

Extracting built-up areas from TerraSAR-X data using object-oriented classification method

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Abstract. Based on single-polarized TerraSAR-X, the approach generates homogeneous segments on an arbitrary number of scale levels by applying a region-growing algorithm which takes the intensity of backscatter and shape-related properties into account. The object-oriented procedure consists of three main steps: firstly, the analysis of the local speckle behavior in the SAR intensity data, leading to the generation of a texture image; secondly, a segmentation based on the intensity image; thirdly, the classification of each segment using the derived texture file and intensity information in order to identify and extract built-up areas. In our research, the distribution of BAs in Dongying City is derived from single-polarized TSX SM image (acquired on 17th June 2013) with average ground resolution of 3m using our proposed approach. By cross-validating the random selected validation points with geo-referenced field sites, Quick Bird high-resolution imagery, confusion matrices with statistical indicators are calculated and used for assessing the classification results. The results demonstrate that an overall accuracy 92.89 and a kappa coefficient of 0.85 could be achieved. We have shown that connect texture information with the analysis of the local speckle divergence, combining texture and intensity of construction extraction is feasible, efficient and rapid.

1. Introduction

Urban expansion has been served as one of the most important dynamic change processes in the context of global land use changes. The detrimental consequences of urban sprawl result in various urban environmental and ecological challenges, especially in most developing countries [1]. Therefore, in order to reduce the negative consequences, it is valuable for urban sustainable development to estimate and map accuracy built-up areas (BAs).

Radar satellite systems can acquire data at day and night without the consideration of the weather or environmental conditions. Consequently, radar data are more reliably available compared to optical imagery [2]. And the high spatial Resolution (HR) satellite images can offer a great potential for the extraction of information for urban areas [3]. In order to derive useful thematic maps from HR satellite images, traditional methods to extract information from high resolution satellite data include visual interpretation or pixel-based classification methods. Thomas et al. presented an overview and comparison of various classification methods for HR satellite data [3]. Until now, various advanced approaches have been developed to extract urban information from HR satellite images. Regarding the identification of settlements, based on IKONS data, H. Taubenbock et al. proposed an object-based, multi-level, hierarchical classification framework combining shape, spectral, hierarchical and contextual information for the extraction of urban features [4]. Guo et al. utilized C5.0 decision tree algorithm to select features extracted to build a decision tree for urban impervious surface

classification [5]. Ban performed urban detection using a generalized Kittler-Illingworth minimum error thresholding algorithm [6]. D. Marmanis implemented a deep learning technique for classifying above-ground objects within urban environments by using a multilayer perception model and VHSR DEM data [7]. Mourad Bouziani et al. proposes a new method for change detection of buildings in urban environments from very high spatial resolution images (VHR) and using existing digital cartographic data [8]. Andreas R. et al. demonstrated and discussed the potential of very high resolution radar imaging of urban areas by means of SAR and interferometric imaging [9]. Fauvel et al. proposed a technique called decision fusing, combining several individual classifiers [10]. Meher et al. presented a wavelet feature based classification method analysing the spatial and spectral characteristics of a pixel along with its neighbours [11]. T. Esch and Michael Thiel et al. presented an approach toward the semi-automated detection of BAs based on single-polarized TSX images [12]. There are several attempts to detect urban areas, utilizing medium-resolution images to map urban areas has solely focused on the settlements, industrial, and commercial zones. However, HR images can produce more detailed urban land cover such as individual roads and buildings in the urban environment. Based on segmentation and object-oriented classification method, we can take advantage of texture and intensity information to acquire more accurate result.

In this paper, based upon method presented by T. Esch et al [12], we improved this method to quickly extract BAs from single-polarized TerraSAR-X (TSX) stripmap model (SM) image. Firstly, accuracy true texture image is calculated by analysing local speckle characteristics. Secondly, the multi-resolution segmentation is performed using the original intensity image based on the software eCognition Developer. Finally, the objects of BAs are derived by combining information on the local true texture and local backscatter intensity.

2. Study area and data collection

Dongying City located in the north of Shandong province with longitude $118^{\circ}7'$ to $119^{\circ}10'$ and latitude $37^{\circ}20'$ to $38^{\circ}10'$. Land use of this area is dominated by settlements, roads, vegetation and water body. The data is based on single-polarized TerraSAR-X(TSX) images acquired in stripmap mode on June 11,2013. The average ground resolution of the image is $3\text{m} \times 3\text{m}$, with incidence angle of 44.47° .

