**Reviewer #1:**

The paper reports the result of a study using deep learning to model urban land development by applying the U-Net architecture to a study area of the North China Plain. The subject addressed in this article is worthy of investigation and appropriate to the journal.

Thanks for confirming the value of this study.

However, the methodology is not clearly described w.r.t the data used for the development of the two U-Net models and the novel methodological contributions.

To better explain the data used to train the U-Net models, we added a table in the “Data processing” section.

*Table 3. The data used to train U-Net models. (This table is inserted in the “2.4. Data preprocessing”)*

|  |  |  |  |
| --- | --- | --- | --- |
| *Data* | *Time* | *Source* | *Resolution* |
| *Urban land use* | *1994, 2006, 2018* | *Wang et al. (2021b)* | *30 m* |
| *Elevation* | *2000\** | *Shuttle Radar Topography Mission* | *30 m* |
| *Slope* | *2000\** | *Derived from elevation* | *30 m* |

*\* Note, the elevation and slope data were used in 1994, 2006, and 2018 despite their being acquired in 2000.*

*4.1. Mimicking real-world urban patterns and dynamics*

*U-Net was able to model urban land-use change at high accuracy as well as capture and assimilate high-level spatial patterns of urban development in the North China Plain. First, the model captured neighborhood effects. The transition potential map revealed that lands near existing urban areas were more likely to transition to urban land-use in the future and that urbanization amongst larger expanses of non-urban land would be unlikely (Fig. 9). Second, U-Net was able to assimilate small-scale neighborhood effects into large-scale gravity effects. Larger areas of land near larger cities were predicted to become urbanized in the future, while much smaller areas were predicted to become urbanized around smaller, more remote villages (Fig. 10). Third, U-Net, rather than just simply buffering spatial features, captured the tendency of urban expansion to follow linear patterns. For example, the elongated development trend of Fengning County controlled by valley terrain was identified in the prediction (Fig. 12), and areas along major transport routes were allocated high transition potentials (Fig. 9). However, the U-Net model was unable to predict new planned developments that sprouted up some distance from existing urban areas, such as Binhai Zhen, Yangkou Zhen, Huying Zhen, and Xuancheng City (Fig. 10).4.2. Reducing subjectivity by automatically constructing transition rules*

*The large-scale spatial patterns identified by U-Net, in particular the gravity effect of large cities, would not have been captured by existing CA models. A large neighborhood is required for a CA model to incorporate information at a large scale which tends to decrease simulation performance. Wang et al. (2021a) found that the best neighborhood size to simulate urban development in Beijing was 25 × 25 pixels, while Roodposhti et al. (2020) observed that a 9 × 9 pixel neighborhood outperformed other settings. However, the unique design of the U-Net model is capable of incorporating more extensive information than previous CA model structures, enabling the neighborhood influence to be learned from the data and urban development to be simulated with more refined spatial configurations.*

*U-Net did not require extensive amounts of forcing data or parameterization to simulate urban land-use changes, except for the learning rate and the size of the training images. The transition rules were automatically generated in the form of learned weights, and training was an automatic process that required few subjective decisions to be made. In contrast, CA model structures have often required a complex calibration process to determine suitable parameters. For example, Feng and Tong (2020) developed a framework that integrated three algorithms and different neighborhood settings to simulate urban growth in Shanghai, whereas an array of parameters including inertia weights, decay magnitude, spatial heterogeneity, and variable scaling, needed to be specified before running the model. Many studies determine these parameters according to expert knowledge (Chen et al., 2020; Mustafa et al., 2017; Tripathy and Kumar, 2019), potentially leading to subjective biases. Other studies went through a systematic parameter selection process to find the best parameters (Roodposhti et al., 2020; Yu et al., 2021), but this process is time-consuming and impractical given the many unknown parameters.*

Somehow, the conclusions are not well supported by the study results, e.g., "The U-Net model successfully captured neighborhood effects, gravity effects, and linear expansion along transportation routes in the urban dynamics", where "linear expansion along transportation routes" seems to be concluded based on visual inspections of 11 smaller areas.

