GAN-based Transportation Noise Prediction via Satellite Maps: A Case Study in New York

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Abstract: Traditional noise prediction models, reliant on on-site monitoring, are hindered by data and computational constraints. This research addresses this challenge by introducing Generative Adversarial Networks (GAN) in conjunction with satellite maps. Based on the inherent interconnectedness between traffic noise and urban morphology elements, the research proposes a GAN model-based framework capable of generating noise heat maps from high-resolution satellite maps, offering a cost-effective and efficient alternative. This research also examines how model performance is influenced by input images through qualitative and quantitative methods. Using New York City as a case study, the proposed GAN-based models demonstrate accuracy in predicting noise distributions. Three parameters of input images likely to be influential in noise prediction accuracy were proposed. We also compare the model performance in different urban contexts. The study presents a valuable tool for architects and urban planners, enabling optimized urban planning and design strategies.

Keywords: Transportation noise prediction, satellite maps, urban plans, generative adversarial networks

1 Introduction

With the progression of urbanisation and the increasing number of vehicles, traffic noise has emerged as the predominant noise source in urban environments (OUIS 1999). Urban traffic noise is closely related to people's physical health (BABISCH 2008), psychological state, quality of life (NOURMOHAMMADI et al. 2021), and environmental performance and ecology. Consequently, accurately quantifying transportation noise has become a critical issue, where noise prediction serves as an essential tool for noise control.

Most noise prediction relies on on-site monitoring, which, when conducted across different roads and environments, becomes costly. To address this, various countries have developed traffic noise prediction models, such as the FHWA Traffic Noise Model, RLS-90 model and Stop and Go model (ALAM et al. 2020). However, these models demand substantial input data, including vehicle type, speed, traffic volume, and road level. Obtaining this information can be challenging, particularly in cities in developing countries. Moreover, the simulation process itself requires significant computational resources and time.

Built environment conditions play a crucial role in transportation noise prediction, with models like the FHWA Traffic Noise Model considering acoustical characterization and topography of intervening ground, walls, berms and their combinations, intervening rows of buildings and intervening areas of heavy vegetation. Some research also emphasizes the importance of components, such as pavement type and the design of terrain geometry (ROCHAT

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et al. 2002), road and building coverage ratio(WANG & KANG 2011), the green space pattern (MARGARITIS & KANG 2016), and other characteristics in noise prediction. Therefore, exploring the interconnectedness between traffic noise and various elements of urban morphology presents a valuable avenue for informing healthy urban design strategies.

With the rise of satellite maps, new opportunities have emerged to quantify noise level predictions. Satellite maps show advantages in terms of quantity, timeliness, quality, cost-effectiveness and content diversity in capturing the features of built environment conditions. Satellite maps capture the morphological factors of built environments, and those morphological features have inherent relationships with transportation noise (HAVERKAMP 2002). Therefore, automatic conversion from satellite map to noise map becomes a potential approach for predicting traffic noise.

In recent years, artificial intelligence generative content has gained attention in architectural planning and landscape research. Numerous spatial prediction models have been introduced due to the crucial role of traffic noise and its connection to urban structure. Researchers are increasingly focusing on artificial neural networks (ANN), support vector regression (SVR) (TORIJA & RUIZ 2016) and random forest (RF) (ADULAIMI et al. 2021). These models are gaining prominence due to their potential to enhance prediction accuracy by comprehensively addressing the nonlinear connections between noise levels and environmental factors. Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have traditionally found applications in tasks like image classification and natural language processing (NLP). However, for vector-based image-to-image translation tasks, these models may not be the most suitable choice. In contrast, deep learning methods centred on Generative Adversarial Networks (GAN) (ISOLA et al. 2017) have shown immense potential for image-to-image transformation tasks within architectural and planning research.

The utilization of GANs can assist architects and urban planners in tasks like generating floorplans and visualizing real-time implications of land use decisions. Notably, previous studies have demonstrated GANs' applicability in rapidly and accurately generating Land Surface Temperature (LST) maps with the input of city plans(LI & ZHENG 2023), and predicting crime distribution swiftly with the input of floor plans (HE & ZHENG 2021). It is crucial to emphasize that this paper does not intend to compare the effectiveness of various generative models. Instead, our focus is specifically on addressing noise generation. Therefore, we have chosen to explore the widely used GAN model due to its extensive applications, remarkable capabilities in fine-grained image processing, accurate image generation in a rapid, interactive manner, and its relevance to the study's objectives.

