Supplementary Materials: Mapping Urban Expansion Using the NFS Method

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1. Identifying the Transition Zones

Similar to DEM images, the NSL data have obvious ridges (high DN value regions) and valleys (low DN value regions). Identifying dividing lines between ridges and valleys is equivalent to distinguishing urban and non-urban areas. Due to the blooming effect of NSL data [1–3], these lines are actually transition zones including both urban and non-urban areas in the NSL data. In this study, the first step to extract urban areas is identifying the transition zones. Because the transition zones are more heterogeneous landscapes, the pixel values of transition zones vary dramatically compared to other regions in the NSL data [4]. Therefore, the differences in pixel values between maximum and minimum-NFS-generated outputs are much higher than those in other regions. Here, we took the Pearl River Delta (PRD) of China (Figure 1) as an example to comprehensively illustrate the detailed steps. We first produced maximum and minimum-NFS outputs of the NSL data in a 3 × 3 cell neighborhood window. Then, we subtracted the minimum from maximum-NFS outputs. The subtracted results were generally treated as topographic maps of NSL data (Figure S1a,b). With reference of Su et al. [4], an identical threshold value of 8 was found to be effective for distinguishing the transition zones from other parts in the topographic maps (Figure S1c,d).

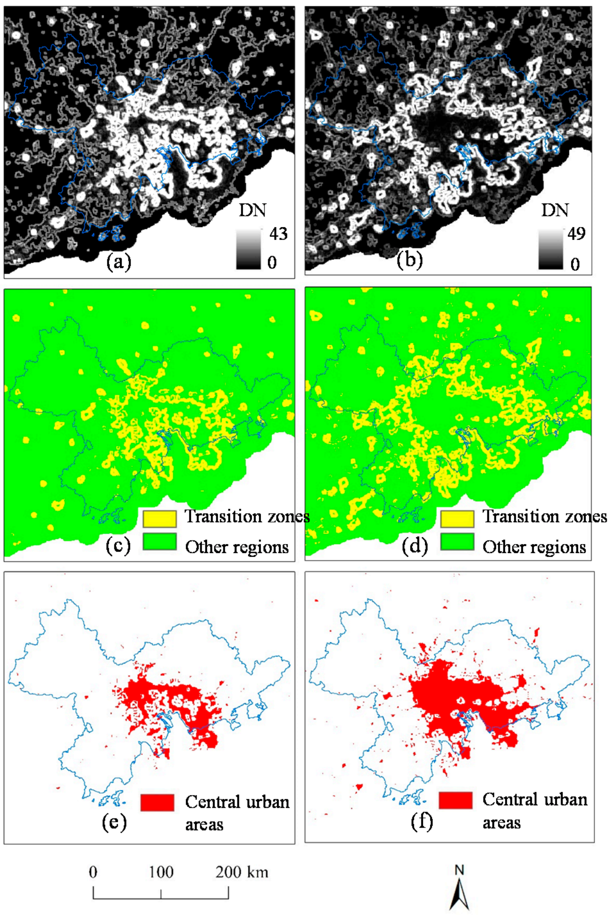

Figure S1. Identifying the transition zones and central urban areas from the topographic maps. (**a**,**b**) represent the topographic maps; (**c**,**d**) represent the transition zones; (**e**,**f**) represent central urban maps.

2. Quantifying Central Urban Areas

After the transition zones were identified, the study areas were divided into two parts: the transition zones and other regions (Figure S1c,d). As we known, the pixel values of urban areas are much higher than those of non-urban areas in the NSL data. According to the above differences, the regions with relatively high values on the side of transition zones would be classified as central urban areas (Figure S1e,f). In addition, the parts with pixel values that were relatively lower than the opposite side of transition zones would be classified as non-urban areas.

3. Defining Marginal Urban Areas

To extract the marginal urban areas in the transition zones, we first separately generated two outputs from the NSL data using the minimum NFS method in a 3 × 3 and 5 × 5 cell neighborhood window. These two outputs were called Min3 and Min5, respectively. In the transition zones, the pixel values of Min3 were usually higher than those of Min5. Therefore, the urban areas hidden in the transition zones could be extracted by subtracting Min3 from Min5 (Figure S2a,b). The subtracted results would be regarded as mixed maps in this study. Next, an effective threshold should be identified from mixed maps to extract marginal urban areas. Compared with the extracted results between the different thresholds, we found that an identical threshold value of −7 could be effective for extracting the maximum marginal urban areas without fragmenting urban patches (Figure S2c,d).