We computed the patch number and landscape shape index to quantitatively assess the performance of the U-Net simulation. However, “neighborhood effects, gravity effects, and linear expansion effects” could not be quantified by current landscape shape indexes which have limited power to capture these high-level characteristics (Frazier and Kedron, 2017; Pontius et al., 2008; Uuemaa et al., 2009). Indeed, assessing the quality of output features remains a significant challenge even in the deep learning community because of the heterogeneity in spatial features that are beyond the ability of simple shape indexes to describe mathematically (Ghosh et al., 2020; Wang et al., 2020). Instead, it is common to evaluate the performances of deep learning models by observing the resulting images (Gonog and Zhou, 2019; Xu et al., 2018) and qualitatively assessing and categorizing the results via human interpretation to complement the quantitative metrics as we have done.

Our conclusions are not based on the 11 inset areas presented but rather they are based on detailed visual interpretation and query of the entire map outputs at a range of scales as we describe in the Methods section. The 11 small-scale (1km – 10km) regions were simply chosen to illustrate the urban patterns learned by U-Net (i.e., the neighborhood, gravity, and linear effects) to the reader. The illustrative inset areas were selected to cover the full gradient of city size and span the entire study area. The reason for choosing small-scale regions is that urban expansion simulation usually performs less accurately in small areas than in larger regions (Pontius et al., 2008). If the simulation in a small area looks sensible, readers are more likely to be convinced that the deep learning architecture could simulate the urban development well at the broader scale. The full dataset is available online (https://doi.org/10.6084/m9.figshare.19880671.v1) if the reader wishes to make a more detailed inspection or inspect specific areas.

To ensure that readers are clear around the role and purpose of our visual inspection-based pattern evaluation, we added the following in the “2.7 validation and accuracy assessment” as below:

*we selected 11 cities of varying sizes from across the study area for visual inspection in order to qualitatively evaluate the ability of U-Net to simulate realistic spatial urban land-use patterns and development characteristics.*

We also discussed the reasons for using visual inspection to evaluate the performance of U-Net and discuss the need for better tools to quantitatively assess the complex spatial shapes in the urban land-use change process in the “4.5. Limitations and prospects” section:

*Spatial patterns of urban development are highly complex. Very few tools currently exist to quantitatively compare these patterns. The shape index employed in this study revealed a high level of agreement between the U-Net projection of urban areas and the reference land-use map. However, our assessment of the ability of the U-Net to mimic specific patterns was largely based on visual inspection. No quantitative metrics currently exist to objectively assess whether projected urban patterns and shapes look plausible. Expert human interpretation such as the visual inspection method used in this study can effectively assess the realism of projection urban patterns but it is a qualitative and imprecise process. Better tools and metrics are required to quantitatively assess these complex spatial shapes and patterns to complement qualitative assessment based on human interpretation.*

The highlight states "U-Net achieves similar accuracies with CA models with lengthen calibration". What do you mean about "lengthen calibration"? How does your study result support "similar accuracies"? What makes the U-Net models better than CA models? Perhaps, the highlight needs to be revised and a corresponding quantitative comparison and discussion are needed in the discussion section.

‘Lengthen calibration’ was a typo for which we apologise. With regards to comment on ‘similar accuracies’ we have completely rewritten this section (4.3. Accurate prediction and robustness in capturing spatial patterns) to improve the clarity of the comparison…

*There are challenges to comparing model performance across studies. Pontius et al. (2008) reported two factors that profoundly influence urban land-use simulation accuracy: 1) the area of urban expansion, and; 2) the spatial resolution. A positive relationship exists between the FoM and observed land-use change. Prediction errors vanished when the simulation maps were resampled into coarser resolution (Pontius et al., 2008). Given these sensitivities, to enable a fair comparison of the accuracy of our U-Net model outputs with CA model outputs, we selected two CA-based studies with similar historical urbanization areas and the same 30m spatial resolution as our study. Wang et al. (2021c) used a particle swarm optimization algorithm, iterated a range of parameter settings such as a self-recognition component, a social component, inertia weights, and the number of particles, to finally arrive at the best model with an FoM of 0.193 for Zhuji, China. Wang et al. (2021a) developed 17 sub-models incorporating four periods of historical urban land-use and tested eight different neighborhood sizes (5\*5 to 41\*41) for each sub-model to ultimately identify the best simulation which achieved a FoM of 0.219 for Beijing, China. The FoM (computed from 76 prefectures) in our study ranges from 0.177 - 0.215 (interquartile range) which covers the 0.193 reported by Wang et al. (2021c) but is slightly lower than the 0.219 found by Wang et al. (2021a). This higher FoM reported by Wang et al. (2021a) may be explained by the very large amount of urbanization in their study area (i.e., Beijing) (Pontius et al., 2008).* ***This comparison demonstrates that U-Net achieved similar predictive accuracies to comparable CA-based urban land-use models.***