In summary, a significant research gap exists, particularly in integrating the generation of traffic noise with the capabilities of GAN and utilizing automated algorithms for large-area traffic noise prediction. Additional gaps include the need for a deeper understanding of the complex relationships among predictors of traffic noise and the variations in accuracy observed across different urban morphologies. Aiming to address the existing knowledge gaps, in this research, by introducing GAN, we present an approach to predict transportation noise maps utilizing satellite maps. By utilizing open-source satellite maps as input, GAN efficiently generates a transportation noise map, leveraging the identified inherent connections between the built environment and noise. Additionally, we investigate the impact of input parameters on accuracy through both qualitative and quantitative methods.

Our research contributes to the following aspects:

(1) Using advanced Generative Adversarial Networks (GAN) techniques to predict the transportation noise map based on the corresponding satellite map in a low-cost, large-area and high-resolution way.

(2) Conducting a comprehensive sensitivity analysis with Machine Learning (ML) tools to quantitatively and qualitatively reveal the intricate relationships between built environments and traffic noise levels.

(3) Identifying optimal input and output image parameters for accurately predicting traffic noise, aiding architects and urban planners in optimizing urban planning and design.

The immediate prediction of corresponding noise distributions has significant applications, not only for the analysis of current sites but also for urban design. By making simple modifications to the size and distribution of architectural masses and streets, designers can efficiently produce corresponding urban plans for input images. The proposed GAN model can then recognize and output noise prediction maps, enabling recursive analysis for design iterations. This iterative analysis provides valuable insights for architects and urban planners, enhancing their understanding of the impacts of policies and strategies. This, in turn, facilitates the optimization of urban planning and design. Moreover, the model plays a crucial role in mitigating noise levels in specific urban areas, contributing to sustainability and human health. By incorporating the noise predictions into the design process, architects and planners can make informed decisions to create environments that prioritize well-being and minimize negative impacts. This integration of predictive noise analysis into urban design practices aligns with the broader goal of creating more liveable and sustainable cities.

2 Methodology

2.1 Framework

By introducing Generative Adversarial Networks (GAN), this research proposed a low-cost, large-area and high-resolution way to predict the transportation noise heat map based on a corresponding satellite map. The selection of a GAN architecture was contingent on our research objectives and the characteristics of the data. By taking open-source satellite maps as the input, the model can quickly output transportation noise map, based on the identified intrinsic relationships between urban form and transportation noise (see Fig. 1).

2.2 Study Area

New York, the largest and most influential American metropolis, is chosen as the study case of this research. Each area in New York has a high level of development intensity, and traffic noise is the main source of the noise. It should be noted that Joan F. Kennedy International Airport, the primary international hub, is located in the central area and may be subject to aeroplane noise. The transformation of LaGuardia Airport which is located in the north area attracts more travellers. The rail stations of New York are mostly in the Central area and West area which could generate a significant amount of noise (see Fig. 2).