3. Methodology

3.1. The principle of modelling build-up radar footprints

There are three main characteristics of buildings in SAR: layover, double-bounce, and shadowing effects, which are caused by the side-looking and ranging properties of radar sensor. In order to throw light upon this, Fig. 1 shows a schematic view of the scattering profile of a simplified gable-roof building model, which is imaged by a sensor with incidence angle θ . The annotation a refers to backscattering from the ground surface. acd denotes the layover area where scattering from the ground, from the vertical building front wall and from parts of the flat roof are superimposed since these parts have the same distance to the sensor [13]. b stands for double bounce effect that due to the ground-wall compose a corner reflector. d denotes the roof-scattering only. There is shadow effect in e. In Figure. 2(a) shows an example of a flat-roof building in 3m resolution TerraSAR-X data with viewing direction from left. The double-bounce line is highlighted with a red arrow, (b) is the same building in Google Earth. For gable-roof buildings as shown in Fig. 3, besides the main three scattering mechanisms, metallic structures lead to bright spots. acd is at the sensor close side resulting from direct backscattering from the roof. In Figure. 4(c) gives an example of gable-roof buildings with small aspect angles in 3m resolution TerraSAR-X data with viewing direction from left. The double-bounce and roof scattering lines are highlighted with red and yellow arrows, respectively, (d) is the same buildings from (c) in Google Earth.

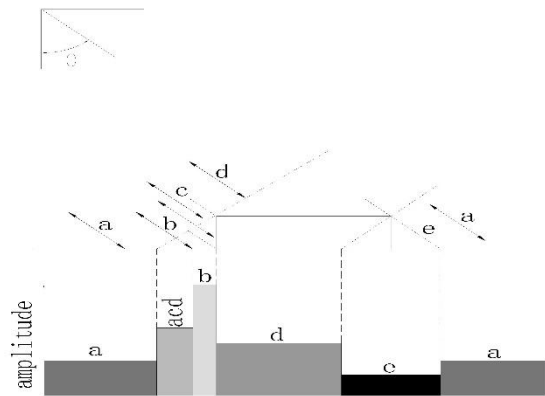


Fig.1 Scattering model for a flat-roof building

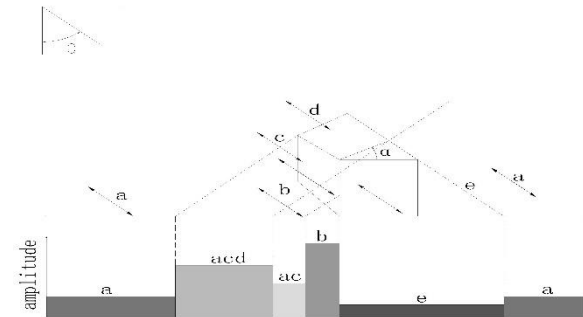


Fig.3 Scattering model for a gable-roof building

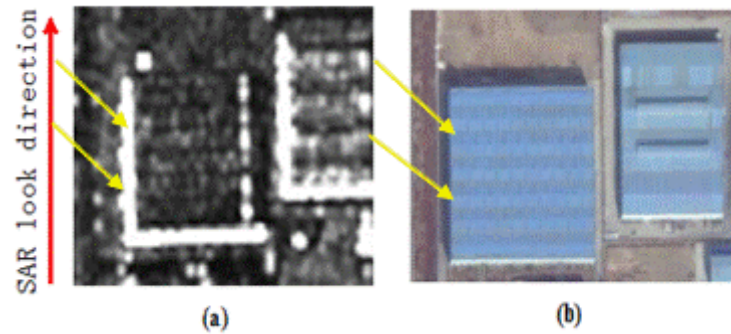


Fig.2 (a) Building in 3m resolution TerraSAR-X data. The double-bounce line is highlighted with a yellow arrow. (b) The same building in Google Earth.

