



GIS-Enabled Digital Twin System for Sustainable Evaluation of Carbon Emissions: A Case Study of Jeonju City, South Korea

Jiman Park¹ and Byungyun Yang^{2,*}

- ¹ Smart Mobility Research Center, Myongji University, Yongin-si 17058, Korea; 2002310095@naver.com
- ² Department of Geography Education, Dongguk University, Seoul 04620, Korea
- * Correspondence: yby94@dgu.ac.kr

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Abstract: Despite the growing interest in digital twins (DTs) in geospatial technology, the scientific literature is still at the early stage, and concepts of DTs vary. In common perspectives, the primary goals of DTs are to reduce the uncertainty of the physical systems in real-world projects to reduce cost. Thus, this study is aimed at developing a structural schematic of a geographic information system (GIS)-enabled DT system and exploring geospatial technologies that can aid in deploying a DT system for a real-world project—in particular, for the sustainable evaluation of carbon emissions. The schematic includes three major phases: (1) data collection and visualization, (2) analytics, and (3) deployment. Three steps are designed to propose an optimal strategy to reduce carbon emissions in an urban area. In the analytics phase, mapping, machine learning algorithms, and spatial statistics are applied, mapping an ideal counterpart to physical assets. Furthermore, not only are GIS maps able to analyze geographic data that represent the counterparts of physical assets but can also display and analyze spatial relationships between physical assets. In the first step of the analytics phase, a GIS map spatially represented the most vulnerable area based on the values of carbon emissions computed according to the Intergovernmental Panel on Climate Change (IPCC) guidelines. Next, the radial basis function (RBF) kernel algorithm, a machine learning technique, was used to forecast spatial trends of carbon emissions. A backpropagation neural network (BPNN) was used to quantitatively determine which factor was the most influential among the four data sources: electricity, city gas, household waste, and vehicle. Then, a hot spot analysis was used to assess where high values of carbon emissions clustered in the study area. This study on the development of DTs contributes the following. First, with DTs, sustainable urban management systems will be improved and new insights developed more publicly. Ultimately, such improvements can reduce the failures of projects associated with urban planning and management. Second, the structural schematic proposed here is a data-driven approach; consequently, its outputs are more reliable and feasible. Ultimately, innovative approaches become available and services are transformed. Consequently, urban planners or policy makers can apply the system to scenario-based approaches.

Keywords: digital twins; geospatial technology; carbon dioxide emissions; machine learning; artificial neural network; sustainable city

1. Introduction

1.1. Background

With a rapidly growing interest in the Fourth Industrial Revolution, engineers have defined the concept of a digital twin (DT). DTs are considered a virtual development or representation of a real system or world [1]. According to the Gartner Hype Cycle in 2018, DTs are one of five emerging



technology trends. Gartner stated that hundreds of millions of things would have DTs within five years [1]. They enable urban planners to create, test, assess, and monitor a virtual environment coming from the real world [2,3]. Before implementation, DTs enable urban planners to visualize, simulate, and evaluate real-world projects [4,5]. Eventually, they can minimize the failure rates of real urban planning and reduce the uncertainty of the physical systems from real-world projects to reduce their costs.

Furthermore, DT systems reliably assess a real-world project. Thus, DT systems require a realistic representation of physical objects (geographic objects). Despite the many advantages, several challenges remain that require continuous discussion and research activities; the scientific literature does not provide a unique definition of the term "digital twin." The concept of a DT in geospatial technology is at the early stage and not yet well-defined. Accordingly, we propose a new structural schematic of the DTs in geospatial technology. The target subject of this study is associated with strategically reducing carbon emissions in an urban area.

In 2018, the Intergovernmental Panel on Climate Change (IPCC) recommended reducing carbon dioxide emissions (CO_2) emissions by 45% to limit global warming to below a 1.5 °C increase [6]. In highly dense urban areas, buildings account for 94% of electricity usage and 75% of greenhouse gas emissions [7]. Accordingly, carbon emissions in urban areas are the most significant factors accelerating global warming [8]. City gas, electricity usage, and household waste are major factors for increasing carbon emissions—factors primarily driven by human activities [6,9,10].

According to the 48th IPCC meeting held in Incheon, South Korea, in 2018, South Korea aims to reduce CO_2 emissions by 45% by 2030 due to highly increased CO_2 emissions. Furthermore, as of 2019, the rates increased by an annual average of 2.3%. South Korea was the world's thirteenth largest emitter of greenhouse gases in 2015 [11]. The management system for monitoring carbon emissions covers a broader scale than a regional scale. Estimates of CO_2 emissions are usually predicted based on the country's annual CO_2 emissions or the average person's emissions. Accordingly, South Korea has provided statistical summaries of CO_2 emissions at city and province levels, but the summaries at smaller spatial levels are not publicly available. Thus, the current system does not provide information on CO_2 emissions on a fine-scale map equivalent to a regional scale or smaller.

Consequently, there is a significant need for measuring, estimating, and forecasting carbon emissions at a local scale or an appropriate scale that can sustainably monitor carbon emissions rates in an urban area. Moreover, the public has the right to know the information associated with carbon emissions rather than gaining such information through a top-down approach. It is critical to understand what citizens need, rather than a city just providing such information. Thus, citizens, urban planners, and even policy makers need to know carbon emissions data at a local level, rather than the current global-scale data or general statistical summaries without locational information. The questions raised in this research are as follows:

- (1) How can DT technologies or ideas reduce carbon emissions?
- (2) How can DTs assist in improving current decision-making processes to lessen failures of new planning?
- (3) What are the roles of DTs in geospatial analyses or technology fields?
- (4) What types of Fourth Industrial Revolution technologies can be combined with the new DTs?

This research aims to address these research questions by developing a geographic information system (GIS)-enabled DT system for sustainable evaluation of carbon emissions. First, the research proposes a logical workflow of a DT environment for sustainable evaluation of carbon emissions. Second, this research applies four factors causing carbon emissions and estimated values of carbon emissions in cluster maps. The estimated values of carbon emissions are used to predict spatial patterns of carbon emissions through support vector machine (SVM) and artificial neural network (ANN) algorithms. Furthermore, this research determines vulnerable areas of carbon emissions resulting from

spatial statistics to investigate spatial homogeneities of carbon emissions. Third, this study implements a GIS-enabled DT system in 3D buildings, which represents a virtual representation of the study area.

As a result, this research turns out the following key contributions:

- First, this study contributes to the current definitions of DTs in geospatial technology. As stated earlier, the DT has been booming in the manufacturing field, but its definition in geospatial technology has not been clearly defined yet.
- Second, this study also guides what technologies are associated with the DT environment or system. Even though a DT system can computerize counterparts of a physical world, it is not merely a digital component of a physical world. Employment of a DT system is not just construction of 3D city models. Thus, it is necessary for city planners or geospatial analysts to comprehend how to establish new skills, particularly connected with the Internet of Things (IoT) technologies. This can help us clearly comprehend how DTs contribute to the digital transformation of society.
- Third, the construction of DTs can help urban areas to become more environmentally and economically sustainable because the DT environment enables urban planners to simulate urban planning models that help cities face complex issues such as disasters, carbon emission or infectious diseases like the coronavirus pandemic.
- In addition, through this research we expect that the DTs in geospatial technology will bring up a variety of benefits such as efficiency of services, sustainability, safety, economic growth, and more for smart cities.
- As such, the DTs in geospatial technology can experimentally mirror real-world problems and resolve urban environmental issues such as carbon emission. Accordingly, this study will help communicate with the general public wanting to acquire carbon emissions information on a local scale.