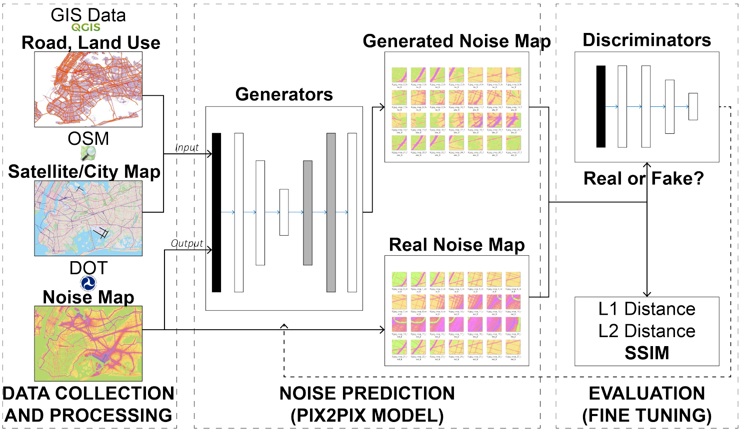

Fig. 1: Analytical Framework Diagram

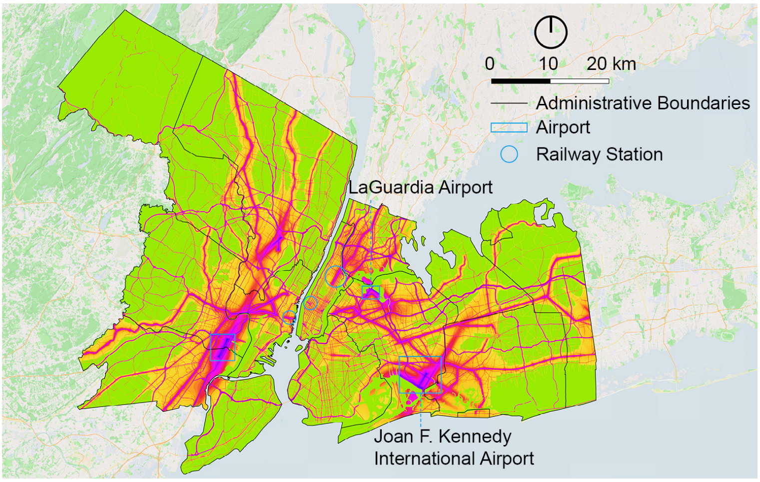

Fig. 2: Transportation noise mapping

2.3 Data Source

To generate the input map for the built environment, satellite imagery data from Google Earth is employed. According to existing literature, traffic noise can be closely related to urban plan elements such as buildings and road networks. To augment urban plan elements features in the map, we downloaded rail and road network data (acquired from the Bureau of Transportation Statis-tics Open Data site) and GIS data (acquired from OpenStreetMap), then combined the basic satellite map raster data and urban plan elements data in one map and assigned colours to different elements.

For the transportation noise output map, we use the noise dataset, including U.S. road, flight and passenger rail and aviation noise in 2020, acquired from the United States Department of Transportation. Noise level results below 45 dB(A) LAeq is not included. Aircraft, road and passenger rail noise inventories are provided both separately and as combined GIS layers. Aviation noise is based on measured source data from actual aircraft and flight operations are averaged into a single average annual day. Furthermore, the road noise data was derived from TNM results. Passenger Rail Noise is calculated by the General Transit Feed Specification (GTFS) data, which provides information on traffic accounts, and train speed.

2.4 Data Preprocessing

2.4.1 Image Splitting

After obtaining the satellite maps and the transportation noise maps, it is necessary to split them into one-to-one corresponding images for later training. Using QGIS, we align the projected transportation output map with the satellite input map within a single data frame and export them individually as high-resolution images (2000 dpi). In Manhattan, the standard block is about 80 m x 274 m. The ideal size covers an area of about 1500m * 1500m, which contains around 100 blocks. Then we utilized a Python script (sliding window) to partition two large images into smaller ones with dimensions of 1000 pixels by 1000 pixels, with a sliding interval of 400 pixels. Subsequently, these images were individually compressed to 256 by 256 pixels, and then correspondingly assembled to form the training set.

By another Python script, the images from input and output images are combined one-to-one corresponding images with 256 pixels by 256 pixels. Eventually, 2450 image pairs were obtained, and about 10% (225) pairs were selected to serve as the test set, 10% (225) pairs were selected to serve as the validation set, while the remaining 2000 sets were used as the training set (training: test: val = 8:1:1) for the model training and evaluation in the next step. Sample input/output maps and training/testing set distribution are as Figure 3.

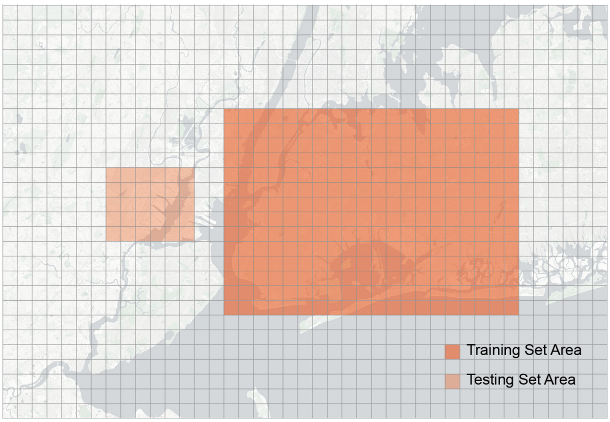

Fig. 3:
Training/test set distribution

The test set was located in Jersey City, in the vicinity of New York City, exhibiting similarities in street scale and architectural texture. Furthermore, the selected area is waterfront, encompassing both airport and train station regions, making it a suitable test set for evaluating the accuracy of the model. We also acknowledged that this geography-based training-test split may lead to imbalance issues in the ultimate model.

