Quantifying annual changes in built-up area in complex urban-rural landscapes from analyses of
PALSAR and Landsat images

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Abstract: Built-up area supports human settlements and activities, and its spatial distribution and temporal dynamics have significant impacts on ecosystem services and global environment change. To date, most of urban remote sensing has generated the maps of impervious surfaces, and limited effort has been made to explicitly identify the area, location and density of built-up in the complex and fragmented landscapes based on the freely available datasets. In this study, we took the lower Yangtze River Delta (Landsat Path/Row: 118/038), China, where extensive urbanization and industrialization have occurred, as a case study site. We analyzed the structure and optical features of typical land cover types from (1) the HH and HV gamma-naught imagery from the Advanced Land Observation Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR), and (2) time series Landsat imagery. We proposed a pixel- and rule-based decision tree algorithm to identify and map built-up area at 30-m resolution from 2007 to 2010, using PALSAR HH gamma-naught and Landsat annual maximum Normalized Difference Vegetation Index (NDVI_{max}). The accuracy assessment showed that the resultant annual maps of built-up had relatively high user (87 - 93%) and producer accuracies (91 - 95%) from 2007 to 2010. The built-up area was 2,805 km² in 2010, about 16% of the total land area of the study site. The annual maps of built-up in 2007-2010 show relatively small changes in the urban core regions, but large outward expansion along the peri-urban regions. The average annual increase of built-up areas was about 80 km² per year from 2007 to 2010. Our annual maps of built-up in the lower Yangtze River Delta clearly complement the existing maps of impervious surfaces in the region. This study provides a promising new approach to identify and map built-up area, which is critical to investigate the interactions between human activities and ecosystem services in urban-rural systems.

Keywords: Built-up, Impervious surface, Urban-rural area, Landsat, PALSAR, Shanghai

1. Introduction

Human activities are changing the world's landscapes in pervasive ways to obtain food, fiber, timber and other ecosystem services, and these disturbances alter a series of ecological functions for many ecosystems (DeFries et al. 2004). Artificial impervious surfaces (cities, towns and settlements) are the most intensive disturbance to natural ecosystems. Although they cover only a small fraction ($< 1\%$) of the world's land surface (Schneider et al. 2010), their expansion has a significant impact on regional temperature (Kalnay and Cai 2003; Weng et al. 2011) and rainfall (Miao et al. 2011; Zhang et al. 2009), biodiversity loss (Güneralp and Seto 2013; Seto et al. 2012), public health (Gong et al. 2012), and the carbon cycle (Seto et al. 2012).

Remote sensing can map urban and impervious surfaces in a repeat and consistent way (Lu et al. 2014; Weng 2012). Various image statistics based algorithms have been used to map urban and impervious surfaces (Weng 2012), including visual image interpretation, supervised image classification, unsupervised image classification, and spectral index threshold methods. Several sub-pixel algorithms have also been developed, as the spectral mixture features of urban and impervious surfaces can be described as linear combinations of 3- (high albedo, dark and vegetation) or 4- (high albedo, low albedo, vegetation and soil) end-members (Lu and Weng 2006; Small 2005).

Urban and impervious surfaces can be mapped through broadband optical remote sensing imagery (Table 1). Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat imagery are two major data sources for urban and impervious surface mapping. The global urban extent and spatio-temporal changes of urban extent in East-Southeast Asia were generated from MODIS imagery at 500-m spatial resolution (Schneider et al. 2009, 2010; Schneider and Mertes 2014; Schneider et al. 2015). As Landsat datasets in the U. S. Geological Survey (USGS) archive

64 become freely available to the public, 30-m Landsat imagery is being increasingly used for
65 mapping the expansion of large cities from the 1980s (Bagan and Yamagata 2012; Gao et al.
66 2012; Li et al. 2015; Schneider and Mertes 2014; Wang et al. 2012). However, none of the
67 above-mentioned data products explicitly separate built-up from impervious surfaces. Built-up
68 areas are the main component of human settlements and the major place for human activities.
69 Accurate maps of built-up are fundamentally important for human settlement design, planning
70 and management, and for investigating how to balance the trade-off between urban development
71 and ecosystem services (Yu et al. 2010).

72 **Table 1.** Summary of impervious surface and built-up area mapping from analyses of imagery from multiple sensors.

Land cover	Optical data				LiDAR data	SAR data		SAR/Optical data integration		
	MODIS	DMSP/OLS	Landsat/ASTER	IKONOS/QuickBird/SPOT	LiDAR	TerraSAR-X	PALSAR	TerraSAR-X/SPOT	ENVISAT ASAR/Landsat/SPOT	PALSAR/Landsat
Impervious surface	(Schneider et al. 2009, 2010)	(Pandey et al. 2013; Zhang and Seto 2011)	(Li et al. 2015; Weng et al. 2009)	(Lu and Weng 2009)	-	-	-	(Zhang et al. 2014)	(Zhang et al. 2012; Zhang et al. 2014)	(Lu et al. 2011; Zhu et al. 2012)
Built-up area	-	-	(Xu 2008; Zha et al. 2003)	(Florczyk et al. 2016; Gueguen et al. 2013; Pesaresi and Gerhardinger 2011; Pesaresi et al. 2008; Syrris et al. 2015) (Pesaresi et al. 2011) (Pesaresi et al. 2013)	(Yu et al. 2010)	(Esch et al. 2013; Esch et al. 2010)	(Zhang et al. 2011)	-	-	This study

