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Air Flow Data Packing and Visualization in Digital Twin and Environmental Impact Assessments

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In this study, we present a novel approach to visualizing and compressing air flow data based on sensor-derived environmental datasets. By leveraging sensor-based atmospheric observations and applying digital twin technology, we enhanced environmental impact assessments (EIAs) by transforming nonvisible elements such as wind flow into intuitive 3D web-based visualizations. Traditional EIA methods face challenges in effectively communicating nonvisible environmental factors, such as wind flow, particularly to nonexpert stakeholders. To address these challenges, we developed solutions that combine dynamic 3D visualization with optimized data compression and transmission techniques, which enable both efficient representation and real-time interaction with large-scale atmospheric datasets. By employing advanced data packaging algorithms, the solution significantly reduces the volume of air flow data—spanning vast spatial and temporal scales—without compromising visualization quality. These innovations facilitate seamless transmission over web-based platforms, enhancing accessibility and reducing user waiting times. The results demonstrate the effectiveness of this approach in transforming air flow data into intuitive visual narratives, thereby fostering a better understanding and greater engagement among diverse stakeholders. This research represents a pivotal step toward digitalizing EIA processes, promoting both environmental sustainability and public participation in development projects.

1. Introduction

Environmental impact assessments (EIAs) have long served as pivotal tools for evaluating the potential environmental ramifications of development projects, forming the foundation of legal and institutional efforts to mitigate adverse effects on ecosystems.(1) Despite their utility, conventional EIA methodologies often struggle to effectively communicate the impacts of nonvisible environmental variables such as noise, air quality, and wind flow. These elements are typically presented through static visualizations or tabulated data, creating barriers to comprehension, particularly for nonexpert stakeholders.

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To address these limitations, we proposed an innovative Digital Twin-based Environmental Assessment (DT-EIA)[2] during the 2023 Institute of Electrical and Electronics Engineers (IEEE) Smart World Congress. This methodology leverages digital twin technologies to visualize nonvisible environmental elements, such as wind flow, within an interactive spatiotemporal[3] framework. By incorporating dynamic 3D visualization, the system enhances stakeholder engagement and deepens environmental analyses. Building on our previous work, in this paper, we further advance air data visualization and introduce new methods for processing and transmitting air data to facilitate efficient visualization.

As the application scope of digital twins continues to broaden, their integration with EIA has become increasingly sophisticated.[4] One of the most critical and complex challenges in developing an environmental evaluation system based on digital twins lies in the digitalization, analysis, and prediction of invisible airflow data.[5] There have been airflow and environmental studies evaluating the impact of land cover on air pollution,[6] researching the airborne transmission pathways of infection during the COVID-19 era,[7] and investigating improvements in air quality,[8] but studies linked to digital twins remain insufficient.[9]

Regarding the necessity of visualizing air data, during the early stages of an EIA, community participation is essential to achieve sustainable outcomes. This involves public hearings and collaborative proposals, but communication barriers often arise owing to the technical nature of expert reports,[10] making it challenging for nonexperts to understand. This gap can lead to miscommunication, inefficient decision-making, and unintended outcomes. To overcome these issues, tools that simplify and visualize EIA predictions, such as maps, charts, and simulations, are needed.[11,12] These tools improve public understanding and facilitate more effective engagement during project reviews. Particularly for environmental impact elements that are difficult to verify with the naked eye, such as noise, wind flow, ground vibration, and air quality, this visualization technique is even more critical because it can provide prediction results in a way that is easy to understand even for nonexperts. In this context, digital twin technologies offer numerous benefits to stakeholders by simulating and visualizing development projects before and after their implementation in a virtual environment.[13,14] Previous studies on EIA visualization have focused primarily on static or 2D representations of environmental data, often failing to convey complex atmospheric phenomena to nonspecialist stakeholders. Unlike prior work, our approach incorporates sensor-acquired data in multi-altitude atmospheric layers and applies graphics processing unit (GPU)-accelerated rendering for easier interaction with nonspecialist stakeholders. This fusion of sensing technologies with digital twin environments enables participatory and transparent EIA processes.

