Adaptive land cover classifier using directional neighborhood rough set (DNRS)

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Land cover classification maps are used for various purposes, such as climate change prediction and natural disaster monitoring. Various classifiers have been proposed for land cover classification. However, the perfect classifier doesn't exist, and using each classifier appropriately based on its features is important. We focused on a classifier, directional neighborhood rough set (DNRS), which has never been used for land cover classification. DNRS is a kind of rough set theory extended to extract decision rules from data sets where the explanatory variables are numerical, and the response variables are categorical, and classification. One of its conceptual features is that it represents arbitrary sets using two approximations: a lower approximation set, which is an approximation set of certainty, and an upper approximation set, which is an approximation set of possibility.

In this study, we examined the performance of DNRS as a land cover classifier. Further, the improvement of DNRS was also examined. The classification results were compared with those obtained by support vector machine (SVM) and random forests (RF), which are often used for land cover classification.

In the experiments, we used Landsat-8 images in Ibaraki, Japan, and assessed the classification accuracy by overall accuracy (OA), accuracy of excluding the unclassified area and class-specific accuracies. The OA obtained by applying original DNRS was 85.4%. To improve the accuracy of the DNRS, the following improvements were made. First, the lower approximation classification step of the DNRS algorithm was divided into "cases where only one class has a grade" and "cases where multiple classes have a grade." The accuracy of excluding the unclassified area was 94.8%. This indicates that this method can extract the area with high certainty. Furthermore, a threshold for difference of grade was set to decrease unclassified pixels within which the 94.8% accuracy did not almost decrease, and unclassified pixels were classified using the original DNRS's third step. The grade threshold adopted at this time was 0.004. As a result of these improvements, the new DNRS's OA was 87.1%.

The OA of land cover classification with the DNRS, SVM, and RF was 87.1%, 88.3%, and 86.6%, respectively. Z-tests between the DNRS and SVM and between the DNRS and RF were conducted under the 5% significance level and showed no significant difference. Thus, the DNRS was statistically as accurate as the existing classifiers. From this experiment, in order to analyze the cause of accuracy differences between approximately 80% of the area which was classified with 94.8% accuracy, and the remaining 20% area which decreased to 87.1% accuracy, we analyzed the remaining 20% of the area. As a result, it was found that approximately 70% of them were mixed pixels. These results show that by taking advantage of the properties of DNRS, the classifier is characterized by its ability to adaptively obtain classification results that include only pure pixels or both pure and mixed pixels, depending on the purpose of creating the land cover map. We are going to confirm its versatility for various target areas and satellite images.

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