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High and very high spatial resolution images from both optical sensors (e.g., SPOT, QuickBird) and airborne LiDAR provide opportunities for identifying built-up area (Myint et al. 2011; Pesaresi et al. 2011; Pesaresi and Gerhardinger 2011; Pesaresi et al. 2008; Pesaresi et al. 2013; Syrris et al. 2015; Weng 2009). The broad application of these high and very high spatial resolution images and LiDAR data at large scales have some challenges. First, these data are not freely available in many fast-developing regions, such as East-Southeast-South Asia and South America. Second, shadows of land cover may account for a significant proportion of high spatial resolution optical images, especially in urban areas (Zhou et al. 2009). Third, for the application of object-based algorithm, the level of scale to segment objects and the thresholds for built-up identification need further assessments in different regions (Myint et al. 2011; Weng 2012).

Microwave remote sensing (e.g., synthetic aperture radar, SAR) is independent of weather and day/night, and can capture the land cover structure and vegetation biomass. The potential of different SAR datasets (C and X bands) for urban extent mapping was recently explored (Esch et al. 2013; Esch et al. 2010; Gamba et al. 2011; Taubenbock et al. 2011). A recent study reported the use of multi-temporal, dual-polarization ALOS PALSAR images for built-up mapping (Zhang et al. 2011). However, relatively large commission and omission errors exist in their maps, as built-up have similar backscatter characteristics with forests and other land cover types; therefore only radar imagery is not sufficient to identify built-up accurately (Chen et al. 2016; Qin et al. 2015). Recent studies showed that the use of both radar and multispectral optical imagery could combine complementary information and hold great potential for improving land cover maps, for example, forests (Chen et al. 2016; Dong et al. 2012; Qin et al. 2016; Qin et al. 2015) and impervious surfaces (Zhang et al. 2012; Zhang et al. 2014; Zhu et al. 2012).

The objectives of this study are: (1) to develop a new and robust algorithm that combines ALOS PALSAR and Landsat images in a year to identify and map built-up in urban/rural settings at 30-m spatial resolution; and (2) to apply the pixel-based algorithm to evaluate the dynamics of built-up over years and generate annual maps of built-up areas at 30-m spatial resolution. We selected the lower Yangtze River Delta, China (Landsat Path/Row: 118/038) as the case study area, where rapid urbanization and industrialization has taken place over the past few decades, and provides an example of the urbanization in China (Liu et al. 2014). Specifically, we used PALSAR and Landsat images to track temporal changes of built-up from 2007 to 2010 at individual pixels and generate annual built-up maps in the lower Yangtze River Delta, China.

2. Material and methods

2.1. Study area

Our study area is located in the lower Yangtze River Delta of eastern China (Fig. 1), and covers an area of 17,076 km². This study area is flat, and the elevation has a range from sea level to 100 m. This region has a marine monsoon subtropical climate, with hot and humid summer, cool and dry winter, and warm spring and fall. The annual mean temperature is 16 °C, with the highest average temperature in July (27.8 °C) and the lowest average temperature in January (3.5 °C). The annual average rainfall is 1,160 mm, and 60% is concentrated from May to September.

Cropland and built-up land are the dominant land cover types, and each of them accounts for about 40% of the total land area (Yin et al. 2011). This study area has the largest megacity in China (Shanghai), along with some small to medium cities and rural areas. The built-up land extent has experienced unprecedented expansion since the “reform and opening-up policy” in 1978. The

area percentage of built-up land in Shanghai increased from 4% in 1979 to 42% in 2009 (Yin et al. 2011). The total human population increased from 11 million in 1979 to 22 million in 2009, with the population density from 1,838 people/km² to 3,486 people/km² (Ma and Ma 2014).

Fig. 1. The location of the study area and data availability in the lower Yangtze River Delta. a) False color composition of ALOS PALSAR Fine Beam Dual Polarization (FBD) data in 2010: Red (HH), Green (HV) and Blue (HH - HV), and the acquired date of PALSAR FBD data from 2007 to 2010. b) False color composition of Landsat TM image, acquired on April 18, 2011, with Red (SWIR), Green (NIR) and Blue (Green), and seasonal statistics of the numbers of Landsat TM/ETM+ images from 2006 to 2011.

2.2. Landsat and ALOS PALSAR imagery processing

We built a workflow to process time series Landsat TM/ETM+ and ALOS PALSAR images for mapping built-up area (Fig. 2). For Landsat imagery, the workflow included atmospheric correction, the identification of bad quality observations (Scan Line Corrector (SLC)-off strips, clouds, cloud shadows, and snow/ice), vegetation index calculation, and water body

mask. For ALOS PALSAR imagery, the digital number (DN) was converted into backscattering coefficient in decibels.

Fig. 2. The workflow for tracking and mapping built-up areas in the lower Yangtze River Delta, based on the combination of Landsat TM/ETM+ and PALSAR FBD images.

2.2.1. Landsat TM/ETM+ images and preprocessing

We downloaded all the available Landsat TM and ETM+ images (path/row 118/038) from 2006 to 2011 from the USGS EDC website, a total of 73 Landsat TM images and 101 Landsat ETM+ images. The standard Level 1 Terrain-corrected (L1T) images, and other images with

different processing levels are all included in the data processing. About 35 images are available in 2006, 2007 and 2008, and about 20 images in 2009, 2010 and 2011, respectively (Fig. 1b).