2.4.2 Noise Prediction Model Training

In this research, we used Pix2pix, a backbone conditional GAN Architecture as our core algorithm. GAN consists of two neural networks, a Generator and a Discriminator. The generator is based on a "U-Net"-based architecture, and the discriminator is based on a convolutional "PatchGAN" classifier, which only penalizes structure at the scale of image patches. As Figure 4, this "U-Net"-based architecture will first encode the input image to the bottleneck layer through several steps and then the output image is generated through steps of decoding and upscaling. The "PatchGAN" discriminator used in this research is a CNN that performs conditional image classification. The default setting of 200 epochs was retained to increase the accuracy and maintain the stable visual tendency.

The Pix2pix algorithm will be trained based on the competing procedure between real output transportation noise heatmap D(x) and predicted output transportation noise heatmap D(G(z)). During the training process: first, the two are entered as pairs of images (x, y) into the discriminator (D) of the pix2pix model; subsequently, generator G generates a fake noise map G(x) and merges it (G(x)) and the actual noise map (x) into the discriminator (D). The generator and discriminator compete with each other as the accuracy improves. The generator G is trained to produce outputs that cannot be distinguished from "real" images by an adversarial trained discriminator, D, which is trained to do as well as possible at detecting the generator's "fakes". When the discriminator can hardly set apart the generated data from the real data x, the model is considered well-performed. The ultimate goal of training is to optimize parameters to equalize D(x) and D(G(z)) while maximizing D(x) and minimizing D(G(z)).

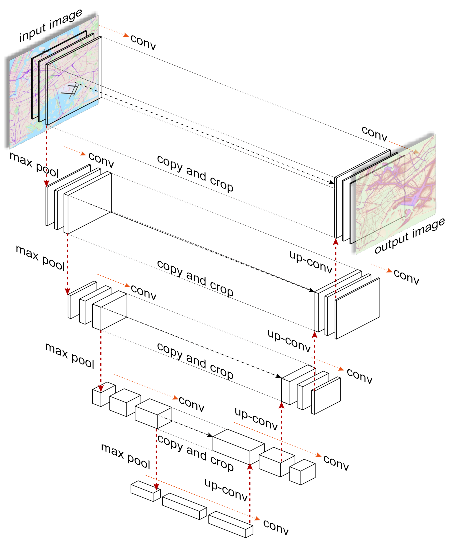

Fig. 4:
U-net Architecture used in the pix2pix algorithm

2.5 Parameter Comparison and Result Evaluation

The sensitivity analysis (SA) focused on three parameters and relationships that were likely to be influential in prediction accuracy, namely: (1) the size of image segmentation (size and slide); (2) input satellite map style (including urban plans and satellite maps); (3) output noise map colours. Furthermore, the study employed a comparative analysis of multiple models to discern the desired outcomes. Specifically, the research aimed to delineate the optimal combination of parameters that would yield superior prediction accuracy. Through this model comparison, it was anticipated that insights into the nuanced relationships between the selected parameters and the accuracy of noise predictions would be gained.

For a quantitative assessment of the training accuracy of GAN models, based on existing literature, we employed three commonly used metrics including L1 distance (Manhattan Distance), L2 distance (Euclidean Distance), and structural similarity index metric (SSIM) to evaluate GAN models.

L1 distance and L2 distance are two types of distance metrics for calculating the similarity between data points. They are used to measure differences in images at the pixel level. A lower L1 distance or L2 distance is better, indicating a more similar result to the real sample.