This paper is structured as follows. The following sub-section introduces previous studies associated with DTs. Section 2 addresses a structural schematic diagram for a spatially enabled DT system proposed in this study and the study area and a methodological explanation of the SVM algorithm, ANN algorithm, and spatial statistics. Section 3 presents various mapping results in terms of carbon emissions and outputs of the simulation. Furthermore, GIS analysis is introduced to represent vulnerable areas for carbon emissions on GIS maps. We also introduce how the 3D city model is applied to the DT system. Section 4 discusses the key contributions of this research and gaps pertaining to DTs. In Section 5, we present the conclusions of this study.

1.2. Previous Studies

In 2003, the concept of the DT was first introduced in the class delivered by Dr. Michael Grives, a product design expert [1]. Since its introduction, the demands of DTs have rapidly increased in manufacturing sectors, but the term has only been used in industry and research fields [12–15]. In initial DT applications, NASA was the first to experiment with the integrated technology roadmap in the areas of modeling, simulation, and information technology [12]—building two identical space vehicles to enable mirroring the conditions of the space vehicle [14]. Ultimately, this was to operate, maintain, and mitigate the damages of physical systems to increase the probability of mission success and living space [12].

First, the concept of DT varies among researchers. Michael proposed that DTs are the virtual and digital equivalents of a physical product [1]. Söderberg et al. suggested that they are digital copies of physical systems to perform real-time optimization [16]. Erkoyuncu et al. defined DTs as digital representations of physical products or systems on multiple scales, created as a digital representation of a physical item or assembly using integrated simulations and service data [17]. Grieves and Vickers defined a DT as a set of virtual information from the micro-atomic level to the macro-geometrical level [18]. Alam and El Saddik proposed that a DT is an exact cyber copy of a physical system that represents its complete functionality [19]. Although many slightly different definitions have been

proposed over the last two decades, the goals of DTs are to reduce failures from real-world projects and make a success of the real-world projects.

Second, the scientific literature is still in an early phase. DTs have the same strategies that lower costs and the chances of failing in the real world [20,21], but they also reduce the uncertainty of physical environments or systems [22]. Accordingly, DTs can improve current decision-making processes by providing the most probable outcomes. The outcomes that are possible from a well-developed virtual model consist of testing, planning, simulating, and monitoring the counterparts of physical objects or systems. Simulation enables virtual models to produce optimized outcomes, compared with physical systems [20].

Third, although the virtual model or its representation is the counterpart of a physical object and may have functionality similar to a physical system, it is intrinsically different from the original physical world. Thus, the virtual environment must have a sophisticated mechanism to plan, simulate, assess, and monitor the physical world. A computerized environment mirroring the real world must be able to simultaneously and infinitely test, simulate, evaluate, and repeat steps of all possible analytical approaches—lessening the risk of failure from a real-world project. Thus, proper and optimized approaches will be required, for which machine learning or deep learning algorithms can be considered. These are the emerging technologies driving the Fourth Industrial Revolution.

This study uses SVM and ANN machine learning algorithms. These technologies enable machines or systems to learn processes and identify problems [23]. SVM is a supervised machine learning model based on statistical learning theory. This model is used to predict and classify data sets in a hyperplane [24]. Radial basis functions have been used in a wide variety of disciplines, such as surveying, mapping, geology, and 3D object representations [25]. The ANN model is widely used to solve various classification and forecasting problems [24,26]. It is useful for training large data sets and simplifies complicated processes.

Fourth, although a review of the scientific literature is not well defined, there is growing interest in DTs for geospatial technology. Very recently, DTs received considerable attention as a useful virtual platform that enables urban planners to capture changes to a physical system, monitor all associated activities and movements occurring in cities, and simulate real-world projects [27,28]. The growing interest is associated with research and applications of smart cities [3,28–34]. DTs require connections to data and information that connect the virtual and physical worlds [1].

Representing the physical world in a digital format requires a realistic 3D representation of physical systems or worlds, especially in an urban environment. Thus, it is essential that DT applications are built by integrating GIS and building information modeling (BIM), which can represent real objects such as buildings, vegetation, terrain, roads, and even people's behavior patterns. Furthermore, levels of 3D representation result in different perspectives in terms of the physical space for each urban planner. Some DTs function to enhance and optimize real-world processes and to monitor and simulate scenario-based projects used to mitigate risks and increase resilience [31]. Accordingly, the integration of GIS and BIM is an essential technology to deploy DTs to cities.

Concerning DT studies in a city, although the scientific literature is in an initial stage, there is growing interest in terms of exploring developing DT systems in various fields. The DT concept is not just a virtual representation of a physical world but has integrated geospatial technologies that result in lessening the risk of failure due to unforeseen problems, resolving uncertainty from feasible smart city projects, and increasing the spatial perception of the general public that leads to active participation in regional projects.

DTs can provide optimized outcomes for where to focus, which methods to use, and whom to be concerned about for sustainable urban development and preservation in terms of carbon emissions. This research raised the following questions in terms of management of sustainable carbon emissions in a DT system:

(1) What are the optimal geospatial technologies to employ GIS-enabled DT systems for carbon emissions?

- (2) What if we develop scenario-based approaches to mitigate the risk of carbon emissions? What would happen if we change this?
- (3) How can an urban planner deliver carbon-related information to citizens in real-time?

This research addressed the questions raised in this study by developing a GIS-enabled DT system for the sustainable evaluation of carbon emissions.

2. Materials and Methods

2.1. Materials

2.1.1. Study Area

The areas of interest in this study include Jeonju city, which is located in western South Korea and is the capital of North Jeolla Province. The city was chosen as a Creative City for Gastronomy as part of UNESCO's Creative Cities Network. The city is one of the most popular tourist attractions in South Korea because of Jeonju Hanok Village, a traditional heritage village with dwellings known as Korean hanok houses. As of 2017, the total population of the city was approximately 652,392 [35].

Figure 1 depicts Jeonju city in South Korea (Figure 1a). The city includes several land-use and cover types, such as forest, farmlands, grasslands, and urban areas, including tourist attractions, residential areas, industrial districts, and commercial places (Figure 1b). The area in the red box of Figure 1b was developed as a new town over the last two decades. Thus, the area is no longer bare land. As illustrated in Figure 1c, areas in red show highly populated areas. In the most recent years, the city's carbon emissions rate has increased more than the average increase of 6.5% in South Korea. Over the past 10 years, the carbon emissions rate has increased to 22% [35].



Figure 1. Description of the study area: (**a**) Location of research area in South Korea; (**b**) Land use and cover types; (**c**) population density in Jeonju city.

