Investigation of the capability of multitemporal RADARSAT-2 fully polarimetric SAR images for land cover classification: a case of Panyu, Guangdong province

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\textbf{ABSTRACT}

Synthetic aperture radar (SAR), with all-day and all-weather observation capabilities, can capture the phenology of crops with short growth cycles to improve land cover classification results. The present study carried out a land cover classification using multitemporal RADARSAT-2 fully polarimetric SAR (PolSAR) images that are 24 days apart. The objectives of this study were 1) examining the land cover classification capacity of multitemporal fully PolSAR data processed with multiple polarimetric decomposition methods, 2) investigating the contribution of multi-type polarimetric decomposition methods to multitemporal PolSAR image classification, and 3) determining optimal image acquisition dates and polarimetric parameters for land cover classification. Overall accuracy and kappa coefficient attained using the multitemporal PolSAR data were 96.55\% and 0.96, respectively, which were improved by as much as 16.77\% and 0.20, respectively, compared with those obtained with a single scene. Compared with the multitemporal PolSAR image classification using coherency matrices alone, the use of polarimetric decomposition methods improved overall accuracy and kappa value by 2.22\% and 0.03, respectively. Using decision tree algorithms for feature selection, we found that April 14, May 8, June 1, and June 25 and Pauli, Cloude, Neumann3, An&Yang4, Freeman3, Barnes2, and MCSMS5 decomposition methods were optimal for the land cover classification.

\textbf{Introduction}

Land cover has been recognized as an essential component of the current global changes and used to understand regional development rates and trends (Foley et al., 2005; Lex et al., 2005; Dou & Chen, 2017). Optical remotely sensed images are primary data sources for land cover classification (Chen et al., 2014; Jia et al., 2014). Multitemporal images can achieve higher land cover classification information than a single image (Dong et al., 2013; Gómez et al., 2016). However, traditional optical images are susceptible to weather conditions, especially cloudy or foggy weather (Azzari & Lobell, 2017; Joshi et al., 2016); hence, they have some difficulties in obtaining fragmental changes in the growth cycle, especially those with short growth cycles.

Synthetic aperture radar (SAR), with all-day and all-weather observation capability and short revisit cycle, has certain superiorities in utilizing crop phenological information for land cover classification (Jin et al., 2014). Many SAR systems, including SIR-C/X-SAR, ENVISAT-ASAR, ALOS PALSAR, and TerraSAR-X, have been used in land cover classification (De-Yong et al., 2008; Uhlmann & Kiranyaz, 2014). Numerous studies have examined the capabilities of multitemporal SAR images in land cover classification (Waske & Braun, 2009; Wegmüller et al., 2013). However, most of these studies are based on traditional single-polarization SAR images, whose land cover classification capability is limited by the inadequate spectrum information and substantial speckle noise (Qi et al., 2015; Xu et al., 2018).

Polarimetric SAR (PolSAR) performs better than single-polarization SAR in land cover classification because it can capture much information of backscattering mechanisms corresponding to different geometrical and geometrical properties of ground targets (Alberga, 2007; Du et al., 2015). On the other hand, in comparison with single PolSAR image, multitemporal PolSAR images have exhibited certain advantages in identifying specific crops (Jiao et al., 2014; Yuzugullu et al., 2017; Masoud; MahdianPari et al., 2019; Shuai et al., 2019; Guo et al., 2020). Additionally, several studies were conducted on the contribution of multitemporal PolSAR data, especially fully polarimetric ones, to land cover classification (Jeffrey W. Cable et al., 2014; Niu & Ban, 2014; Tao et al., 2014).
Besides, polarimetric decomposition methods have been proposed to interpret the scattering mechanism of the ground targets observed by PolSARs (Cloude & Pottier, 1996; Freeman, 2007; Freeman & Durden, 1998; Vanzyl, 1993; Yamaguchi et al., 2005). These methods are proven to be greatly useful in improving land cover classification accuracy (Cloude & Pottier, 1997; Lee et al., 1999; Qi et al., 2012; B. Liu et al., 2013; Srikanth et al., 2016; Subhadip Dey et al., 2020). Mohammadimanesh et al. (2018) already analyzed multi-temporal, multi-frequency, and multipolarization coherence and SAR backscatter analysis of wetlands.