L1 distance is the sum of absolute differences between points across all the dimensions. The formula for calculating L1 distance is as follows:

$$EU(x,y) = \sum_{i=1}^{n}|x_i - y_i| \quad (1)$$

L2 distance represents the shortest distance between two vectors. The formula for calculating L2 distance is as follows:

$$MH(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (2)$$

SSIM evaluates the perceived quality of images by considering how alterations impact the structural information within them. This extends beyond a mere assessment of pixel-level changes, as SSIM incorporates perceptual aspects related to luminance masking and contrast masking. SSIM value is generally no larger than 1, and when it equals 1, it indicates that the two images are the same. The formula for calculating SSIM is as follows:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (3)$$

With μ_x being the average of x, μ_y the average of y, σ_x^2 the variance of x, σ_y^2 the variance of y, σ_{xy} the covariance of x and y, C_1 and C_2 as two variables to stabilize the division with a weak denominator, L the dynamic range of the pixel values, and k_1 = 0.01 and k = 0.03 by default.

3 Results and Discussion

In assessing the precision of GAN training, we performed both qualitative and quantitative accuracy analyses. Since the test set was not part of the training process, GAN models did not directly learn from it. Consequently, the accuracy of the test set may offer a more accurate reflection of the GAN models compared to the training set.

3.1 Qualitative Analysis

Initially, we generate data in the test set to unveil the training outcomes of the neural network. As depicted in Figure 5, it is evident that, on the whole, the GAN model effectively predicts noise levels based on varying building density, green space, and rail networks in different areas, utilizing city maps as input. For different sizes of image segmentation such as a and b models, the b model, with the size of 1000 pixels by 1000 pixels in 400 pixels slide, performed and distinguished different noise levels better than a model, with the size of 500 pixels by 500 pixels in 250 pixels slide.

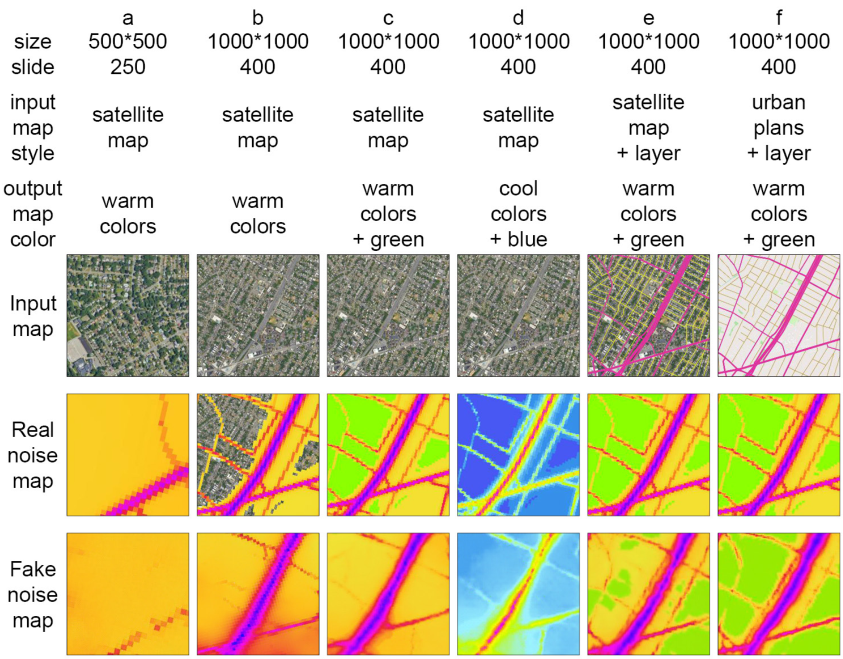

Fig. 5: Predicted results for the test images. For each group of images: Top: input map; Middle: real noise map; Bottom: generated noise map

With its smaller coverage area, the 500 pixels by 500 pixels satellite imagery, when compressed into a 256 by 256 pixel training set, allows each pixel to provide a more detailed representation of specific features within the plan. This enables a more nuanced depiction of details, including small ponds and cars in parking lots. However, it has minimal impact on the recognition of traffic noise distribution. This issue may arise due to the model's inclination to overly prioritize pixel color variations originating from different materials during the image recognition process, and it can be addressed by expanding the scale of image segmentation. This enlargement facilitates a block-wise colour expression, thereby reducing errors in model predictions caused by noise.