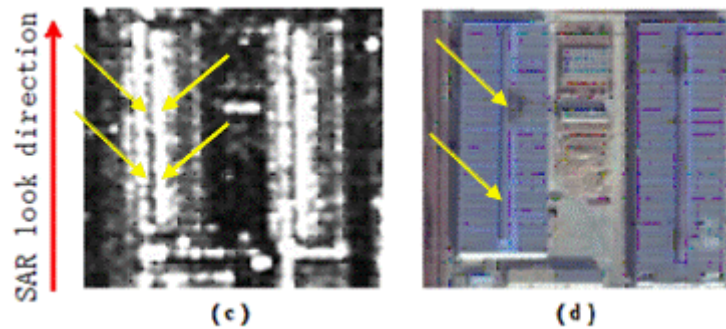


Fig.4. (c) Buildings in 3m resolution TerraSAR-X data with viewing direction from left. The double-bounce and roof scattering lines are highlighted with yellow arrows, respectively. (d) The same building from (c) in Google Earth.

3.2. Methodology

The workflow of the method is described (as showed in Fig.5). Firstly, accuracy true texture image is calculated by analysing local speckle characteristics. Secondly, the multi-resolution segmentation is performed using the original intensity image based on the software eCognition Developer. Finally, the objects of BAs are derived by combining information on the local true texture and local backscatter intensity.

