Assessment of Polarimetric and Spatial Features for Built-up Mapping using ALOS PALSAR Polarimetric SAR Data

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Key words: ALOS PALSAR, support vector machine, random forest, built-up mapping

SUMMARY

Fully polarimetric synthetic aperture radar (PolSAR) has the advantage for working at all time and all weather compared with optical remote sensing. It can provide four channel data, including HH, HV, VH, and VV, which is usually called sinclair matrix. The sinclair matrix can be used to describe the relative pure targets. Concerning to the distributed targets, it is necessary to use coherence or covariance matrices that computed from the sinclair matrix. Sinclair matrix, coherence matrix, or covariance matrix are directly related to the physical properties and backscattering mechanisms of natural medium. Based on these matrices, target decomposition theorem can be used to explore more additional information for the scattering medium. However, in the urban areas, the surrounding environment is complex and difficult to describe. Different targets may contribute to the same scattering mechanisms, and the same medium may produces the different scattering responses. Therefore, it is necessary to utilize the complementary information between the polarimetric and spatial feature parameters. Spatial features can reveal the orientation, geometry, and material of urban structures, which can provide essential information for built-up mapping. In this study, the polarimetric and spatial feature parameters are assessed for built-up mapping based on support vector machine (SVM) and random forest (RF). The Cloude decomposition parameters, including scattering entropy, scattering angle, and anisotropy, are selected as the representative polarimetric feature parameters. The texture parameter computed from gray level co-occurrence matrix (GLCM), including the mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation, are chosen as typical spatial feature parameters. The SVM and RF are used as the classifiers to assess the performance of feature parameters for built-up mapping. ALOS PALSAR full PolSAR data are used to conduct the experiment. From the mapping results, it is concluded that both polarimetric and spatial feature parameters, SVM and RF are effective for built-up mapping. Further works have to be continued on the selection of effective feature parameters and classifiers for built-up mapping.

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1. INTRODUCTION

Synthetic aperture radar (SAR), depending on its high spatial resolution, multiple work modes, flexible polarizations, and interference ability, have attracted more and more attentions in the field of land use and land cover mapping (Zhu et al., 2012; Du et al., 2015). In particularly, polarimetric SAR (PolSAR) can provide unique information that can be used to interpret the complex scattering mechanisms between the radar signal and the natural media (Cloude and Pottier, 1996, 1997; Freeman and Durden, 1998; Yamaguchi et al., 2006; Touzi, 2007). However, due to the SAR imaging mechanism and complexity of ground surface, built-up mapping using PolSAR image still remains challenged (Zhu et al., 2012; Niu and Ban, 2013; Du et al., 2015).

The polarimetric properties and scattering mechanisms of built-up targets are complex and difficult to describe (Zhu et al., 2012; Niu and Ban, 2013). That's because the backscattering from the built-up areas is a mixture of various scattering mechanisms, which is contributed by the orientation, geometry, and material of urban structures (Niu and Ban, 2013). Single scattering, double scattering, and volume scattering can be occurred randomly (Freeman and Durden, 1998; Yamaguchi et al., 2006; Touzi, 2007). To effectively interpret the scattering mechanisms of built-up, different classifiers and machine learning methods have been used for PolSAR image classification (Du et al., 2015), such as support vector machine (SVM), random forest (RF), ensemble learning (EL), linear discriminative Laplacian eigenmaps (LDLE), maximum likelihood (ML), fuzzy c-means (FCM), and artificial neural networks (ANNs). As a matter of fact, the classification or mapping performance not only depends on the robustness of the classifiers, but also on the quality of feature parameters and training samples, especially for supervised classifiers (Niu and Ban, 2013; Du et al., 2015). Therefore, selecting effective feature parameters have been extensively investigated from different aspects in PolSAR applications.

Target decomposition theorems have been proved to be a useful tool to fully understand the PolSAR information and interpret the scattering mechanisms of the natural media (Cloude and Pottier, 1996, 1997; Freeman and Durden, 1998; Yamaguchi et al., 2006; Touzi, 2007). Several coherent and incoherent decomposition methods have been developed. Among them, Cloude decomposition (Cloude and Pottier, 1996, 1997) and Freeman decomposition (Freeman and Durden, 1998) are most widely used. The former is more of mathematical nature and seems to be exclusively intended for classification purpose. Compared with Freeman decomposition, which can separate three scattering mechanisms, Cloude decomposition can explain all the scattering mechanisms based on its decomposition parameters (Cloude and Pottier, 1996, 1997). Both of coherent and incoherent decomposition parameters have been investigated for PolSAR applications. In addition, the use of spatial features derived from image segmentation, texture analysis, or mathematical morphology, proves useful to classification processes (Zhu et al., 2012; Du et al., 2015). Among them, texture is an effective representation of spatial relationship and contextual information. Various texture measures based on histogram statistics, gray level co-occurrence matrix (GLCM), Markov random fields (MRFs), and Gabor wavelets have been widely investigated in PolSAR image classification (Franklin and Peddle, 1990; Gong and Howarth, 1992; Du et al., 2015). Therefore, it is promising for PolSAR applications by combining the polarimetric and spatial features to provide additional information to handle classification task.