One of my main concerns is the description of the data used in the study, which is not clear and consistent considering the following listed example lines. You actually used land use maps of 1994, 2006, and 2018 only, plus elevation/slope data (not sure if also of these three years), but the way the data are described is confusing.

We added table 3 in the “Data processing” section to make it clear to readers that only land-use maps (1994, 2006, and 2018) and elevation/slope data were used in this study.

*Table 3. The data used to train U-Net models. (This table is inserted in the “2.4. Data preprocessing”)*

|  |  |  |  |
| --- | --- | --- | --- |
| *Data* | *Time* | *Source* | *Resolution* |
| *Urban land-use* | *1994, 2006, 2018* | *Wang et al. (2021b)* | *30 m* |
| *Elevation* | *2000\** | *Shuttle Radar Topography Mission* | *30 m* |
| *Slope* | *2000\** | *Derived from elevation* | *30 m* |

*\* Note, the elevation and slope data were used in 1994, 2006, and 2018 despite their being acquired in 2000.*

Line 97-98: "used high-accuracy maps of urban land-use between 1993 and 2012 to train the model" and tested the model by the projected spatial distribution of urbanization for 2018

We apologise for this error. We changed “between 1993 and 2012” to “between 1994 and 2006.”

To avoid confusion about how the U-Net was validated using a reference map, we modified the description to:

*We then projected the spatial distribution of urbanization for 2018 using this model and thoroughly tested its ability to accurately capture the high-level spatial features, shapes, and patterns of urban development against the reference urban land-use of 2018.*

Line 100-101: THIS trained model was then used to project patterns in 2030

To make it clear for readers which model was used to projecte the urban land-use in 2030, we modified the description as below:

*Last, we trained another U-Net model on land-use maps for 2006 and 2018 to project urban land-use in 2030 based on the extrapolation of historical urbanization rates.*

Line 111-113: here you start talking about using different years of data for two different U-net models.

In our initial submission, we denoted the different historical periods with different names (1994–2006 and 2006–2018 are referred to as “base,” 2018 and 2030 were called “target,” and the true 2018 urban map was called “reference”) and we described the U-Net as “U-Net trained on base/target years”. We now see that this notation could confuse the reader because they need to go back to the method section to discern the differences between “U-Nets trained on base/target years”. To avoid confusion between the two models trained in this study, we modified the description when introducing the two U-Net models in the “2.1. Method overview” section:

*We created two U-Net models (Table 1) where one was trained/validated by historical data to evaluate the model performance and the other one was trained on more recent data to predict future urban land-use. U-Net-A was trained for the validation purpose by comparing its projected land-use map with the reference map using a range of accuracy and pattern-based metrics. U-Net-B was trained to predict future urban land-use for 2030.*

|  |  |  |
| --- | --- | --- |
| *Model name* | *Training years* | *Prediction year* |
| *U-Net-A* | *1994, 2006* | *2018* |
| *U-Net-B* | *2006, 2018* | *2030* |

Table 1. Brief description of the U-Net models trained in this study.

Line 108-109: "We used Landsat data to map urban development in the study area for the years 1994, 2006, and 2018" - I think you are talking about "map land use". The terms used throughout the manuscript need to be clearly defined or understood and consistent, e.g., urban dynamic map, urban map, urban land-use map, urban land use map, urban pixel number, urban pixels, urban images

Yes, this assumption is correct. We have now changed “urban dynamic map, urban map, etc.” to “urban land-use map” throughout the manuscript.

Line 196-199: what are the spatial resolutions of land-use, elevation, and slope data, assuming they are rasters?

We added a table 3 in the “Data processing” section to make it clear to readers that all data used were in raster format with a spatial resolution of 30m.

Line 213-215: what's urban map here? Here, what data were used to train which model?