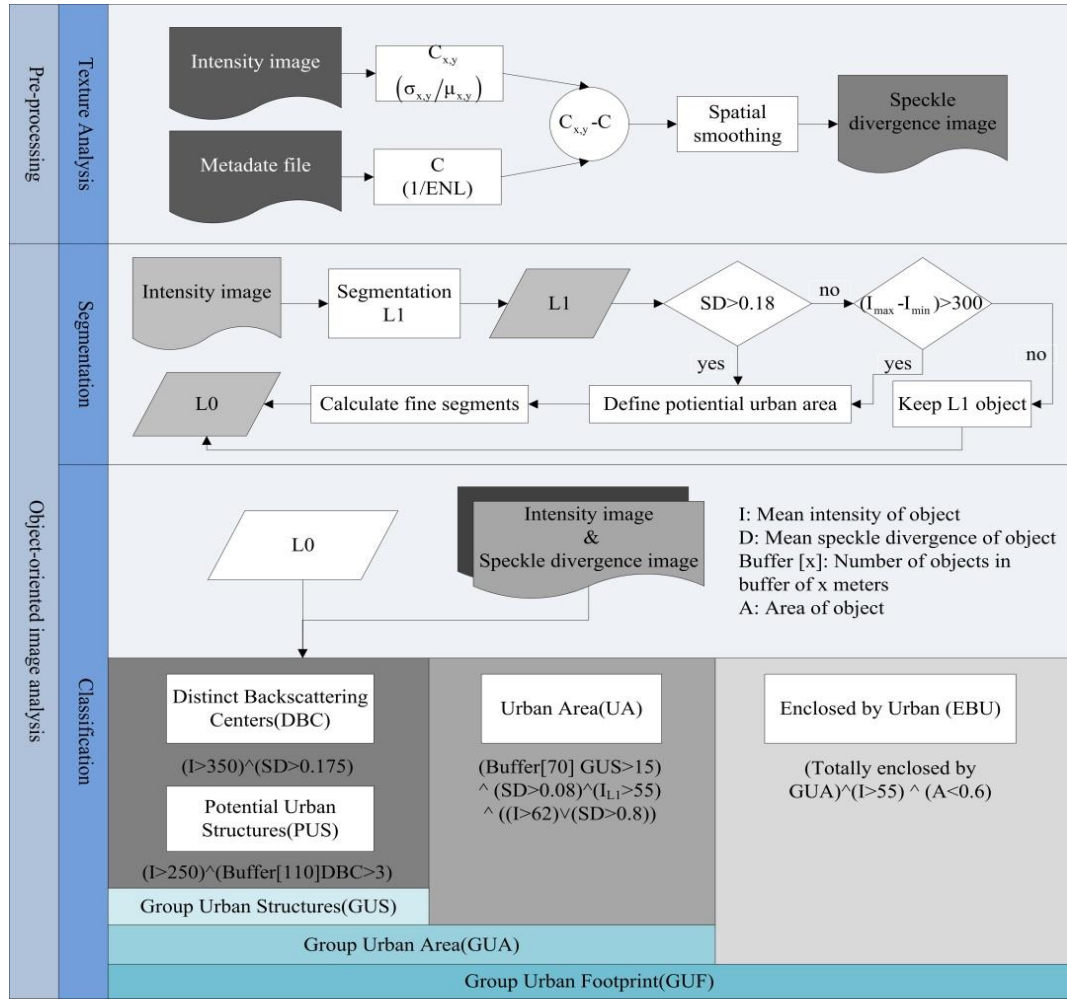


Fig.5 The workflow of extracting urban information from single TerraSAR-X data

3.2.1. Generation of texture image based on speckle analysis

Speckle appearing in SAR images is due to the coherent interference of waves reflected from many elementary scatterers [14]. This effect causes a pixel-to-pixel variation in intensities, and the variation manifests itself as a granular noise pattern in SAR images. A reasonable representation of fully developed speckle is a multiplicative noise model assuming a Gaussian distribution, and the standard deviation of data is related to mean of signals, thus multiplicative. However, this assumption is not applicable for urban sceneries since the multiple-scattering processes within a resolution cell frequently show a directional behaviour instead of a random distribution.

A conventional parameter to quantify the multiplicative noise in SAR data is the coefficient of variation C

$$C = s / m \quad (0)$$

Where σ is standard deviation and μ is mean value.

The equivalent number of looks (ENL) is a good indicator of the speckle noise level in SAR images.

$$ENL = L_a + L_g = 1 / C \quad (2)$$

With L_a and L_g defining the effective number of looks in the azimuth and range.

The local speckle divergence $D_{x,y}$, which means the difference between the local estimated coefficient of variation and the calculated scene-specific coefficient of variation. It can be quantified by

$$D_{x,y} = C_{x,y} - C \quad (3.1)$$

$$C_{x,y} = s_{x,y} / m_{x,y} \quad (3.2)$$

Where C denotes the theoretical heterogeneity due to the fully developed speckle, $C_{x,y}$ providing the local coefficient of variation defined by the local standard deviation $\sigma_{x,y}$, and the local mean $\mu_{x,y}$ calculated via the

maximum-likelihood estimated in a defined local neighbourhood. In this paper, $D_{x,y}$ was calculated with the best compromise window size of 15 pixels for the study area.

3.2.2. Object-oriented mapping and region-growing algorithm of urban extraction

The first step of an object-oriented image analysis is image segmentation, which is a way to separate the image into simple regions with homogeneous behaviour. The multi-resolution segmentation algorithm is a bottom-up region-growing technique within the eCognition Developer software, starting at the seed points, in numerous threshold-based which shows completely in Fig. 5, then discriminate regions on the basis of intensity value difference between pixels, merging into larger ones. There are three main parameters dominate the object generation during segmentation: scale parameter, shape and compactness. At first, a coarse segmentation level (L1:150, 0.3, 0.8) was created, acquiring large-scale features such as settlement bodies. The more detailed objects can get from subdivided level (L0:25, 0.3, 0.8), which was focused on potential urban areas, through some threshold like high value $D_{x,y}$ or high intensity $I_{x,y}$.

Based on scattering properties of man-made structures, the distinct backscattering centres (DBC) are composed of direct reflection and double- or multiple-bounce effects in urban sceneries, which characterised by an extremely high $I_{x,y}$ and $D_{x,y}$. In order to identify further detailed settlements---the potential urban structures (PUS), we focus on the neighbourhood of the DBC objects. Then, DBC and PUS are combined to the urban structure (GUS). PUS features a very high $I_{x,y}$. After these threshold, the potential location and shape of the build-up areas are achieved. By using the GUS segments as seed objects, the surrounding area of 25 pixels are classified as UA, aiming at the water bodies and rivers, which shows a high intensity or a very high speckle divergence. All objects are enclosed by segments classified as GUA, and enclosed by urban (EBU). Finally, GUA and EBU are merged into one.

3.2.3. Validation

We generated 957 randomly distributed reference points by cross-validating QuickBird data and geo-referenced field sites, confusion matrices with statistical indicators are calculated and used for quantitatively assessing the classification results.

We adopted two statistics, overall kappa coefficient (OK) and overall accuracy (OA) based on confusion matrices, to evaluate the classification performances, and the two formula are listed below:

$$Kappa = \frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r (X_{i+} X_{+i})}{N^2 - \sum_{i=1}^r (X_{i+} X_{+i})} \quad (4)$$

$$OA = \frac{\sum_{i=1}^r X_{ii}}{\sum_{i=1}^r X_{+i}} \quad (5)$$

4. Results and analysis

Based on Object-based and region growing delineation of urban footprints from Fig. 6 (a) TSX intensity image and (b) speckle divergence image starting with (c) the identification of DBC and followed by (d) the definition of PUS and (e) the supplementation of UAs and (f) regions completely EBU objects before (g) finishing with the reconstruction of the urban footprint (GUF) and smoothing the border line of the extracted settlement object. And the extraction result of Dongying city is showed in Fig. 7.