Despite numerous studies on land cover classification using multitemporal PolSAR data, most of them focused on crop classification and employed one or two decomposition techniques. There are limited studies on multitemporal PolSAR image classification that involves fully polarimetric data, multi-type decomposition methods, and a classification system that contains not only crops but also other land cover types. The capability of multitemporal fully PolSAR data still needs further examined for land cover classification. However, the integration of different polarimetric decomposition methods into multitemporal PolSAR image classification results in numerous redundant and irrelevant features. The knowledge of selecting optimal polarimetric parameters and image acquisition dates remained poorly known for achieving the best land cover classification results and reducing the cost of data collection and processing. This study carried out land cover classification by using multitemporal RADARSAT-2 PolSAR images. Six repeat-pass RADARSAT-2 fully PolSAR images were used for land cover classification that involved banana trees, bare land, built-up areas, crop/natural vegetation, forests, lawns, paddy fields, fishponds, and rivers/reservoirs. An approach that integrates multiple polarimetric decomposition techniques, object-oriented image analysis, decision tree algorithms, and random forest algorithms was employed for the classification. This study aimed to 1) examining the land cover classification capacity of the multitemporal fully PolSAR data with the support of multiple polarimetric decomposition methods, 2) investigating the contribution of polarimetric decomposition methods to multitemporal PolSAR image classification, 3) and determining optimal PolSAR image acquisition dates and polarimetric parameters for land cover classification.

**Study area and data**

The study site is Panyu district of Guangzhou City in southern China (Figure 1). This district lies in the south-central part of Guangzhou City and in the geographical center of Guangdong Province. Panyu was an agricultural area. After 2000, Panyu became a core area of Guangzhou’s southern expansion strategy and retreated into the Guangzhou administrative region, thereby experiencing a rapid urbanization development. Various land cover types exist in Panyu, making it an ideal area for this study.

Six sequential repeat-pass RADARSAT-2 Fine Quad-Pol images were acquired over the study area from 21 March 2009, to 19 July 2009, at an interval of 24 days. RADARSAT-2 is a commercial C-band PolSAR satellite. The images obtained for this study
had full polarizations of HH, HV, VH, and VV, a resolution of $5.2 \times 7.6 \, \text{m}^2$ (ground range by azimuth), and an incidence angle of $31.5^\circ$ and the beam is FQ12 (Table 1).

The training and validation samples were selected in the study area for all nine land cover types: banana trees, bare land, built-up areas, crop/natural vegetation, forests, lawns, paddy fields, and fishponds, and rivers/reservoirs. Forests and banana trees were perennial plants, whereas paddies were transplanted in April and harvested in July. Crop/natural vegetation included other crops or plants, excluding paddies, bananas, forests, and lawns. A total of 1,839 field plots were selected across the typical land cover types in the field investigations, and at least 40 samples were collected for each category (McCoy, 2005). The training and validation groups comprised of 910 and 929 sample plots, respectively. (Table 2) shows the number of plots and pixels selected for each land cover class in both groups.

### Methods

Land cover classification using multitemporal PolSAR images mainly consisted of four steps (Figure 2). First, the multitemporal PolSAR images were preprocessed through radiometric calibration, speckle filtering, and terrain correction. Second, polarimetric decomposition methods were implemented on the multitemporal PolSAR images to generate various polarimetric parameters. Third, multitemporal PolSAR images were segmented together to delineate image objects, for which a variety of features was extracted from the polarimetric parameters. Lastly, object-oriented land cover classification was conducted using random forests.

#### Preprocessing of multitemporal PolSAR images

The preprocessing of PolSAR data mainly included radiometric calibration, speckle filtering, and terrain correction. After the radiometric correction of the PolSAR images, there was a lot of noise in the PolSAR images, which affected the quality of the data. The Lee sigma speckle filter was employed to suppress the speckle noise (Lee et al., 2008). The window size is $7 \times 7$, the sigma is 0.9 and the target window size is $3 \times 3$. The abovementioned operations were completed using PolSARProv5.1 software (Pottier et al., 2013). The pixel spacing of...
the image in this study is 10 meters. NEST DAT 5.1 was used to perform the range-Doppler terrain correction (Engdahl et al., 2012).