2.2.1.1. Atmospheric correction

The Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) software was used to convert the raw DN values from Landsat images to land surface reflectance. The LEDAPS applies MODIS 6S radiative transfer models to retrieve top of atmosphere reflectance and land surface reflectance (Masek et al. 2006; Vermote et al. 1997); using Landsat images and ancillary datasets, such as water vapor, ozone, geopotential height, aerosol optical thickness and digital elevation.

2.2.1.2. Bad quality observations

Bad quality observation detection is an essential step for the utilization of optical remote sensing images. In this study, the bad quality observations include SLC-off strips, clouds, cloud shadows and snow/ice cover. These bad quality observations were excluded for data analysis:

1) SLC-off strips. The SLC onboard Landsat 7 failed after May 31, 2003, which result in SLC-off strips to Landsat ETM+ images. A SLC-off strips layer (gap_mask) is available to label and mask no observation pixels in individual Landsat ETM+ images.

2) Clouds and cloud shadows. Clouds and shadows are a significant problem for time series analysis of Landsat imagery (Goodwin et al. 2013), and their detection is an initial step in most analysis. Fmask software was applied to develop clouds and cloud shadows layers for each of the Landsat TM and ETM+ images (Zhu and Woodcock 2012).

3) Snow and ice covers. Snow and ice cover have high reflectance in the visible spectral bands and can potentially affect the values of vegetation indices, especially for Land Surface Water Index (LSWI) and Enhanced Vegetation index (EVI) (Xiao et al. 2006; Xiao et al. 2005). We used the Normalized Difference Snow and Ice Index (NDSI) and reflectance of NIR ($NDSI > 0.4$ and $NIR > 0.11$) to generate snow/ice masks for each image (Hall et al. 1995; Hall et al. 2002).

2.2.1.3. Statistical analysis of good quality observations of time series Landsat images

The numbers of good quality observations at individual pixels from 1-year Landsat TM/ETM+ images vary over space (Fig. 3a-d). About 98.4%, 98.4%, 98.2% and 97.8% of pixels had more than 10 good quality observations for 2007, 2008, 2009 and 2010, respectively (Fig. 3i). We calculated the percentage of good quality observations at pixel level, *i.e.*, the ratio of good quality observation numbers to the total observation numbers within a year (Fig. 3e-h). About 89.9%, 94.0%, 95.8% and 96.4% of pixels had more than 20% good quality observations for 2007, 2008, 2009 and 2010, respectively (Fig. 3j).

Fig. 3. The numbers and percentage of good quality observations at pixel level from 1-year Landsat TM/ETM+ images. (a-d) and (e-h) are the numbers and percentage of good quality observations of Landsat images in nominal years (3-year moving window), Y2007 (2006 - 2008), Y2008 (2007 - 2009), Y2009 (2008 - 2010), and Y2010 (2009 - 2011), respectively. i) and j) are the statistics of the numbers and percentage of Landsat good quality observations for 2007, 2008, 2009, and 2010, respectively.

2.2.1.4. Vegetation indices

We calculated three vegetation indices (NDVI, EVI and LSWI) for each Landsat image, which were used to analyze the spectral and biophysical features of typical land cover types. NDVI (Rouse et al. 1974) and EVI (Huete et al. 2002; Huete et al. 1997) were used to assess the greenness of land surface. LSWI is sensitive to leaf water and soil moisture (Xiao et al. 2002a, b). We applied $LSWI - EVI \geq 0$ to map inundated pixels, including water bodies (Xiao et al. 2006; Xiao et al. 2005). We calculated annual maximum NDVI ($NDVI_{max}$) for 2007-2010, respectively (Fig. 4a).

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}$$

$$EVI = 2.5 \times \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + 6 \times \rho_{red} - 7.5 \times \rho_{blue} + 1}$$

$$LSWI = \frac{\rho_{nir} - \rho_{swir}}{\rho_{nir} + \rho_{swir}}$$

where ρ_{blue} , ρ_{red} , ρ_{nir} and ρ_{swir} are the land surface reflectance values of Blue (0.45 – 0.52 μm), Red (0.63 – 0.69 μm), NIR (0.77 – 0.90 μm) and SWIR (1.55 – 1.75 μm) band for Landsat TM/ETM+ images.

Fig. 4. The spatial distribution of annual maximum NDVI (a), water frequency (b), HH gamma-naught (c), and HV gamma-naught (d) in 2010.

2.2.2. 25-m ALOS PALSAR ortho-rectified mosaic dataset and preprocessing

The 25-m PALSAR ortho-rectified mosaic data at Fine Beam Dual Polarization (FBD) mode from 2007 to 2010 is available from Japan Aerospace Exploration Agency (JAXA). They were aggregated from the original observation with minimum response to surface moisture (Shimada et al. 2014). The dataset is organized in latitude-longitude coordinates, and has 4500 columns by 4500 rows per tile. The dataset includes HH and HV gamma-naught backscatter, local incidence angle and mask information, and total dates since the ALOS launch. The HH and HV data are slope corrected and orthorectified, and radiometrically calibrated.

The DN values (amplitude values) were converted into gamma-naught using a calibration coefficient, which is insensitive to the focus of the impulse response (Shimada et al. 2009). A 3 by 3 pixel median filter was applied on PALSAR HH and HV imagery to reduce speckle noise. Then we resampled the 25-m PALSAR HH and HV imagery into 30-m imagery (Fig. 4c and 4d) to match 30-m Landsat imagery using the nearest neighborhood interpolation.

$$\gamma^{\circ} = 10 \times \log_{10} \langle DN^2 \rangle + CF$$

where γ° is the backscattering coefficient in decibel; DN is the digital number value of pixels in HH or HV; and CF is the absolute calibration factor of -83.