We changed “urban map for 1994” to “urban land-use map for 1994.” To clarify the data used to train U-Net, we added more information in parentheses for explanation:

*The samples included three-layer input data (e.g., urban land-use map for 1994, elevation and slope for U-Net-A) and a single-layer future urban land-use map (e.g., urban land-use map for 2006 for U-Net-A).”*

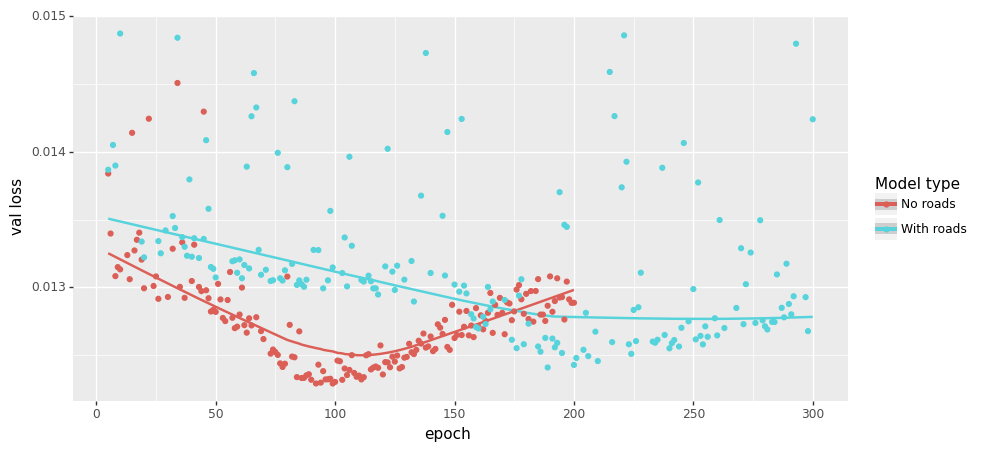
Line 226: what are the input images here? Land use maps?

The input images refer to the combination of the land-use map and the elevation/slope data. To clarify this concept, we added more information in the parenthesis for explanation:

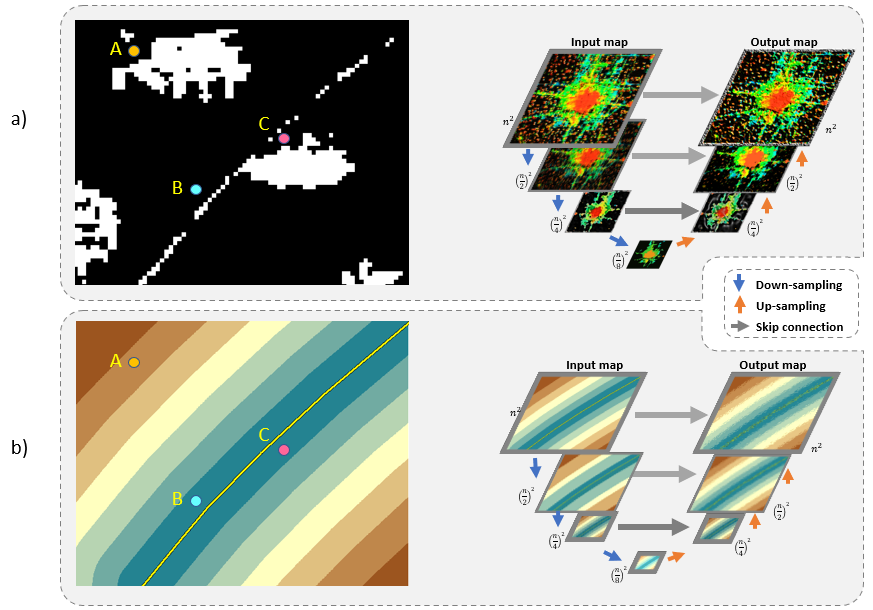
*The input data (e.g., for U-Net-A a three-layer raster of urban land-use for 2006 and the elevation/slope data) was split into tiles, supplied to the trained U-Net model to produce separate outputs, and then the outputs were mosaicked into a single transition potential map.*

Line 204-205: any previous studies that prove "little additional useful information" provided by distance factors?