**Polarimetric decomposition**

Polarimetric decomposition methods were implemented to extract polarimetric information corresponding to the scattering mechanism of physically constrained target interpretation. Numerous polarimetric decomposition methods have been proven to be useful for land cover classification (Qi et al., 2012). In this study, the commonly used polarimetric decomposition methods, including Pauli (Cloude & Pottier, 1996), MCSM5 (Zhang et al., 2008), Barnes (Barnes, 1988), Huynen (Huynen, 1970), H/A/Alpha (Cloude & Pottier, 1997), Cloude (Cloude, 1985), Holm (Holm et al., 1988), Freeman3 Components (Freeman & Durden, 1998), VanZyl (Vanzyl, 1993), Yamaguchi (Yamaguchi et al., 2005), Neumann3 (Neumann et al., 2009), and An&Yang4 (An et al., 2011), were implemented to support PolSAR image classification (Figure 3). Pol-SARPro_v5.1.1 software was used to implement these polarimetric decomposition methods for extracting polarimetric information. A total of 246 (6*41) polarization decomposition images extracted from the multitemporal PolSAR images were used for land cover classification. (There were 6 periods, and 13 polarization decomposition methods with a total of 41 channels in each period.)

**Segmentation of multitemporal PolSAR images**

Compared with pixel-based image analysis, object-oriented image analysis can improve PolSAR image classification accuracy (Hussain et al., 2013; Qi et al., 2012). This study integrated object-oriented image analysis into the land cover classification of multitemporal PolSAR images. Image segmentation is an essential step in object-oriented classification. The Pauli RGB composition image of PolSAR images is commonly used for image segmentation (Qi et al., 2012). To ensure the accurate delineation of land parcels, we fused the Pauli RGB composition images of each PolSAR data for segmentation (Figure 4). The fused image was averaged from all Pauli RGB composition images to contain the temporal information for image segmentation.

The multiresolution segmentation algorithm was performed on the fused Pauli RGB composition image to delineate image objects. The multiresolution segmentation was an optimization procedure for minimizing the average heterogeneity and maximizing the homogeneity in a given number of image objects (Jiao et al., 2014). The multiresolution segmentation scale parameter greatly influenced the segmentation.

![RGB composition images of different polarimetric decomposition methods.](image-url)
results, and the optimal scale parameter is commonly determined by a heuristic process (Benz et al. 2004). By trying different scale parameters, we found that the scale parameter of 20 was optimal for the multitemporal images in delineating accurate land parcels and avoiding fragmental image objects (Figure 5).

**Object-oriented land cover classification**

Numerous classification methods, including decision trees (DTs), support vector machines (SVMs), and random forests (RFs), have been employed for PolSAR images (Du et al., 2015; Huang et al., 2018; Khosravi et al., 2017; W. Liu et al., 2018). DTs can select the most important features for classification and achieve better classification results than SVMs, especially under numerous features (Qi et al., 2012). RF algorithms are widely used in various studies due to their flexible and practical characteristics. Many studies have found that random forest algorithms can produce better classification results than DT algorithms (Breiman, 2001; Loosvelt et al., 2012). Therefore, RF algorithms were adopted in this study for the object-oriented land cover classification using multitemporal PolSAR images. RF algorithm embedded in eCognition Developer 64 9.01 software was used for land cover classification. DT-RF algorithms were used to determine the optimal polarimetric parameters and PolSAR image acquisition dates for land cover classification. DT algorithm was used to select the most useful channel layers for learning training samples. Then, RF algorithms were adopted in this study for the object-oriented land cover classification using the selected channel layers.

**Results and discussion**

**Improvement by multitemporal PolSAR data for land cover classification**

Land cover classification results were produced using the multitemporal PolSAR images and each single PolSAR image, respectively (Figure 6). Among all the classifications, the multitemporal scene attained the highest overall accuracy and kappa coefficient, which were 96.55% and 0.96 (Figure 7), respectively. The overall accuracies and kappa coefficients of different single scenes were different. The overall accuracy and kappa coefficient were lower in March and April than in the other months. The scene on April 14 produced the lowest overall accuracy and kappa coefficient, which were 79.78% and 0.76, respectively. Among all the single scenes, the scene on May 8 attained the highest overall accuracy and kappa coefficient, which were 92.89% and 0.91, respectively. The classification accuracy decreased from May 8 to July 19. The producer’s and user’s accuracies of each land cover class were also calculated for different classifications (Figure 8). We found that the multitemporal scenes achieved higher producer’s and user’s accuracies than any single
scene for each land cover class, especially for paddy fields, bare land, fishponds, rivers/reservoirs, cropland, and forests.

