continuous spatiotemporal data. Additionally, different fields require different scientific models to account for multiple variables and integration for estimation. To achieve a complete digital twin simulation, it is essential not to focus solely on models from a single domain. Instead, it requires the integration of multiple cross-disciplinary scientific models, combined with the dynamic input of real-time sensor data. This allows the models to influence and calibrate each other, thereby improving simulation accuracy and enhancing its application value.

As mentioned, to establish a complete digital twin, it is essential to integrate cross-disciplinary scientific models with digital twin system and incorporate diverse IoT time-series sensor data for real-time tracking and prediction of physical world changes. Given the rapid increase in extreme precipitation events in Taiwan (Tung et al., 2016), which may lead to drainage difficulties in densely populated and highly developed urban areas, resulting in flooding, localized traffic disruptions, and evacuation challenges, this study starts with the prevention and control of extreme precipitation disaster events. Using the assessment of urban flood areas caused by heavy precipitation as a case study, this research aims at integrating diverse sensor data, the numerical weather prediction model, and the urban flood model to establish a digital twin flood forecast system and, based on this forecast, assess passable areas and develop an urban flood navigation system to plan disaster prevention routes.

The paper is organized as follows. The Literature Review section reviews past research on the coupling of numerical weather prediction models with hydrological models, as well as the characteristics of atmospheric models and hydrological models. The Study Area section describes the characteristics of the study area and the reasons for selecting this area for study. The Modeling Description section introduces the scientific models used in this study, and the Data section introduces other relevant data. The Methodology section sequentially describes the development methods and processes for the urban flood navigation system. The Results and Discussion section presents the outcomes of model coupling and phenomena discovered in the urban flood navigation system. The Conclusion and Recommendation section provides an overall review of the study and mentions related recommendations.

Literature Review

Wu et al. (2014) and Wan and Xu (2011) indicate that rainfall–runoff modeling produced by coupling numerical weather prediction models with hydrological models achieves higher accuracy compared to rainfall–runoff modeling that relies on rain gauge station data paired with hydrological models. Regarding the integration of weather and hydrological models, studies by Tian et al. (2020) and Camera et al. (2020) have explored this topic. Tian et al. (2020) investigated the coupling of the Weather Research and Forecasting (WRF) model with the Hebei model (Tian et al., 2019) at different spatial scales in northern China's watersheds. Using four storm events as case studies, they analyzed the relationship between rainfall with uniform spatial distribution and the selection of the optimal coupling scale. Camera et al. (2020) applied the WRF-Hydro model to 22 watersheds on the northern slopes of the Troodos Mountains in Cyprus, comparing the performance of WRF, WRF-Hydro, and a calibrated version of WRF-Hydro in simulating river basin discharge. Notably, Tian et al. (2020) found that a finer coupling scale between atmospheric and hydrological models facilitates the use of higher-resolution rainfall data; however, higher resolution does not always achieve a better result, as the choice of grid size is significantly related to rainfall uniformity.

Regarding the performance of atmospheric and hydrological models, Benoit et al. (2000) found that the characteristics of atmospheric simulations generally aligned with observations, although the model produced errors at specific times and locations during events. Hapuarachchi et al. (2011) highlighted that the quality of flood forecasting is largely dependent on the accuracy of the rainfall input. Similarly, Nanditha and Mishra (2021) pointed out that accurate, high-resolution weather forecasts, along with ground station data for assimilation, are crucial in developing effective flood forecasting systems. Hence, this study aims to improve the accuracy of urban flood forecasts by integrating the high-resolution numerical weather prediction model with IoT sensor data, ultimately developing an urban flood navigation system that supports real-time disaster response and evacuation planning.

Study Area

The study area for this study is Shanhua District in Tainan City, which is adjacent to the Southern Taiwan Science Park, as shown in Figure 1. In recent years, significant development at Shanhua District has attracted a large number of populations, leading to a substantial increase in housing demand. This surge in demand has stimulated the development and price increase of real estate in the surrounding area, significantly altering the land use patterns of what was once a traditional rural area. As urbanization progresses, the increase in impervious surfaces leads to greater runoff, placing immense pressure on sewer and hydraulic infrastructure and correspondingly raising the risk of flooding.