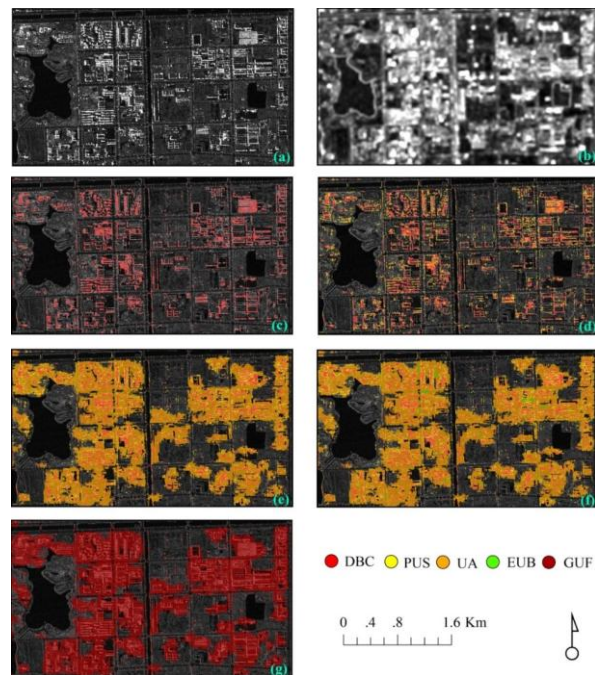


Fig. 6 the detail of Object-based delineation of Dongying urban footprints from TerraSAR-X image

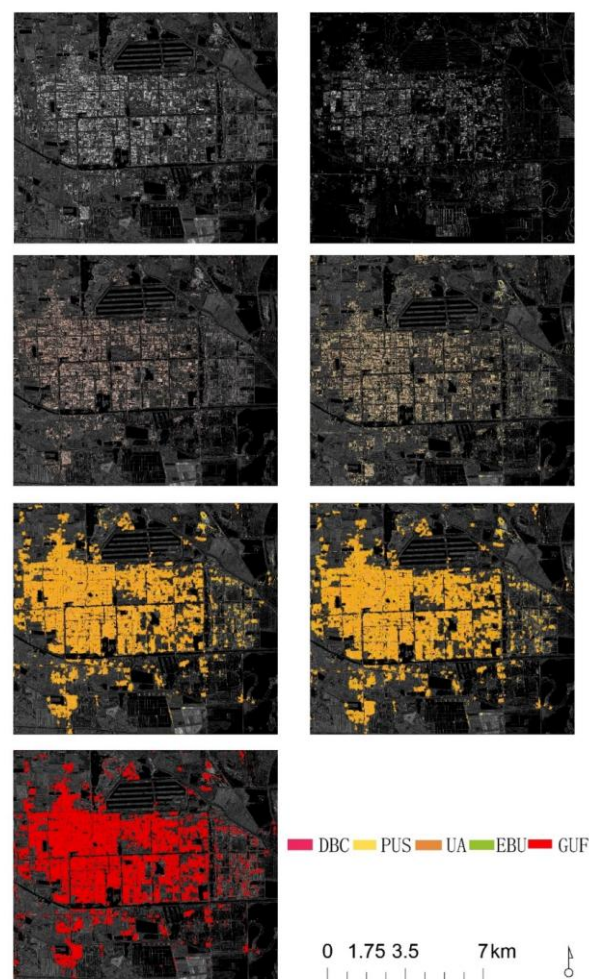


Fig.7 Object-based delineation of Dongying urban footprints from TerraSAR-X image

The method was applied to single-polarized TSX scene of Dongying city. The result of the object-oriented classification procedure is shown in Fig. 7, the figure illustrates the derived urban footprints provide accurate

information on both the actual location and shape of the settlements. We validated the classification result generating 957 randomly distributed reference points by cross-validating QuickBird data and geo-referenced field sites, confusion matrices with statistical indicators are calculated and used for quantitatively assessing the classification results. The accuracy assessment for classification is summarized in Table1. From the Table1, we found that the overall accuracy 92.89% and a kappa coefficient of 0.85 can be achieved.