In this research, we focus on the acquired data processing and visual representation method of the atmospheric sector, one of the six areas evaluated in South Korea's EIA system.[15] Specifically, we aim to present methods for the visualization of air flow analysis using 3D digital twin technology to make the invisible air flow visible through programming, along with the data processing techniques employed (Fig. 1). This approach seeks to enhance the understanding and management of atmospheric impacts within the framework of EIAs.

When handling air data, two major challenges arise: First is the issue of spatial scale, as air occupies a large volume encompassing both vertical and horizontal dimensions. Second is the

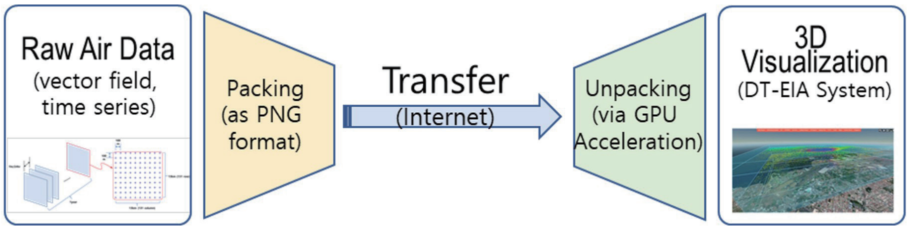


Fig. 1. (Color online) Conceptual framework for airflow data visualization in this study.

temporal scale, as air continuously changes over time. These challenges result in a significant increase in data volume, resembling common issues encountered in managing big data. Moreover, visualizing such big data in a web-based environment poses a significant challenge. To address these challenges, efficient data compression and streamlined visualization techniques are essential. Without such techniques, handling and sharing the vast amount of air flow data required for effective EIAs become impractical.

2. Materials and Methods

In the field of EIA for air quality, visualization encompasses areas such as the mapping of pollution sources, air quality data visualization, air quality modeling, the visualization of wind speed and direction, and charting for reports.[15] In digital-twin-based data visualization, modeling air quality data and its flow in a three-dimensional space requires efficiently handling a large volume of data and adapting it for easy user comprehension.

2.1 Raw data of air quality and odor in DT-EIA

For the development of the system, sample data from the experimental area—spatially interpolated on the basis of actual sensor-collected data—was utilized. The sample data covers an area of 13 km × 13 km, and the temporal range spans one year, utilizing atmospheric environmental observation modeling data produced on an hourly basis throughout the year. The quality of the air was recorded at grid points spaced 100 m apart, totaling 17161 data points, collected in a time series on an hourly basis (Fig. 2). The amount of data for one substance at one site for 1 h is approximately 100 bytes. Such planar layers were constructed for seven height segments [0 (ground surface), 10, 20, 30, 60, 100, and 200 m] to facilitate the analysis of 3D spatial data.

The volume of data constructed in this manner is large, necessitating the transmission and processing of 4.45 GB of data to visualize a year's worth of data in three-dimensional space through animation. When operating over a web service, server and data communication mean that users attempting to view this via a web browser would face a waiting time of nearly 15 min, posing a significant issue. Using a simple ZIP algorithm with maximum compression can reduce the data size to approximately 445 MB, but even then, it would take around 36 s to transfer over a typical home network with a 100 Mbps connection. Addressing this problem is crucial for facilitating smooth evaluation and information sharing within the EIA process.

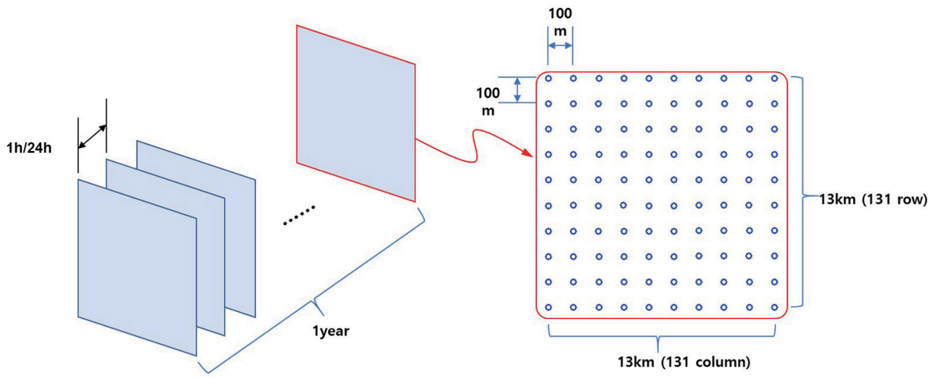


Fig. 2. (Color online) Air quality model sample data structure schematic representation.