Thus, according to Figure 5-c, we fill regions where sound levels below 45 45 dB(A) LAeq with a green colouration to mitigate the adverse effects of multiple colours in the generated images, ultimately leading to improved accuracy of GAN model outputs. However, as shown in Fig.5-c and d, transitioning from warm to cool tones did not yield a noticeable improvement in model training. On the contrary, there are instances where the predicted levels at locations with elevated noise levels surpass the actual values. This leads to a more concentrated distribution of noise as predicted by the neural network, particularly concerning road networks. At this point, the model with 24-bit RGB warm colour performed higher accuracy in prediction.

In addition, as shown in Figure 5-e and f, incorporating layers of road networks at various hierarchical levels in input images significantly enhances the model's precision in capturing noise distribution. Simultaneously, replacing the satellite maps with urban plans predominantly characterized by color blocks allows for a more effective capture of urban environmental factors, such as the width of roadways and setbacks of buildings. This approach helps reduce errors caused by varying pixel colors due to factors like lighting, stemming from the same material. Consequently, it further narrows the disparity between real and fake images, thereby enhancing the overall predictive capabilities of the model.

3.2 Quantitative Analysis

3.2.1 Comparison of Parameters of Input Images

The Average L1 distance value for model a is 119.02, the Average L2 distance value is 75.90, and the Average SSIM value is 0.5801. However, due to the disparate initial image coverage of the model compared to other models, which results in varying noise pixel inclusions, a lack of comparability exists in quantitative analysis. Hence, it is omitted for the sake of meaningful comparison.

Table 1: L1 distance, L2 distance, and SSIM comparison of each model on test data

	b	c	d	e	f
Size and slide	500*500 250	1000*1000 400	1000*1000 400	1000*1000 400	1000*1000 400
Input map style	satellite map	satellite map	satellite map	satellite map + layer	urban plans + layer
Output map color	warm colors	warm colors	cool colors + blue	warm colors + green	warm colors + green
Average L1	126.59	116.80	147.15	120.01	117.97
Average L2	81.97	88.57	86.86	88.72	88.31
Average SSIM	0.4294	0.4942	0.4868	0.5280	0.5341

Table 1 visualizes the quantitative performance difference among six GAN-based models by calculating the three values and we have two key observations. First, as shown in models b and c, green colouration further improves prediction accuracy, indicating the effectiveness of the output image parameter. This is reflected in its 6.48% increase in SSIM. Second, models e and f work better than the others, indicating the effectiveness of the network layer. Thus, among the b-f GAN models, model f, with ideal input size of image segmentation, 24-bit RGB warm colour output map and input urban plans, performed best. The predictive accuracy of model f averages at 53%, and visually, its accuracy appears to be high to the human eye.

In terms of noise prediction evaluation metrics, SSIM is used to evaluate the predicted result accounting for the fact that it is sensitive to changes in local structure and can capture intricate characteristics. Therefore, the simulation results were evaluated for each of the four different areas through SSIM.

3.2.2 Comparison of Different Environmental Contexts

From Figure 6, the GAN model demonstrated strong performance across areas characterized by diverse environmental features, particularly in residential and green spaces, with accuracy rates of 64.5% and 74.7%, respectively. Differentiating primary, secondary, and tertiary roads in urban settings was achieved through the use of distinct colors and line thickness, while simultaneously concealing architectural textures, enhancing the alignment of identification and prediction results with actual values.