To inform this decision, we conducted a separate experiment that showed that “distance to road provided little additional useful information.” We collected historical road data (vector) from *OpenStreetMap*, computed the distance to roads in raster format, and appended this data as additional drivers to train the U-Net. The evaluation (MSE of 5k 256\*256 tiled images against their corresponding reference 256\*256 tiled images) shows that introducing road distance information makes the U-Net harder to train (longer training time and slightly higher MSE).



One possible explanation is that U-Net is sensitive to “visual signals (i.e., spatial features)” but distance hardly provides any robust spatial features. Below is a conceptual illustration of urban land-use (a) and distance-based driver (b) being processed by U-Net. The distance-based driver exhibits a monotonical increasing pattern perpendicular to the road, and this pattern remains unchanged in the U-Net. However, the overall urban land-use change patterns were captured in the down-sampling process and the finer patterns were reconstructed in the up-sampling process. Therefore, the monotonicity of distance-based drivers may prevent U-Net to learn additional patterns from roads/town centers, etc.



To make this clearer to readers, we provided a supplementary document to explain the reason for not including distance data in our study.

Line 285-286: "to historical urban land-use maps for the period 1994-2006" - the expression implies maps of more than two years

We changed this to “historical urban land-use maps of 1994 and 2006”.

What message does Fig. 5 convey? How does it show the dynamics of urban land use? What do you mean about "urban dynamic map"? Do you really need this large map while showing the details as small snapshots?

The purpose of Fig. 5 was to introduce the historical urban land-use in the study area to the reader. We agree that this figure is probably extraneous and have now moved it to supplementary documents.

Line 310-312: Is SuiXian a large town? What are those smaller villages which have the same phenomena - high transition potential?

There are several small towns, including Suixian, which have been selected to illustrate transition potential calculated by U-Net. The high transition potential effects are because of a “standard deviation” stretch method being applied to the map. We have now realized that applying a stretch method would exaggerate the transition potentials surrounding initial urban area and removed the stretching method.

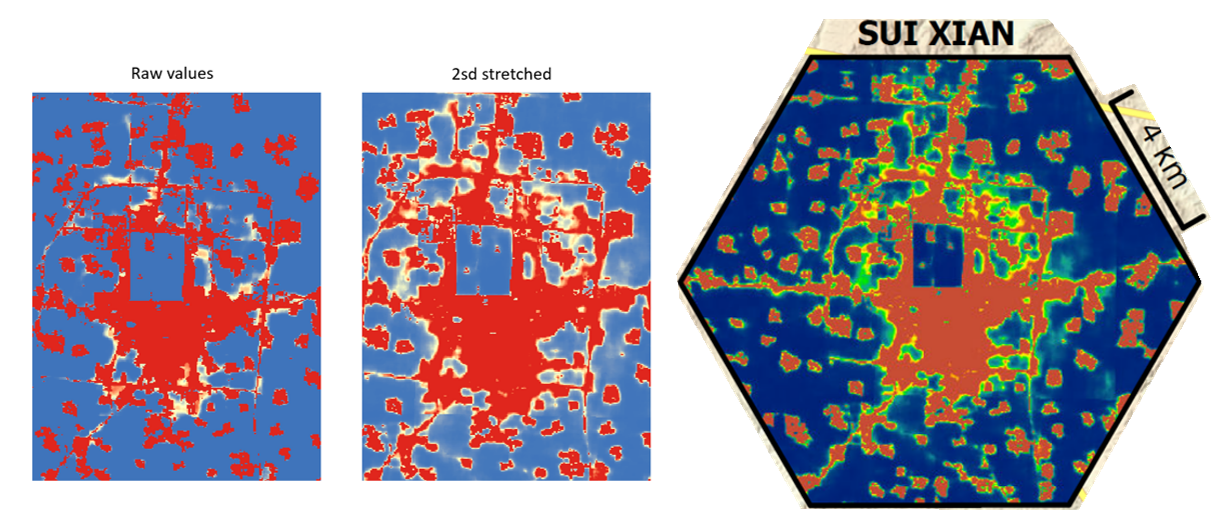


Figure 10 - do you really need this large map while showing the details as small snapshots?

Figure 11 - do you really need this large map while showing the details as small snapshots?