2.2 Current 2D air data visualization methods and limitations

Visualizing a particle floating in a particular wind field means that the particle is moving along the vector field's streamline. The schematic representation of a vector field of wind data and its streamline is shown in Fig. 3.

The method of visualizing a wind field on a 2D map in a web browser already exists. The key to the existing method on a 2D map is to create animation frames by separately generating images for spatial information and images for the trajectory of a wind flow marker, and then mixing them.

The existing 2D technology is mixing memory that composes the image at an array level, which is a quick and suitable approach for web services with performance limitations.[14] However, it is difficult to apply this technology to 3D because the third dimension includes an additional height axis (*z*-axis), making it difficult to easily produce images for wind flow markers.[16] Even if we were to produce images for wind flow markers, because it is an image fusion method, whenever screen manipulation (e.g., screen movement, zooming in, zooming out, or changing the camera direction) occurs, we would need to reset the existing screen, create new images for the wind flow markers, and redraw the screen. In other words, every time screen manipulation occurs, the continuity of the wind flow marker's animation effect is not guaranteed.

To animate the flow of air on 3D spatial information, the existing 2D visualization technology (Fig. 4) cannot be utilized. Instead, it must be implemented by directly drawing symbols into each animation frame.[16] However, the task of calculating and updating new positions for the N number of wind symbols that will be visualized on the screen for each animation frame requires significant computational power.[17] Hence, it is typically impossible to implement this in web services with resource constraints by conventional methods. Therefore, we devised a method for executing air flow symbol animation by leveraging the high-speed computational capabilities of graphic cards.

Fig. 3. Schematic representation of a vector field and its streamline.

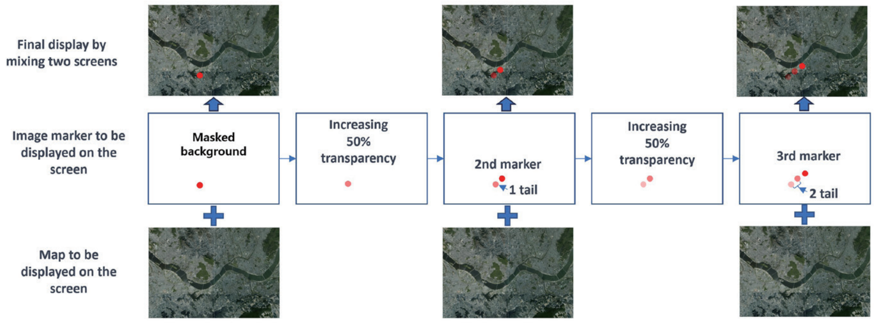


Fig. 4. (Color online) Current method of visualizing the movement of particles representing air flow on a 2D map.

3. Air Flow Data Management

3.1 Air flow prediction data packing

As mentioned in Sect. 2.1, owing to the size of air quality/odor data, a method was devised to optimize the data for service delivery. The exploration culminated in the decision to employ the Portable Network Graphics (PNG) format for the web-based visualization of air quality and odor data, predicated on the following four rationales:

(a) Air quality and odor data, structured as grid data with concentration values assigned to regular grid points, logically parallel the data structure in image files where each pixel represents RGBA (Red, Green, Blue, and Alpha for transparency) values. This structural congruency suggests a seamless transformation of air quality data into an image-based format.(18)

(b) A single pixel in a PNG image file, described by a 4-byte unsigned integer, can encapsulate an 8-byte floating number through value coding, enabling the storage of concentration values within each pixel's data structure.