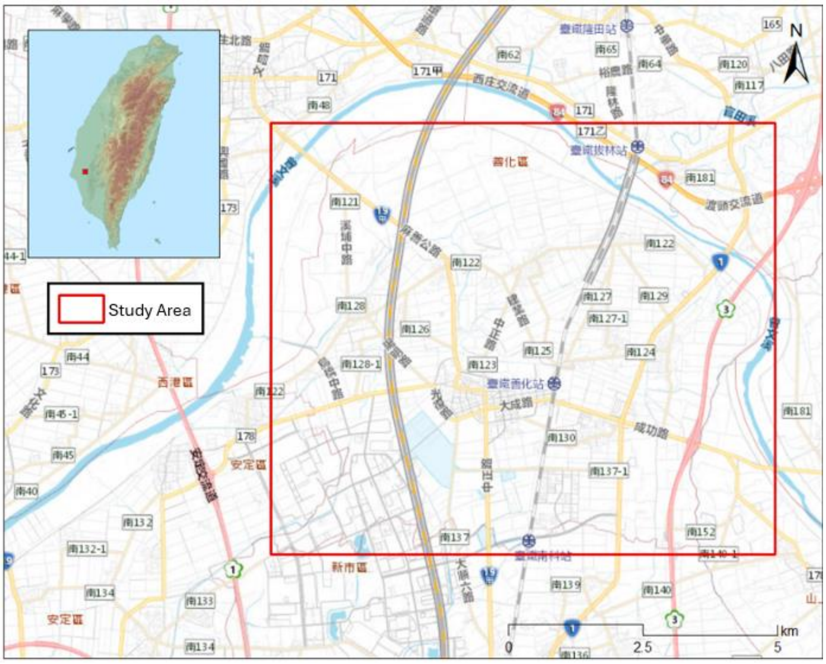

Figure 1: Study Area

Modeling Description

a. High-Resolution Numerical Weather Prediction Model

This model extends the system of multiple meteorological satellite observations, utilizing satellite observation data to improve the initial conditions of the numerical weather prediction model. The foundation of this model is based on version 3.9 of the Weather Research and Forecasting (WRF) model developed by the National Center for Atmospheric Research (NCAR) and version 3.7 of the Grid-point Statistical Interpolation (GSI) data assimilation system developed by NCAR and the Developmental Testbed Center (DTC). The system incorporates satellite observation data, including sea surface wind fields from the Advanced Scatterometer (ASCAT) on the European Metop satellite, atmospheric temperature and humidity profiles from the Cross-track Infrared Sounder (CrIS) and Advanced Technology Microwave Sounder (ATMS) on NOAA satellites, as well as routine observational data provided by the Global Telecommunications System (GTS) of the World Meteorological Organization (WMO) and Final Analysis (FNL) from the National Centers for Environmental Prediction (NCEP). Additionally, Internet of Things (IoT) sensor observations of atmospheric temperature and humidity are utilized.

Prior to forecasting, the GSI system is used for data assimilation. Subsequently, coarse grid data with a resolution of 0.25° × 0.25° from the NCEP Final Analysis (FNL) are employed as boundary conditions for the forecasting process. After generating the initial conditions, these are used for model operation and downscaling. The system then performs bidirectional forecasting using the WRF model, with a four-level nested grid setup that progressively refines the forecast from coarse to fine scales. Each grid level increases in resolution to achieve higher forecast accuracy. During the forecasting process, the system assimilates the latest IoT observation data into the model every hour. This real-time update ensures that the forecast data reflects the most recent observational conditions. The model performs the final forecast on a fine grid with a resolution of 1 kilometer to meet high-resolution requirements.

b. Urban Flood Model

This study utilizes the Coupled Overlandgully-Sewer Flow model (COS-Flow) for urban flooding simulations (Jang et al., 2018; Jang et al., 2019). The COS-Flow model incorporates terrain, 3D building, and hydraulic infrastructure modeling to perform high-precision simulations of two-dimensional overland flow and one-dimensional gullies and sewer pipes modules (Cunge & Wegner, 1964).

In terms of boundary conditions, the elevation of each grid cell is determined by Digital Elevation Model (DEM) data. Rainfall time series data is applied directly to each grid cell as lateral inflow, while downstream boundary conditions are linked to tidal levels at river mouths, allowing inflow to the nearest two-dimensional grid for hydrodynamic computations. The model simulates the interactions between two-dimensional overland flow and one-dimensional gullies and sewer pipes modules. In riverine areas, overflow exceeding levee heights can inundate adjacent flatlands, forming overland flow. Overland flow is managed through gates or pumps into river channels, facilitating interactions among river, regional drainage, and overland flow systems. Additionally, overland flow may enter sewers via stormwater gutters, or, when sewers are full, overflow through manholes to the surface, creating exchanges between sewer systems and overland flow. This water exchange is handled through node-based interactions. These scenarios are modeled with a one-to-one relationship between two-dimensional grids and one-dimensional nodes, enabling a distributed and independent connection between overland flow and channel flow.

