A Geospatial Generative Adversarial Network Approach for Future Urban and Infrastructure Resilience

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Abstract
Rapid urbanization, especially in data scarce regions, demands innovative tools to simulate future urban growth and understand resilience. This study introduces a geospatial framework combining agent-based modelling and Generative Adversarial Networks (GANs) to generate realistic urban form scenarios. Applied to Phnom Penh, Cambodia the model translates projected population growth to generate plausible road networks and building layouts. Validation of the trained model against observed development shows good performance. Under five different socio-economic scenarios, projections range from 39–106% increase in buildings and 22–72% for road length. The framework supports decision-makers in visualizing future urban morphologies and evaluating strategies to mitigate climate-related risks such as flooding and heatwaves. It offers a scalable, data-efficient approach to guide sustainable urban planning in fast-growing cities.

Keywords: Urban growth; Generative AI; Agent-based modelling; Urban form; Infrastructure networks

Introduction
Urbanisation is a global driver of change, with the majority of the world's population now living in urban areas. This growth is particularly pronounced in developing regions. Given the role of urban form in climate risk, it is essential to simulate the future layout, character and structure of urban areas to understand how risk and resilience might change. Urban growth modelling offers decision-makers a valuable tool to understand the complexities of urban dynamics, anticipate future transformations, and design sustainable and resilient cities. Current approaches typically use raster grids or administrative polygons to project changes in population and thus exposure to climate hazards. These do not consider different possible building layouts or infrastructure configurations that modulate resilience through changes to the vulnerability, exposure, and hazard components of risk. This paper introduces a novel geospatial framework that uses Generative AI methods to simulate, explore and characterise future urban form scenarios.

Case study site

Phnom Penh, Cambodia, was selected as a case study due to its rapid urban expansion, data-scarce environment, and the relatively small proportion of built-up area. Cambodia is one of the most rapidly developing countries within the Greater Mekong region. Between 2000-2010, Cambodia's built-up area and population increased by 4.3% and 4.4 % per year (National Institute of Statistics, 2019). The population of the capital city, Phnom Penh, grew to 2.2 million (Figure 1). The associated urbanisation of floodplains increased impervious surface area, coupled with climate change, this has increased the risks of flooding, posing a significant hazard to human life and infrastructure (Tierolf et al., 2021).

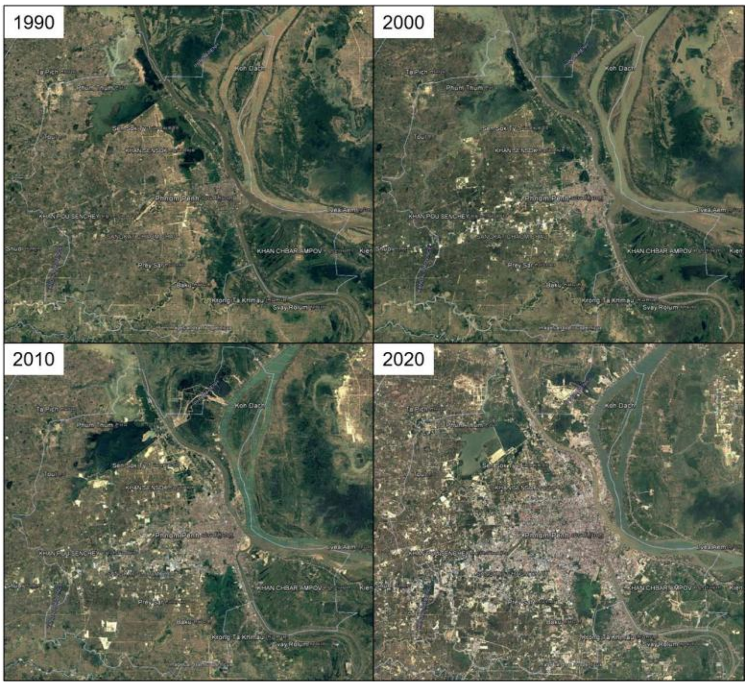

Figure 1. Phnom Penh urban land expansion between 1990-2020.

Methodology

The framework first uses agent-based modelling (ABM) to simulate future urban growth. The ABM represents interactions between key actors, such as urban planners, property developers, landowners and residents to provide projects of future development according to land parcels (Figure 2).

