Urbanization is one of the most important anthropogenic activities (Qiu et al. 2020; Chu et al. 2017; Kalnay and Cai 2003). Correctly projecting the future urban layout enables efficient resource management (Lin et al. 2021) and waste neutralizing (Yue et al. 2020), and prompts sustainable urban development (Wang et al. 2021b). Urbanization is modeled with two major objectives: the prediction models aim at creating future urban maps based on historical urban dynamics (Gantumur et al. 2020; Shafizadeh-Moghadam et al. 2017), and the participatory models focus on projecting stakeholders’ impacts to balance conflicting interests (Clarke and Johnson 2020; Mansour et al. 2020; Peng et al. 2020). The nuances between the prediction and participatory models lead to a diverging focus on parameter setups: the former takes regression tools or machine learning (ML) algorithms to create accurate projections for urban planning and decision-making; the latter ingest stakeholders’ interests and are calibrated with expert knowledge to inform the understanding for the urbanization mechanism. The Cellular Automata (CA) has been widely adopted in both models because of its mathematical resemblances to the real-world urban dynamics (Tong and Feng 2020; Li et al. 2017). CA models are primarily built on transition rules and neighborhood status, which were combined to convert driving factors and their interactions to the probability of a cell to be urbanized in the future (Roodposhti et al. 2020; Wang et al. 2021a). The transition rules were retrieved using logistic regression (Mustafa et al. 2018), uncertainty quantifications (Mansour et al. 2020), neuron networks (Gantumur et al. 2020), heuristic methods (Carneiro and Oliveira 2013), or decay functions proposed by experts. The neighborhood status was identified according to different structures, sizes, and weights. Although CA models are flexible with a large array of combinations given various transition rules and neighborhood status, the sophisticated urbanization process still poses challenges to urban modeling.

Urbanization is a complex process associated with social, cultural, economic, geographical, and political factors (Tzaninis et al. 2021). This process follows some universal rules as urban development must conform to physical constraints that regulate human exploitation on lands, meanwhile, stochasticity also drives urban development because to build or not depends on the specific local conditions. The first law of geography abstracts such universal rules as geographical correlations: “everything is related to everything else, but near things are more related to each other” (Tobler 1970). The second law of geography describes the local stochasticity as “geographic variables exhibit uncontrolled variance” (Goodchild 2004). These two laws were combined to form the foundation of CA models. For example, some CA models assign the central pixel with a higher weight than surround cells upon creating transition rules to mimic the first geography law (Clarke and Johnson 2020; Prayitno 2020). Many studies incorporate the shape index and texture information to reflect the second law of geography (Zhai et al. 2020; Ruiz Hernandez and Shi 2018). Some studies tried to balance these two laws by subsetting the study area into separate zones, allowing independent transition rule sets to be constructed to align with the unique condition in each zone (Qian et al. 2020; Xia and Zhang 2021). Despite having successfully constructed transition rules within the neighborhood scope, these studies presented mismatches comparing to real-world urbanization: 1) prediction models oversimplified the spatial heterogeneity of driving factors, and 2) participatory models introduced subjectivities upon constructing the transition rules and determined neighborhood status. Distances and spatial configurations of geographical factors are key to urban development in the real world. However, the participatory models measure the impacts of these factors with decay functions developed by experts, and subjectivities are inevitably raised given the gap between human knowledge and real-world urban dynamics. The prediction models, although retrieve the transition rules automatically to avoid subjectivity, underestimate the spatial heterogeneity of the urbanization process: the complex spatial configuration within a neighborhood is represented by a single shape index, which hardly captures the pattern information of geographical drivers. A shared problem of prediction and participatory models is overlooking the large-scale features of driving factors. The optimum neighborhood sizes of these models were usually small (< 20), but the large-scale configurations, e.g, the shape of the built city, influence the urban development as well. Therefore, the advances for existing urban simulation models should be 1) capturing the large-scale spatial heterogeneity of driving factors, and 2) assimilating geographical variables automatically to reduce subjectivity.

The advanced Deep Learning (DL) technology enables the spatial configurations, rather than proxied variables like decay distances, of driving factors to be integrated into urban development simulation. Hubel and Torsten N. Wiesel (1962) found that different cells in the cat’s cortex responding to different simple stimulations such as light, orientation, and movement, and the neuron system integrated these stimulations to produced high-level visuals. The Convolutional Neuron Network (CNN) is a computation mimic to such vision systems that extract and assimilate low-level spatial features into high-level patterns (Krizhevsky et al. 2017), and it has been introduced to CA models to simulate urban development. For example, Zhai et al. (2020) used CNN to extract the spatial features from driving factors within a neighborhood and improved the performances of urban development simulation. Qian et al. (2020) proposed a 3-D CNN model that coupled historical urban dynamics with CNN and found it outperformed conventional CA models. Although the spatial features introduced by CNN improved the simulation performance, the conventional CA models, built on regression or ML algorithms to create transition rules in a neighborhood scope, were incapable of processing these features into high-level patterns. Therefore, more advanced DL structures that fully take advantage of CNN’s pattern recognition ability, i.e., integrate low-level spatial features to high-level patterns, are required to simulate urban development.

We adopted the UNET to mimic the urbanization process in this study. UNET is a DL structure that was first introduced for biomedical image segmentation and the unique design allowing it to extract and assimilate spatial features at different levels (Ronneberger et al. 2015). The robust segmentation performance enables UNET to be used in multiple fields such as geography (Singh et al.), environmental engineering (Nezla et al.), remote sensing (Ji et al. 2019), etc. More variations of the UNET were developed to better suit different purposes. For example, pixel-wise regression using UNET was applied to sharpen images (Yao et al. 2018), 3-D UNET was proposed to segment volumetric images (Çiçek et al. 2016), and TernausNet linked existing DL structure to improve the segmentation performance (Iglovikov and Shvets 2018). We used the basic UNET structure in this study because it is simple and efficient enough for urban dynamic pattern recognition. Down-sampling layers, up-sampling layers, and skip-connections are the primary components for UNET. The down-sampling layer enables UNET to extract the general contexts from the input data. The up-sampling layers refined these contexts to precise shapes. The skip-connections balance the generalization of down-sampling and the refinement of up-sampling (Ronneberger et al. 2015). Unlike CA models that have a definite neighborhood size, the UNET, in essence, deploys a series of moving windows of 3 × 3, 7 × 7, …, 65 × 65 (this study) to extract large scope spatial features gradually and then assimilate these features automatically to produce transition rules. The intuition of using UNET is that shapes matter in the real world: given the same distance to existing urban areas, the one near road crosses is more likely to be urbanized than the one near a straight road section. We hypothesis that UNET supplements the conventional urban simulations with two advancements: 1) identify and assimilate large scope spatial patterns that drive urban development, and 2) reduce the subjectivity upon calibrating the simulation models.

This study aims at mimicking and projecting urban development using advanced DL architecture. Conventional CA models can not fully ingest spatial features, which are, however, key to the urbanization process in the real world. We used the UNET to integrated large-scale spatial configurations for urban development simulation in the North China Plain. The primary objectives are: 1) visualizing and investigating the high-level features identified by the UNET model, and 2) validating the simulation and projecting the urban map to 2030. We discussed the advantages of the UNET and its promising prospect to supplement conventional CA-based urban simulations. Local and regional sustainable development could benefit from improved urban dynamic simulations using advanced DL technology.

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