A Practice of City-scale 3D Geographic Entity Representation and Application in China: The Smart Chongqing City Centre

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Keywords: Smart City Disaster Management, Geographic Entity, 3D Scene Representation, Geographic Knowledge Graph.

Abstract

The Chinese photogrammetry industry is currently experiencing a significant revolution driven by digital intelligence technologies. Traditional city-scale 3D modelling, typically reconstructed from oblique photogrammetry or laser points, is facing increasing limitations in refined expression, real-time rendering, machine recognition, data sharing, and interoperability due to its large data volume and mesh structure. These limitations make it difficult to meet the substantial demands of spatial analysis, simulation, and prediction. The concept of geographic entities, which are machine-recognizable spatial data structures, is anticipated to provide a competitive solution for these challenges. This work employs 3D scene modelling and geographic knowledge graphs to construct geographic entities with semantic relationships at city-scale, addressing the limitations encountered in the application of traditional mesh/point-based 3D models. A case study in Chongqing city centre demonstrates the feasibility and effectiveness of the proposed approach and its potential applications in simulation, prediction, early warning, and feedback for urban planning and smart city management.

1. Introduction

Traditional 3D models at a city-scale are typically reconstructed from satellite images, oblique photos, or laser points. These photogrammetry and remote sensing techniques can accurately capture the geographic location and realistic texture of scenes, often embedding a measurable Triangulated Irregular Network (TIN) or point-based model (Döllner, 2020; Gruen, 2021). However, these data structures have limitations stemming from three aspects. Firstly, TIN or point models are in mesh structures, which restrict their usability in geospatial analysis. In addition, the format of mesh data hinders interoperability and the ability of machines to recognize it, limiting its potential applications in simulations and autonomous learning. Furthermore, these data structures pose challenges in reorganizing and lightweighting for real-time data rendering and sharing.

The digital geographic entities are abstractions and virtual representations that humans use to describe and express geographical phenomena with specific spatial ranges, forms, processes, relationships, and related attributes in the geographical world (Zheng, 2024). In contrast to TIN or point-based models, the data structure of geographic entities is vector-based elements with attribute tables, making it effective for conveying professional information that includes geographic location, spatial codes, as well as various attributes and semantic relationships. Integrated with knowledge graphs, the geographic entities are machine recognizable and friendly to interact. Additionally, what also sets this apart is its substantial information load with moderate data volume compared to TIN or point-based data, making it competitive for data exchange and sharing.

This research aims to construct 3D geographic entity representations at city-scale in an effective and cost-efficient manner, and to explore applications in simulation, prediction, early warning, and feedback of the entity-deployed 3D scenes. Recent studies have investigated the potential of large-scale construction of geographic entities. In the 1960s, the National Aeronautics and Space Administration (NASA) designed a virtual object from its physical counterpart, which are deemed as a pioneer idea of managing a physical object using digital representations (Dihan et al., 2024). The following decades saw rapid and large-scale investment in geographical digitization. In the 1990s, the Australian Surveying and Land Information Group (AUSLIG) built the Spatial Data Infrastructure Program (Nairn et al., 1999) to collect and transfer land related information. In 1994, the Mapping Science Committee (MSC) of the U.S. established the National Spatial Data Infrastructure (NSDI) via deploying entity-oriented data models. In the 2000s, the U.K. deployed the Digital National Framework, assigning unique identification codes for all digital geographic entities for relevant applications (Murray, 2003). The European Union built the Spatial Information Infrastructure (INSPIRE) based on digital geographic entities (Tóth et al., 2007). In recent years, the construction of geographic entity data in China has been rapidly progressing, with several institutions now investigating and exploring at different scales (Zheng, 2024). The above research mainly focuses on data collection, processing, and management, while growing demand for applications is expected to be met with the increasing interest in digital technologies. The applications of geographic entities, including simulation, prediction, early warning, and feedback to the real world, encompass the entire life cycle of what the 3D scene representation aims to achieve. To deploy these applications, the relationships between entities, rather than the entities themselves, become essential. Knowledge graphs are an emerging technology addressing relationships between entities and properties(Zhang et al., 2022). Through digital intelligence technologies, these graphs make semantic relationships machine-recognizable. In the realm of the geographic industry, geographic knowledge graphs benefit various geospatial applications. Several geographic knowledge graphs have been developed, including CSGKB (Zhang et al., 2008), NCGKB (Li et al., 2017), CrowdGeoKG (Chen et al., 2017), YAGO2 (Hoffart et al., 2013), and GeoKG (Wang et al., 2019). These geographic knowledge graphs require more validations to demonstrate their adaptability and flexibility.