The temporal change of the scattering mechanisms of different land cover classes was analyzed to investigate how the multitemporal PolSAR data improved the land cover classification accuracy (Figure 9). The PolSAR backscatter of paddy fields varied significantly with time. The growth cycle of paddies in the study area was from March to July, and the PolSAR backscatter from paddy fields changed significantly with their growth (Figure 10). The author ran through the research area in 2009 and conducted a specific survey, and there three large and hundreds of small pieces of paddy fields. Paddies experienced three growth phases, namely, seedling transplanting, young panicle differentiation, and maturation. Paddies were at the seedling stage in late March to early April, during which paddy fields were difficult to distinguish from fishponds, rivers/reservoirs, and bare land. As a result, the producer’s and user’s accuracies of paddy fields were relatively low in March and April (Figure 11). With the growth of paddies, the confusion among paddy fields, rivers/reservoirs, and bare land decreased, and the producer’s and user’s accuracies of paddy fields increased from April 14 to June 25. Paddy fields matured in July and were easily confused with other vegetation types, such as crops, natural vegetation, and forests. Consequently, the user’s and producer’s accuracies decreased substantially (Figure 11).

The multitemporal PolSAR data captured the radar return change caused by the paddy growth, which was significant for distinguishing paddy fields from other vegetation types. Therefore, the multitemporal PolSAR data performed considerably better than a single scene for identifying paddy fields. In comparison with a single PolSAR image, multitemporal PolSAR data increased the producer’s and user’s accuracies of paddy fields by 62.67% and 51.8%, respectively (Figure 11). Their accuracies of bare land, fishponds, rivers/reservoirs, cropland, and forests were also increased. The results indicated that the improvement was mainly because of the capability of multitemporal PolSAR images to capture the radar return change caused by the paddy growth.

Contribution of polarimetric decomposition to multitemporal PolSAR image classification

The contribution of the polarimetric decomposition methods was investigated by comparing the
multitemporal PolSAR image classification using such methods and that using coherency matrices alone. The overall accuracy and kappa coefficient obtained using coherency matrices alone were 94.44% and 0.93, respectively, which decreased by 2.11% and 0.03 compared with those attained by using polarimetric decomposition methods. The use of polarimetric decomposition methods also improved the producer’s and user’s accuracies of different land cover classes (Figure 12), especially fishponds and rivers/reservoir. The study area is in the middle and lower reaches of the Pearl River Delta, where many fishponds are distributed. Substantial confusion between fishponds and rivers were observed in the land cover classification using the coherency metrics alone because of the similar backscattering mechanism. Fishponds were typically distributed together in coastal areas, and each fishpond had “thin boundaries” (i.e., land surrounding a fishpond). In the process of image segmentation, fishponds tended to merge with their “thin boundaries” to form image objects, which could feature higher radar backscatter than image objects of pure water. The use of polarimetric decomposition could reveal the differences in scattering mechanisms between fishponds and rivers/reservoirs (Figure 13). The producers’ accuracies of rivers and fishponds increased by 1.11% and 7.38%, respectively, when polarimetric decomposition methods were incorporated into the classification. The results indicated that the polarimetric decomposition methods still contribute to land cover classification when applied with multitemporal PolSAR data.