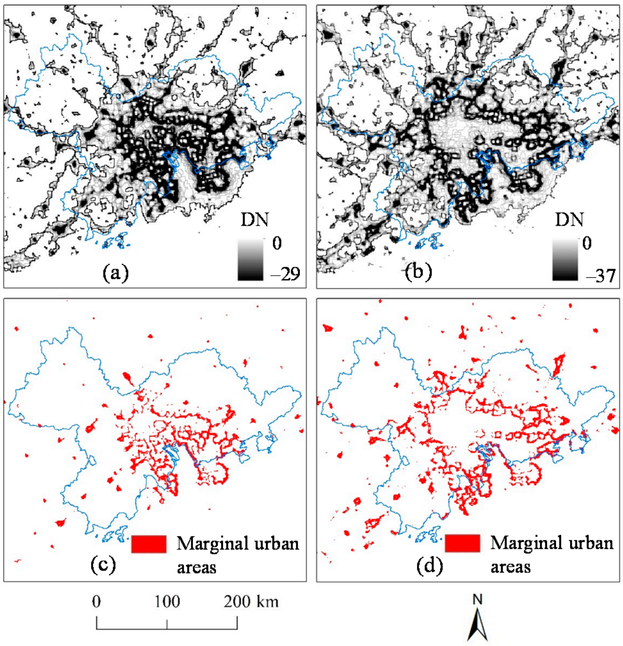

Figure S2. Extracting the marginal urban areas from mixed maps. (**a**,**b**) represent the mixed maps; (**c**,**d**) represent the marginal urban maps.

4. Mapping Urban Expansion

The primary urban maps could be obtained by overlaying central and marginal urban areas (Figure S3a,b). However, there were some misclassifications in these primary urban maps. For example, natural features such as small forests, wetlands, and water bodies might be classified as urban if they were located within urban regions [5]. As we know, an NDVI value of less than 0.1 is generally regarded as desert, glaciers, and bare rock; larger than 0.9 is theoretically seen as forest [6]. Additionally, Xiao et al. [7] assumed that an NDVI value larger than 0.6 is detected as non-urban. Hence, NDVI data with a pixel value larger than 0.1 and less than 0.6 were used as a mask to remove natural features situated within urban areas from the primary urban maps in China. Based on the difference of geographic environment, a mask with values between 0.1 and 0.5 was applied in Xinjiang, Tibet, Qinghai, Gansu, Ningxia, Inner Mongolia, Yunnan, and Shaaxi. NDVI data from July were selected as the mask in this study because they could commendably reflect the distribution of vegetation [7]. Moreover, water body data were further applied to identify small water bodies in the primary urban maps. The reclassified results were generally treated as the reclassified urban maps (Figure S3c,d) in this study. The urban areas were assumed to continuously grow outward [8], and an urban pixel of reclassified urban maps in an earlier year would remain as urban in a later year. In this study, we applied an identical threshold value of 5 km as the growth limit for every four years. In other words, urban expansion continuously grows outward within a 1.25 km buffer in a later year. Based on the above principle, the data process can be summarized by the following formula:

$$DN_{(n,i)} = \begin{cases} 0 & DN_{(n+1,i)} = 0 \\ 1 & DN_{(n-1,i)} = 0 \; or \; DN_{(n-1,i)} = 1' \end{cases} \quad (1)$$

where $DN_{(n,i)}$ and $DN_{(n\text{-}1,i)}$ are the class values (urban or non-urban) at the ith pixel in the nth and $n-1$th years respectively. A class value of 1 represents urban while 0 represents non-urban.

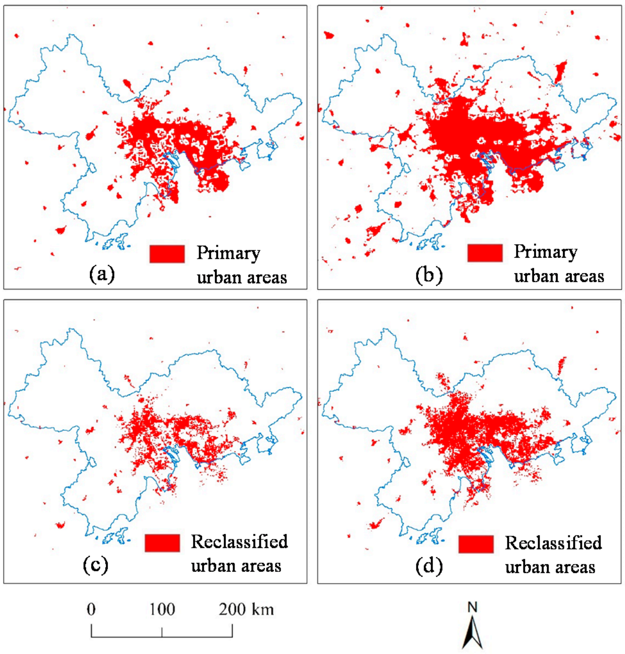

Figure S3. Mapping primary and reclassified urban maps. (**a**,**b**) represent the primary urban maps; (**c**,**d**) represent the reclassified urban maps. Note: based on current data availability and coordination, the 2010 NDVI data were adopted as an alternative in 2013.

References

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