2.3. Ground reference data for algorithm training from very high spatial resolution images

As the landscape is complex and fragmented, relatively small Region of Interests (ROIs) are suitable to reduce the influence from mixed pixels. We created 2,000 60-m $\times$ 60-m random

rectangles in the shapefile format, with a minimum distance of 1,000 m between ROIs. These 2,000 polygons were converted into kml format and overlaid to very high spatial resolution images in Google Earth. The very high spatial resolution images of the main growing season for each year were selected for land cover type interpretation. If no image was available in a certain year, the very high spatial resolution images before and after this year were chosen as the referenced images. Each ROI (a 60-m $\times$ 60-m rectangle) with 50% or more area occupied by built-up area was classified as built-up area. Out of the 2000 polygons, 821 ROIs (3,280 pixels) are common (consistent) from 2007 to 2010, and thus used for algorithm training (Table 2). These include 80 built-up ROIs (320 pixels), 2 forest ROIs (8 pixels), 43 cropland ROIs (172 pixels), 2 grassland ROIs (8 pixels), 20 pond ROIs (80 pixels), 76 wetland ROIs (304 pixels), and 598 water ROIs (2,388), respectively. The spatial distribution of selected ROIs for algorithm training is shown in Fig. 5a.

Table 2. Annual ground reference data for the algorithm training of built-up area identification and the validation of the resultant built-up/nonbuilt-up areas from 2007 to 2010.

Land cover		2007 (ROIs# (pixels#))	2008 (ROIs# (pixels#))	2009 (ROIs# (pixels#))	2010 (ROIs# (pixels#))
Training samples	Built-up	80 (320)	80 (320)	80 (320)	80 (320)
	Forest	2 (8)	2 (8)	2 (8)	2 (8)
	Cropland	43 (172)	43 (172)	43 (172)	43 (172)
	Grassland	2 (8)	2 (8)	2 (8)	2 (8)
	Pond	20 (80)	20 (80)	20 (80)	20 (80)
	Wetland	76 (304)	76 (304)	76 (304)	76 (304)
	Water	598 (2,388)	598 (2,388)	598 (2,388)	598 (2,388)
	Total	821 (3,280)	821 (3,280)	821 (3,280)	821 (3,280)
Validation samples	Built-up	69 (276)	77 (308)	96 (384)	104 (416)
	NonBuilt-up	571 (2,278)	583 (2,326)	830 (3,308)	976 (3,892)
	Total	640 (2,554)	660 (2,634)	926 (3,692)	1,080 (4,208)

Fig. 5. Random ground reference for algorithm training (a) and map accuracy assessment (b) of built-up area at the spatial resolution of 60 meters in 2010, acquired from high spatial resolution images in Google Earth.

2.4. Algorithm for identifying built-up area through PALSAR and Landsat images

In this study, built-up pixels are defined as the areas covered by 50% or more built-up area (Li et al. 2015; Schneider et al. 2009, 2010). Compared with other land cover types, built-up area

has three of the following biophysical features. First, built-up area is covered by various human-made materials with different colors, shapes and spectral characteristics. Second, built-up area is usually mixed with other land cover types (e.g., trees, shrubs, grassland, and water bodies), and have low greenness. Third, built-up area has obvious 3-dimensional structure above the ground.

2.4.1. Signature analysis of land cover types

Fig. S1 in the supplementary material shows an example of the 2-dimensional scatter plot/density maps of PALSAR HH and Landsat NDVI_{max}, and PALSAR HV and Landsat NDVI_{max} in the Yangtze River Delta in 2010. Most of the water pixels have low HH, HV and NDVI_{max} values. The other land cover types hold their specific distribution patterns, while their HH, HV and NDVI_{max} boundaries are blurred, which may be contributed to by the mixed pixels in the fragmented landscapes.

For signature analysis of major land cover types, we investigated the relationship between NDVI_{max} and HH, and HV for each year. We calculated their mean and standard deviation values, and generated eight 2-dimensional scatter plots between NDVI_{max} and HH, and HV of typical land cover types from 2007 to 2010, respectively (Fig. 6). Water has the lowest backscatter values in both HH and HV, because of the smooth surface and can reflect most of the backscatter through specular reflectance. Built-up and forests show high backscatter values in both HH and HV due to their strong corner reflectance. Forests have leaves, branches, stems and trunks, which can result in relatively more complex structure and internal reflection environment than those of built-up areas. Therefore, built-up areas have relatively stronger backscatter in HH, and weaker backscatter in HV than those of forests. Croplands, wetlands, grasslands and ponds have low backscatter values in both HH and HV. Therefore, HH is selected for mapping built-up area in this study.

266 NDVI_{max} shows good ability to distinguish built-up area from other typical land cover types
267 (Fig. 6). Open surface water bodies have little or no vegetation, and its NDVI_{max} value is around
268 0. Built-up have a relatively low amount of vegetation, and their average NDVI_{max} values are
269 around 0.4, while forests and croplands have large vegetation and their average NDVI_{max} values
270 are around 0.8. Thus, NDVI_{max} is used to further reduce commission errors from forests and
271 croplands, and refine built-up area.