2.1.2. Developing a Schematic Diagram and Data Collection

This research proposed a DT system for sustainable carbon emissions management that enables urban planners to plan, test, visualize, simulate, and evaluate systems that produce optimized outcomes for carbon emissions management. Figure 2 is a structural schematic of the GIS-enabled digital system for sustainable evaluation of carbon emissions that ties the virtual and physical worlds together.

As illustrated in the left side of Figure 2, target assets in the study are factors causing carbon emissions. There are several sources causing carbon emissions, such as transportation, electricity generation, industrial processes and activities, and commercial and residential causes [6,8,36–38]. However, this research only used the four primary factors, following the IPCC guidelines: electricity, household gases, waste discharge, and vehicle gases. Detailed descriptions of the factors are addressed in the following section.



Figure 2. Structural schematic of the GIS-enabled digital twin (DT) environment for sustainable evaluation of carbon emissions.

First, this study formulated the DT system by collecting the data of the four factors and visualizing the values of the four factors in GIS maps. Furthermore, the values were stored in 3D building data in GIS format. The data were provided by the public data portal website of the Korean government. Second, the carbon emissions values of the four factors were estimated through the IPCC guidelines and stored in the GIS database that would be used for the subsequent simulation process. Third, this study performed an analysis. In this step, machine learning techniques were used to predict carbon emissions trends in the study area. Then, spatial statistics were used to visualize the spatial association between the primary factors and to analyze hot and cold spot trends to identify the most vulnerable areas from sources of carbon emissions. Fourth, this study used a GIS-enabled DT system, including the creation of 3D models—the final step before the system deploys to the physical system. When the system is applied to the real world, it can feed back to the DT system for updates and refinement.

2.2. Methodology

2.2.1. Quantifying the Four Indicators

This study used four sources that are major causes of carbon emissions. Table 1 presents the four sources directly associated with carbon emissions.

Indicators	Equations in Accordance with the Intergovernmental Panel on Climate Change (IPCC) Guideline	Sources			
Electricity usage (Month)	Electricity energy consumption (1 Mwh) × carbon emission factor (0.460)	Energy conversion division of Jeonju city			
City gas consumption (Month)	Energy consumption × carbon emission factor × combustion rate × carbon conversion factor (44/12)	Household gas company			
Household waste (Month)	Total waste x dry content x carbon fraction (CF) × Fossil carbon fraction (FCF) Oxidation coefficient × carbon conversion factor (44/12)	Resource circulation division of Jeonju city			
Number of vehicles (Year)	Average daily mileage by type of car \times emission factor by vehicle type	Transportation division of Jeonju city			

Table 1. Physical assets in terms of four primary sources of carbon emissions.

First, the monthly electricity usage for all facilities was provided by Jeonju city. According to the Korea Energy Economics Institute, the usage of electricity is computed as follows. Electricity energy consumption is converted to a megawatt-hour (Mwh), and a 0.46 carbon emission factor is multiplied by the Mwh [39].

Second, data on city gas consumption was provided by the JeonBuk City Gas Company, located in Jeonju city. As for the spatial resolution of the data, monthly data were collected from each of the buildings in the study area. For city gas consumption, this research used the emissions factor provided by the IPCC guideline [6], which is computed as follows: energy consumption × carbon emissions factor × combustion rate × carbon conversion factor (44/12).

Third, data on monthly household waste was supported by the Resource Circulation division of Jeonju city. The division provided the data, which is referenced to the smallest level of the administrative district, which is "Dong" in South Korea. The average of each district was equally divided by all buildings. It was computed as follows: total waste × dry content × carbon fraction in dry matter (CF) × fossil carbon fraction (FCF) × oxidation coefficient × carbon conversion factor.

Finally, this research used data associated with the quantity of CO_2 emitted by cars. For this computation, we received data on the number of cars in Jeonju city. The following equation was applied: average daily mileage by type of car × emissions factor by vehicle type [37]. The total number of cars was approximately 303,580: Standard cars (254,315), vans (10,156), trucks (38,235), and special cars (874). The values of the CO_2 emissions were 199.66 (standard cars), 646.93 (vans), 656.20 (trucks), and 1388.20 (special cars), respectively. The values of the CO_2 emission were equally divided and assigned to each of the buildings in the study area. The equation used in this research was based on the framework used by the IPCC guidelines, which is applied to calculate the direct CO_2 emissions from household energy uses [39–42]. Furthermore, the four data sets were stored in a GIS database to visually represent a higher density of carbon emissions in the study area.

2.2.2. Analysis Step: Visualization and Simulation

The next step was an analysis to predict spatial trends of carbon emissions and visualize spatial associations of carbon emissions by spatial statistics. There were three major processes that represented and predicted spatial trends of carbon emissions patterns and explored spatial associations among the four major factors.

First, total values of the four major sources stored in all buildings were assigned to a 300×300 m array of cells. After that, we used the Iso Cluster and Maximum Likelihood classification tool, which is an unsupervised classification method. This was to statistically classify the values of the carbon emission into 10 clusters. There were 2187 cells in 10 clusters, and each cluster contained enough cells to accurately represent the cluster. Ultimately this was to spatially represent the locations of the most vulnerable areas on a map (See Figure 3). In the next step, the 10 clusters were used to forecast spatial trends of carbon emissions.

Second, this research used machine learning techniques to predict spatial trends of carbon emissions. This simulation was based on the GIS data sets we created in the first analysis step. In this step, the radial basis function (RBF) kernel model was used—an SVM kernel algorithm. SVM is the most popular algorithm for classification and is a type of supervised machine learning algorithm. This model is used to correctly classify unseen data. The RBF kernel classifies data that are not linearly separable and is trained in a maximum likelihood framework by maximizing the probability of the data. This model is the most used type of kernel function because it is used when there is no prior knowledge about the data [43].



Figure 3. Carbon emission map of 2187 cells (300 × 300 m) by four variables: (**a**) electricity; (**b**) city gas; (**c**) waste discharges; (**d**) vehicles.

The RBF kernel model is defined by the following equation.

$$K(x_i, x_j) = exp\left(\frac{||x - x'||^2}{2\sigma^2}\right),\tag{1}$$

where *K* is the RBF model. *x* and *x'* are vectors, where x' is a point-of-reference vector. \parallel is Euclidean distance. Sigma is a free parameter.

Next, a backpropagation neural network (BPNN) was applied to investigate one of the four factors that primarily influence carbon emissions. This was to quantitatively determine which factor was the most influential among the four data sources. A BPNN is a supervised learning algorithm. The method has three layers: input, hidden, and output [44]. The four factors were used as input layers. This study used the R neuralnet package, which trains multi-layer perceptrons in the context of regression analysis [24]. As introduced earlier, the ANN model is widely used to solve various classification and forecasting problems and simplify complicated processes [25]. In this research, we used the ANN model to identify the factor with the highest impact on carbon emissions. Section 3.3 provides the processing of the model in more detail.

