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Academic Article

Prediction of the impacts of urbanization using a new assessment system combining an urban expansion model and WRF -Case study for Guangzhou in China-

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ABSTRACT

This study presents a new urban environment assessment system that allows for a dynamic special appraisal by integrating Weather Research and Forecasting (WRF), a numerical simulation model for mesoscale climate and Cellular Automata (CA) Model, the urban growing prediction model as a whole. Changes in land-use information in WRF can strongly influence simulation results, this system first predicts the growth of urban areas over several years by using remote sensing (RS) images, and a modified CA model. This modified CA model is an evolution of the CA-Markov model with improved flexibility and variability, and with control conditions designed to dominate urban expansion patterns. The predicted urban land-use results are then imported into the WRF simulation for an environment assessment, to evaluate the impact on the urban environment by a given pattern of expansion, as well as control conditions. A study based in the Guangzhou area, in China, is cited as an example to clarify the workings of this system.

Key Words : Mesoscale urban environment, Urban sprawl, WRF simulation, CA model

1. Introduction

China has been undergoing a period of economic reform and expansion since the 1970s, accompanied by rapid and widespread urbanization, and a deterioration of urban environments caused by urban heat islands(1).

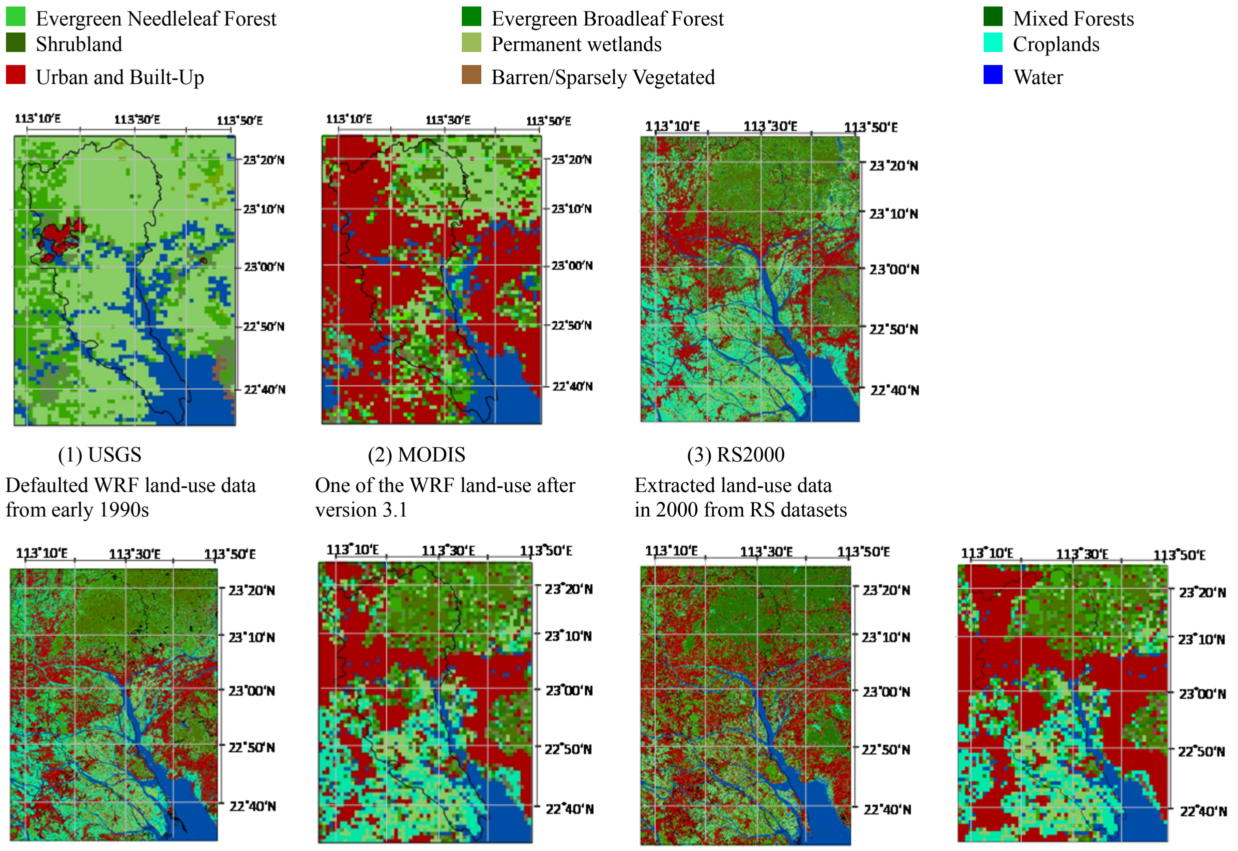
In this study, a new urban environment assessment system was developed by combining prediction models for urban expansion and mesoscale climates. The developed system contains two components: a land-use prediction model and a mesoscale meteorological model used for regional environment simulations. In this study, urban expansion was simulated by a modified Cellular Automata (CA) model, based on land-use data extracted from remote sensing data, while Weather Research and Forecasting (WRF) was used to simulate the regional environment. For simulations using WRF, we rewrote the default land-use data in WRF with land-use information as predicted by the CA model.