The objective of this research is to assess the performance of polarimetric and spatial features extracted from PolSAR data for built-up mapping using SVM and RF classifiers, respectively. Scattering entropy, scattering angle, and anisotropy computed from the Cloude decomposition are used to represent the polarimetric features, and the texture parameters extracted by the GLCM represents spatial features. The paper is organized as follows. The study area and SAR data are described in section 2. The classification methods are fully given in section 3. The experiment results and analyses are demonstrated in section 4. Finally section 5 draws the conclusions of this work.

2. STUDY AREA AND SAR DATA

2.1 Study area

The study area is situated in the Kushiro, Hokkaido, Japan (Figure 1). The central coordinates of the test site area is 42º59'05.45" N, 144º22'50.10" E. The dominant land cover includes water, farmland with different crop types, forest, built-up, bridge, major road and street, and bare soil. The municipality of Kushiro is surrounded by the water, farmland, and forest. The reference map used is collected by photo-interpretation of high resolution optical images in the Google Earth (Figure 2), which has been used in the previous studies (Du et al., 2015).

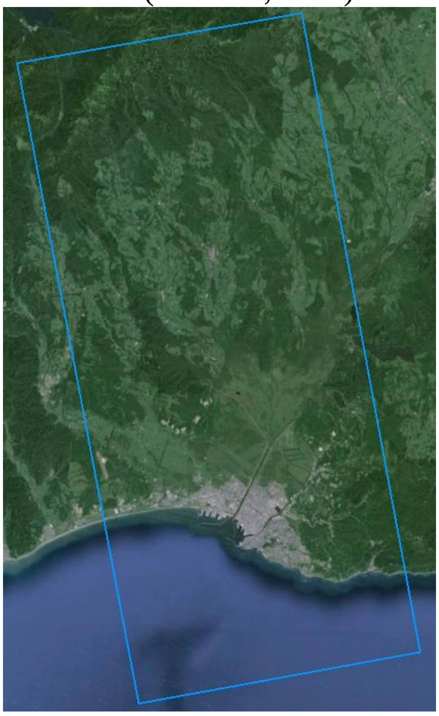


Figure 1. Coverage of study area displayed in the Google Earth

2.2 PALSAR Data

The L-band ALOS PALSAR data used in this study are acquired in full polarization mode on April 4, 2009. The single look complex product includes four observations from HH, HV, VH, and VV polarization with nominal pixel spacing of 9.37m and 3.56m in the range and azimuth directions, respectively. The center incidence of the image is 23.83º with ascending orbit. There are 18432×1248 pixels in the original image, and only a part of sub-region is selected to continue the subsequent experiments (Figure 2). The red polygons in Figure 2 stand for the reference built-up areas.