The third step of the analytics stage was to identify the spatial association of carbon emissions among the four factors. The analysis was computed from values of each of the four major sources. Accordingly, we used hot spot analysis with Getis-Ord Gi*, which can determine statistically significant

hot or cold spots and reveal spatial trends in the clustering of polygon features: For example, the method uses three confidence levels at 90% (p < 0.1), 95% (p < 0.05), and 99% (p < 0.01), and it assesses where high values of carbon emissions are spatially clustered [45–49]. The Getis-Ord *Gi* * equation is defined as follows.

$$G_{i}^{*} = \frac{\sum_{j=1}^{n} w_{ij} x_{j} - \overline{X} \sum_{j=1}^{n} w_{ij}}{S \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{ij}^{2} - (\sum_{j=1}^{n} w_{ij})^{2}\right]}{n-1}}},$$
(2)

where x_j is the attribute value for feature j, w_{ij} is the spatial weight between features i and j, and n is equal to the total number of features:

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n},\tag{3}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\overline{X})^2}$$
(4)

Getis-Ord G_i^* ,

When using Getis-Ord G_i^* , we can visualize the most vulnerable areas from carbon emissions as hot spots in red. The spatial trends can help determine an optimal scenario by monitoring the increase or decrease in carbon emissions rates in areas of interest. For the weight values of the model, this research used the default weight for Self-Potential in the Hot Spot Analysis tool in ArcGIS.

2.2.3. Deployment Step: GIS-Enabled DT System

In the deployment step, we created a 3D city model that included spatial pattern trends of carbon emissions in the study area. Furthermore, the 3D city model was embedded in a GIS environment.

3D city models require complex knowledge of computational geometry, photogrammetry, and digital image processing [50,51]. The city model can be created through various approaches, such as image-based, laser-scanner-based, and a hybrid of aerial images and ground-based methods. When creating the 3D city model, the degrees of abstraction of 3D city models contribute to designing urban planning. The appropriate degree of realism of virtual environments is always questionable [50–53]. Levels of 3D representation are crucial to increasing spatial perceptions of geographic phenomena [50,51]. Thus, it is important for geospatial analysts to use the highest level of 3D building models, and the level of detail depends on the subject to be applied.

This study followed the guidelines of the Open Geospatial Consortium (OGC) on the level of detail (LOD). LOD defines the degree of abstraction of real-world objects (OGC2012) at four levels. According to the guidelines, LOD 1 represents extruded footprints of the 3D city model. LOD 2, 3, or 4 can represent more detailed building models and even supplement with interior features. Thus, the determination of LOD is crucial for users to accurately recognize a virtual environment mirrored from a physical world. Nonetheless, a LOD model is essential when the intent is to use a DT system in a real-time application. Rather than focusing on developing a highly-detailed 3D city model, this research concentrated on formulating a DT model or system. Accordingly, we used LOD 1, which represents extruded footprints. Furthermore, we created a GIS-based DT system that included the 3D city model and its associated descriptive statistics. Such a system helps urban planners to monitor the results of analytics and review training modes in situations that have never occurred before.

3. Results

3.1. Mapping Carbon Emissions by the Primary Four Factors

As introduced in Section 2, all values of the four major sources were inserted into a 300×300 m fishnet grid that covered the entire study area and included 2187 cells. The value of each cell was classified into 10 classes. Table 2 presents basic statistical summaries of the four factors in the study area.

Carbon Emission	Mean	SD	Max	Min
By electricity	51,834.8	327,807.2	8,189,923.5	0.001
By city gas	27,353.4	59,159.8	786,394.9	0
By household waste	1113.5	2039.8	14,052.9	0.002
By the number of vehicles	121,488.5	215,419.8	1,670,293.5	0.132

Table 2. Summaries of descriptive statistics for the four factors (unit: a metric ton).

As indicated in Table 2, the carbon emission values of electricity were much higher than other factors at more than 8 million. Electricity was the riskiest factor in increasing carbon emissions. Mean carbon emissions by household waste suggested that the number of vehicles in each cell was much higher than the others, even electricity. For standard deviation (SD), the household waste factor was the lowest. With lower electricity usage and fewer vehicles, carbon emissions will decrease. Figure 3 illustrates maps spatially representing the values of carbon emissions based on the four factors.

The maps in Figure 3 spatially illustrate the locations of the most vulnerable areas for each of the four factors in the study area. Class 1 (Cluster 1) indicates small values of carbon emissions, and Class 10 (Cluster 10) represents high values of carbon emissions. Figure 3a illustrates the values of carbon emissions by electricity. High values of carbon emissions were concentrated around Palbog-dong, where a high-tech industrial complex is located. For city gas (Figure 3b), when comparing with the map of land use in Figure 1, almost all urban areas had high values of carbon emissions, except those with land cover.

Classes (Clusters) 8, 9, and 10 are widely distributed in the urban area but highly clustered around residential areas close to Jeonju City Hall, Songcheon-dong, near the Jella buk-do office and Hyoja-dong (red circle in Figure 3b). Figure 3c indicates the values of carbon emissions by household waste discharge. High values were clustered in Gosa-dong and Jeonju Hanok Village. The areas surrounding the traditional Korean houses contain many commercial establishments. Figure 3d illustrates the values of carbon emissions by the number of vehicles registered in Jeonju city. The locations near Jeonbuk University, Inhu-dong, and Hyoju-dong had the highest values for Class 10. However, the spatial cluster patterns were similar to those in the Figure 3b map. This indicates that the two factors occurred mostly in highly developed urban areas (both residential and commercial) due to frequent human activities.

Figure 4 illustrates the total value of the four factors for 10 classes. Classes 8, 9, and 10 with high values are predominantly clustered at the three red circles. As expected, high-tech industrial complexes, commercial districts, and high-density residential areas were the most vulnerable areas in the city.

3.2. Predicting Simulation Results of Machine Learning Techniques

In this step, we used the RBF model to predict the spatial trend of carbon emissions. In regard to the model, we used exhaustive cross-validation to assess how the results of a statistical analysis were generalized to an independent data set, specifically, 70% of the entire data set (an array of 2187 cells), which was equivalent to 1531 grid cells. A 30% (656 grid cells) portion of the entire data set was used as validation data set. This was to avoid the overfitting problem when performing a machine learning experiment. Consequently, this research identified the locations of the most vulnerable areas based on the four factors. Table 3 presents the results of prediction accuracy simulated through the RBF model. Consequently, Clusters 5, 6, and 7 exhibited prediction accuracies of 100%, 68.7%, and 78.1%, respectively.



Figure 4. Accumulated values of carbon emissions associated with the four factors.

Cluster		Predictive Variables by Cluster													
Cluster	1	2	3	4	5	6	7	8	9	10	Accuracy				
1	359	836	7	4	-	-	-	-	-	-	29.8%				
2	-	8	253	39	11	-	-	-	-	-	2.7%				
3	-	-	-	148	33	-	-	-	-	-	0.0%				
4	-	-	-	-	137	-	-	-	-	-	0.0%				
5	-	-	-	-	115	-	-	-	-	-	100.0%				
6	-	-	-	-	31	68	-	-	-	-	68.7%				
7	-	-	-	-	16	-	57	-	-	-	78.1%				
8	-	-	-	-	17	-	38	-	-	-	0.0%				
9	-	-	-	-	6	-	17	-	-	-	0.0%				
10	-	-	-	-	1	0	6	-	-	-	0.0%				

Table 3. Prediction accuracy of support vector machine (SVM) simulation.

