# Reliability Evaluation and Migration of Wetland Samples

Xin Yan and Zhenguo Niu

***Abstract*—As one of the most important steps in classification and mapping research, sample acquisition and updating cost a lot of time and energy of researchers. The high temporal and spatial dynamic characteristics of wetland make the reliable wetland sample selection more challenging. It is especially important for time series wetland classification to address the problem of how to apply sample sets to images with different periods. This article evaluated the reliability of the historical samples by using optical and synthetic aperture radar remote sensing data from the perspective of water inundation frequency, and three sample migration methods based on rule set, reclassification, and spectral similarity were proposed to carry out wetland classification experiment in the Tibetan Plateau. In addition, the relationship between the number of samples and classification accuracy is analyzed. The migration and reuse of sample sets can quickly obtain accurate wetland sample sets, which lays the foundation for the study of wetland mapping in time series.**

***Index Terms*—Reliability, remote sensing, sampling methods, water.**

## I. Introduction

WETLAND ecosystem is one of the most productive and biologically diverse ecosystems and also one of the most threatened ecosystems of the earth [1]. They not only provide habitat for many wild animals and plants but also provide a variety of ecological services for human beings, such as water conservation, climate regulation, pollution degradation, carbon fixation, oxygen release, erosion control, nutrient cycle, and so on [2]. However, in the context of global warming, with the acceleration of globalization, human beings have carried out large-scale development for social and economic developments, and more and more wetlands have been converted into agricultural or urban land, which leads to obvious degradation or even disappearance of wetlands in the global scope [3], [4]. The deterioration of wetland environment has caused significant ecological consequences, including biodiversity loss, ecological function change, habitat fragmentation, flood, and drought, which will have adverse effects on human health, livelihood, and well-being. It is of great significance to accurately obtain and update the spatial distribution information of wetlands for global climate change and ecological research.

As a unique ecosystem formed by the interaction between land and water, wetland is usually located in the transitional geographical position between terrestrial ecosystem and aquatic ecosystem. It can be considered that wetland is composed of vegetation, water, and soil, which makes wetland ecosystem transitional, spatial heterogeneity, and temporal dynamics and also determines that wetland is more difficult to distinguish from other land cover/use types [5]. Especially with the alternation of dry and rainy seasons, the wetland presents the characteristics of seasonal and interannual dynamic changes, and then it becomes a major difficulty in the field of wetland research to accurately obtain and update the location and scope of wetland. A challenge hindering the progress of large-scale wetland mapping research is still the lack of timely, accurate, and large-scale coverage training samples, which is the key requirement to produce reliable wetland datasets [6].

Wetland sample set is the basis of accurate wetland classification and mapping, which determines the quality of the whole classification process [7]. For large-scale wetland mapping, it is a time-consuming and laborious process to obtain samples through field observation or visual interpretation, and the sample accuracy seriously depends on the subjective decision of the sample interpreters [8]. For example, Gong *et al.* [9] collected 91 433 training samples by 27 image analysts with remote sensing image interpretation experience when making global 30-m land use/cover products. Similarly, Tateishi *et al.* [10] selected 312 753 training points from 2080 training polygons. Although there are some historical wetland sample sets, most of the samples are obtained at a specific time, which only serve the corresponding research. In addition, the wetland type may change with the time, and the samples obtained at a specific time cannot be used in other periods without verification, resulting in a waste of time, energy, and data [7]. Therefore, the historical wetland sample datasets are usually unable to achieve consistency in time and space. The lack of accumulation and sharing among sample sets leads to increased workload and inadequate utilization of results [11]. Especially in the time series classification, the characteristics of wetland types changing with time put forward a great test for sample collection. Making full use of the existing sample set can effectively save the time and energy spent on sample collection. Huang *et al.* [12] developed an automatic training sample migration method. By measuring the

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spectral similarity and spectral distance between the reference spectrum and the image spectrum, the change status of training sample pixels in 2010, 2005, 2000, 1995, and 1990 was detected and recognized, and good results were obtained. The proposed sample migration theory, such as the stable classification of limited samples, provides a theoretical basis for rapid wetland mapping [13].

Therefore, to meet the needs of sample set reuse, in this article, we proposed several methods of sample set reliability evaluation and migration. For the reliability evaluation of historical samples, this article proposed to use the water frequency data generated by optical data and synthetic aperture radar (SAR) data to preliminarily identify the sample types, and the threshold method was used to determine the wetland subtype combined with time series NDVI and NDWI. In addition, this article proposed three sample migration methods based on rule set, reclassification, and spectral similarity and compared the classification results and accuracy of the three methods in the Tibetan Plateau. Aiming at the problem of reducing the number of samples in the process of sample migration, this article also explores the relationship between the number of samples and the classification accuracy. High frequency accurate samples are obtained by sample migration and reuse, which lays the foundation for time series wetland mapping research.

## II. Study Area and Data

### A. Study Area

In the part of sample evaluation, we choose China rather than small area as our research area, which makes the research results more universal. In the part of classification experiment of sample migration, restricted by the ability of classifier, we choose Tibetan Plateau as the study area (26° N–39° N, 73° E–104° E). Because of its high altitude, Tibetan Plateau is called "Roof of the World" and "Third Pole." The average sea level is above 4000 m and annual average temperature is below 0 °C The total area is about 2.5 million km$^2$. The plateau is rich in animals, plants, light, geothermal, mineral, and water resources.