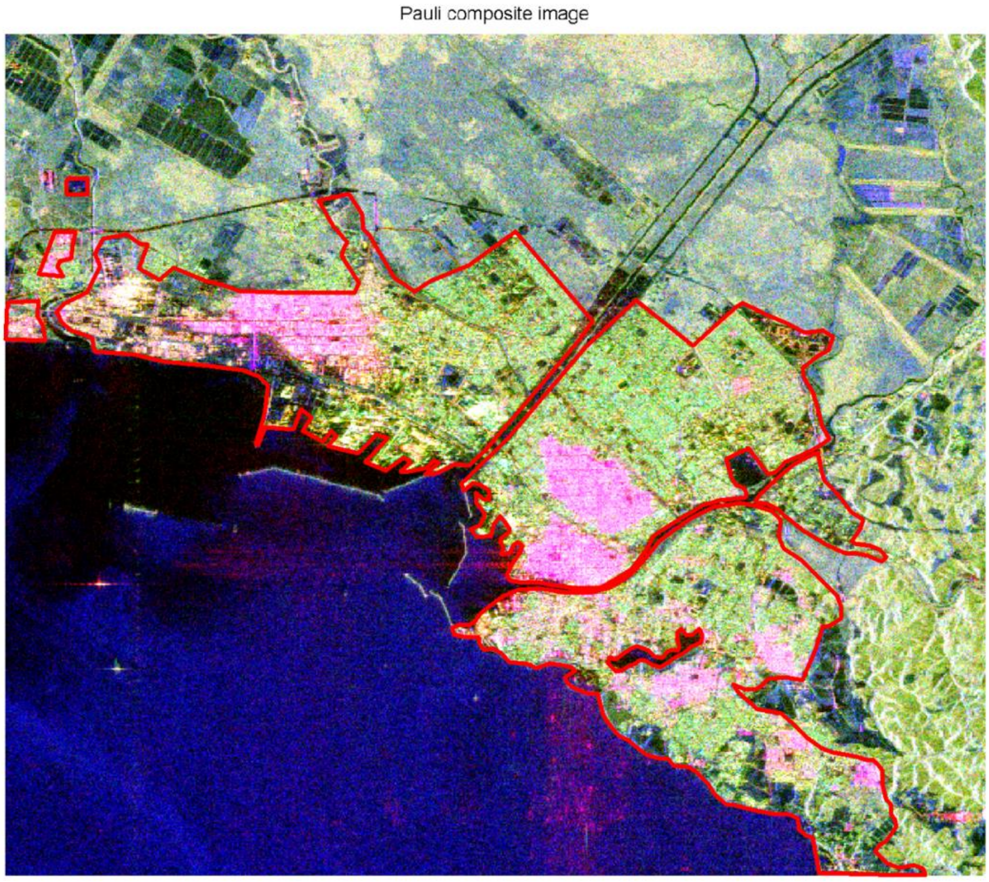


Figure 2. Selected sub-region of the study area, which is displayed in the RGB composites of Pauli decomposition parameters

The preprocessing for PolSAR data is done with PolSARPro (http://earth.eo.esa.int/polsarpro/) software, which is an open access PolSAR processing tool developed for and maintained by the European Space Agency (ESA). To reduce the spatial resolution, the multilooking process in the azimuth direction is done on the original single look complex (SLC) SAR data. Subsequently, enhanced Lee filter with 5×5 sliding window is used to eliminate the effect of speckle (Lee et al., 1999). The filter size is chosen to preserve detail and spatial resolution. To extract the polarimetric decomposition parameters, the Cloude decomposition is processed on the covariance matrix. The texture parameters of span are computed by the ENVI software.

3. CLASSIFICATION METHODS

3.1 Feature parameters

Polarization of electromagnetic fields of target not only depends on the polarization of incident electromagnetic fields, but also the characteristics of targets, which can be recorded by the scattering matrix [S].

$$[S] = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} \tag{1}$$

Where H and V denote the horizontal and vertical polarization, respectively. For simplicity, a complex vector can be defined by the element of scattering matrix as (Lee and Pottier, 2009),

$$k = \begin{bmatrix} S_{HH} & S_{HV} & S_{VH} & S_{VV} \end{bmatrix}^T \tag{2}$$

Where T indicates the matrix transposition. For backscattering from a reciprocal medium, $S_{HV} = S_{VH}$. In case of backscattering, the scattering vector k can be rewrite as,

$$k = \begin{bmatrix} S_{HH} & \sqrt{2}S_{HV} & S_{VV} \end{bmatrix}^T \tag{3}$$

When the scattering matrix is available, the interaction between the radar wave and the medium can be fully described in terms of complete polarization responses.

The polarimetric covariance matrix [C] is defined as,

$$[C] = \begin{bmatrix} S_{HH}S_{HH}^* & \sqrt{2}S_{HH}S_{HV}^* & S_{HH}S_{VV}^* \\ \sqrt{2}S_{HV}S_{HH}^* & 2S_{HV}S_{HV}^* & \sqrt{2}S_{HV}S_{VV}^* \\ S_{VV}S_{HH}^* & \sqrt{2}S_{VV}S_{HV}^* & S_{VV}S_{VV}^* \end{bmatrix} \tag{4}$$

Where * denotes the complex conjugate. Target decomposition theorems are effective to provide interpretation of scattering mechanism for the average target invariant to changes in wave polarization basis, and promote the polarization information being fully utilized. As proposed by Cloude and Pottier, the average covariance matric [C] can be decomposed into the sum of three independent coherent matrixes [C_i] by means of eigendecomposition (Cloude and Pottier, 1996, 1997),

$$[C] = \sum_{i=1}^{3} \lambda_i [C_i] = \lambda_1 e_1 e_1^* + \lambda_2 e_2 e_2^* + \lambda_3 e_3 e_3^* \tag{5}$$

Where λ_i and e_i denote the corresponding eigenvalues and eigenvector, which represent the primary parameters of the eigendecomposition. Base on this, three polarimetric feature parameters including the scattering entropy H, scattering angle $\overline{\alpha}$, and anisotropy A are computed (Cloude and Pottier, 1996, 1997).

$$H = \sum_{i=1}^{3} -P_i \log_3 P_i, P_i = \frac{\lambda_i}{\sum \lambda_i} \tag{6}$$

$$\overline{\alpha} = \sum_{i=1}^{3} P_i \alpha_i \tag{7}$$

$$A = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3} \tag{8}$$

The entropy, ranging from 0 to 1, represents the randomness of a scattering medium from isotropic scattering (H=0) to totally random scattering (H=1). The scattering angle reveals the averaged scattering mechanisms from surface scattering to double scattering. The anisotropy reflects the relative magnitude of the second and third eigenvalues.