(c) Given the lossless compression supported by PNG,(18) converting air quality and odor data into this image format facilitates further data compression, significantly reducing the overall data size while preserving the integrity of the original data.

(d) The widespread adoption of the PNG format in web services, combined with its direct compatibility with GPUs without the need for additional encoding or decoding processes, enhances the efficiency of data binding, defined as the uploading of data from the CPU/RAM space to the GPU/VRAM space, and simplifies its integration into the existing web infrastructure.

The execution of code value mapping, through which the data's minimum and maximum concentration values are mapped to the integer range between 0 and 0xFFFFFFFF (decimal 4294967295) and interpolated to the nearest integer for intermediate values, enabled the production of a PNG file representing a single time slice of seven layers of data (Fig. 5). This process resulted in a marked reduction in original data size from 4.45 GB to 65.5 MB (0.0655 GB), amounting to a mere 1.5% of the original volume. In comparison, even when using maximum compression with a standard ZIP algorithm, the data size typically decreases to only around 445 MB, demonstrating the superior efficiency of our method.

3.2 Air flow visualization

The method explained here refers to a visualization technique that represents moving particle animation based on wind field data to depict the flow of air on a 3D digital twin, utilizing the computational capabilities of the graphics card to simulate particles floating in the air, which was mentioned in Sect. 2.2 (see the right side of Fig. 1).

In the DT-EIA system, the aspect of visually understanding the effect of wind includes two key components: the prediction of instantaneous wind intensity and direction, and the simulation of the atmospheric dispersion of pollutants. Therefore, air flow visualizations must be categorized and visualized in two distinct ways: (1) short-term wind tail visualizations that represent wind speed and direction, and (2) spatial dispersion model visualizations used in pollutant diffusion modeling.

To begin with, the short-term wind tail is introduced. An air flow symbol is a visual element designed to represent the movement of air particles in the wind through animation. By appending a trailing tail to each particle, the afterimage effect is amplified, thereby enhancing the perceptual clarity of wind direction and velocity.

Both the head and the tail are visualizations of a point shape, differing only in size. Animation is the process of making static images appear to move by rapidly showing them in a sequence at

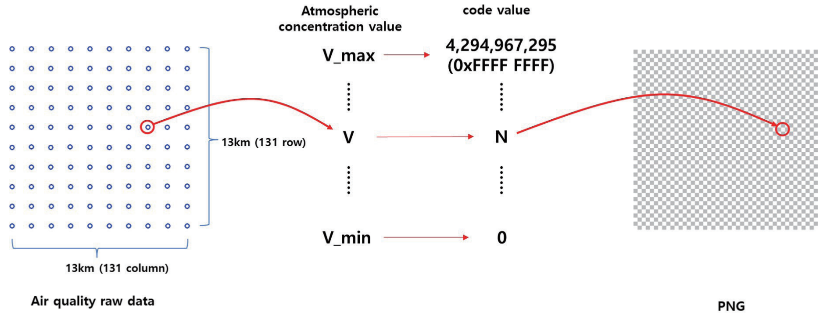


Fig. 5. (Color online) Optimizing air quality/odor data for web services using PNG encoding.

a speed that human eyes cannot distinguish. Therefore, by updating and rendering the positions of the wind symbols for each frame, we can make the wind symbols appear to flow like particles (Fig. 6).

Wind flow markers symbolize the particles in the wind; therefore, the positions of the points making up the head/tail are the actual spatial positions of the particles recorded for each frame. The head represents the current position of the particle, and the farther the tail from the head, the more it corresponds to the particle's position in the more distant past frames. Thus, by remembering the particle's position for each animation frame, we can draw a wind flow marker. When visualizing multiple wind flow markers, the corresponding amount of memory must be allocated in advance to store the positions of all particles, making their simultaneous visualization possible (Fig. 7).

The technique involves processing the vector information of the wind field received from the server and the particle's position information in a time-parallel manner on the graphic cards to display them on the screen. The diagram in Fig. 8 illustrates the rendering process according to the aforementioned flowchart.