Table1 Accuracy assessment for classification based on Object-oriented

Category	Build-up	No Build-up	Sum-up
Build-up	492	43	535
No Build-up	25	397	422
Sum-up	517	440	957
OK (%)	92.89		
OA (%)	0.85		

The Fig. 8 shows (a)-(c) the TSX intensity data; (d)-(f) the derived speckle divergence; (g)-(i) the result of the classification process; and (j)-(l) an HR optical image for comparison. Potentials and limitations of the developed approach in terms of detecting Bas such as (c), (f), (i), and (l) industrial sites; (a), (d), (g), and (j) farmsteads; and (b), (e), (h) and (k) high-density housing. Analysing the most frequent errors of omission and commission, in countryside area (a), (d), (g) and (j), some isolated homesteads can be derived, but the hedges and grasses will deteriorate the result, leading to overestimated build-up areas. In the fringe between countryside and country, due to bare soil exists, natural land cover types are located close to settlements and some build-up areas are under constructions, misclassifications are unavoidable. In commercial zones, errors are often emerged in the cause of foreshortening or layover in mountainous areas. We could verify that the large-area specular reflection at asphalted surfaces such as squares or broad streets and large flat roofs of factory buildings. The corresponding regions appear as zones with a very low $I_{x,y}$ and $D_{x,y}$ [Fig. 8 (b),(e),(h) and (k)]. Due to lake of distinct corner reflection, the buildings are strongly interspersed with trees and hedges [Fig. 8 (a),(d),(g) and (j)]. Based on $I_{x,y}$, the woodland and bare soil can hardly be discriminated from the settlement, resulting in the overestimate of urban area[Fig. 8 (c),(f),(i) and (l)].

The advantage of using $D_{x,y}$, which is supplemental to $I_{x,y}$, is highlighted by Fig.8(a),(b),(d),(e),(g),(h),(j) and (k)l Fig. 8(a), (d), (g), and (j) illustrates a group of homesteads which can be differentiated from and delineated much better from the surrounding by considering the $D_{x,y}$ image. We came to the conclusion that the object-oriented classification method with intensity and divergence information can improve accuracy in urban area.

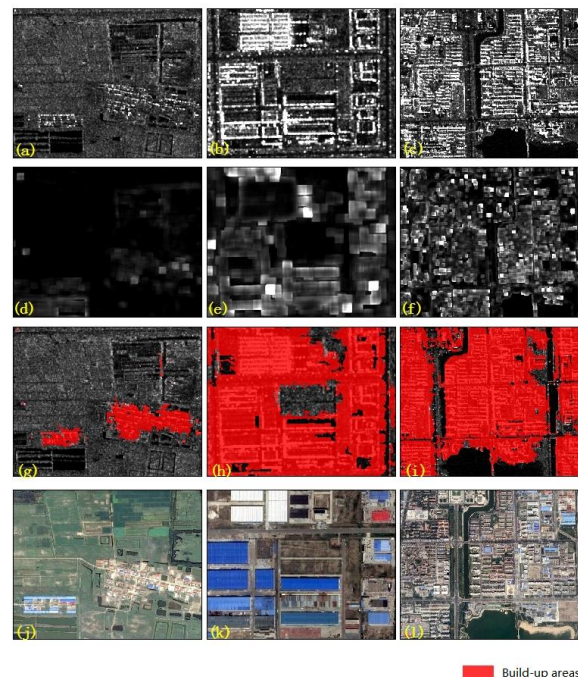


Fig.8 Potentials and limitations of the developed approach in terms of detecting BAs.

5. Conclusion

This paper presented an object-oriented and region growing classification method to extract build-up areas from TSX image. On the basis of image segmentation, combined local true texture and local backscatter intensity, we applied the method in Dongying city. The result illustrated that the overall accuracy was up to 92.89%, manifesting the classification with texture proposed by $D_{x,y}$ and single-polarized intensity information had a high accuracy. However, the error of commission still existed, which may result from the complexity of land covers themselves such as the confusion between detached houses in the outskirts of the settlements and heterogeneous landscapes composed of trees and rocks. Therefore, the future work will focus on the development of the classification rules and automated determination of the thresholds used for the classification.

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