In the spatial dimension, eight texture variables (3×3 pixels window size, 1×1 co-occurrence shift, 64 greyscale quantization levels) are created using GLCM measures, including the mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation (Franklin and Peddle, 1990; Gong and Howarth, 1992; Zhu et al., 2012; Du et al., 2015). The total power in polarimetric radar system called span, which contains the information from the HH, HV, and VV, is used for textural feature parameters extraction,

$$span = \lambda_1 + \lambda_2 + \lambda_3 \tag{9}$$

One of the objectives of this study is to comprehensively explore the different feature parameters for built-up mapping using polarimetric SAR image. Therefore, the following feature combinations are used for built-up mapping. The four different feature combinations are shortened as F1, F2, F3, and F4, respectively.

Table 1. Different feature combinations for built-up mapping

Features combination	Features numbers	Input feature parameters for SVM and RF
F1	3	HH, HV, and VV intensity
F2	11	HH, HV, and VV intensity; span texture
F3	6	HH, HV, and VV intensity; $H/\overline{\alpha}/A$
F4	14	HH, HV, and VV intensity; span texture; $H/\overline{\alpha}/A$

3.2 Classifier

Random forest is one of general form of decision tree based on ensemble methods. It is a combination of tree predictors in which decision trees are constructed using resampling technique with replacement and the inducers randomly samples the attributes and chooses the best split among those variables rather than the best split among all attributes (Du et al., 2015).

Undecided pixels are assigned to each class that is based on a majority voting rule, which assigns a pixel to the class that obtains the maximum number of votes from the group of classification trees (Zhu et al., 2012). A certain percentage of randomly selected training samples are used to train each tree. Due to the important advantages such as handling very large number of input attributes and low time cost, random forest has widely attracted the interests of researchers from the context of remote sensing image classification. The number of decision trees in random forest is set as 100 for comparative analysis.

SVM is a supervised binary classifier, which is aimed to divide the d-dimensional input feature space into two subspaces (one for each class) using a separating hyperplane (Patra and Bruzzone, 2014). An important feature of SVM is related to the possibility to project the original data into a higher dimensional feature space via a kernel function that implicitly models the classification problem into a higher dimensional space where linear separation between classes can be approximated (Patra and Bruzzone, 2014). During the implementation, the LIBSMV, which is popular open source SVM software, is used as the SVM classifier.

3.3 Technical steps for classification

Based on the selected classifiers and feature parameters, the built-up mapping framework is designed. The details for the mapping are given in the following steps (Figure 3).

Step 1: Multi-looking and speckle filtering are processed for the PALSAR SLC data.

Step 2: Extracting the matrix elements C11, C22, and C33 from covariance matrix, which is converted in the unit of DB.

Step 3: The element of span (unit DB) is obtained from covariance matrix, and the texture feature parameters are computed based on GLCM measurements, including the mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation.

Step 4: Cloude decomposition is done on the covariance matrix to extract scattering entropy, scattering angle, and anisotropy.

Step 5: Training SVM and RF based on the selected samples of built-up and non-built-up.

Step 6: Built-up mapping using SVM and RF based on different combinations of feature parameters.