Next, the spatial dispersion model visualizations used in pollutant diffusion modeling are discussed. As shown in Fig. 9, this approach involves simulating the movement of particles within the wind field by calculating air flow vectors and predicting the subsequent positions of each particle over time. Unlike the short-term wind tail visualization, this method omits the

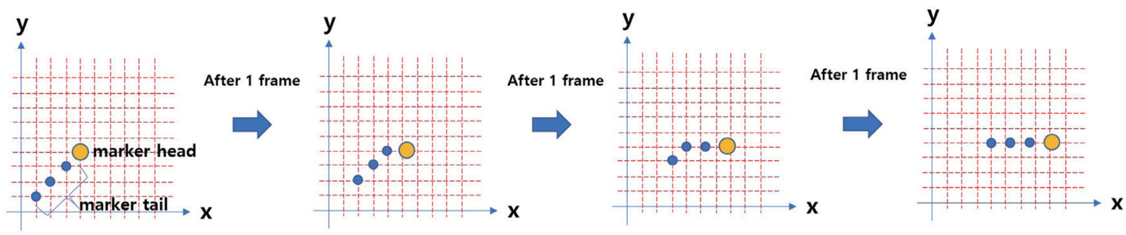


Fig. 6. (Color online) Wind flow marker animation concept.

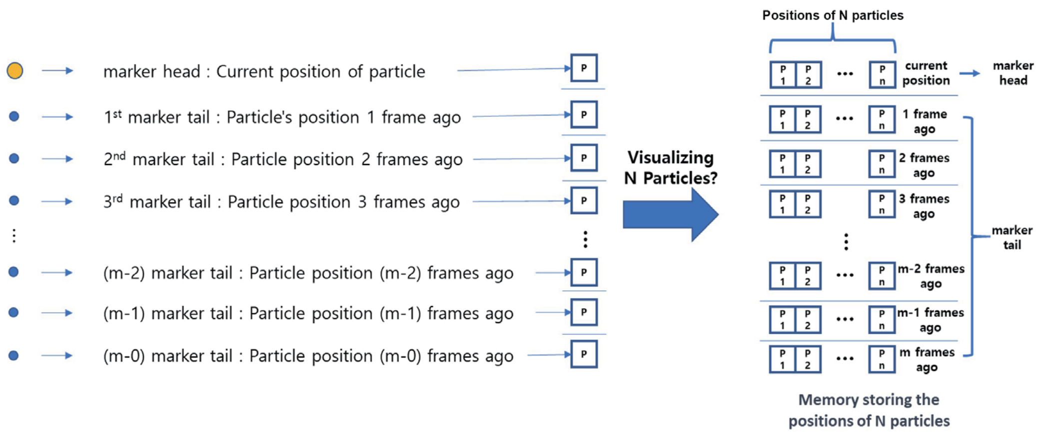


Fig. 7. (Color online) Memory blocks for rendering N wind flow makers.