Data

a. Digital Elevation Model

The Digital Elevation Model (DEM) for Shanhua District in Tainan City features a resolution of 1 meter. This DEM will serve as the ground base within the urban flooding navigation system, complementing road network data and flood forecasts to assess elevation.

b. OpenStreetMap (OSM) Data

OpenStreetMap (OSM) is an open-source geospatial dataset that includes road networks and other geographic features along with their corresponding attribute values. In this study, OSM data, after attribute filtering, is utilized for navigation path searching.

c. IoT Sensor Data

The sensor data used in this study is sourced from platforms including the Internet of Things for Water Resources platform provided by Water Resources Agency and the Open Weather Data platform provided by Central Weather Administration. In a digital twin flood forecast system, this data serves as dynamic attribute information, providing real-time physical conditions to assist in establishing initial conditions and boundary conditions for the numerical weather prediction model and the urban flooding model.

Methodology

Figure 2 illustrates the study flowchart and framework of this study, which can be divided into four main components: Data Acquisition and Link, Data Management, and two distinct Data Computing and Fusion sections.

The Data Acquisition and Link section involves obtaining data from various sources and linking related information. The Data Management section is responsible for storing the acquired data and model output. The left-side Data Computing and Fusion section pertains to the execution of the numerical weather prediction model, while the right-side Data Computing and Fusion section concerns the operation of the urban flood model.

These components correspond to the research methods detailed in the subsequent sections, which will be discussed in the context of each method.