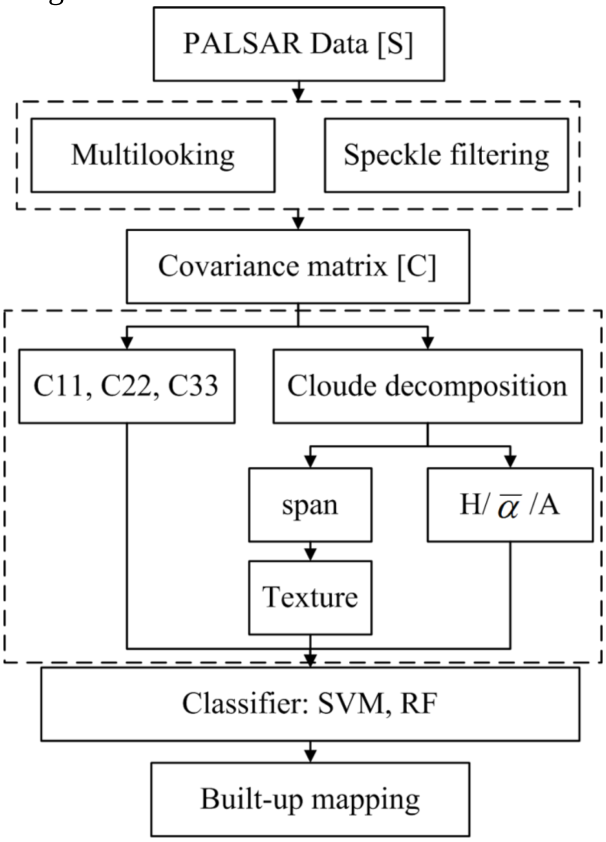


Figure 3. Technical flow for built-up mapping using PolSAR data

4. RESULTS

The SVM and RF are classified as supervised classifiers, which are sensitive to the training samples (Patra and Bruzzone, 2014). The samples of built-up and non-built-up are selected, which is displayed in Figure 4. The built-up types include the high density built-up and low density built-up. The samples types for non-built-up include the water, farmland, bare soil, forest (Figure 4). The major road and street are difficult to capture, therefore the samples belong to this type is not chosen. The kappa statistic is used for evaluating built-up mapping performances of SVM and RF. There is no ground truth for the whole study area, and only the selected samples are involved for evaluation of mapping accuracy.

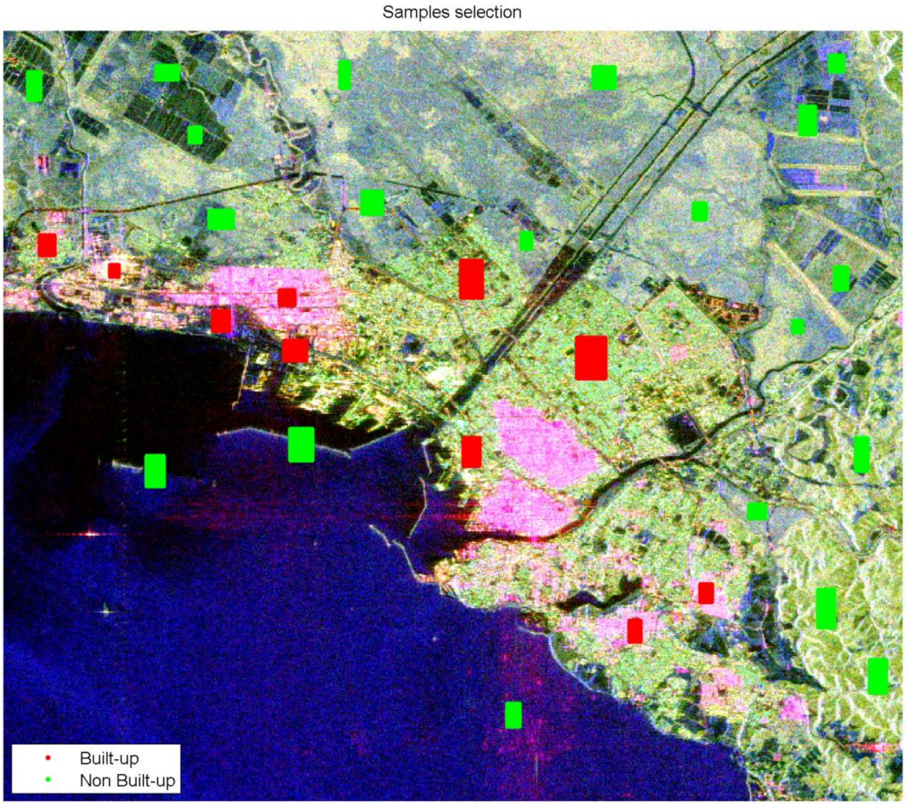


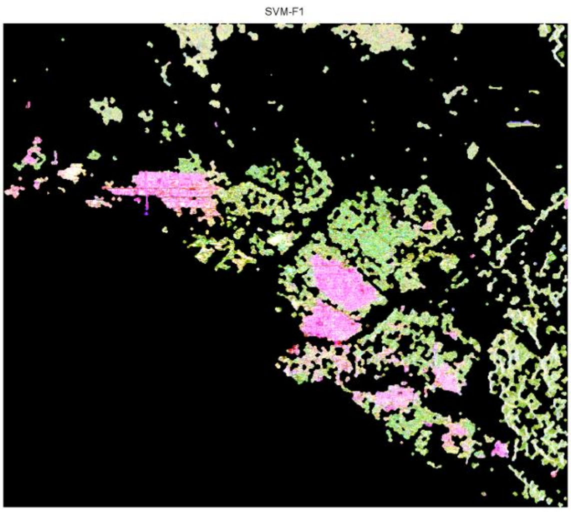
Figure 4. Training samples selectd for built-up mapping

From the results of accuracy evaluation, it is found that both of polarimetric and texture feature parameters contribute to the mapping results. In addition, the RF performs better than SVM for its higher kappa coefficients. To fully validate the effectiveness of polarimetric and texture feature paramater for mapping, the trained SVM and RF are used to the whole sub-image.