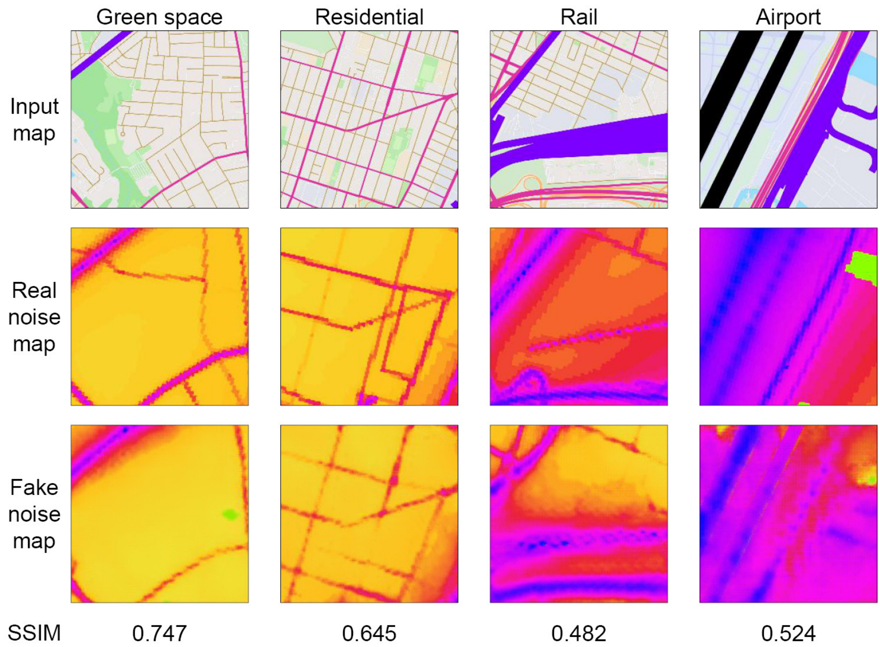

Fig. 6: Predicted results in the f model. For each group of images: Top: input map; Middle: real noise map; Bottom: fake noise map.

Furthermore, when applied to regions around stations and airports, where a significant correlation exists with rail lines and air routes, the GAN model produced results that are still deemed acceptable. Specific considerations were made for the depiction of train routes and airport runways, employing varied colors and line thickness, and utilizing a background color distinct from residential regions. Notably, due to the expansive nature of airport environments, comprehensive coverage in a single image proved challenging, potentially introducing inaccuracies in the data. The SSIM values for these areas were 0.482 and 0.524, respectively. Although numerical accuracy was moderate, the noise maps generated through predictions effectively depicted the distribution of maximum and minimum noise values, providing valuable reference insights.

In general, the GAN model exhibits robust performance in varying environmental contexts, showcasing its versatility in accurately generating results for distinct land-use categories. The observed high accuracy rates, even in areas with transportation hubs, attest to the model's effectiveness in capturing intricate spatial patterns. The conclusion drawn is that the machine learning-based noise prediction model is credible. In this context, a balance between accuracy and computational cost is attained through the use of a proxy model based on GAN. This meets the need for real-time feedback during the early design stage. Consequently, the model exhibits the capability to accurately predict areas with high noise levels, a functionality that can be extended to forecast noise maps in other cities. Ultimately, this can guide urban planners in developing schemes aimed at minimizing noise levels.

4 Conclusion and Outlook

In this study, we have introduced a novel GAN-based approach for predicting transportation noise in New York City, utilizing satellite maps alongside open-source noise data. Our findings indicate that the model, employing a 1000x1000 pixel size with a 400-pixel slide, urban plans as input images, and generating 24-bit RGB color output images, demonstrated optimal performance. This model exhibited the ability to predict noise levels with nearly 75% accuracy, particularly in central areas. Notably, the model excels in accurately predicting high-noise areas, showcasing a capability extendable to forecast noise levels in other cities. With its cost-effectiveness and efficiency, this predictive tool holds promise for broader applications.

By verifying the noise levels of different areas, architects can identify optimal layouts to reduce traffic noise around noise-sensitive buildings, such as hospitals, schools, and nursing homes. This eliminates the need for physically constructing and monitoring design plans over the long term to determine noise distribution. Utilizing genetic algorithms, this model will function as a feedback agent to identify solutions aimed at minimizing traffic noise, with potential future developments leveraging it to create interactive design and planning tools.

An essential aspect is that the research approach presented in this paper can serve as a workflow to evaluate various urban features promptly and visualize them quantitatively. Citizens can use an interactive platform based on this model to modify environmental elements, observe resultant noise changes, and actively engage in bottom-up urban design to create a better living space.

While deep learning approaches, particularly the GAN model, have proven pivotal, it is essential to acknowledge two primary limitations. Firstly, the GAN model's performance may be constrained outside its training range. For instance, a model trained on a limited dataset, such as data from a specific country, might exhibit suboptimal performance when confronted with diverse data beyond the training scope, encompassing various building types and urban morphologies. Secondly, GAN models function as black-box models, concealing their internal mechanisms. Consequently, obtaining a detailed understanding of the individual parameters governing noise map generation may be limited.

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