272

273 **Fig. 6.** Characteristics of typical land cover types from Landsat and PALSAR images. (a-d) are 2-dimension scatter plots between HH
 274 gamma-naught and annual maximum NDVI (NDVI_{max}) from 2007 to 2010, respectively. (e-h) are 2-dimension scatter plots between
 275 HV gamma-naught and NDVI_{max} from 2007 to 2010, respectively. The mean value and error bar (+/- one standard deviation) are
 276 presented.

To quantitatively analyze the separability of these typical land cover types, we calculated the Transformed Divergence (TD) separability index (Swain 1972) using the ground reference data. This index has a value range from 0 to 2.0, which indicates the level of separability of the selected ROI pairs (Jensen 1996). TD values larger than 1.9 indicate that the ROI pairs have a good separability, values between 1.7 and 1.9 for a moderate separability, and values below 1.7 show a poor separability. Most of the TD values were larger than 1.9 in this study (Table 3), which indicated good separability between built-up and forests, croplands, grasslands, ponds, water and wetlands using the combination of PALASR HH, NDVI_{max} and water frequency.

Table 3. Transformed Divergence separability values between built-up and other typical land cover types from 2007 to 2010.

Land cover	2007	2008	2009	2010
Forest	2.000	2.000	2.000	2.000
Cropland	1.975	1.992	1.984	1.994
Grassland	2.000	2.000	2.000	2.000
Wetland	1.918	1.873	1.884	1.919
Pond	1.973	1.984	1.986	1.984
Water	2.000	2.000	2.000	2.000

2.4.2. Algorithm to identify built-up area

We first excluded the boats and wetlands in the Yangtze River, as they may have similar backscatter features with built-up area. We generated an open surface water body map using time series Landsat images in each year. The algorithm counted the numbers of observations in which a pixel had $LSWI - EVI \geq 0$ out of all the good quality observations and then divided it by the total number of good quality observations (Dong et al. 2015; Xiao et al. 2006; Xiao et al. 2005). Those

pixels with a resultant ratio value $\geq 80\%$ are identified as year-long open surface water body (Fig. 4b).

PALSAR HH and Landsat $NDVI_{max}$, representing the structure and greenness, showed stable features for built-up area during 2007 – 2010 (Fig. 6a-d), and were selected to map built-up area. Built-up areas are featured in high HH backscatter values and low $NDVI_{max}$ values (~ 0.6). Built-up are likely to be confused with parts of forest in HH, but forest has large leaf area index (LAI), often higher than $3 \text{ m}^2/\text{m}^2$ (Gamon et al. 1995; Turner et al. 1999), which corresponds to $NDVI_{max}$ values larger than 0.7 (Gamon et al. 1995; Jiao et al. 2014; Turner et al. 1999). The lowest 5% of HH gamma-naught and the highest 5% $NDVI_{max}$ values of ground reference for built-up were excluded, as they may have high probability of random errors. The values of HH and $NDVI_{max}$ at the 95% confidence level, calculated based on the training datasets, were chosen as the thresholds to map built-up area:

$$(HH \geq -9) \&\& (NDVI_{max} < 0.6)$$

A temporal and logical consistency check was applied to reduce the random commission and omission errors of built-up areas (Schneider and Mertes 2014). Each pixel from 2007 to 2010 has 16 different built-up (B) and non built-up (N) combinations over years. The reasonable (NNNN, NNNB, NNBB, NBBB, BNNN, BBNN, BBBN and BBBB) and random (NBNB, NBBN, BNNB and BNNB) combinations remained to be unchanged, while the consistency filter was applied to the unreasonable combinations ($NNBN \rightarrow NNNN$, $NBNN \rightarrow NNNN$, $BNBB \rightarrow BBBB$, and $BBNB \rightarrow BBBB$). After this consistency check, we generated annual maps of built-up areas in 2007-2010.

2.5. Accuracy assessment of the resultant annual built-up maps from 2007 to 2010

The same process as shown in Section 2.3 was used to generate the ground reference data for the accuracy assessment of the annual built-up/nonbuilt-up maps. 3,000 random 60-m $\times$ 60-m ROIs were generated to select the validation ROIs across the study area. In total, we got 69 ROIs (276 pixels), 77 ROIs (308 pixels), 96 ROIs (384 pixels) and 104 ROIs (416 pixels) for built-up and 571 ROIs (2,278 pixels), 583 ROIs (2,326 pixels), 830 ROIs (3,308 pixels) and 976 ROIs (3,892 pixels) for nonbuilt-up from 2007, 2008, 2009 and 2010, respectively (Table 2). Then we used these ROIs to build a confusion matrix for the accuracy assessment of built-up/nonbuilt-up map in each year, including overall accuracy, kappa coefficient, producer accuracy/omission error, and user accuracy/commission error.

2.6. Comparison between the built-up maps and impervious surface maps generated by multiple data sources and algorithms

In this study, another four annual built-up maps were generated by the image-based Support Vector Machine (SVM) algorithm and the same input datasets, *i.e.*, PALSAR HH, NDVI_{max}, and percentage of (LSWI $\geq$ EVI), as did our decision tree algorithm. We also collected four other impervious surface products to compare their consistency and differences, including 30-m FROM-GLC (Gong et al. 2013), 30-m Globeland30 (Chen et al. 2015), 1-km fraction NLCD-China (Liu et al. 2014) and 500-m MCD12Q1 (Friedl et al. 2010). Table 4 shows the general information about the built-up areas and impervious surface maps. We analyzed the consistency and difference between the built-up areas and the impervious surface maps.