The proposed solution consists of two components. First, a 3D geographic entity representation is reconstructed via modelling techniques based on collected TIN/point-based data and other basic surveying and mapping products. Then, the GeoKG method is deployed to establish semantic relationships between entities. Through these two aspects, the limitations encountered in the application of traditional mesh/point-based 3D models are successfully addressed.

Chongqing, one of four municipalities in China, is chosen as a case study for this work. It locates in southwest China and is a modern port city on the upper reaches of the Yangtze River. The city centre of Chongqing is at the confluence of the Yangtze River and Jialing River, making it a regional economic-active zone. The establishment of the smart Chongqing city centre demonstrates its potential applications in simulation, prediction, early warning, and feedback for urban planning and smart city management.

2. Related Work

There are three aspects respectively related in TIN/point-based data collection and modelling, geographic entity construction, and geographic knowledge graphs establishment. Each plays a vital role in shaping the framework for advanced spatial analysis and interpretation, as the following sections explain.

2.1 TIN/point-based Data Collection and Modelling

TIN/point-based data collection and modelling are fundamental processes in generating detailed three-dimensional representations of objects and scenes. This involves the systematic capture, thorough processing, and meticulous analysis of data to accurately depict the physical environment in three dimensions. Aerial photography, where high-resolution images are captured from above the ground, and LiDAR acquisition, which utilizes laser pulses to measure distances to the Earth's surface, are widely employed techniques in this endeavour (Qin and Gruen, 2021). Subsequent processing steps involve refining the acquired data to construct surfaces and textures that closely resemble the real-world features. Despite the advancements in machine learning and artificial intelligence techniques, which are increasingly integrated into various aspects of 3D modelling, the data structure inherent to TIN/point remains primarily oriented towards reconstructing the geographic locations and textures of scenes. While these methods excel at capturing information, they present challenges in terms of interoperability and machine recognition due to the lack of topological relationships. As technology progresses, addressing these challenges will be crucial for enhancing the compatibility and automation of 3D models, thereby further advancing their applications across diverse fields such as urban planning, environmental monitoring, and virtual reality simulations.

2.2 Geographic Entity Construction

Geographic entity construction is a process that involves digitally abstracting and semantically representing the geographical world. Beyond mere geometry reconstruction, it extends to assigning semantic labels to diverse objects or regions within 3D models. This comprehensive approach enhances the interpretability and analytical capabilities of reconstructed environments. Guided by the Ministry of Natural Resources of the People's Republic of China, the National Geomatics Center of China (Zheng, 2024) has developed a systematic workflow for constructing basic geographic entity data products. This workflow encompasses transforming essential geographic information features, constructing attributes and identification codes, and representing combination and association relationships. This standardized methodology is presently undergoing nationwide implementation. However, despite its comprehensive framework, this methodology primarily relies on pre-existing large-scale surveying and mapping products. There exists a pressing need to validate its adaptability and efficacy in relatively local or regional contexts. Expanding its applicability to such areas would not only enhance the granularity of geographic entity data but also enrich the widespread relevance and effectiveness across diverse spatial scales and contexts.