**Optimal acquisition dates and polarimetric parameters for land cover classification**

Although classification with multitemporal PolSAR images can improve land cover classification accuracy, it also increases data collection and processing
Combining all available datasets and polarimetric parameters may be unnecessary because some of them may create a marginal contribution to land cover classification. This study investigated the optimal PolSAR image acquisition dates and polarimetric parameters for land cover classification using DT algorithms. DT algorithms can be used to solve the problem of feature selection in object-oriented classification (Qi et al., 2012). By examining the effects of every input feature to determine every split in a final tree, decision tree algorithms can efficiently select the most important features that achieve the best classification result. After a final tree is constructed based on a full dimensionality of features, the classification rules provided by the tree are easily interpreted. As shown in Figure 14, the decision tree created for the classification indicated that the optimal acquisition dates of PolSAR images were April 14, May 8, June 1, and June 25. In Panyu district, these dates were in the growth stage, long panicle stage and flowering stage of paddies. These acquisition dates contained the radar return change with the growth of paddy fields and could be important for distinguishing between paddy fields and other land cover types (Figure 10). This finding further confirmed that multitemporal PolSAR data improved land cover classification by reducing the confusion between paddies and other land cover types. Furthermore, the Pauli, Cloude, Neumann3,
An&Yang4, Freeman3, Barnes2, and MCSM5 decomposition methods were more useful than other methods for land cover classification. The land cover classification was implemented using random forests based on the acquisition dates and polarimetric parameters selected by DT-RF.
The overall accuracy and kappa coefficient were 96.26% and 0.96, respectively, which were almost the same as the ones (96.55% and 0.96) achieved using all PolSAR images and polarimetric decompositions. Moreover, the classification based on the selected PolSAR images and polarimetric parameters reduced...
the classification time by 95% compared with that based on all PolSAR images and polarimetric decomposition methods. The results showed that the optimal PolSAR image acquisition dates and polarimetric parameters retained the good classification capability and increased the classification efficiency. Therefore, DT-RF methods will be used to quickly study land cover classifications in different regions and variables, like multi periods and parameters.

Conclusions

This study carried out land cover classification using six sequential RADARSAT-2 fully PolSAR images that are 24 days apart. The overall accuracy and kappa coefficient obtained with the multitemporal PolSAR data were 96.55% and 0.96, respectively, which were higher than those obtained with any of the PolSAR images. In comparison with a single PolSAR image, multitemporal PolSAR images increased the overall accuracy and kappa coefficient by as much as 16.55% and 0.20, respectively. The improvement was mainly because of the ability of multitemporal PolSAR images to capture the radar return change caused by the paddy growth. Paddies featured a short growth cycle and variant PolSAR backscatter during their growth and were easily confused with bare land, rivers/reservoirs, and built-up areas at different growth stages. By utilizing the radar return change with the paddy growth, the multitemporal PolSAR data significantly reduced the confusion between paddy fields and other land cover types and improved the user's and producer’s accuracies for paddy fields, bare land, fishponds, rivers/reservoirs, and cropland. Compared with a single PolSAR image, multitemporal PolSAR images increased the producer's and user's accuracy of paddy fields by as much as 62.67% and 51.8%, respectively.

The polarimetric decomposition methods improved the accuracy of multitemporal PolSAR image classification. Polarimetric parameters extracted with different polarimetric decomposition methods vary the scattering properties of the observed objects; thus, they could improve land cover classification accuracy even when applied with multitemporal PolSAR data. In comparison with the multitemporal PolSAR image classification using the coherency matrices alone, the addition of polarimetric decomposition methods improved the overall accuracy and kappa value by 2.22% and 0.03, respectively. Moreover, different polarimetric decomposition methods improved the producer's and user's accuracy for all land cover classes, especially rivers/reservoirs and fishponds. The user's accuracies of rivers/reservoirs and fishponds can be increased by 7.39% and 1.93%, respectively.

This study investigated the optimal PolSAR image acquisition dates and polarimetric parameters for land cover classification using DT algorithms. The optimal acquisition dates were April 14, May 8, June 1, and June 25, and the optimal polarimetric decomposition methods included the Pauli, Cloude, Neumann3, An&Yang4, Freeman3, Barnes2, and MCSM5. In comparison with the land cover classification based on all the images and polarimetric decomposition methods, the classification based on the optimal acquisition dates and polarimetric parameters achieved comparable classification accuracy and reduced the classification time by 95%. Moreover, this classification considerably reduced the cost of data collection and processing.

This study demonstrated the potential of multitemporal fully PolSAR data under the support of multiple decomposition methods and provided knowledge and experiences in steering the selection of appropriate polarimetric parameters and acquisition dates for multitemporal PolSAR image classification. Further research will be conducted in different areas to investigate the land cover classification capability of multitemporal PolSAR data that span over one year.

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Disclosure of potential conflicts of interest

No potential conflict of interest was reported by the author(s).

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