335 **Table 4.** Summary of built-up area and impervious surface maps generated by multiple data sources and algorithms in 2010.

Products	Definition	Data source	Training data	algorithm	Minimum unit (m ²)	Validation data	Spatial resolution (m)	Accuracy
PALSAR/Landsat	Land covered by 50% or more built-up area.	PALSAR HH, Landsat NDVI _{max} , and frequency of (LSWI-EVI ≥ 0)	80 and 741 random selected ROIs (60m $\times$ 60m) for built-up and nonbuilt-up, respectively.	Decision tree	900	104 and 1935 random selected ROIs (60m $\times$ 60m) for built-up and nonbuilt-up, respectively.	30	UA: 87%, PA: 94%
PALSAR/Landsat _{SVM}	Same as above.	Same as above.	Same as above.	SVM	900	Same as above.	30	UA: 72%, PA: 97%
FROM-GLC (Gong et al. 2013)	Artificial cover (asphalts, concrete, sand and stone, bricks, glasses, and other cover materials)	Single Landsat TM/ETM+ from 1984 to 2011	91,433 training samples were interpreted in all available Landsat images.	SVM	900	Five random samples were set in each hexagon and 36,630 random selected samples were selected.	30	UA: 31%, PA: 11%
Globeland30 (Chen et al. 2015)	Artificial surfaces (urban areas, roads, rural cottages and mines).	Single Landsat TM/ETM+ and HJ-1 with few clouds	NA	A pixel-object-knowledge-based (POK-based) classification approach	14,400	159,874 pixel samples were selected from 80 map sheet samples.	30	UA: 87%
NLCD-CHINA (Liu et al. 2014)	Urban, rural settlement and industry-traffic land	Single Landsat TM (90%), CBERS and HJ-1A	Interpretation symbols for each land use/cover type	Visual interpretation	40,000	Repeated interpretation of randomly extracted 10% counties. Extensive field survey.	1,000 (fraction)	> 96%
MODIS12Q1 (Friedl et al. 2010)	Land covered by buildings and other man-made structures.	Twelve sets of 32-day average NBAR, LST and EVI data; annual metrics (minimum, maximum and mean values) of EVI, LST and NBAR bands.	1,860 sites with manual interpretation from Landsat or high spatial resolution imagery. The size of sites ranges from 0.2 km ² to 80 km ² .	Supervised classification	250,000	10-fold cross-validation from training sites.	500	NA

UA: User accuracy, PA: Producer accuracy.

3. Results

3.1. Spatial distribution and area estimation of 30-m PALSAR/Landsat built-up maps in the Yangtze River Delta

Fig. 7 shows the annual PALSAR/Landsat built-up areas at the spatial resolution of 30 meters in the Yangtze River Delta from 2007 to 2010. These four annual built-up maps have similar spatial distribution patterns. The southern region is dominated by the megacity of Shanghai, with large areas of urban and peri-urban built-up areas. The northern region is part of Yangtze Plain, a major agriculture production region in China, and the rural built-up areas are widely distributed in a linear pattern. The areas of classified built-up were about 2,565 km², 2,591 km², 2,599 km² and 2,805 km², about 15.02%, 15.17%, 15.22% and 16.42% of the total study area from 2007 to 2010, respectively.

Fig. 7. Annual spatial distribution of PALSAR/Landsat built-up maps at the spatial resolution of 30 meters in the Yangtze River Delta from 2007 to 2010.

3.2. Accuracy assessment of built-up maps in the Yangtze River Delta

We calculated the confusion matrix based on the built-up and non built-up ROIs (section 2.5) and used them to assess the accuracy of the built-up maps (Table 5). The PALSAR/Landsat built-up maps generated by the rule-based decision tree algorithm were assessed with high accuracies. Each built-up and non built-up map had an overall accuracy of 98%, and Kappa coefficient of 0.90 from 2007 to 2010. Non built-up category had relatively higher user and producer accuracies than those of built-up category. The user accuracies of built-up areas were about 86.9%, 92.7%, 89.9% and 88.2% from 2007 to 2010, which is slightly lower than their producer accuracies (91.3%, 95.1%, 92.2% and 93.5%). The moderate commission errors may come from the mixed pixels in the complex and fragmented landscape. The application of the temporal and logical consistency filter for the built-up/non built-up maps in both 2008 and 2009 yielded relatively higher user and producer accuracies than those in 2007 and 2010.

Table. 5. Accuracy assessment of annual built-up maps in the Yangtze River Delta, using the ground reference data selected from very high spatial resolution images in Google Earth.

Year	Ground truth samples		Total classified pixels	User accuracy (%)	Commission error (%)
	Built-up	Non built-up			
2007	Built-up	252	38	290	86.9
	Non built-up	24	2240	2264	98.94
	Total ground truth pixels	276	2278	2554	
	Producer accuracy (%)	91.3	98.33		Overall accuracy = 97.57
	Omission error (%)	8.7	1.67		Kappa coefficient = 0.88
2008	Built-up	293	23	316	92.72
	Non built-up	15	2303	2318	99.35
	Total ground truth pixels	308	2326	2634	
	Producer accuracy (%)	95.13	99.01		Overall accuracy = 98.56
	Omission error (%)	4.87	0.99		Kappa coefficient = 0.93
2009	Built-up	354	40	394	89.85
	Non built-up	30	3268	3298	99.09
	Total ground truth pixels	384	3308	3692	
	Producer accuracy (%)	92.19	98.79		Overall accuracy = 98.10
	Omission error (%)	7.81	1.21		Kappa coefficient = 0.90
2010	Built-up	389	52	441	88.21
	Non built-up	27	3840	3867	99.30
	Total ground truth pixels	416	3892	4308	
	Producer accuracy (%)	93.51	98.66		Overall accuracy = 98.17
	Omission error (%)	6.49	1.34		Kappa coefficient = 0.90