2.3 GeoKG: Geographic Knowledge Graph

GeoKG (Wang et al., 2019), or Geographic Knowledge Graph, is a specialized form of knowledge graph focusing on representing geographic information and spatial relationships among entities in the physical world. Similar to other knowledge graphs, GeoKG organizes data in a structured format, facilitating efficient querying, reasoning, and analysis of geographic data. It encodes spatial relationships between geographic entities and includes semantic attributes associated with them, providing additional context and descriptive information. GeoKG typically displays a hierarchical structure, categorizing geographic entities into different levels based on their spatial properties and relationships. This hierarchical arrangement aids in navigating and exploring the geographic knowledge graph effectively. By offering a comprehensive and multi-faceted representation of the geographic world, GeoKG serves various purposes, including geographic information retrieval, spatial reasoning, route planning, urban planning, disaster management, environmental monitoring, and geographic knowledge discovery.

3. Methodology

As shown in Figure 1, the proposed methodology encompasses the entire work flow of reconstructing the 3D geographic entity representation of scenes. The process involves four key steps:

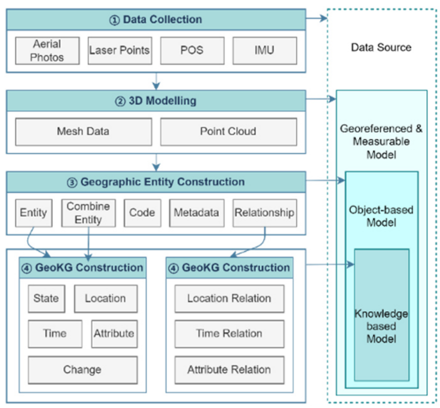

Figure 1. The work flow of 3D geographic entity representation.

Data Source Stage: Data Collection. This encompasses gathering various types of data, including aerial photographs, laser points, and data from POS (Position and Orientation System) and IMU (Inertial Measurement Unit). Aerial photos provide visual information about the scenes from various angles, while laser points offer precise positioning data. POS and IMU provide orientation and location information for aerial photos.

Georeferenced and Measurable Model Stage: 3D Modeling. This stage involves creating 3D models using the collected data. Two primary components of 3D modeling are mesh data and point clouds. Mesh data involves creating surfaces and geo-position from dense matched DSM (Digital Surface Model), while point clouds represent objects or scenes as a collection of 3D points.

Object-Based Model Stage: Geographic Entity Construction. In this step, geographic entities are constructed based on the collected data. As shown in Figure 2, this includes individual entities, combined entities formed by aggregating multiple individual entities, code assignment for identification, metadata for additional descriptive information, and establishment of relationships between entities.

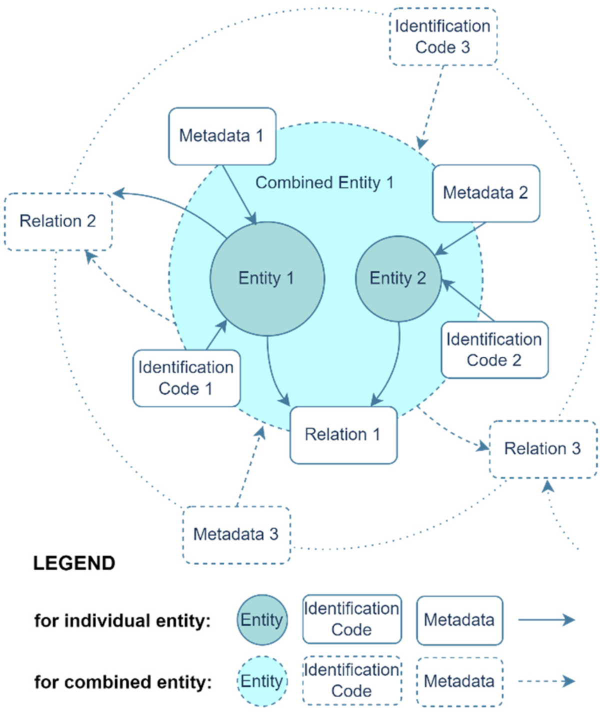

Figure 2. Geographic entity construction for object-based model.