This assessment system was used to investigate the impacts of urbanization in Guangzhou city, the capital of Guangdong Province, located in southern China. The land-use changes from the year 2000 to 2012, under various scenarios of differing urban planning and environment protection strategies, were predicted by the modified CA model developed in this study, and their impacts on the regional environment in Guangzhou were then analyzed using the WRF results.

2. Extraction of land-use maps from remote sensing data and prediction of land-use maps with a standard CA-Markov model

By default, the geogrid program in WRF interpolates land-use categories from USGS data derived from the early 1990s, and is hardly appropriate for the situation of Guangzhou in the year 2000 when compared to RS data from the same year, as the urban area is too small (Fig.1(1)). As well, the urban area in the alternative MODIS geo model(2) provided in WRF after version 3.1 is too large(Fig1.(2)).

So, the land-use map for this region in 2000 was extracted by the present authors using a combination of nine Landsat-7 RS data bands in IDRISI(3), and was classified into MODIS 24-categories. This map was re-sampled in GIS into a resolution



(1) USGS
Defaulted WRF land-use data from early 1990s

(2) MODIS
One of the WRF land-use after version 3.1

(3) RS2000
Extracted land-use data in 2000 from RS datasets

(4) RS2005
Extracted land-use data in 2005 from RS datasets

(5) CA2005
Predicted map by standard CA-Markov model

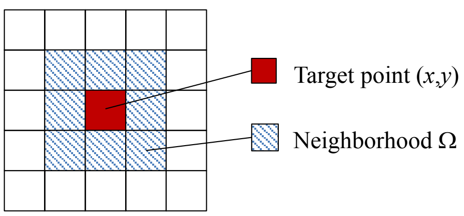
(6) RS2012
Extracted land-use data in 2012 from RS datasets

(7) CA2012
Predicted map by standard CA-Markov model

Figure 1: Default geographic models in WRF and land-use maps derived from the standard CA-Markov model

of 1 km to match that of the calculation mesh in WRF, and renamed as RS2000 (Fig.1 (3)). The extracted RS2000 dataset provided by the present authors was an improved fit for the city, especially for the urban area. Similarly, the land-use maps in 2005 and 2012 were also extracted from RS datasets from separate years, and were renamed as RS2005(Fig.1(4)) and RS2012(Fig.1(6)), respectively.

In order to predict urban expansion, the CA model was taken into consideration(4). Based on the land-use maps of RS2000 and RS2005, a standard Cellular Automata Markov (CA-Markov) model that reflects actual urban growth was established for the land-use simulations. In a CA-Markov model, the Markov chain process controls temporal change among land-use classes, based on the transition matrix, P_{ij}, that describes the probabilities of each land-use category changing from a certain class i to another class j. In this study, this matrix P_{ij} was at first calculated from the initial state in the starting year of RS2000 to mid-year of RS2005 by the Markov chain.



$S^{t+1}(x,y) = f(S^t(x,y), N)$

$S^t(x,y)$: State of point (x,y) at time t

N: Vicinity of target point

Figure 2: The changing rule at the target point

Simultaneously, the CA model in a CA-Markov model controls spatial pattern changes through local rules considering neighborhood configuration and transition to potential maps. As shown in Fig.2, the changing rule of land-use was defined as: if the target point (x,y) is not water and there is developed lands in the vicinity of the target point Ω, the probability of this point changing into urban land in this step will be the mean of the probability of its neighborhood changing into urban land, and if this mean is larger than a certain number μ, the point (x,y) changes into an urban classification. The change in land-use in each year was considered as a single step.