In contrast, other clusters demonstrated a significantly lower percentage of prediction accuracy. It is difficult to believe that areas with less accuracy were the areas vulnerable to carbon emissions.

Figure 5a illustrates the results of the RBF model, and Figure 5b illustrates the results of the prediction accuracy of over 68% extracted from Figure 5a. Palbog-dong, Songchen-dong, Inhu-dong, and Hyoja-dong were the areas most vulnerable to carbon emissions and places of concern to policy makers for reducing carbon emissions.



Figure 5. (a) Description of machine learning SVM results for 10 clusters; (b) Description of Clusters 5 (100%), 6 (68.7%), and 7 (78.1%) with the highest prediction accuracy.

3.3. Influence Analysis of Factors Using ANN

In this step, we identified the factors with the highest impact on carbon emissions. This research performed influence analysis by using a BPNN, which is an ANN algorithm. The BPNN uses a layered hierarchical architecture.

As introduced in Section 2.2.2, there are three layers in the ANN model: input (A in Figure 6), hidden (B), and output (C) layers. As depicted in Figure 6, x_p denotes input variables in the Input layer, z_j is nodes in the hidden layer, and y is an output in the output layer.



Figure 6. Results of ANN: (**a**) Forward propagation in the artificial neural network (ANN) (Error: 0.638335. Steps: 72,491); (**b**) Backpropagation in ANN (Error: 0.434747, Steps: 16,313).

Based on Figure 6b, when there are five hidden nodes, the equations are defined as follows.

$$y = f_2(w_y + \sum_{k=1}^{q} w_{ky} z_k), -(2)E = \frac{1}{2} \sum_{j=1}^{n} (y_i^{obs} - y_i^{nn})^2, -(3),$$
(5)

where Z_j is the nodes of the hidden layer (1). x_j is the attribute value for feature *j*, w_{ij} is the spatial weight between features *i* and *j*, and *n* is the total number of features. Each of the factors (x) corresponds

to the input layers. The input layer is connected to hidden layer via synapse (w_{jk}) . Moreover, *E* is the loss for the output *y*. y_i^{obs} is observed values and y_i^{nn} is network outputs.

Figure 6a illustrates the results of forward propagation. When applying one hidden node and training 72,491 times, the root-mean-square error (RMSE) was 0.638. As depicted in Figure 6b, when using five hidden nodes and training 16,313 times, the RMSE was 0.434—an improved result. Furthermore, the backpropagation network model exhibited 94.6% correlation. Consequently, this study used the improved ANN model (Figure 6b) for influence analysis. Table 4 illustrates the weighted values connected to the five hidden nodes.

	Z1	Z2	Z3	Z4	Z5
Bias 1	0.996	-2.338	-0.526	0.582	-3.685
CO2 CAR (<i>x</i> 1)	-0.018	0.495	9.075	-0.429	5.188
CO2 WAS (<i>x</i> 2)	-0.031	-0.889	0.391	0.0390	-0.090
CO2 GAS (x3)	-1.081	1.973	19.436	2.872	12.820
CO2 ELEC (x4)	-4.568	-1.478	66.844	7.334	34.710

Table 4. In the case of bias 1: Four input nodes and weights for the five hidden nodes.

Table 4 represents weights assigned to each of the four input variables connected to each of the 5 Zs via the synapses. The weights range from -4.568 to 66.884.

Table 5 presents the four input nodes with a weight on the hidden node. The weights range from -1.142 to 0.707. SS group indicates output parameter (y) in the ANN model.

Table 5. In the case of bias 2: Four input nodes and weights for the five hidden nodes.

	Bias 2	Z1	Z2	Z3	Z4	Z5
SS Group (y)	1.250	-1.142	0.707	0.481	-1.050	0.394

Accordingly, electricity usage was the most influential of the four factors. As depicted in Figure 7, the results of the BPNN were as follows. Electricity was 62.3%, which was the most influential of the four factors. Next was city gas at 24.4%, followed by vehicle at 6.8% and household waste at 4.9%.



Figure 7. Results of influence analysis based on the backpropagation neural network (BPNN).

3.4. Visualizing Spatial Association among the Four Factors

This step involved identifying the spatial association of carbon emissions among the four factors. This approach can visualize the spatial trends of carbon emissions that represent statistically significant hot or cold spot areas. Figure 8 illustrates the GIS maps from the hot spot analysis.



Figure 8. Hot spot analysis based on the primary factors: (**a**) electricity; (**b**) city gas; (**c**) household waste discharge; (**d**) vehicles; (**e**) river flow location.

As illustrated in Figure 8, the maps identified statistically significant clustering of the four factors with high (red zones) or low (blue zones) values at three confidence levels. The method used three confidence levels at 90% (p < 0.1), 95% (p < 0.05), and 99% (p < 0.01) to identify the hot and cold spots. A high z-score and a small *p*-value indicated a significant hot spot. A Z-score and *p*-value indicated a significant clustering. In contrast, a low negative z-score and small *p*-value indicated a significant cold spot. Thus, it revealed where features of either high or low values clustered spatially.

As depicted in Figure 8d, hot spots existed primarily in industrial, residential, and commercial areas. The eastern portion from the Jeonju and Samcheon rivers included highly clustered areas with high z-score values of more than 2.575. Although electricity was the most influential, geographically, the eastern portion from the two rivers should attempt to reduce carbon emissions rates. These are high-density residential areas and commercial districts with well-known tourism attractions. The spatial patterns of the maps are locally or globally equivalent to the map of the RBF model (Figure 5b).

3.5. Deploying a GIS-Enabled DT System for Carbon Emissions

This step involved deploying a GIS-enabled DT system for sustainable evaluation of carbon emissions. As introduced earlier, this research used a grid of cells of 300×300 m. Although it was at a fine-scale, it is important for urban planners or policy makers to use the finest map scale to induce participation of the public in this project. Consequently, we input the results of both the RBF model and the hotspot analysis to a building unit. Figure 9 illustrates the results of the RBF model for Clusters 5, 6, and 7.

As depicted in Figure 9, the prediction results revealed that the three clusters were the most vulnerable areas from forecasting results in terms of carbon emissions. Prediction accuracies were 100% for Cluster 5, 68.7% for Cluster 6, and 78.1% for Cluster 7. Table 6 presents a summary of descriptive statistics for Clusters 5, 6, and 7 derived from a building unit and covering the entire study area.

Cluster s	Electricity			City Gas			Household Waste				Vehicle				#s of		
	Mean	Max	Min	SD	Mean	Max	Min	SD	Mean	Max	Min	SD	Mean	Max	Min	SD	Building
5	94,508.4	425,765	2019.1	75,014.8	96,636	342,563.6	5.9	54,476.3	5200.4	11,451.3	276.1	2906.4	364,555.5	563,995.5	49,195.8	95 <i>,</i> 570	17,746
6	129,463.9	674,482.3	2390.5	120,654.9	125,558.6	461,273.3	27,448.5	56,118.1	5906.3	12,390.2	816.6	3425.3	3487.9	36,453	17	3005.3	18,715
7	168,640.5	991,836.6	27,310.1	188,558.6	185,434.5	599,505.6	44,594.4	73,958.4	5410.1	11,381.4	883.4	2334.8	773,562.9	1,069,540	157,701.2	200,251.8	11,052

Table 6. Descriptive summary of statistics for Clusters 5, 6, and 7 in a building unit.