Knowledge-Based Model Stage: GeoKG Construction. This involves creating a structured representation of geographic knowledge. As shown in Figure 3, this includes constructing the state, location, time, and attribute information of individual entities and combined entities within the knowledge graph. Additionally, relationships between entities are captured by constructing location relations, time relations, and attribute relations. By using description logic (Lifschitz, 2007), each entity can be expressed as:

$$E=\{\langle L,T,A,St,Ch,\mathrm{Re}\rangle \mid \exists L \| T \| A \| St \| Ch \| \mathrm{Re} \neq \varnothing \} \quad (1)$$

Where:
$E = geographic\ entity$
$L = location$
$T = Time$
$A = Attribute$
$St = State$
$Ch = Change$
$\mathrm{Re} = \mathrm{Re}lation$

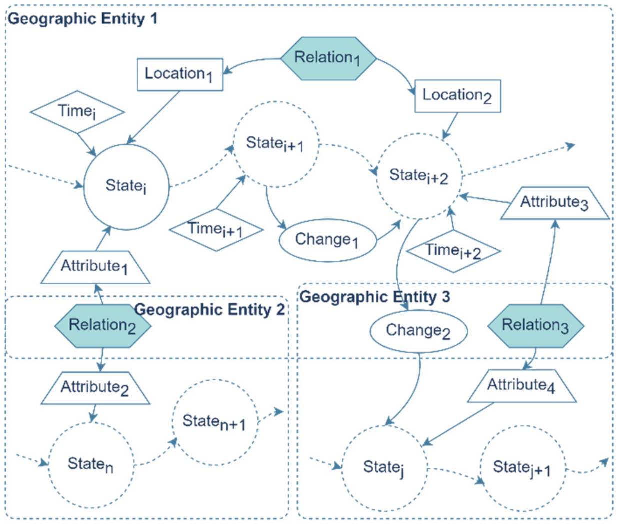

Figure 3. GeoKG construction for knowledge-based model.

In GeoKG models, the Location, Time, Attribute, State, Change, and Relation are respectively expressed as follows:

$$L=\{\exists L\in St_i \mid where\ E_i\neq\varnothing, St_i\in E_i\} \quad (2)$$
$$T=\{\exists T\in St_i \mid where\ E_i\neq\varnothing, St_i\in E_i\} \quad (3)$$
$$A=\{\exists A\in St_i \mid where\ E_i\neq\varnothing, St_i\in E_i\} \quad (4)$$
$$Ch=\{\langle St,act,CE,type\rangle\in E_i \mid \exists St, \#St=2, CE\in\{T,L,A\}, type\in(Ch_d,Ch_e)\ \} \quad (5)$$
$$\mathrm{Re}=\{\langle St,Sem,type\rangle\in E_i \mid \exists St,\#St\geqslant 2, type\in(\mathrm{Re}_l,\mathrm{Re}_t,\mathrm{Re}_a)\} \quad (6)$$
$$St=\{\exists St\in E_i \mid where\ E_i\neq\varnothing\} \quad (7)$$

Where in (5):

$$Ch_d=\{\exists Ch_d=St_i\times St_{i+1} \mid \exists St_i \& St_{i+1}\in O_m, St_i\neq St_{i+1}\} \quad (8)$$
$$Ch_e=\{\exists Ch_e=St_{end}\times St_i \mid \exists St_{end}\in O_m, \exists St_i\in O_n, \exists!\, St_{end}.A_{es}\neq St_i.A_{es}\ \} \quad (9)$$