By using the standard CA-Markov model, land-use maps in 2005 (CA2005) and 2012 (CA2012) were predicted (Fig.1 (5) and (7)) as based on RS2000, with the μ value set to 0.5. This value was determined so that the percentage of urban areas in the entire region in CA2005 and CA2012 were almost identical to those in RS2005 and RS2012, respectively.

3. WRF simulations using predicted and extracted land-use data

In order to validate the prediction results of land-use data with the CA model in 2005 and 2012, as well as to clarify the effect of urban expansion on the thermal environment, numerical experiments with WRF were performed via the three steps shown in Table 1. The nesting of the three calculation domains are shown in Fig.3. The grid size in the horizontal direction in domain 3 was 1 km × 1 km, and the side length was 120 km. For comparison purposes, an assessment area that covers seven main districts in Guangzhou and two comparison points were separately selected in suburban and urban areas, as marked in Fig.3. In this figure, comparison point 1 is a weather station of the global observation dataset established by NOAA.

WRF simulations were performed for a 1-month period, and results for August 1 to August 5, which were rainless days, were obtained through validation with weather records in this study. WRF simulations in step A, using the default geographic models and the extracted RS2000 land-use data, separately proved that simulation results can differ significantly with different land-use models, and that the result obtained from the extracted RS2000 model is much closer to observations as compared with the default models at comparison point 1.

Simulation results from the extracted and predicted maps in 2005 and 2012 were clearly consistent with each other at both comparison points in steps B and C, and all simulation results agreed well with observations at comparison point 1 (see Fig. 4). The spatial distribution results of T2 (temperature at 2 m height) and SET* (the standard effective temperature) in step C are shown in Figures 5 (1) to (4) for 15:00 on August 2, when northerly wind was observed at the observation site. Here, SET* index is defined as the equivalent temperature of an isothermal environment at 50% RH in which a subject, while wearing clothing standardized for the activity concerned, would have the same heat stress (skin temperature) and thermo-regulatory strain (skin wettedness) as in the actual test environment(5). The results show that the standard CA-Markov model provides a satisfactory urban sprawl prediction that accurately reflects the actual urban expansion. It is also clear that the spatial SET* distribution is quite different from that of T2 in the southern area. For the suburban region in the southern area, even though the air temperature in this region is higher than the urban area in the middle from west to east, SET* is lower. This result was caused by the different surface temperature, reflectance, and humidity in between the urban and suburban areas.

Table 1: Analytical conditions

Step A	Case No.	A1	A2	A3
	Simulation Period	2000.07.20, 8:00~2000.08.20,8:00 (GMT)		
	Geo model	USGS	MODIS	RS2000
Step B	Case No.	B1	B2	B3
	Simulation Period	2005.07.20, 8:00~2005.08.20,8:00 (GMT)		
	Geo model	RS2000	RS2005	CA2005
Step C	Case No.	C1		C2
	Simulation Period	2012.07.20, 8:00~2012.08.20,8:00 (GMT)		
	Geo model	RS2012		CA2012

Microphysics Option	WDM 6-class scheme
Shortwave Radiation Option	Dudhia scheme
Longwave Radiation Option	rrtm scheme
Land-surface Option	Unified Noah land-surface model
Boundary Layer	YSU scheme
Cumulus Option	Kain-Fritsch (new Eta) scheme

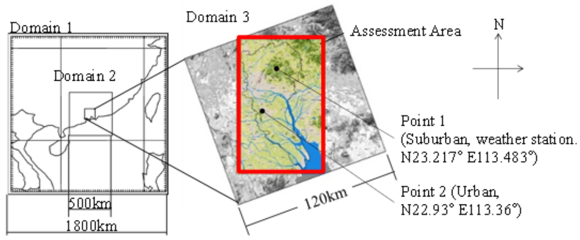
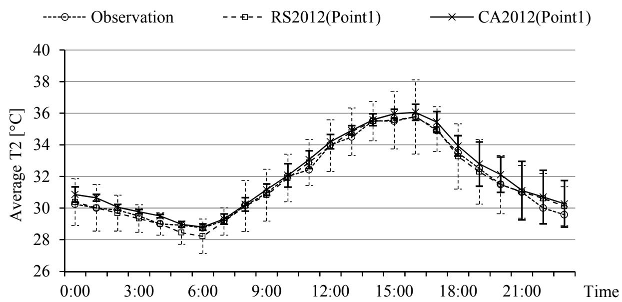
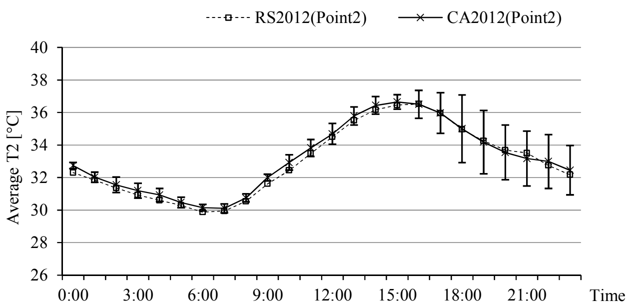