We do need these two figures to demonstrate that U-Net had learned the “gravity, neighborhood, and linear effects” in urban development via visual inspection. We chose to keep the large map as well as show the detailed inset maps to demonstrate to readers the overall view of the whole study area on how U-Net performed and the degree of urban expansion. Also, we found that eliminating the large map won’t necessarily reduce much page space (see below our alternative design) and readers will wonder where these localities are within the region.

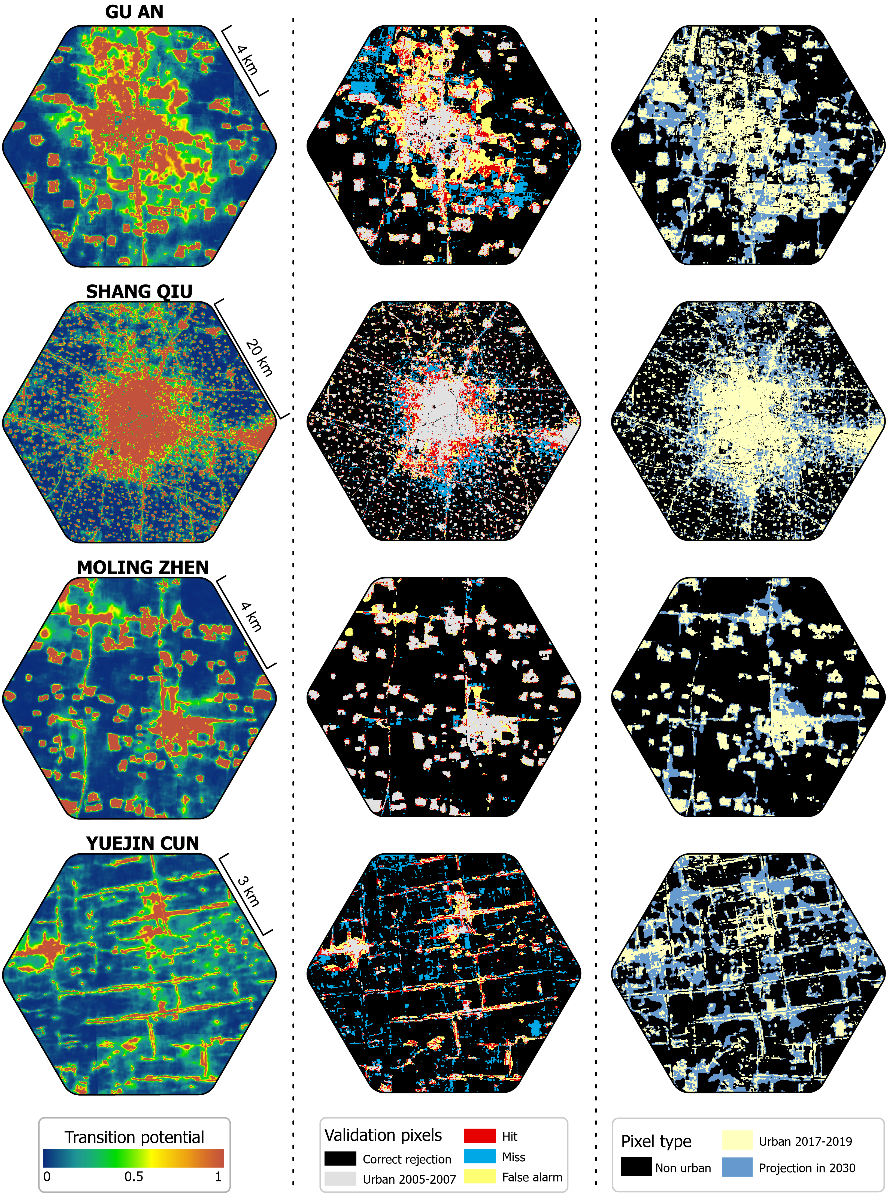
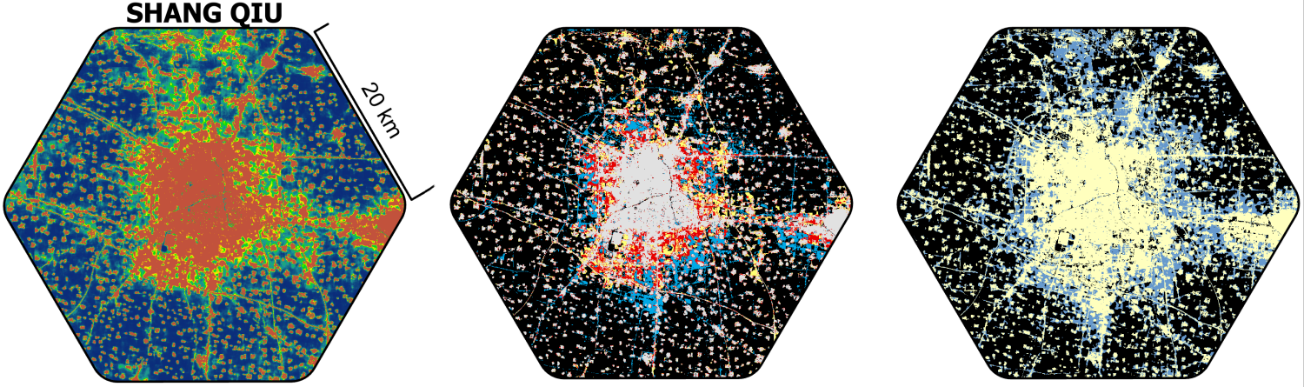