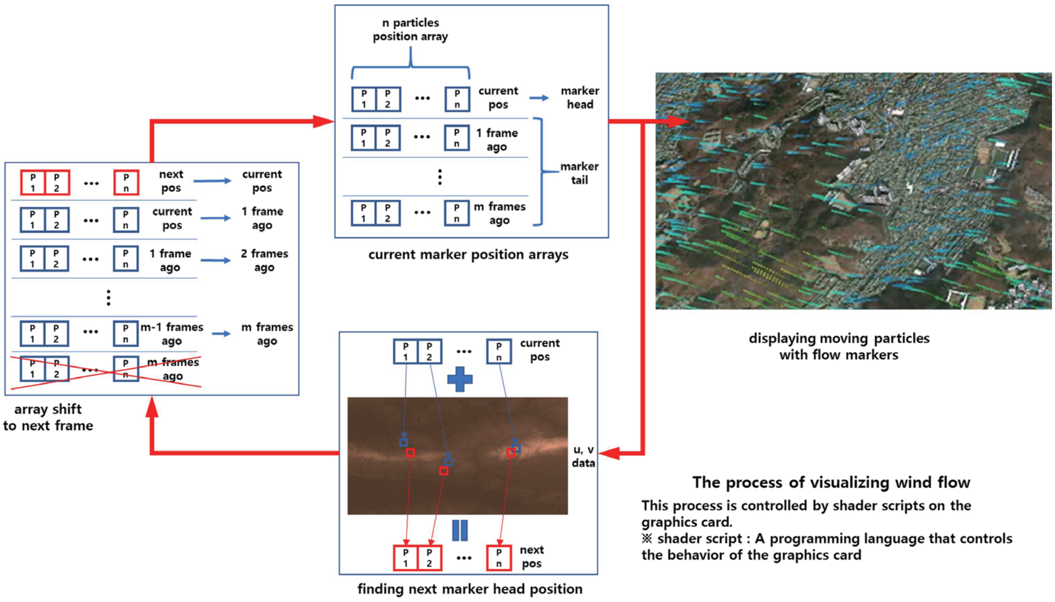


Fig. 8. (Color online) Diagram of the wind flow marker visualization process.

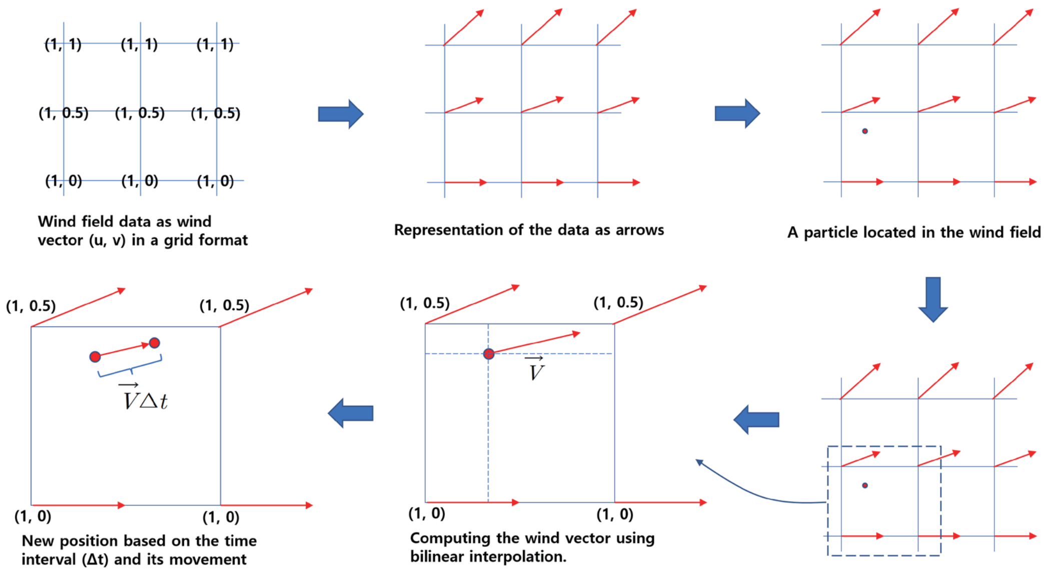


Fig. 9. (Color online) Method for calculating movement positions over time to represent the continuous motion of particles within a wind field.

drawing of particle tails over time, thereby reducing computational load. However, instead of a single vector per grid cell, numerous particles are continuously generated from the pollutant source during each simulation time step (Delta T), resulting in a visual representation of diffusion over time and space, as illustrated in Fig. 10.

The method of finding the particles' positions in the next frame involves using the wind field (u, v) grid data (Fig. 9). The location of the pollutant within the airflow vector field is identified,