A Generative Adversarial Network then uses this future growth to perform image-to-image translation, converting a raster output of population growth into future road network layouts and building footprints. GANs provide a framework for data generation (Goodfellow et al., 2014). They function as a two-player game between two neural networks: a generator and a discriminator, trained simultaneously in an adversarial setup (Figure 3). The generator learns to produce plausible data from random noise sampled from a simple distribution, which serves as fake examples for the discriminator. The discriminator learns to distinguish between real data from the training set and fake data from the generator. During training the generator aims to maximise the probability that the discriminator misclassifies its fake data as real. In contrast, the discriminator aims to minimise this probability, improving its ability to differentiate real and fake data. This adversarial process drives both models to improve iteratively, resulting in generated data that become increasingly indistinguishable from real data.

GANs can generate images conditioned on inputs, enabling context specific data generation suitable for generating urban form or infrastructure networks. The pix2pixHD GAN (Wang et al., 2018) is used here as it can use high-definition images and has been shown to be suitable for operation in the built environment. Here, we used satellite and building footprint data to train the GAN. Wayback Imagery offers a digital archive of satellite imagery since 2014 from providers such as Maxar, Microsoft, and DigitalGlobe (Esri, 2024). Building footprints were taken from Google Buildings which were more complete than other sources for Phenom Penh such as OpenStreetMap (Sirko et al., 2021). To allow for assessment of model validity, the timeseries of observed development from 2014-2023 was split into two periods. Between 2014-2019 was used for model training, whilst 2019-2023 was used for validation.

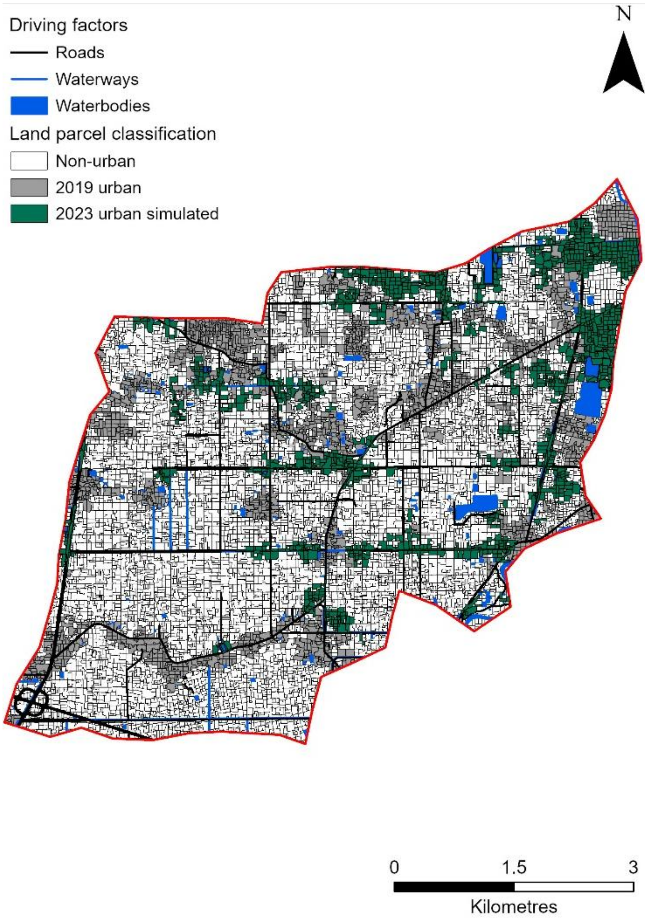

Figure 2. Simulated future urban growth for land parcels within three communes of Phnom Penh: Pong Tuek, Prey Sa, and Prey Veaeng.