Figure 9. Clusters 5 (red), 6 (blue), and 7 (green) resulting from the radial basis function (RBF) model.

For electricity, city gas, and household waste, as Cluster 5 transitioned to Cluster 7, the values of carbon emissions increased. The maximum value of the factor for vehicles is illustrated in Cluster 7 (1,069,540). For the number of buildings in each of the three clusters, buildings in Cluster 6 at 68.7% were 18,715. Cluster 5 had 17,746 buildings with 100% prediction accuracy. Cluster 7 had 11,052 buildings with 78.1% of prediction accuracy.

Another approach for the GIS-enabled DTs is to create a 3D city model with the results of the analytics. Figure 10 illustrates a GIS-enabled DT representing hot and cold spots in a building unit.



Figure 10. GIS-enabled DT systems for sustainability evaluation of carbon emissions: (**a**) by household waste discharge; (**b**) by city gas; (**c**) by vehicles; and (**d**) by electricity.

As addressed in Section 2.2.3, a 3D city model requires complex computational processes and knowledge of photogrammetry and digital image processing. Furthermore, there are various approaches to creating the 3D city model. It is essential to have a sufficient degree of abstraction in the 3D city model because it is directly associated with how well the public or urban planners comprehend the virtual environment mirrored from a physical word. The purpose of this research was to formulate a GIS-enabled DT system, not a 3D building model with the highest level of detail. Consequently, this study used LOD 1, which represented extruded footprints for the 3D city model. Figure 10 illustrates where hot spots and cold spots exist in a 3D building unit. Figure 10a depicts hot and cold spots of carbon emissions affected by household waste discharge. Figure 10b is the 3D map for city gas, Figure 10c is the 3D map for vehicles, and Figure 10d is the 3D map for electricity. Red indicates statistically significant hot spots that represent spatial trends in the clustering of buildings. As addressed in Section 3.4, red identifies statistically significant clustering of each of the four factors with high values at three confidence levels. A high z-score and a small *p*-value indicated a significant hot spot.

The 3D building highlighted (indicated by the arrow in Figure 10) has an attribute table with various items of information in terms of carbon emissions and the building. The carbon emissions in the attribute table of Figure 10a are 31.35, Figure 10d is 3062.4, Figure 10c is 3106, and Figure 10b is 186,175.8. The values of carbon emissions per building is not information about the building but rather the values of carbon emissions affected by each of the four factors. Accordingly, although the four factors have an impact on the values of carbon emissions by the building, the factor driven by electricity is a highly risky source of increasing carbon emissions rates.

4. Discussion

With a rapidly growing interest in DTs in manufacturing sectors, the trend has expanded to various fields. However, this concept still varies, and scientific literature is at an early stage. Even the trend of geospatial technology is at a much earlier stage than for manufacturing sectors. However, in common perspectives, DTs are linked to real-world counterparts and are used to comprehend places where we live and sustainably improve urban systems. Most importantly, DTs are aimed at reducing the uncertainty of physical systems and failures from real-world projects—producing successes for a project and improving current decision-making processes. Thus, it is essential that geospatial scientists design well-developed virtual models consisting of testing, planning, simulating, and monitoring the counterparts of the real-world projects.

Concerning the above goals, this research was aimed at developing a structural schematic of a GIS-enabled DT system for sustainable evaluation of carbon emissions. First, we developed a conceptual model for DTs that had three phases: (1) collection and visualization of physical assets in a GIS environment, (2) analytics, and (3) deployment. The three steps were designed to propose an optimal strategy to reduce carbon emissions in an urban area.

This study on the development of DTs contributes the following. First, based on the DTs, sustainable urban management systems will be improved, and new insights will be developed in a more public manner—reducing the failure of projects associated with urban planning and management.

Second, the structural schematic proposed in this research shows data-driven approaches. Through the system, urban planners and policy makers can apply the system with scenario-based approaches. Consequently, its outputs will be more reliable and feasible.

Third, concerning research, the DTs for evaluation of carbon emissions are mapped in a grid of cells of 300×300 m and a building unit. This dramatically improves the spatial resolution of the geographic data related to carbon emissions and demonstrates a more accurate representation than current carbon management systems. Thus, the research outputs can be directly applied to reality.

In this research, we identified various considerations that could improve the future development of DTs. The research and applications of DTs in geospatial technology are in an early phase. Although DTs can computerize counterparts of a physical world, they are not merely a digital component of a physical world. Thus, it is necessary to consolidate new skills and competencies and clearly demonstrate how DTs contribute to the digital transformation of society. Consequently, geospatial analysts or scientists need to advance DTs over time by improving their abilities to collect data, visualize data, apply the proper analytics, and respond effectively to the objectives of urban planning and management. Consequently, with this research, we propose the following for future DTs projects.

First, as introduced in this research, DTs for carbon emissions management are based on diverse data sources that need to be combined. Thus, it is important to define what types of data will be feasible and how to collect the data. DTs require new skills and technologies. Accordingly,

data collection can be conducted with the IoT connections with sensor technologies to collect real-time data. Furthermore, locational information is an essential source for the deployment of DTs. Consequently, geospatial data and technologies are primary sources for DTs, and the IoT is one of the major drivers in the DT environment.

Second, 3D representation helps urban planners explore, experiment, visualize, analyze, and apply to real-world projects. 3D city models are also important drivers. A higher level of 3D representation is critical to increasing spatial perceptions of events or systems in the real world. When determining the LOD or spatial scale of a 3D city model, we can consider it from the micro- to the macro-geometrical level. The data volume of a 3D city model is burdensome and slows system processing significantly. Furthermore, GIS data comprise the base information used to build a 3D city model. Thus, the optimal map scale and appropriate LOD should be identified for new DTs. The two technologies must be consolidated with the IoT connection.

Third, concerning analytics, the primary goals of DTs are to lessen the risk of failure due to unforeseen problems. Accordingly, well-developed analytics processes must be established. Developers and policy makers must be able to visualize, simulate, evaluate, and then refine and update DTs. Technicians in the manufacturing field use the system daily. Along with the new era of the cloud and big data, machine and deep learning techniques can accomplish the above duties and are also essential elements of DTs. Furthermore, we care about space and place in a virtual environment, even though events are happening in spaces or places. Consequently, engineers must consider the relationships between places, people, and devices when developing DT systems—it is essential to understand how the machine works internally rather than concentrating on the exterior of a device.

Finally, a platform that supports DTs for public and geospatial analysts would be useful. With the Fourth Industrial Revolution, cloud- or web-based applications are popular for those who want to convey information, such as the COVID-19 dashboard developed by The Johns Hopkins University. It enables the public to monitor events and trends, even making decisions and predicting trends on a web-based application. Thus, web-based GIS applications would be one of the major assets for development of DTs.

