# Introduction

Urbanization is a complex socio-economic process associated with geographical and cultural conditions. Urban land carries more than half of the world population and consumes the most significant amount of food, water, and energy, and exports a similar level of wastes like carbon dioxide, polluted water, and heat. Knowing the land to be occupied by urban provides the opportunity for efficient resource management and waste neutralizing, thus prompt sustainable urban development.

Cellular Automata (CA) have been widely applied for urban land projections. The existence of a cell in a CA model depends on its surrounding cells (neighborhood), which could be used to represent the urban dynamics in the real world. CA models are built on transition rules that composed of driving factors (e.g., topology, transportation, population, etc.) and neighborhood status, and produce a transition potential map where each pixel indicating its probability to be urban in the future. For example, in two 9\*9 cell grids, the transition potential of the central cell with five urban cells will be, according to the transition rules, greater than the one with three urban cells. Similarly, the one close to the road will have a higher transition potential than the farther one with other conditions hold the same. However, different neighborhood statuses and the complex combination of driving factors make it hard to retrieve the optimum transition rules.

Two approaches were devoted to increasing the reliability of transition rules. The first one is to introduce Machine Learning (ML) methods to CA models. This approach unravels the complex relationship between driving factors and transition potentials. [some examples from papers] However, the spatial patterns of the neighborhood cells were overlooked. For example, three cells in a 9\*9 grid can be connected as a line or scattered away from each other, and these two kinds of spatial configurations often produce different transition potential to the central cell. But this difference was not well captured in ML methods (such as …). The other way, often called as participatory approach, to retrieve transition rules is to guide CA models using human knowledge. This method was built on the assumption that human deduce more reliable urban expansion rules from the real world than machine does in a finite neighborhood scope. [some examples from papers] However, it is a challenge to transform human perceptions into mathematical functions that regulate the CA models. For example, a prominent knowledge from human to urban expansion is that the transition potential decreased as the distance to transportation increased. But the rate of such decreasing is hard to determine because it often correlated with other parameters such as neighborhood size and decreasing rate of topological factor. The participatory CA models were easily overshadowed by subjectivity because it is infeasible to exhaust all possible parameters originated from human knowledge.

The advancement of Deep Learning (DL) technology enables new designs to simulate urban development. The Convolutional Neuron Network is a typical DL model to extract features and has been used in simulating the land use changes. [some examples from papers] However, these studies only ingesting low-level spatial features (e.g. vertical and horizontal linear shapes) and are still bounded to the design of integrating neighborhood information to the centre cell. The DL models are capable of learning shape and pattern features from parcel images via a training process, which is fundamentally different from the CA design of providing the centre cell with neighborhood information. We hypothesis that these high-level spatial features could be directly used in simulating the urban development and achieve robust projection results.