Figure 3: Configuration of the calculation domains and assessment area



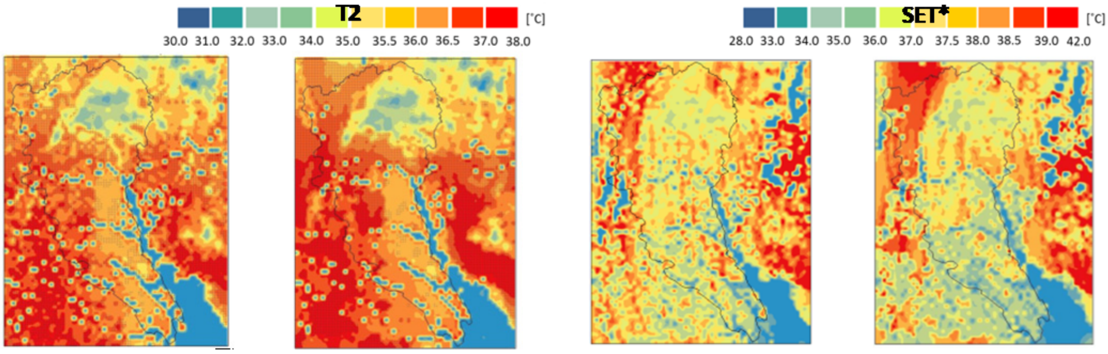
(1) Point 1(Suburban area)



(2) Point 2(Urban area)

Figure 4: Average T2 on sunny days (August 1 -5, 2012)

The error bars show the standard deviations of observation at point 1 with dot line and CA2012 with solid line.



(1) T2 (RS2012) (2) T2 (CA2012) (3) SET* (RS2012) (4) SET* (CA2012)

Figure 5: Spatial distribution of T2 and SET* in step C (15:00 on August 2)

4. Modified CA model and protection proposal for urban expansion

Based on the Standard CA model, a new coefficient *D* was added to control the expansion method of the original city, in order to create different urban development modes for the assessment of future years. According to existing research (e.g., Li and Yeh(6)), this controlled CA model was modified into the following formula:

$$S^{t+1}(x,y)=f\big(S^{t}(x,y),\, D(x,y),\, N\big) \qquad (1)$$

Here, the new parameter, $D(x,y)$, is the extension coefficient of point (x,y). By using this new coefficient, a controlled expansion of the urban areas can be used by the CA model to regulate urban development in various ways. The coefficient *D* can also be modified to obtain a feedback of the environmental assessment results. In this case, the formula can be rewritten as:

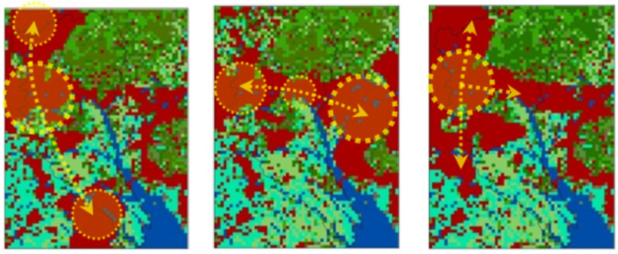
$$S^{t+1}(x,y)=f(P_s^t(x,y)) \qquad (2)$$

$$P_s^t(x,y)=f\big(D(x,y)\times P(x,y)\big) \qquad (3)$$

This modified CA model has been used in previous studies to create urban expansion modes under differing control conditions (e.g., White and Engelen(7)). In the present study, this model was used to introduce environmental effects into considerations of urban expansion.