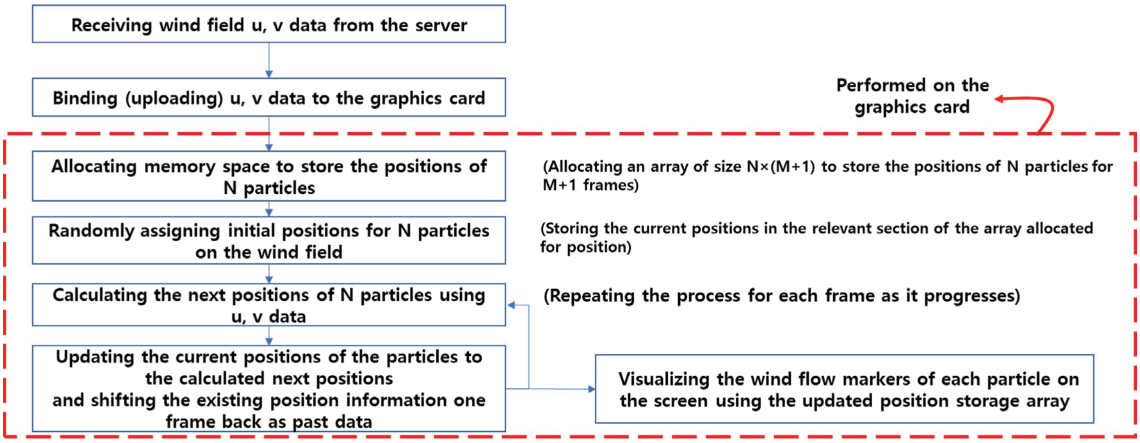


Fig. 10. (Color online) Schematic representation of wind symbol animation technique.

and the vector values at the four vertices of the encompassing rectangle are computed. The directional value per unit time is calculated on the basis of these vector values, and the next position is determined by moving in the computed direction over the elapsed time.

The wind vector applied to the current position of the particle is calculated by bilinear interpolation. Then, by using the time interval between animation frames, the position is determined through a vector equation [Eq. (1)]:

$$\overrightarrow{P_{next}} = \overrightarrow{P_{cur}} + \vec{V}\Delta t. \tag{1}$$

The schematic representation of these techniques is shown in the flowchart in Fig. 10.

Figure 11 is the result of the atmospheric dispersion modeling of pollutants over a 13 km × 13 km × 200 m digital twin area for a full year, incorporating both wind flow simulation and pollutant diffusion analysis.[19]

4. Results and Discussion

As illustrated in Fig. 1, we developed and applied a series of technologies to effectively transmit and visualize sensor-acquired environmental data within the DT-EIA system for general users. These included the compression of large-scale, time-series observational data using PNG encoding for web transmission, GPU-accelerated rendering for real-time processing on client devices, short-term wind tail animation using time-delayed wind markers to visualize airflow direction and speed, and a spatial dispersion modeling technique that predicts particle generation and movement within wind vector fields to simulate pollutant diffusion. These technologies collectively support the three-dimensional visualization of atmospheric flow phenomena in a digital twin environment.

In this study, to visualize the air quality/odor modeling data by transmitting a large amount of data to a web browser, we presented a method to encode the data in the form of PNG to