3.3. Built-up expansion in the Yangtze River Delta from 2007 to 2010

We used the annual PALSAR/Landsat built-up maps to identify their spatio-temporal changes during 2007 – 2010. Built-up extent continued to increase under the influence of economic development and increasing population, with an average increase of 80 km² per year. Built-up areas showed obvious spatio-temporal change patterns. Firstly, the extent of most built-up area is stable, especially in the urban core areas (Fig. 8a), which usually has the priority to be developed with high density of built-up. Secondly, the spatial changes of built-up areas were characterized by outward expansion, mainly located in the peri-urban areas (Fig. 8b). Thirdly, some of rural built-up were out of detection because of the low coverage of built-up in mixed pixels (Fig. 8c&d).

Fig. 8. Spatio-temporal changes of 30-m PALSAR/Landsat built-up areas from 2007 to 2010. a) Built-up in the urban core area, b) built-up in peri-urban area, c) and d) built-up in rural area. (a1 – d1) are the zoom-in PALSAR/Landsat built-up areas. (a2 – d2) are Landsat TM image acquired

on April 18, 2011, with the false color composition: R (SWIR), G (NIR), and B (Green). (a3 – d3)
are high spatial resolution images from Google Earth acquired around 2010.

4. Discussion

4.1. A comparison between the maps of built-up area and the maps of impervious surfaces

Built-up are a subset of impervious surfaces and have smaller area and spatial extent than those of impervious surfaces. Fig. 9 showed the spatial distributions of the built-up maps from 30-m PALSAR/Landsat, and the impervious surface maps from 30-m FROM-GLC, 30-m GlobeLand30, 1-km NLCD-China and 500-m MCD12Q1 in 2010. The total area of built-up estimated by our approach (2,805 km²) is smaller than the impervious surface area estimated by the GlobeLand30 (3,151 km²) and NLCD-China (3,167 km²), but much larger than the impervious surface area estimated by the FROM-GLC (2,339 km²) and MCD12Q1 (1,728 km²). Both the GlobeLand30 and NLCD-China were generated by interactive visual interpretation of single Landsat TM/ETM+ images, therefore, they had a reasonable estimation of impervious surface area (Chen et al. 2015; Liu et al. 2014). The user and producer accuracies of the FROM-GLC impervious surfaces are only 31% and 11%, and the spatial resolution of MCD12Q1 is about 500 meters, which is too coarse for mapping the built-up (Friedl et al. 2010; Gong et al. 2013). The comparison in this study suggests that both the FROM-GLC and MCD12Q1 impervious surface maps need substantial improvement in the future.

At the pixel level, we aggregated these built-up and impervious surface maps from original spatial resolutions into 1-km fraction maps using nearest neighborhood resampling algorithm and further compared their spatial consistencies and differences (Fig. 10). Significant linear relationships exist between PALSAR/Landsat built-up map and the impervious surface maps (Fig.

10e-h). The area of GlobeLand30, NLCD-China, FROM-GLC, and MCD12Q1 impervious surface were about 105%, 105%, 90%, and 74% of the area of PALSAR/Landsat built-up, respectively. In the urban core, the area fraction of the built-up map was reasonably lower (~ 0.1) than those of impervious surface maps, except for parts of the FROM-GLC (Figs. 10 and S2a). In the peri-urban and rural area, the area fraction of the built-up maps had relatively larger estimation (≥ 0.2) than those of impervious surface maps, especially for the FROM-GLC and MCD12Q1 (Figs. 10 and S2b-c). The spatial comparison between our built-up map and the impervious surface maps clearly provide insight for the improvement of the impervious surface maps in the future.

Fig. 9. Spatial distribution of built-up and impervious surface maps in 2010. a) 30-m PALSAR/Landsat built-up map. b) 30-m impervious surface from FROM-GLC. c) 30-m impervious surface from Globeland30. d) 1-km area fraction of impervious surface from NLCD-China. e) 500-m impervious surface from MCD12Q1.

Fig. 10. Spatial differences between PALSAR/Landsat built-up map and impervious surface maps from FROM-GLC (a), Globeland30 (b), NLCD-China (c) and MCD12Q1 (d). Linear relationships between PALSAR/Landsat built-up map and impervious surface maps from FROM-GLC (e), Globeland30 (f), NLCD-China (g), and MCD12Q1 (h) at the spatial resolution of 1-km.

4.2. A comparison of built-up area identification algorithms: image-based SVM versus pixel- and rule-based decision tree method

At the 30-m pixel scale, the PALSAR/Landsat built-up maps had good agreement with PALSAR/Landsat_{SVM} built-up maps from 2007 to 2010. Fig. 11 showed the spatial comparison between PALSAR/Landsat built-up maps and PALSAR/Landsat_{SVM} built-up maps. The urban core areas have high density of built-up and not much vegetation coverage, and both pixel-based

decision tree algorithm and image-based SVM work well for built-up identification and present good consistency. In total, about 92.7%, 93.1%, 93.2% and 95.5% of built-up and non built-up were identified by both the decision tree algorithm and SVM for 2007, 2008, 2009 and 2010, respectively (Fig. 11).