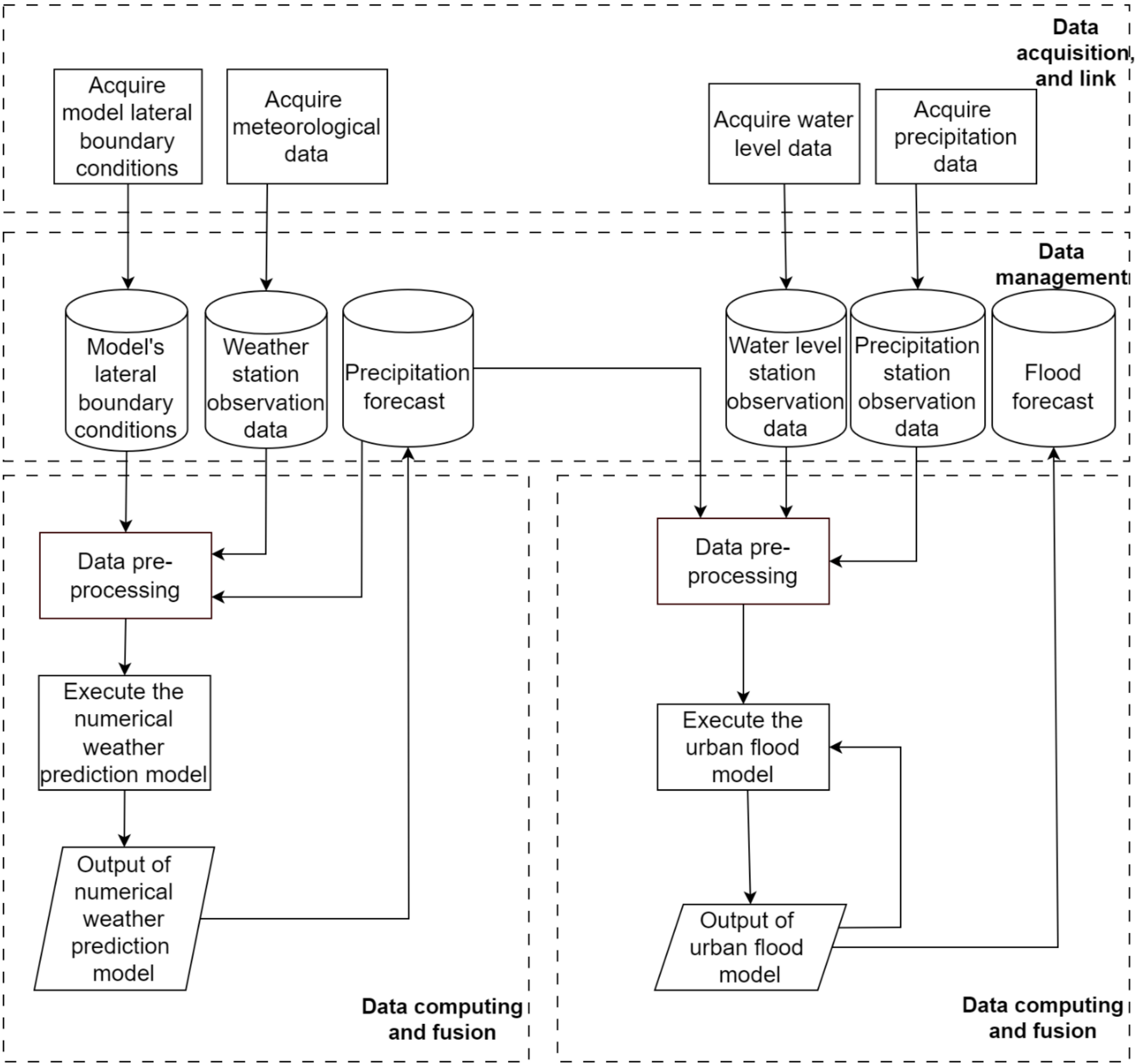

Figure 2: Study Flowchart

a. Collection and Integration of Diverse IoT Sensor Data

The objective of this study is to develop an urban flood navigation system, which will support pathfinding based on flood forecasts generated by urban flood models. In this study, the numerical weather prediction model is employed to estimate point-based station data, enabling the precipitation forecast to have higher spatial density and provide predictive insights beyond the capabilities of rainfall gauge stations. This enhancement aims to improve the accuracy of urban flood model forecasts.

This step corresponds to the Data Acquisition and Link and Data Management section of the study flowchart. As described in the modeling description section, assimilating IoT sensor data into the numerical weather prediction model can improve forecast resolution. The physical quantities of sensors participating in data assimilation include station elevation, atmospheric pressure, temperature, relative humidity, wind speed, and wind direction. Additionally, the urban flood model can use water level and precipitation data as boundary conditions. Therefore, before executing the two models, it is necessary to acquire and prepare the relevant sensor data from open data platforms and store them in different data repositories according to data types.

However, there are several issues associated with using these data. First, the format of IoT data is inconsistent. Due to government policy initiatives, various governmental agencies have gradually opened access to the data within their respective jurisdictions. However, in the domain of IoT sensor data, there is no unified format. The file formats vary, including CSV, JSON, XLSX, etc. Even when using the same file format, the structure of the data provided by different agencies may differ. Additionally, updates to data from the same source may change the format or structure used. Furthermore, the semantic meanings of identical terms may vary across different data sources. These issues prevent a consistent method for data access, increasing the development and maintenance costs of systems using this data, and even leading to the misinterpretation of data. Second, unified data after processing requires substantial storage space. Even if the data from different sources is processed and converted into a unified format, adequate capacity is required to store, manage, and backup the data. As the volume of data increases, it is necessary to consider the feasibility of expansion solutions. Third, stored data requires access interfaces. The original open API data on the internet usually provides different API links depending on the data type, allowing the retrieval of only the required data types. Similarly, locally stored data must have corresponding API access depending on the data type.

To address these challenges, our research team developed the digital twin system (Chiang et al., 2020; Huang & Wu, 2016; Huang & Chang, 2021), which includes a Data Converter Microservice Management Module, an IoT Data Repository Microservice Management Module, and a Data Computation Program Microservice Management Module. Below is an introduction to the functions of each module.

The Data Converter Microservice Management Module provides data converter services. Users can write and deploy data converters within the system to convert IoT sensor data into the OGC SensorThings API data format. The IoT Data Repository Microservice Management Module provides storage space for data converted by the data converters and manages the data. Different types of data can be stored in different repositories, and API services are provided for each repository over the network, ensuring consistent data access. The Data Computation Program Microservice Management Module provides environmental resources and computational resources, allowing users to deploy computation programs with varying environments and data requirements within the system. This module interacts with the IoT Data Repository Microservice Management Module to subscribe to and notify data computation programs of new data, triggering corresponding actions upon receiving notifications.