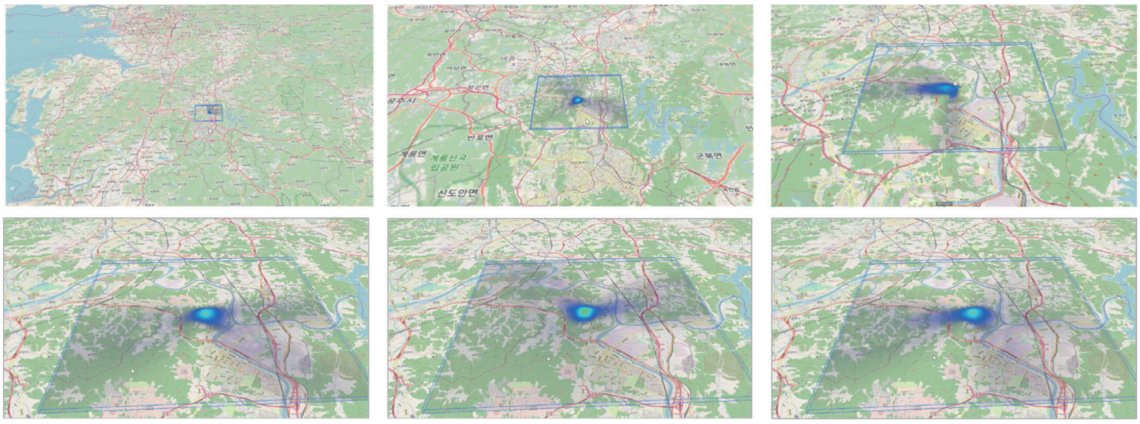
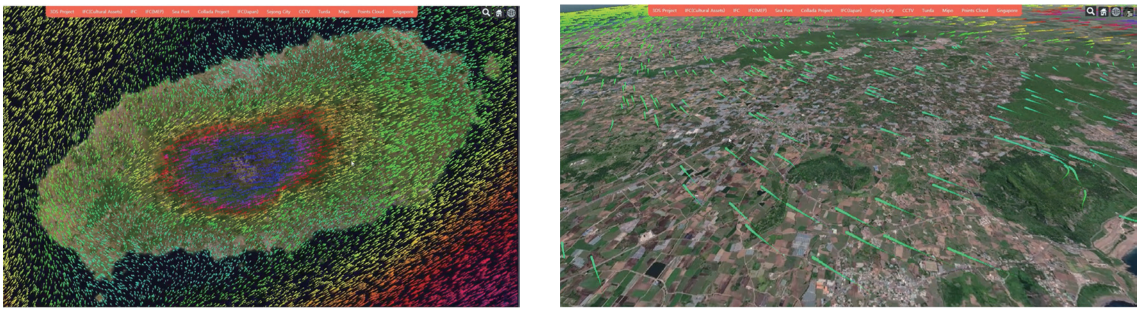


Fig. 11. (Color online) Atmospheric dispersion modeling results in the digital twin area of 13 km × 13 km × 200 m for one year.



(a) (b)

Fig. 12. (Color online) Wind flow markers by regional temperature: (a) throughout Jeju Island and (b) zoomed in on a specific area of Jeju Island.

efficiently realize the spread of pollutants in the digital twin space without the loss of information. Different dispersion models were applied on the basis of the type of air pollution source.(20) The result of visualization technology through graphic card computational processing enables wind marker animation in 3D space (Fig. 12).(21) This technique involves directly drawing and updating wind symbols on the screen in each frame, allowing for continuous visualization even in vertical visualization scenarios where the height of the horizontal intersection plane can be controlled. It is applicable not only when 3D spatial information is visualized on a web browser's screen but also when the wind field data is available at different altitudes.

By using PNG compressing and time stacking air data, we visualized the element of air flow in EIAs in a 3D web environment. The air data on the digital twin platform has the spatiotemporal characteristics of time and 3D space, which has limits to be visualized using traditional 2D-based air data visualization techniques. To overcome this limitation, we utilized a method of memorizing particle positions frame by frame and rapidly drawing wind symbols to visualize the wind data. This approach enables the easy visualization of temporal wind data on the web and provides flexibility to explore and visualize wind data along vertical planes.

5. Conclusions

We presented a technical solution for implementing an efficient 3D visualization system of time-series wind data in a DT-EIA platform. By leveraging PNG compression for data transmission and GPU acceleration for real-time rendering, the system effectively processes and visualizes large-scale spatiotemporal wind data, enabling intuitive and interactive analyses of atmospheric flow dynamics.

The core value of this visualization system lies in its ability to represent nonvisible environmental sensing data in an accessible format. This capability ultimately enhances the public understanding of environmental impacts, facilitates communication among stakeholders, and contributes to more informed and participatory land use planning through EIA processes.

However, in this research, we focused solely on the air flow and pollutant dispersion component of EIA. Since environmental systems are inherently complex and interdependent, future studies should aim to integrate various environmental factors—beyond mere wind velocity—into the DT-EIA framework. Furthermore, the current implementation visualizes only horizontal dispersion based on stacked time-slice data. To ensure comprehensive environmental modeling, further research is required to standardize data processing and visualization techniques for vertical atmospheric changes.

These enhancements are essential for advancing the capabilities of DT-EIA platforms and realizing their full potential in supporting sustainable spatial planning and environmental decision-making.

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