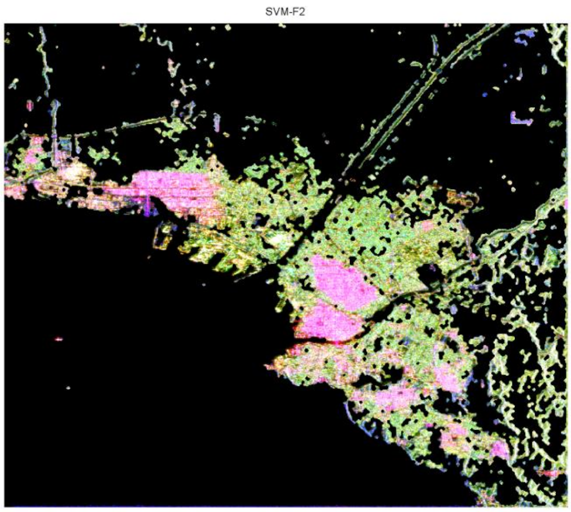
Table 2. Built-up mapping accuracy for SVM and RF classifier based on different feature parameters combinations

Features combination		B	B->N	N->B	N	Kappa
SVM	F1	0.6384	0.3616	0.0891	0.9109	54.93%
	F2	0.9416	0.0584	0.1165	0.8835	82.51%
	F3	0.9764	0.0236	0.0015	0.9985	97.49%
	F4	0.9935	0.0065	0.0054	0.9946	98.81%
RF	F1	0.9995	0.0005	0.0002	0.9998	99.93%
	F2	0.9998	0.0002	0.0001	0.9999	99.97%
	F3	0.9994	0.0006	0.0002	0.9998	99.92%
	F4	0.9998	0.0002	0.0001	0.9999	99.97%

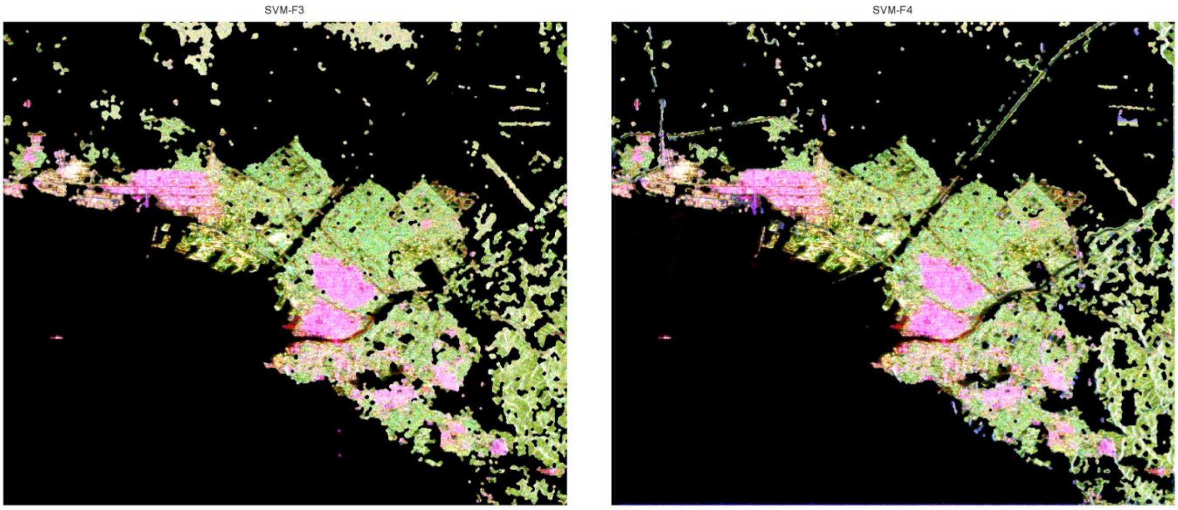
Figure 5 and Figure 6 give the built-up mapping results. Both of polarimetric and texture feature parameters have better results to those of SAR intensity. The roads are classified as built-up area based on the texture parameters. That’s because the roads have the rule structure, which is similar to the built-up. Scattering entropy, scattering angle, and anisotropy can distinguish different scattering mechanisms. The dominant scattering mechanisms for roads may be single scattering with double scattering being the second scattering type. The built-up, especially surround by the forest and farmland, may produce single, double, or volume scattering randomly with the surrounding environment. Concluded from the results, it is better for built-up mapping in urban areas using polarimetric parameters, and in rural areas using texture parameters, which is just referred based on SVM and RF classifiers.