In this step, the study utilizes the Data Converter Microservice Management Module and the IoT Data Repository Microservice Management Module to process, convert, and store IoT sensor data from open data platforms, addressing the above three challenges. Furthermore, the access to sensor data and outputs generated by scientific models will be performed through the services described above.

b. Integration of Cross-Disciplinary Scientific Models

This step corresponds to the Data Management and two Data Computing and Fusion sections of the study flowchart. The study uses precipitation forecasts from the numerical weather prediction model as boundary conditions for the urban flood model.

Firstly, prior to executing the numerical weather prediction model, it is necessary to retrieve the corresponding data to establish initial conditions and boundary conditions. Once this preparation is complete, the model can be executed. After execution, the precipitation forecasts are stored back into the data repository and serve as inputs for the urban flood model. Subsequently, the urban flood model uses the precipitation forecasts and other data as boundary conditions. After execution, the flood forecasts are then stored back into the data repository.

To establish this integration, the following issues must be addressed. First, the interfaces of these two models differ, necessitating conversion or adaptation processes. The numerical weather prediction model outputs forecasts in NetCDF file format, whereas the urban flood model uses a custom document format for boundary condition settings. Second, the discrepancy in grid systems between the two models needs to be reconciled.

The numerical weather prediction model utilizes a custom grid system, while the urban flood model employs the Quantitative Precipitation Estimation (QPE) grid system. Third, there must be a method for interaction and integration between the two models to ensure seamless data exchange and functionality. Last, the models require IoT data as initial conditions and boundary conditions, necessitating synchronization with the most recent IoT data. Addressing these issues is crucial for achieving effective model integration and ensuring accurate and reliable flood forecasts.

To address the first two issues, it is necessary to develop a program that reads the precipitation forecasts from the numerical weather prediction model, interpolates them to match the grid system of the urban flood model, and then formats the interpolated results into the required boundary conditions format. This study employs bilinear interpolation for this purpose. Once the boundary conditions are set, executing the urban flood model will yield flood forecasts.

To address the third and fourth issues, the integration of these cross-disciplinary models operates within the digital twin system developed by our research team, utilizing the Data Computation Management Microservice Module as mentioned above. Disciplinary models and related computational programs can be uploaded to this service, with subscriptions to required IoT sensor data or computation frequency settings. The service can perform real-time computations upon receiving new sensor data or operate at fixed intervals. When the model outputs are returned to the data repository, other models subscribing to this repository will receive notifications and perform corresponding actions, achieving interactive effects.

c. Establishment of an Urban Flood Navigation System Based on Model-Generated Flood Forecasts

Subsequently, the flood forecasts generated by the urban flood model are utilized in the development of an urban flood navigation system. To make the system service more accessible, we have chosen to develop a web application.

Firstly, OpenStreetMap data is preprocessed to extract the road network, and a graph data structure is created within the system based on this road network. During the graph construction process, the system compares road nodes with the corresponding water levels which are from flood forecasts. If the water level exceeds 30 centimeters above a road node, the node is deemed impassable and excluded from the graph. When users set starting and ending points on the map, the system dynamically adds or removes road nodes based on the aforementioned criteria and uses the shortest path algorithm to compute the navigation route. This study employs the Dijkstra algorithm for route planning. Once the computation is complete, the system renders the route on the web map.

Results and Discussion

This study successfully integrated data collected from various IoT sensors for analysis and fusion, combined with cross-disciplinary scientific models, to achieve real-time monitoring and forecasting of changes in the physical world. The study integrated point-based in-situ station data and merged them with the numerical weather prediction model and urban flood models to provide flood area assessments. Figure 3 shows the flood event case used for validation, presenting the rainfall forecast generated by the numerical weather prediction model (Figure 3a), and the corresponding flood forecast generated by the urban flood model after using the precipitation forecast as a boundary condition (Figure 3b). The figure demonstrates that the distribution and intensity of precipitation and flood areas in these two forecasts correspond to each other, indicating a successful coupling between the numerical weather prediction model and the urban flood model.