Even though there are multifaceted contributions of this research, there are direct limitations that should be considered in future studies. First, level of detail in a 3D city model is important, particularly for the public, because it is directly associated with improving spatial recognition of reality. However, this study used LOD 1, which represents only a coarse prismatic model of the 3D buildings. Second, in regard to the web-based GIS application, this research provides only GIS-enabled DTs and not an interactive map like a dashboard. In this study, GIS enabled DTs were not built in a cloud or web-based environment with intuitive and interactive data visualization and analysis. Thus, this will also be one of the major tasks we work on in future studies. Lastly, even though we used machine learning techniques such as SVM and ANN, deep learning algorithms were not considered in this study. Thus, improved ANN algorithms will be considered in future studies.

Consequently, DTs have the potential to massively alter and improve our urban environments, particularly for the sustainable evaluation and management of carbon emissions. Accordingly, it is time for DTs in geospatial technology to evolve and for us to discuss how DTs can contribute to the digital transformation of society or where we live.

5. Conclusions

This study was aimed at developing a structural schematic of a GIS-enabled DT system for the sustainable evaluation of carbon emissions. First, we developed a conceptual model for DTs for evaluating carbon emission rates to reduce carbon emissions in an area of interest. For this research, we used data sources and computational approaches such as mapping, simulation, and spatial analysis. The resultant outputs will be valuable sources for those who want to develop or extend a DT system with locational information or subjects relevant to sustainable urban planning or management. We also proposed considerations that can help improve new DTs used in geospatial technology. With the

contributions of this study, future studies can focus on developing cloud-based spatial decision support systems with a Geo-AI enabled DT system with sensors.

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References

- 1. Grieves, M. Digital twin: Manufacturing excellence through virtual factory replication. *White Paper* **2014**, *1*, 1–7.
- 2. Schrotter, G.; Hürzeler, C. The Digital Twin of the City of Zurich for Urban Planning. *PFG J. Photogramm. Remote Sens. Geoinf. Sci.* **2020**, 1–14. [CrossRef]
- 3. Sepasgozar, S.M.; Hawken, S.; Sargolzaei, S.; Foroozanfa, M. Implementing citizen centric technology in developing smart cities: A model for predicting the acceptance of urban technologies. *Technol. Forecast. Soc. Chang.* **2019**, *142*, 105–116. [CrossRef]
- 4. Richter, A.; Löwner, M.O.; Ebendt, R.; Scholz, M. Towards an integrated urban development considering novel intelligent transportation systems: Urban Development Considering Novel Transport. *Technol. Forecast. Soc. Chang.* **2020**, *155*, 119970. [CrossRef]
- Washburn, D.; Sindhu, U.; Balaouras, S.; Dines, R.A.; Hayes, N.M.; Nelson, L.E. *Helping CIOs Understand* "Smart City" Initiatives: Defining the Smart city, Its Drivers, and the Role of the CIO; Forrester Research, Inc.: Cambridge, MA, USA, 2010.
- 6. Intergovernmental Panel on Climate Change [IPCC]. *Global Warming of* 1.5 °C: An IPCC Special Report on the Impacts of Global Warming of 1.5 °C above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty; IPCC: Geneva, Switzerland, 2018.
- 7. Jain, R.K.; Smith, K.M.; Culligan, P.J.; Taylor, J.E. Forecasting energy consumption of multi-family residential buildings using support vector regression: Investigating the impact of temporal and spatial monitoring granularity on performance accuracy. *Appl. Energy* **2014**, *123*, 168–178. [CrossRef]
- Stocker, T.F.; Qin, D.; Plattner, G.-K.; Alexander, L.-V.; Allen, S.K.; Bindoff, N.L.; Bréon, F.-M.; Church, J.A.; Cubasch, U.; Emori, S.; et al. Technical Summary. In *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M., Eds.; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2013; pp. 33–115.
- Ruiz-Guerra, I.; Molina-Moreno, V.; Cortés-García, F.J.; Núñez-Cacho, P. Prediction of the impact on air quality of the cities receiving cruise tourism: The case of the Port of Barcelona. *Heliyon* 2019, *5*, e01280. [CrossRef]
- Górecki, J.; Núñez-Cacho, P.; Corpas-Iglesias, F.A.; Molina, V. How to convince players in construction market? Strategies for effective implementation of circular economy in construction sector. *Cogent Eng.* 2019, *6*, 1690760. [CrossRef]
- 11. The Carbon Brief Profile: South Korea. Available online: https://www.carbonbrief.org/the-carbon-brief-profile-south-korea (accessed on 10 December 2019).
- Shafto, M.; Conroy, M.; Doyle, R.; Glaessgen, E. Modeling, Simulation, Information Technology and Processing Roadmap. *Technol. Area* 2012, 1–33. Available online: https://www.nasa.gov/sites/default/files/ 501321main_TA11-ID_rev4_NRC-wTASR.pdf (accessed on 2 November 2020).
- 13. Tuegel, E.J.; Ingraffea, A.R.; Eason, T.G.; Spottswood, S.M. Reengineering aircraft structural life prediction using a digital twin. *Int. J. Aerosp. Eng.* **2011**, 2011, 1–14. [CrossRef]