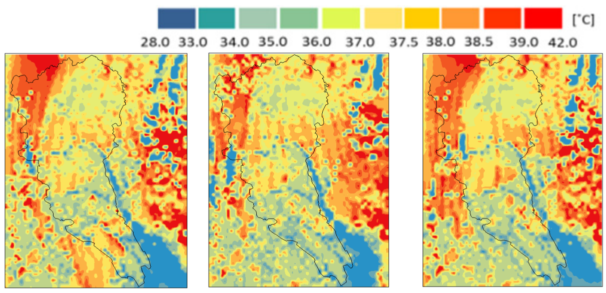
5. Investigation of the effect of urban expansion patterns on the thermal environment

In order to evaluate the influence of various urban expansion patterns, three different urban sprawl typologies were defined in this study: (1) A South-North expanded city mode (SN_12), which is most similar to the existing urban planning of Guangzhou city (Fig.6 (1)); (2) An East-West expansion pattern (EW_12) to create a linearly extended urban pattern (Fig. 6 (2)); and (3) A Centered mode (Center_12), which is a common sprawl mode in Chinese cities such as Beijing (Fig.6 (3)). The



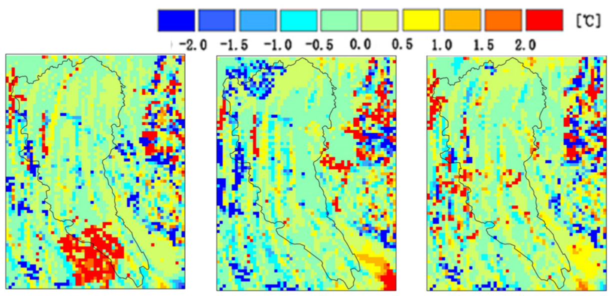
(1) South-North expanded city mode (SN_12) (2) East-West expanded city mode (EW_12) (3) Centered mode (Center_12)

Figure 6: Three different urban sprawl typologies



(1) SN_12 (2) EW_12 (3) Center_12

Figure 7: Spatial distributions of SET* on periods of northerly wind



(1) SN_12 – CA2012 (2) EW_12 – CA2012 (3) Center_12 – CA2012

Figure 8: Spatial distributions of SET* difference between each urban expansion case (SN_12, EW_12 and Center_12) and actual situation predicted by CA model (CA2012)

regional environments in these three land-use conditions were simulated in WRF.

Spatial distributions of averaged SET* during periods of northerly wind (Fig.7) suggest that urban forms can exert various influences on air temperature distributions. Fig.8 illustrates the spatial distributions of SET* difference between each urban expansion case (SN_12, EW_12, and Center_12) and the actual situation case predicted by the standard CA-Markov model (CA2012). In case SN_12 (Fig.8(1)), SET* in the southern part of the expanded city area clearly increased compared to that in case CA2012. However, SET* in this area is still not as high as the other city areas because this area is surrounded by cropland and located near the sea. In case EW_12 (Fig.8(2)), SET* decreased from the north west region to the south west region. In case Center_12 (Fig.8(3)), SET* in some areas in the middle of the western part increased even though SET* in this region was already high. Fig.9 shows the probability densities of T2 only in the urban area for the three different cases of sprawl patterns during the northerly wind period. The figure indicates that centralized sprawl patterns (Center_12) will cause a clear increase in the size of the high-temperature area. For the linearly developed modes of SN_12 and EW_12, the proportions of high-T2 areas do not differ, while the cooler area in SN_12 is larger than that in EW_12, as the southern urban area in this case is near the sea (Fig.8).

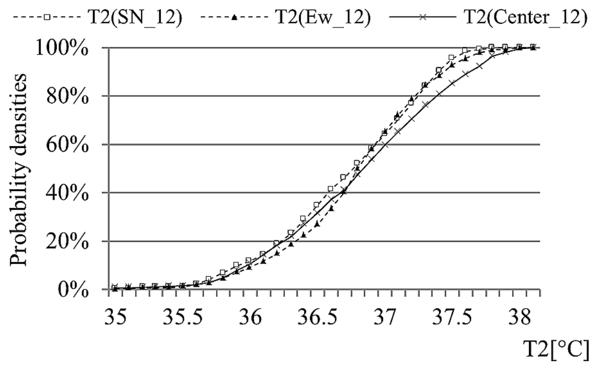


Figure 9: Probability densities of T2 during the period of northerly wind

6. Conclusions

As the modification of land-use data can have a significant impact on WRF simulation results, this study has provided a new consideration of urban land-use and environment analysis by combining remote sensing data, urban sprawl models, and numerical simulations. Numerical predictions of urbanization impacts in Guangzhou, China, using the developed system were performed to provide an example. Linear expansion modes can release heat to open spaces and avoid increases in the size of high temperature areas that are prevalent in over-sized cities.

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