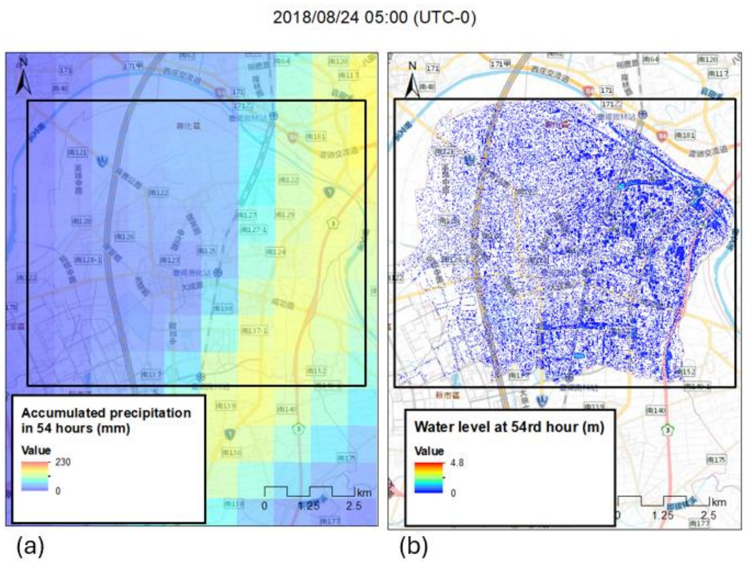

Figure 3: Comparison of Forecast Between the Numerical Weather Prediction Model and the Urban Flood Model, and Assessment of Flood Area

Furthermore, based on the digital twin flood forecasts, this study has developed a prototype of an urban flood navigation system. This system integrates building models, digital elevation models, and lane networks to plan disaster prevention routes, aiming to facilitate evacuation and sheltering during flood events. Figure 4 illustrates a scenario prior to a flood event, where the blue lines represent roads, and the red lines denote the shortest driving routes between the start and end points. Figure 5 depicts the situation after a flood event, showing some roads submerged and thus impassable, resulting in their disappearance from the map, and corresponding changes in the shortest driving routes between the start and end points. The practical implementation of this study demonstrates the application value of digital twin technology in urban disaster prevention and mitigation, highlighting the crucial role of cyber-physical integration technologies in enhancing urban resilience and emergency response capabilities.

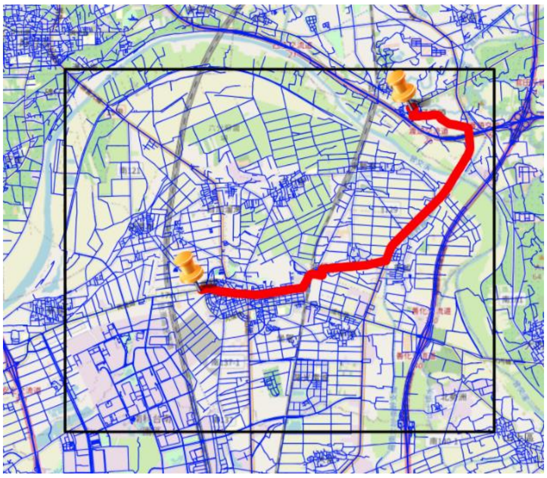

Figure 4: Flood-Free Navigation Routes

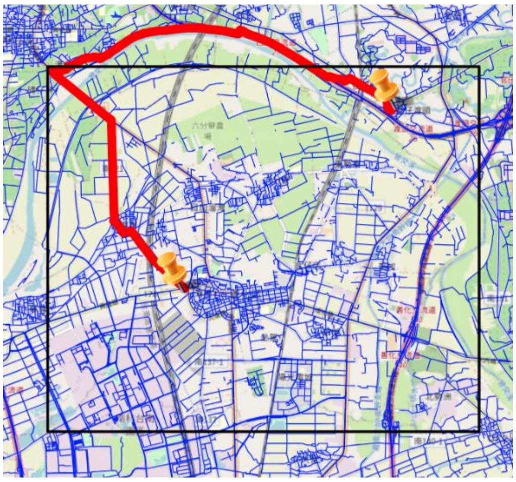

Figure 5: Partially Flooded Navigation Routes

Conclusion and Recommendation

This study successfully integrates diverse sensor data, the numerical weather prediction model, and the urban flood model to provide a comprehensive description of changes in the physical world. Through the assessment of flood areas in the urban area, the evaluation of accessible areas, and the planning of disaster prevention routes, the system facilitates rapid evacuation and sheltering, thereby reducing disaster-related losses. This demonstrates the high application potential of digital twin technology in urban disaster prevention and mitigation. The results further confirm that the integration of cyber-physical systems through digital twin technology can enhance urban resilience and emergency response capabilities, providing significant technical support for future disaster prevention and mitigation efforts.