Where in (6):

$$\mathrm{Re}_l=\{\exists \mathrm{Re}_l=L_i\times L_j \mid \exists St_i\&St_j, St_i\neq St_{i+1}\} \quad (10)$$
$$\mathrm{Re}_t=\{\exists \mathrm{Re}_t=T_i\times T_j \mid \exists St_i\&St_j, St_i\neq St_{i+1}\} \quad (11)$$
$$\mathrm{Re}_a=\{\exists \mathrm{Re}_a=A_i\times A_j \mid \exists St_i\&St_j, St_i\neq St_{i+1}\} \quad (12)$$

In the proposed methodology, each step contributes to building a comprehensive understanding of the geographic environment. Data collection provides the raw information needed for modeling, while 3D modeling transforms this data into visual representations. Geographic entity construction adds semantic meaning to the data, allowing for more nuanced analysis. Finally, GeoKG construction facilitates advanced spatial reasoning and knowledge discovery by organizing geographic information into a structured graph format. By following these steps, analysts can gain valuable insights into the spatial relationships and attributes of the geographic world.

4. Case Study and Discussion

4.1 Study Area

Based on the aforementioned methodology, this paper selects a specific study area within Chongqing as a typical case for practical application. As shown in Figure 4, This area embodies Chongqing's strategic positioning at the national level and benefits from top-level design and policy support at both national and provincial (municipal) levels. Furthermore, the area is characterized by its picturesque setting amidst mountains and rivers, featuring scattered spaces, a blend of traditional and modern architectural elements, and an abundance of geographical and cultural attributes (Figure 5). These characteristics provide an ideal environment for the exploration and implementation of city-scale 3D geographic entity representation, encompassing land, water, terrain, and urban levels.

Figure 4. Study area: The Chongqing city centre.

Figure 5. The real scene of Chongqing city centre.

4.2 Mesh Data Modelling

The construction of mesh models involves following key steps. Initially, a series of high-resolution images or LiDAR scans of the target area are captured from different perspectives. These data sources are then processed to create a dense point cloud representing the surface geometry of the scene. Next, the point cloud data is used to generate a mesh, which consists of a network of interconnected vertices, edges, and faces that approximate the surface of the objects in the scene. Once the mesh is generated, it is refined and optimized by smoothing out irregularities, removing noise or outliers, and filling in missing data. Finally, textures and colours are applied to the mesh by projecting the original images onto the mesh or using texture mapping techniques to apply predefined textures (Figure 6).

Figure 6. Mesh data modelling of Chongqing city centre.

4.3 Geographic Entity Construction

The geographic entity can be utilized to construct a digital twin of Chongqing city centre. This process involves collecting and organizing constructed mesh models, fundamental geographic information feature data at a scale of 1:2000, along with Digital Orthophoto Map (DOM) and other relevant natural resource survey and thematic data. Following this, data undergoes preprocessing steps such as format conversion, coordinate system transformation, and integrity checks. Subsequently, data conversion occurs, establishing a 3D geographic entity data layer with attribute fields and creating a mapping table for feature conversion. Connections and fusion between adjacent production units are facilitated, integrating both current and historical data. Classification codes, spatial identification codes, and unique identification codes are assigned to basic geographic entities, followed by the construction of semantic relationships based on geographic entity data (Figure 7). Metadata production is undertaken to document the dataset, and quality inspection procedures are implemented to ensure data integrity and accuracy.

Figure 7. Geographic entity construction.

4.4 Geographic Knowledge Graph Construction

By utilizing GeoKG method, each geographic entity consists of a series of states, changes, and relations. As a case, the entity Raffles in Chongqing city centre can be expressed as in Figure 8.