- 14. Glaessgen, E.; Stargel, D. The digital twin paradigm for future NASA and US air force vehicles. In Proceedings of the AAIA 53rd Structures, Structural Dynamics, and Materials Conference, Honolulu, HI, USA, 23–26 April 2012; pp. 1–14.
- 15. Cerrone, A.; Hochhalter, J.; Heber, G.; Ingraffea, A. On the effects of modeling as-manufactured geometry: Toward digital twin. *Int. J. Aerosp. Eng.* **2014**, 2014, 1–10. [CrossRef]
- 16. Söderberg, R.; Wärmefjord, K.; Carlson, J.S.; Lindkvist, L. Toward a digital twin for real-time geometry assurance in individualized production. *CIRP Ann.* **2017**, *66*, 137–140. [CrossRef]
- 17. Erkoyuncu, J.A.; Butala, P.; Roy, R. Digital twins: Understanding the added value of integrated models for through-life engineering services. *Procedia Manuf.* **2018**, *16*, 139–146.
- Grieves, M.; Vickers, J. Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In *Transdisciplinary Perspectives on Complex Systems*; Kahlen, F.J., Flumerfelt, S., Alves, A., Eds.; Springer: Cham, Switzerland, 2017; pp. 85–113.
- 19. Alam, K.M.; El Saddik, A. C2PS: A digital twin architecture reference model for the cloud-based cyber-physical systems. *IEEE Access* 2017, *5*, 2050–2062. [CrossRef]
- 20. Schleich, B.; Anwer, N.; Mathieu, L.; Wartzack, S. Shaping the digital twin for design and production engineering. *CIRP Ann.* **2017**, *66*, 141–144. [CrossRef]
- 21. Wagner, R.; Schleich, B.; Haefner, B.; Kuhnle, A.; Wartzack, S.; Lanza, G. Challenges and potentials of digital twins and Industry 4.0 in product design and production for high performance products. *Procedia CIRP* **2019**, *84*, 88–93. [CrossRef]
- 22. Ambra, T.; Caris, A.; Macharis, C. The Digital Twin concept and its role in reducing uncertainty in synchromodal transport. In Proceedings of the IPIC 2019, 6th International Physical Internet Conference, London, UK, 8 July 2019.
- Li, D.; Shen, X.; Yu, Y.; Guan, H.; Li, J.; Zhang, G.; Li, D. Building Extraction from Airborne Multi-Spectral LiDAR Point Clouds Based on Graph Geometric Moments Convolutional Neural Networks. *Remote Sens.* 2020, 12, 3186. [CrossRef]
- Park, J.; Cho, D.; Lee, S.; Lee, M.; Nam, H.; Yang, H. A study on the methodology of extracting the vulnerable districts of the aged welfare using artificial intelligence and geospatial information. *J. Cadastre Land InformatiX* 2018, 48, 169–186.
- 25. Farin, G.; Hoschek, J.; Kim, M.S. *Handbook of Computer Aided Geometric Design*; Elsevier: Amsterdam, The Netherlands, 2002.
- 26. Günther, F.; Fritsch, S. Neuralnet: Training of neural networks. R J. 2010, 2, 30–38.
- 27. Qi, Q.; Tao, F.; Hu, T.; Anwer, N.; Liu, A.; Wei, Y.; Wang, L.; Nee, A. Enabling technologies and tools for digital twin. *J. Manuf. Syst.* **2019**. [CrossRef]
- 28. Shirowzhan, S.; Tan, W.; Sepasgozar, S.M. Digital Twin and CyberGIS for improving connectivity and measuring the impact of infrastructure construction planning in smart cities. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 240. [CrossRef]
- 29. Albino, V.; Berardi, U.; Dangelico, R.M. Smart cities: Definitions, dimensions, performance, and initiatives. *J. Urban Technol.* **2015**, *22*, 3–21. [CrossRef]
- 30. Parslow, P. ISO/IEC JTC1/WG11 (IT aspects of) Smart Cities. Presented at the Smart Cities Domain Working Group (DWG) of the 107th OGC Technical Committee, Ft. Collins, CO, USA, 4–8 June 2018.
- 31. Digital Underground. Available online: https://digitalunderground.sg/ (accessed on 20 June 2020).
- 32. Smart Cities Council Australia New Zealand. Digital Twin. Data Leadership Guidance Note. Available online: https://anz.smartcitiescouncil.com/system/tdf/anz_smartcitiescouncil_com/public_resources/ guidance_note_digital_twin_issue.pdf?file=1&type=node&id=7255&force= (accessed on 2 November 2020).
- 33. Geospatial Technology Trends. Available online: https://www.ogc.org/OGCTechTrends (accessed on 16 July 2020).
- 34. UN-GGIM. Future Trends in Geospatial Information Management: The Five to Ten Year Vision, 3rd ed. (draft v1.0). Available online: https://ggim.un.org/future-trends/ (accessed on 16 July 2020).
- 35. JeonJu's Sustainable Development Committee (JSDC). *Report for Sustainable Index Assessment;* Jeonju City: Jeonju, Korea, 2018; pp. 159–226.
- 36. Yin, X.; Hao, Y.; Yang, Z.; Zhang, L.; Su, M.; Cheng, Y.; Zhang, P.; Yang, J.; Liang, S. Changing carbon footprint of urban household consumption in Beijing: Insight from a nested input-output analysis. *J. Clean. Prod.* **2020**, 258, 120698. [CrossRef]

- 37. Lu, H.; Liu, G.; Miao, C.; Zhang, C.; Cui, Y.; Zhao, J. Spatial pattern of residential carbon dioxide emissions in a rapidly urbanizing Chinese city and its mismatch effect. *Sustainability* **2018**, *10*, 827. [CrossRef]
- Liu, W.; Spaargaren, G.; Heerink, N.; Mol, A.P.; Wang, C. Energy consumption practices of rural households in north China: Basic characteristics and potential for low carbon development. *Energy Policy* 2013, 55, 128–138. [CrossRef]
- 39. Ministry of Environment (ME) of South Korea. Manual of the Greenhouse Gas Discharge Estimate. 2012, p. 77. Available online: http://www.me.go.kr/home/file/readDownloadFile.do?fileId=96230&fileSeq=1 (accessed on 10 September 2020).
- 40. Kadian, R.; Dahiya, R.P.; Garg, H.P. Energy-related emissions and mitigation opportunities from the household sector in Delhi. *Energy Policy* **2007**, *35*, 6195–6211. [CrossRef]
- 41. Lee, S.; Lee, B. The influence of urban form on GHG emissions in the US household sector. *Energy Policy* **2014**, *68*, 534–549. [CrossRef]
- 42. Sanches-Pereira, A.; Tudeschini, L.G.; Coelho, S.T. Evolution of the Brazilian residential carbon footprint based on direct energy consumption. *Renew. Sustain. Energy Rev.* **2016**, *54*, 184–201. [CrossRef]
- 43. Björkman, M.; Holmström, K. Global optimization of costly nonconvex functions using radial basis functions. *Optim. Eng.* **2000**, *1*, 373–397. [CrossRef]
- 44. Hinton, G.E.; McClelland, J.L.; Rumelhart, D.E.; Rnmelhart, D.E. *Parallel Distributed Processing: Explorations in the Microstructure of Cognition;* MIT Press: Cambridge, MA, USA, 1986.
- 45. Yang, B. GIS crime mapping to support evidence-based solutions provided by community-based organizations. *Sustainability* **2019**, *11*, 4889. [CrossRef]
- 46. Hwang, C.S.; Hong, S.Y.; Hwang, T.; Yang, B. Strengthening the statistical summaries of economic output areas for urban planning support systems. *Sustainability* **2020**, *12*, 5640. [CrossRef]
- 47. Park, J.; Kim, J.; Yang, B. Spatializing an artist-resident community area at a building-level: A case study of Garosu-gil, South Korea. *Sustainability* **2020**, *12*, 6116. [CrossRef]
- 48. Anselin, L. Local indicators of spatial association-LISA. Geogr. Anal. 1995, 27, 93-115. [CrossRef]
- Resch, B.; Puetz, I.; Bluemke, M.; Kyriakou, K.; Miksch, J. An Interdisciplinary Mixed-Methods Approach to Analyzing Urban Spaces: The Case of Urban Walkability and Bikeability. *Int. J. Environ. Res. Public Health* 2020, 17, 6994. [CrossRef]
- 50. Lee, J.; Yang, B. Developing an optimized texture mapping for photorealistic 3D buildings. *Trans. GIS* **2019**, 23, 1–21. [CrossRef]
- 51. Yang, B. Developing a mobile mapping system for 3D GIS and smart city planning. *Sustainability* **2019**, *11*, 3713. [CrossRef]
- 52. Ross, D.I.L. Virtual 3D City Models in Urban Land Management. Doctoral Dissertation, Technischen Universitat, Berlin, Germany, 2010.
- 53. Open Geospatial Consortium [OGC]. *OGC City Geography Markup Language (CityGML) En-Coding Standard;* Open Geospatial Consortium: Wayland, MA, USA, 2012.

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