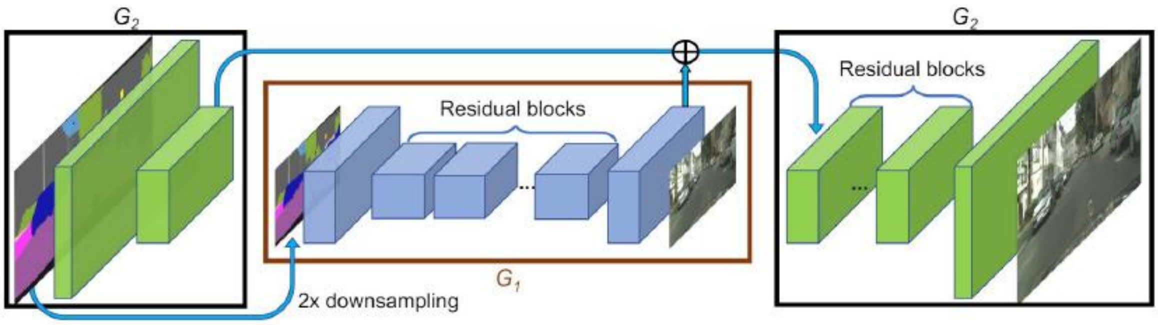

Figure 3. Pix2pixHD generator architecture (after Wang et al., 2018).

Key findings

The modelling framework is able to achieve varied, distinct and plausible patterns of growth. Notably, the GAN model is demonstrated to provide a feasible and practical technique to create realistic and convincing future urban and infrastructure form (Figure 4). Moreover, the model is able to integrate new infrastructure seamlessly with existing urban morphology.

Simulations were compared against observed development in the validation time period for a number of metrics, including the degree distribution of the road network; building footprint perimeters; and Fréchet Inception Distance (FID), which compares the distribution of the generated images to the distribution of real images by computing the distance between the feature vectors of real and generated images. Here, simulations were able to achieve an FID of close to 40, which shows solid performance especially for urban growth modelling where FIDs can often exceed 80 (Wu and Biljecki, 2023). Further analysis showed the performance was sensitive to input image resolution and the content (i.e. type of buildings and form) used for training.

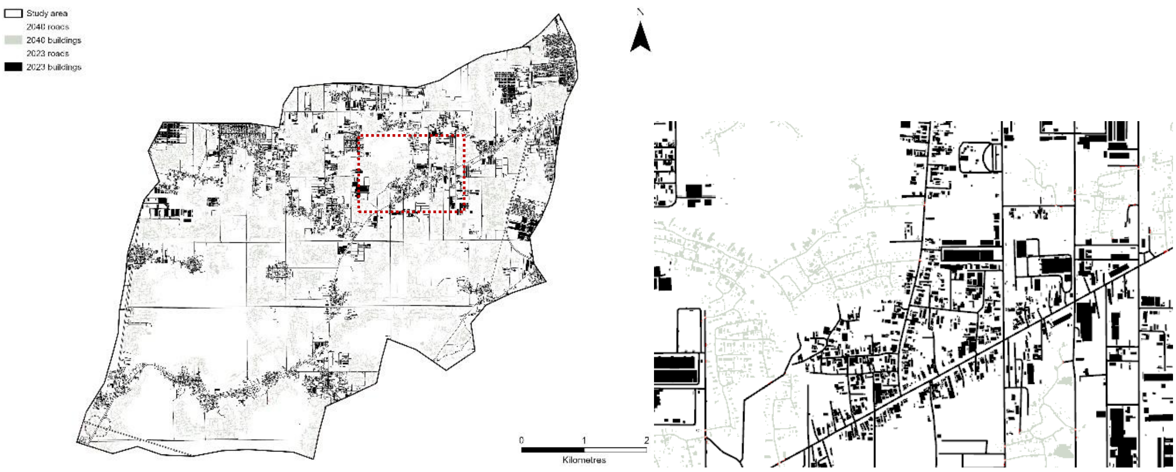

Figure 4 (i) Indicative output of the GAN showing new road network and building form to meet projected population growth for the case study area, with (ii) zoom into the dotted inset box.

Exploration of five future socioeconomic scenarios shows the number of buildings could increase by between 39-106% and the length of road by 22-72%, with different spatial patterns, infrastructure topologies and urban morphologies. This demonstrates how urban development may unfold in the coming decades and supports the municipal authority to manage these developments effectively and devise strategies to mitigate potential negative impacts including flood and heatwave risks and greenhouse gas emissions. Future work will integrate a diverse range of built environment forms and infrastructure networks with models of natural hazard to understand how different patterns and topologies influence risks.

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