Fig. 10, 11, and 13 show 11 smaller urban areas, no large urban centers. How will you generalize the observations from the patterns around these areas to more general urban development?

Readers can zoom into the large cities to see the generalized simulation of urban land-use with our high-resolution figure. The data will also be made available freely online. We have tried to include large cities as inset maps, but the visual effects are less clear than in the small towns because the subtle details are obscured by large-scale transition potential patterns (see below figure).



What's the purpose of including the projection of 2030 urban land use? Is it just to demonstrate the use of the trained U-Net models?

The complete workflow of urban land-use simulation in this study is: 1) develop the U-Net architecture, 2) validate the trained U-Net against historical reference urban land-use map, and 3) apply the U-Net to project urban land-use to a future date. As the reviewer rightly recognizes, the primary purpose of including the projection to 2030 is to demonstrate the use of the trained U-Net. However, as one of the fastest urbanized regions in the world as well as the food bowl of China, knowing the accurate future urban land-use in the future provides significant practical value to support the regulation of urban development and evaluation of the impacts on sustainability. Urban land-use is a key proxy for socioeconomic assessment and environmental protection. Studies focusing on sustainable development and climate change can benefit from our accurate future land-use predictions.

We explained the importance of future urban land-use to North China plain in the 2.2. Study area section and future discussed the implication of the prediction in the discussion section.

*This region is crucial to China’s economic development and holds a strategic role in safeguarding China’s food security, generating over one-third of its national gross domestic product (GDP) and grain supply (National Bureau of Statistics of China, 2019a). Managing the tension between urbanization and agricultural land-use in the study area requires accurate, spatially explicit projections of future urban development to address the interconnected challenges of food security, environmental protection, urbanization, and socio-economic development.*

*… Our projections for 2030 also captured urban development in the three megacity groups (Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Central Plains) that account for one-third of China’s GDP (National Bureau of Statistics of China, 2019b). China’s strategic development planning process can benefit from the predictions arising out of this study in many ways. For example, in urban area predictions can be used to plan for infrastructure to support socio-economic development. Simulations can assist policy formulation that is tailored to the expected rate, location, and patterns of urbanization …*

**Reviewer #2:**

I have reviewed this article carefully; I agree that it is a promising new idea to apply U-Net to urban growth simulation and prediction.

Thanks for confirming the value of this study.

However, this method focuses on the characteristics of images (i.e., urban land use landscape), rather than understanding the process of urban growth from the driving factors (i.e., the combined effects of nature and society, etc.) that drive landscape evolution. Therefore, this method cannot understand the mechanism of urban evolution.

There are two types of CA-based urban land-use simulation models: one is called a regressive model which focuses on increasing the simulation accuracy and finding the optimum functions to decompose drivers (e.g., suitability, proximity, stochastic factors, etc.) into transition rules (Gantumur et al., 2020; Shafizadeh-Moghadam et al., 2017). The other one, often called the participatory model, emphasizes balancing the interests of stakeholders in the urbanization process to reveal the mechanisms/drivers behind urban land-use change (Clarke and Johnson, 2020; Mansour et al., 2020).