(a) SVM-F1



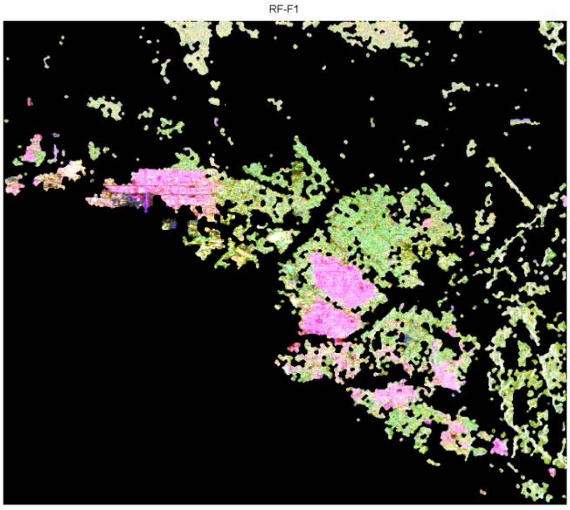
(b) SVM-F2

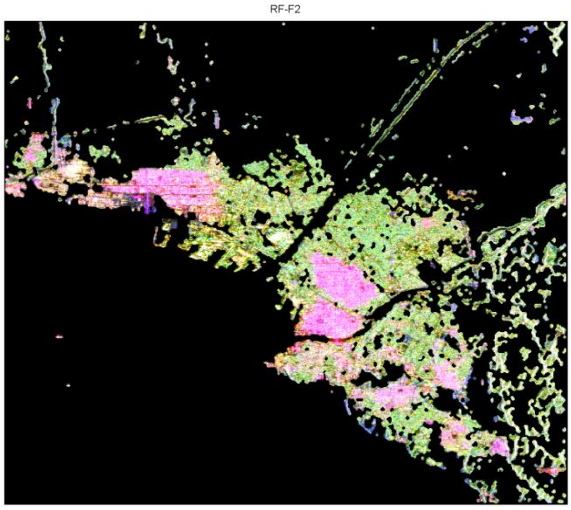


(c) SVM-F3 (d) SVM-F4

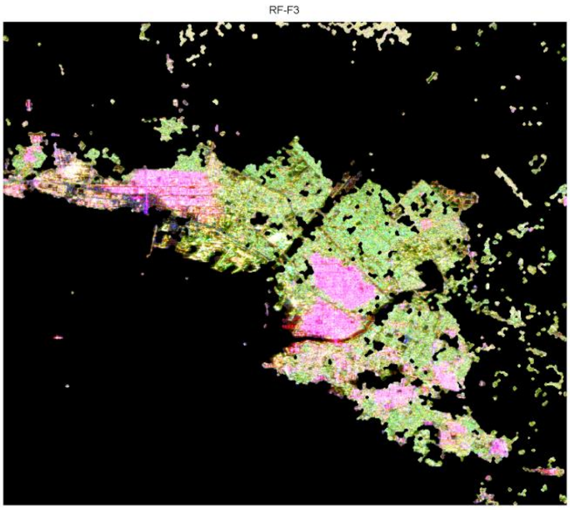
Figure 5. Built-up mappings derived from different combinations of feature parameters based on SVM classifier

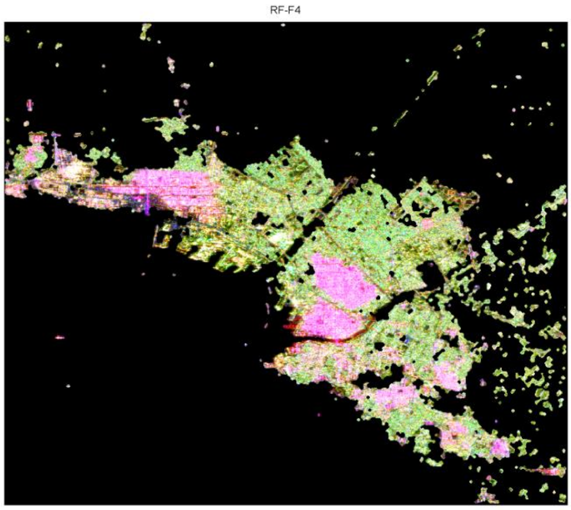
Though the selected polarimetric and texture parameters achieve a good performance, there is still some farmlands and forests are classified as built-up, especially in the boundary between the built-up and forest. Built-up can be seen as the constant target in the short time interval, whose scattering behavior may be largely influenced by human activity. Concerning to the farmland and forest, they are not only influenced by the human activity but also by the season change. Therefore, it is necessary to improve the built-up mapping from two aspects. On one hand, other polarimetric parameters, such as Freeman decomposition (Freeman and Durden, 1998), Yamaguchi decomposition (Yamaguchi et al., 2006), and Touzi decomposition parameters (Touzi, 2007), should be given more attenuations. On the other hand, multi-temporal SAR data may be effective to distinguish the built-up from the farmland and forest (Niu and Ban, 2013). Further studies will be concentrated on these two aspects.