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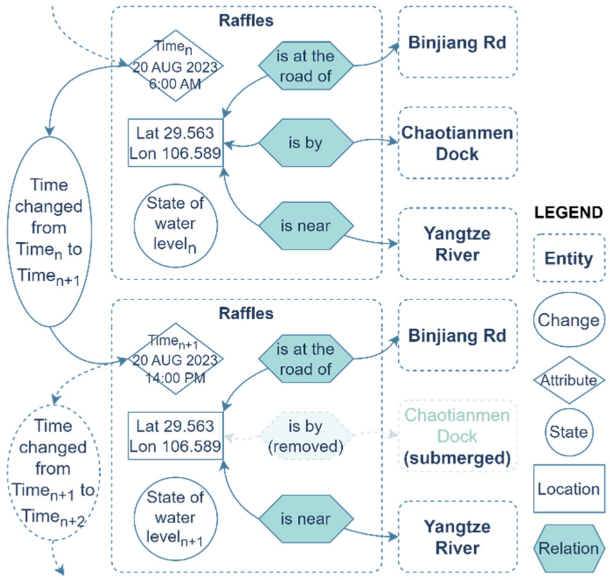

Figure 8. Raffles: A case of entity expression.

Thus, in this case, the definition of the entity Raffles in description logic (DL) can be expressed as follows:

$$E_{rf} = \begin{cases} S_{rf} \subseteq E_{rf}, C_{rf} \subseteq E_{rf}, R_{rf} \subseteq E_{rf} | \\ S_{rf} = \{S_{rf.number} | S_{rf.number} = 2\} \\ C_{rf} = \{C_{rf.number} | C_{rf.number} = 1\} \\ R_{rf} = \{R_{rf.number} | S_{rf.number} \geqslant 2, S_{rf.number} \leqslant 3\} \end{cases} \tag{13}$$

4.5 Application: Knowledge Feedback of Smart City Simulation for Water Level Analysis

Our application focuses on the simulation of water levels using knowledge-based 3D models. We simulate various water levels under different scenarios. As depicted in Figure 9, the water level changes of the Yangtze River are simulated, allowing us to predict potential flood extents and assess flood risk. The water level of the Yangtze River could influence many buildings, such as Raffles City, Baixiang Street, and Chaotianmen Dock. By visualizing the simulated water levels in 3D, stakeholders can better understand the potential impacts of flooding and make informed decisions regarding flood risk management strategies, emergency response planning, and infrastructure development.

Figure 9(a). Simulation of water level at 170m.

Figure 9(b). Simulation of water level at 185m.

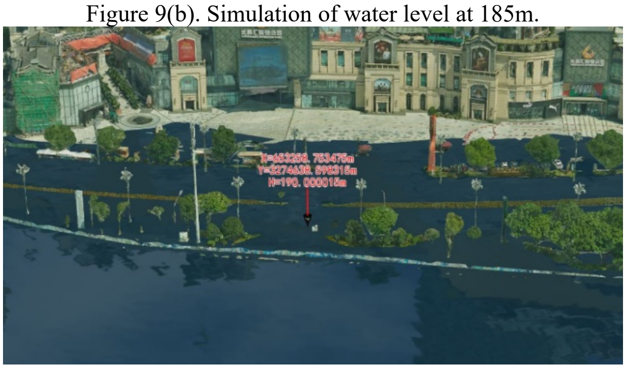

Figure 9(c). Simulation of water level at 190m.

Such simulations can provide decision-makers with feedback, including real-time monitoring and early flood warnings. The early warning application calculates the range and distance that flooding may affect based on the trend of the water level changes, providing advance notice to the relevant areas' personnel to take precautionary measures. For instance, places like Hongyadong, Baixiang Street, and Raffles are prone to flooding due to their relatively low elevation. As depicted in Figure 10, the distance of the flood from a certain building (e.g., Hongyadong, Baixiang Street, or Raffles) is calculated based on water level changes. The simulations within 3D models provide decision-makers with distance-based early warning statistics in various directions.