Several future work directions are identified for this study. First, quantitative analysis and validation are needed to compare the integration accuracy of the numerical weather prediction model and the urban flood model with existing in-situ station data. Additionally, the operational time of the numerical weather prediction model and the urban flood model is currently lengthy; improving the efficiency of these models is essential to support near-real-time disaster response applications. Furthermore, beyond passive navigation based on simulated flood areas, future work could include simulating active flood management measures such as pumps from a traffic perspective to support disaster relief applications.

References

1. Benoit, R., Pellerin, P., Kouwen, N., Ritchie, H., Donaldson, N., Joe, P., & Soulis, E. D. (2000). Toward the use of coupled atmospheric and hydrologic models at regional scale. Monthly Weather Review, 128(6), 1681–1706. https://doi.org/10.1175/1520-0493(2000)128<1681>2.0.CO;2
2. Camera, C., Bruggeman, A., Zittis, G., Sofokleous, I., & Arnault, J. (2020). Simulation of extreme rainfall and streamflow events in small Mediterranean watersheds with a one-way-coupled atmospheric–hydrologic modelling system. Natural Hazards and Earth System Sciences, 20(10), 2791–2810. https://doi.org/10.5194/nhess-20-2791-2020
3. Cunge, J. A., & Wegner, M. (1964). Numerical integration of Barré de Saint–Venant's flow equations by means of an implicit scheme of finite differences. La Houille Blanche.
4. Grieves, M. (2017). Digital twin: Manufacturing excellence through virtual factory replication. Florida Institute of Technology.
5. Hapuarachchi, H. A. P., Wang, Q. J., & Pagano, T. C. (2011). A review of advances in flash flood forecasting. Hydrological Processes, 25(18), 2771–2784. https://doi.org/10.1002/hyp.8040
6. Huang, C. Y., & Chang, Y. J. (2021). An adaptively multi-attribute index framework for big IoT data. Computers and Geosciences, 155, 104841.
7. Huang, C. Y., Chiang, Y. H., & Tsai, F. (2022). An ontology integrating the open standards of city models and Internet of Things for smart-city applications. IEEE Internet of Things Journal, 9(20), 20444-20457. https://doi.org/10.1109/JIOT.2022.3178903
8. Huang, C. Y., & Wu, C. H. (2016). A web service protocol realizing interoperable Internet of Things tasking capability. Sensors, 16(9), 1395.
9. Jang, J. H., Chang, T. H., & Chen, W. B. (2018). Effect of inlet modelling on surface drainage in coupled urban flood simulation. Journal of Hydrology, 562, 168-180.
10. Jang, J. H., Hsieh, C. T., & Chang, T. H. (2019). The importance of gully flow modelling to urban flood simulation. Urban Water Journal, 16(5), 377-388.

11. Nanditha, J. S., & Mishra, V. (2021). On the need of ensemble flood forecast in India. Water Security, 12, 100086. https://doi.org/10.1016/j.wasec.2021.100086
12. Tian, J., Liu, J., Wang, Y., Wang, W., Li, C., & Hu, C. (2020). A coupled atmospheric–hydrologic modeling system with variable grid sizes for rainfall–runoff simulation in semi-humid and semi-arid watersheds: How does the coupling scale affect the results? Hydrology and Earth System Sciences, 24(8), 3933–3949. https://doi.org/10.5194/hess-24-3933-2020
13. Tian, J., Liu, J., Yan, D., Li, C., & Yu, F. (2019). Ensemble flood forecasting based on a coupled atmospheric-hydrological modeling system with data assimilation. Atmospheric Research, 224, 127–137. https://doi.org/10.1016/j.atmosres.2019.03.029
14. Tung, Y.-S., Chen, C.-T., Min, S.-K., & Lin, L.-Y. (2016). Evaluating extreme rainfall changes over Taiwan using a standardized index. Terr. Atmos. Oceanic Sci., 27, 705–715. https://doi.org/10.3319/TAO.2016.06.13.03
15. Wan, Q., & Xu, J. (2011). A numerical study of the rainstorm characteristics of the June 2005 flash flood with WRF/GSI data assimilation system over south-east China. Hydrological Processes, 25, 1327–1341. https://doi.org/10.1002/hyp.7882
16. Wu, J., Lu, G., & Wu, Z. (2014). Flood forecasts based on multi-model ensemble precipitation forecasting using a coupled atmospheric-hydrological modeling system. Natural Hazards, 74, 325–340. https://doi.org/10.1007/s11069-014-1204-6