(a) RF-F1 (b) RF-F2





(c) RF-F3 (d) RF-F4

Figure 6. Built-up mappings derived from different combinations of feature parameters based on RF classifier

To compare the results between the two classifiers, the difference of built-up mapping between SVM and RF is given in Figure 7. From the difference image, it is found that the majority of the built-ups have been detected by SVM and RF. However, part of forest areas have been classified as built-up by SVM. The mapping results not only depend on the feature parameters but also on the classifier. Therfore, subsequent works have also to be paid on the improvement of classifier for built-up mapping.

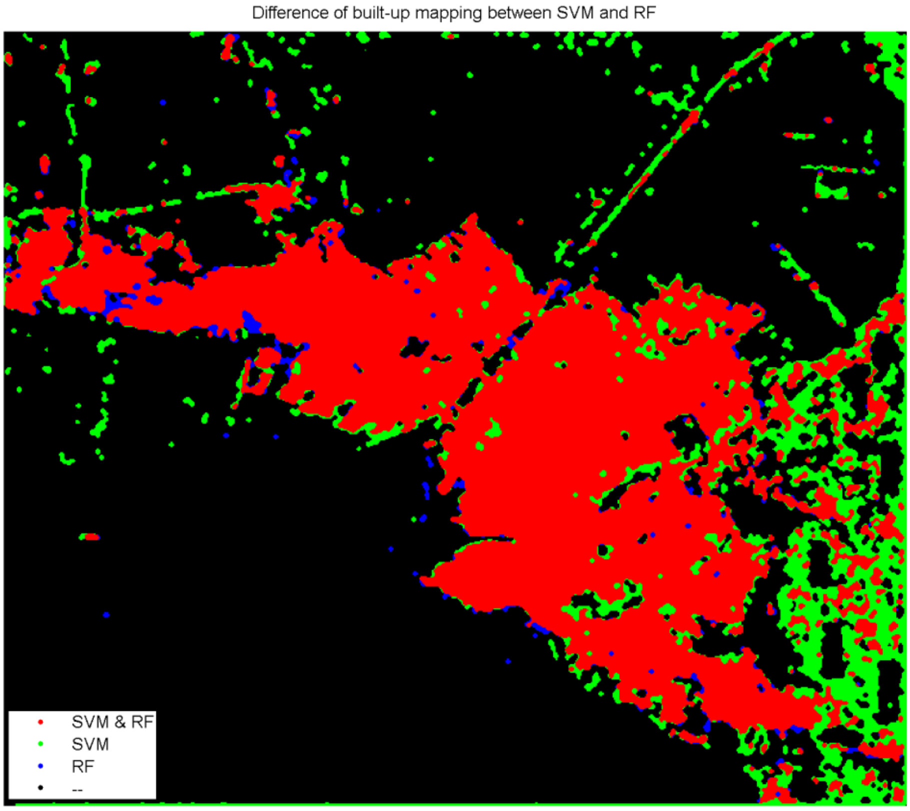


Figure 7. Difference of built-up mapping between SVM and RF classifier

5. CONCLUSIONS

The main contributions of this study include: 1) assessing the polarimetric and spatial feature parameters for built-up mapping; and 2) comparatively investigating the performance SVM and RF classifiers. The Cloude decomposition parameters, including scattering entropy, scattering angle, and anisotropy, are used as representative polarimetric parameters. Texture parameters computed from GLCM, including the mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment, and correlation, are used as representative spatial feature parameters. The results show that both polarimetric and spatial feature parameters are effective for built-up mapping. In addition, SVM and RF are adequate built-up mapping using ALOS PALSAR data. Both methods are only based on a few input variables and provide relatively accurate mapping results. It is regretted that the performance of SVM and RF are not good to distinguish built-up from forest. Further work will be focused on the separation of built-up and forest by considering other polarimetric and spatial feature parameters and improving the performance of classifier. In addition, high performance computing techniques for accelerating the SVM and RF is worthy to be investigated as well.

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