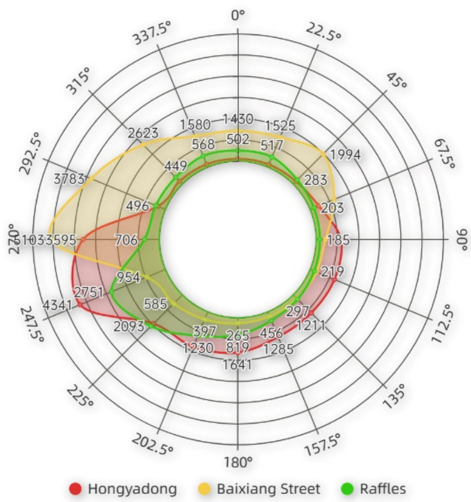

Figure 10(a). Distance (range) of the flood from the geographic entities with water level at 170m.

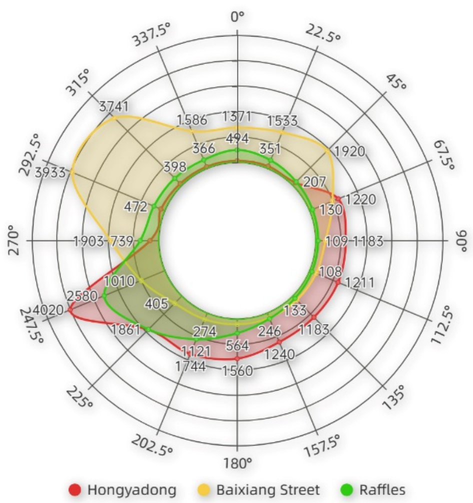

Figure 10(b). Distance (range) of the flood from the geographic entities with water level at 185m.

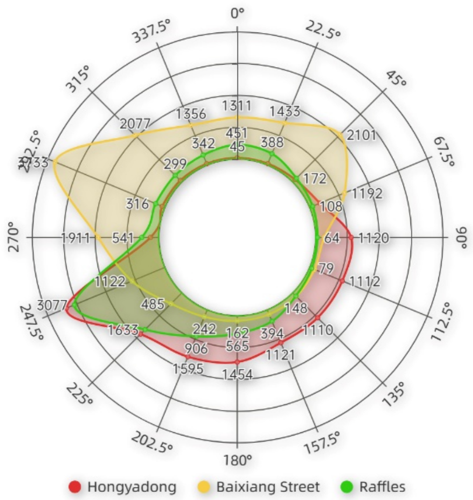

Figure 10(c). Distance (range) of the flood from the geographic entities with water level at 190m.

Figure 11 displays the monitoring calendar generated from knowledge-based 3D models. The highest water level recorded each day is crucial for smart city disaster management.

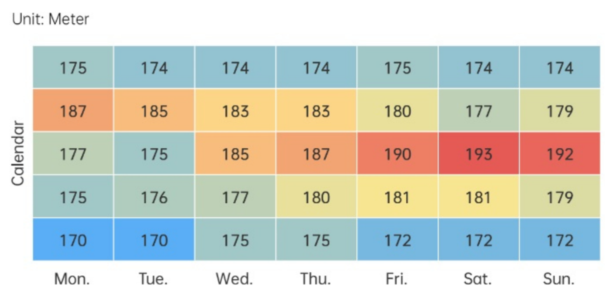

Figure 11. Monitoring calendar of highest water level.

5. Conclusions and Outlook

The utilization of geographic entities and knowledge graphs, featuring machine-recognizable spatial data structures, offers a promising solution for effective smart city disaster management. Leveraging these digital technologies, we have developed geographic entities with semantic relationships on a city-wide scale, overcoming the limitations associated with traditional mesh/point-based 3D models. Illustrated by a case study conducted in Chongqing city centre, this approach demonstrates its potential in various aspects of smart city management, including simulation, prediction, early warning, and feedback. This article initiates a preliminary exploration of a technical framework for scenario-based early warning simulation in mountainous urban planning, encompassing dynamic inundation early warning simulations in typical areas. Besides this application, future applications will cover multiple areas, including traffic management, public safety, infrastructure management, and citizen services. We anticipate these technologies will advance the contributions of the photogrammetry and remote sensing industry to the broader community.

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