PALSAR/Landsat_{SVM} built-up maps had higher commission errors (~30%) than those of PALSAR/Landsat built-up maps (Table S1). Image-based SVM is derived from statistical learning theory, and separates land classes with a decision surface that maximized the margin between classes. SVM has three major disadvantages (Suykens J.A.K. et al. 2003): (1) high algorithmic complexity, (2) extensive memory requirements, and (3) certain risk that some pixels may not fit the user-defined classes. The SVM overestimated the built-up area by about 1,174 km² (6.9% of the total pixels), 1,135 km² (6.6%), 1,097 km² (6.4%) and 625 km² (3.7%), in comparison to the pixel- and rule-based decision tree algorithm for 2007, 2008, 2009 and 2010, respectively. These overestimated pixels were mainly located at the edge of urban areas, or in peri-urban and rural areas (Fig. 12), contributed to by the mixed pixels of built-up and other land cover types. In addition, the built-up maps identified by SVM does not show the continuity of built-up expansion, as the annual built-up areas were about 3,664 km², 3,677 km², 3,632 km² and 3,286 km² from 2007 to 2010.

Built-up areas have similar spectral, spatial and texture features (Weng 2012). The thresholds for built-up identification in PALSAR HH and Landsat NDVI_{max} are consistent from 2007 to 2010, based on their feature analysis from the ground reference data (Fig. 6). The pixel- and rule-based decision tree algorithm has relatively simple, explicit and intuitive classification structure, and no assumption about the distribution of input dataset (Friedl and Brodley 1997).

Therefore, the pixel and rule-based decision tree algorithm provides better built-up mapping result than did image-based SVM method, using PALSAR HH and Landsat NDVI_{max}.

Fig. 11. Spatial comparison between PALSAR/Landsat built-up maps and PALSAR/Landsatsvm built-up maps from 2007 to 2010.

Fig. 12. Zoom-in regions of the spatial comparison between PALSAR/Landsat built-up and PALSAR/Landsat_{SVM} built-up from 2007 to 2010

4.3. Potential of our pixel- and rule-based decision tree algorithm for identifying and mapping built-up area

Recent studies have been focusing on urban and impervious surface expansion and their impacts on carbon emission (Seto et al. 2012), biodiversity loss (Güneralp and Seto 2013; Seto et al. 2012) and climate change (Kalnay and Cai 2003; Miao et al. 2011; Weng et al. 2011; Zhang et al. 2009). However, the area, spatial distribution and density information of built-up along urban-rural areas have been hardly investigated. The pixel-based decision tree algorithm proposed in this study has the potential to map built-up in both urban and rural settings at the spatial resolution of 30 meters, which enables people to investigate the spatial patterns of built-up in the urban/rural landscapes. Accurate built-up maps could be used to estimate population density in different communities. Use of these maps could help to investigate their pressure on environment, which will deepen our understandings about effects of human activities on both climate and global environment change (He et al. 2014; IPCC 2007; Kalnay and Cai 2003; Sellers et al. 1997).

From the perspective of optical remote sensing, built-up in urban cores are often difficult to distinguish from barren land and sparse vegetation classes, while built-up in peri-urban and rural areas are easily confused with vegetation classes (Friedl et al. 2010). We extended the identification features for built-up from spectral space to both spectral and structure spaces. PALSAR HH gamma-naught and Landsat NDVI_{max} presented stable and similar features for built-up over years, even though they were acquired in different months (Fig. 6). The potential of their combination was proven for built-up identification in the Yangtze River Delta. Based on the literature review, urban areas showed similar features of PALSAR HH backscatter in different climate regions, including boreal zone (Lonnqvist et al. 2010; Thiel et al. 2009), temperate zone (this study), subtropical zone (Chen et al. 2016) and tropical zone (Dong et al. 2012; Qin et al.

2015), respectively. Similar and slightly different thresholds from greenness ($NDVI_{max}$) and structure (HH gamma-naught) are expected to be effective for identifying and mapping built-up in other regions.

In this study, the 30-m Landsat and ALOS PALSAR imagery works well for large patches of built-up, but has limited ability to map small and scattered built-up in rural areas (Fig. 8). Finer spatial resolution imagery is needed to refine these mixed pixels and further calibrate the built-up maps. 10-m spatial resolution images would be suitable for mapping built-up in the complex urban-rural landscape (Lu et al. 2011), such as Sentinel-2 multispectral images and ALOS-2 PALSAR-2 Fine model L-band images.

5. Conclusions

Accurate estimation of the area, spatial distribution, and the density of regional built-up are fundamental information for human settlement design, planning and management. We proposed a novel approach to map spatial and temporal patterns of built-up through the integration of 30-m Landsat and 25-m ALOS PALSAR imagery. We used a combination of structure, greenness and water coverage information to map built-up area. The results showed that the proposed pixel- and rule-based decision tree algorithm can identify built-up area reasonably well in both urban and rural areas from 2007 to 2010, and improvement was achieved over image-based SVM algorithm. The average annual increase of built-up areas was about 80 km^2 per year. The built-up maps could refine current impervious surface products generated by optical images and prompt their improvement. The application of this proposed algorithm in large regions needs further validation, including additional case studies in hotspots of urbanization across the world. Annual built-up

maps at fine spatial resolutions are needed for better understanding the interaction between human activities and natural ecosystems.

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