The U-Net shares the same goal the regressive model of increasing prediction accuracies but does so using a deep learning approach rather than building a regression between driving factors and urban land-use. It possesses several significant advantages: 1) it automatically extracts transition rules without the requirement of manually setting parameters such as neighborhood size and decay rates (Feng and Tong, 2020; Peng et al., 2020; Roodposhti et al., 2020), and 2) it uses computer vision technologies to learn the spatial patterns of urban development. Therefore, deep learning architectures bring about the significant potential to complement CA-based models with comparable simulation performances and the automatic recognition of complex spatial patterns.

The U-Net model revealed, via visual inspection, three significant urban development processes such as neighborhood effects, gravity effects, and linear expansion effects. However, these learned patterns are hidden in the ~30 million weights within the U-Net. There are several potential ways to transform the trained U-Net into human recognizable rules, i.e., revealing the mechanism of urban evolution. The explainable machine learning techniques enable the abstracting of knowledge from deep learning architectures (Dosilovic et al.; Gunning et al., 2019). However, there are uncertainties if these measures can be successfully applied to U-Net and they also exceeded the topic of this study. To make readers clear about the limited capability of U-Net models as well as the potential ways to extract human-recognizable rules from them, we described the advancement in the deep learning technology as a potential solution to help understand the urban land-use change mechanism in the discussion section:

*Emerging developments in extracting human-recognizable knowledge from deep learning architectures (Dosilovic et al.; Gunning et al., 2019) could be applied to U-Net models for a better understanding of the mechanisms behind urban land-use dynamics.*

On the other hand, the author does not strongly prove that the simulation accuracy of this method is better than the results of traditional CA-based results. I noticed that the author mentioned in the article that U-NET achieved higher accuracy than CA in some cities. But this does not mean that U-NET performs better in a large area, such as the study area of this paper.

The primary goal of introducing deep learning to urban land-use simulation is to compare the pros and cons and explore how deep learning could complement CA-based land-use modeling, rather than to demonstrate that deep learning is superior. The comparison between U-Net and other studies showed that these two methods are very comparable from an accuracy metrics perspective.

The accuracy of the simulated urban land-use is profoundly impacted by 1) the net urbanized area and 2) the spatial resolution of the raster data (Pontius et al., 2008). We compared our result with two CA-based studies that iterated multiple parameters (window sizes, inertia weights, iteration number, etc.) or developed 17 sub-models to get the best simulation outcome (Wang et al., 2021c; Wang et al., 2021a). The comparison showed that the FoM in this study, computed from 76 prefectures, with the 1st quantile value of 0.177, the 3rd quantile of 0.215, and the median of 0.197, was close to 0.193 reported by Wang et al. (2021c), and 0.219 found by Wang et al. (2021a).

U-NET achieved higher accuracy than CA in some cities because the FoM is positively related to the urbanization rate (Pontius et al., 2008): some cities had more net urbanized areas and are more likely to have higher FoM. However, the interquartile value of FoM from U-Net simulation is very close to the selected CA-based studies.

We have modified the manuscript where comparing U-Net with CA-models as bellow:

*Wang et al. (2021c) used a particle swarm optimization algorithm, iterated a range of parameter settings such as a self-recognition component, a social component, inertia weights, and the number of particles, to finally arrive at the best model with an FoM of 0.193 for Zhuji, China. Wang et al. (2021a) developed 17 sub-models incorporating four periods of historical urban land-use and tested eight different neighborhood sizes (5\*5 to 41\*41) for each sub-model to ultimately identify the best simulation which achieved an FoM of 0.219 for Beijing, China. The FoM (computed from 76 prefectures) in our study ranges from 0.177 - 0.215 (interquartile range) which covers the 0.193 reported by Wang et al. (2021c) but is slightly lower than the 0.219 found by Wang et al. (2021a). This higher FoM reported by Wang et al. (2021a) may be explained by the very large amount of urbanization in their study area (i.e., Beijing) (Pontius et al., 2008). This comparison demonstrates that U-Net achieved similar predictive accuracies to comparable CA-based urban land-use models.*

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