Tibetan Plateau is the main wetland distribution area in China. It has a vast area of alpine swamp and more than 1500 lakes, and it is also the birthplace of many rivers. The melting water of ice and snow is the main supply source of inland rivers. However, due to the cloudy characteristics of the Tibetan Plateau, it is difficult to obtain high-quality optical images, which often cannot completely cover the whole study area for a month or even several months, which brings great challenges to the remote sensing research of wetlands in the Tibetan Plateau.

### B. Data Sources

The boundary of the Tibetan Plateau used in this article is from the plateau climate area in the climate regionalization data and is downloaded from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences. It is derived from the 1951–1970 climate data compiled by the National Meteorological Administration of China based on the water index and heat index.

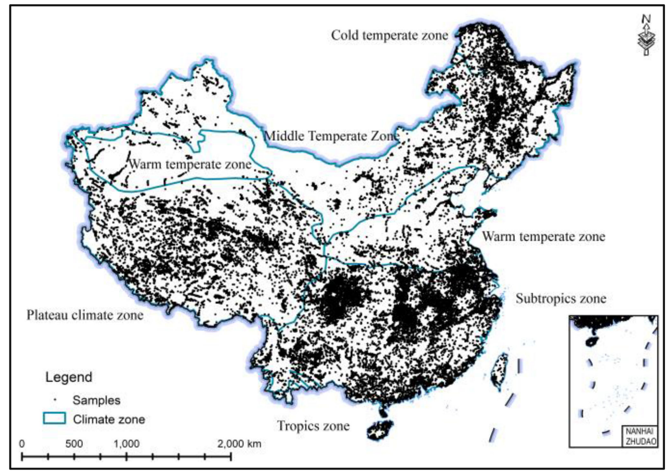


Fig. 1. Samples distribution in China.

The samples used in this article are based on the field sampling and visual interpretation of Landsat and CBERS-02B images, which were applied in the first China wetland mapping in 2008. A total of 60 661 samples were used that did not change in type during the four periods 1978, 1990, 2000, and 2008 (Fig. 1); so the samples themselves have high consistency and credibility. The interpretation results of wetland classification in 2008 were verified by field survey in 2009, and the overall accuracy was 0.7, which proved that the samples can be used for research. Among them, in order to meet the needs and feasibility of classification, 1542 samples were selected from the Tibetan Plateau for the study of sample migration.

The first evaluation dataset is High Spatial-temporal Water Body Dataset in China (HSWDC) with monthly temporal resolution and 10 m spatial resolution, which was generated by the threshold method based on the Google Earth Engine (GEE) cloud-computing platform using the Sentinel-1 SAR data from 2016 to 2018[1] [14]. Sentinel-1 is the earth observation satellite in the Copernicus project (GMES) of the European Space Agency, which is composed of two satellites and can provide continuous images (day, night, and various weather), which can provide high-resolution image foundation for global monitoring applications [15].

Another evaluation dataset is Joint Research Centre (JRC) Global Surface Water Mapping Layers product, where each pixel was individually classified into water/nonwater using an expert system. Pekel *et al.* [16] used more than 3 million terrestrial satellite images to quantify changes in global surface water over the past 32 years with a resolution of 30 m. This product consists of one image containing seven bands, and the "Seasonality" band is mainly used in our article. The Seasonality map provides information concerning the intra-annual behavior of water surfaces for a single year (2018) and shows permanent and seasonal water. The values from 0 to 12 are discrete, which is the number of months that water was present from January to December 2018.

In this article, 9620 high-quality Landsat 8 OLI images of China in 2018 are obtained on the GEE platform to get NDVI

[1] [Online]. Available: https://scihub.copernicus.eu/dhus/#/home

and NDWI time series data. Three thousand one hundred and seventy-three Landsat 8 OLI images in 2020 and 3324 Landsat 8 OLI images in 2015 are used in the wetland classification research based on sample migration in the Tibetan Plateau. These data have been atmospheric corrected using LaSRC algorithm, including using CFMASK algorithm to generate cloud, shadow, water, and snow masks, as well as per pixel saturation mask, and using its cloud and cloud shadow mask to remove poor quality pixels. NDWI is calculated by using the near-infrared (0.85–0.88 $\mu$m) and green (0.53–0.59 $\mu$m) spectra of the OLI image, and NDVI is calculated by using the red (0.64–0.67 $\mu$m) and near-infrared spectra of the OLI image. The time interval of time series dataset in the study is usually consistent with the revisit cycle of Landsat 8, unless the data is missing due to data quality problems. In order to avoid the problems of missing and abnormal data, we use Savitzky–Golay filter to smooth the time series curve. A Savitzky–Golay filter is a digital filter that is achieved in a process known as convolution, by fitting successive subsets of adjacent data points with a low-degree polynomial by the method of linear least squares [17]. Then, each sample has two continuous NDVI and NDWI time series diagrams.

In addition to reflectance data, terrain and land surface temperature (LST) data are added as data sources to better classify wetlands to test the effect of sample migration. The terrain data is from digital elevation data (SRTMGL1_003) of Shuttle Radar Terrain Mission (SRTM) and calculates the local gradient of four adjacent pixels of each pixel to get the slope data. The SRTM V3 product (SRTM plus) is provided by National Aeronautics and Space Administration Jet Propulsion Laboratory (NASA JPL) with a resolution of 1 arcsec (about 30 m), which can obtain global scale digital elevation model. The dataset has been filled with open-source data (ASTER GDEM2, GMTED 2010, and NED).

Currently, three correction methods are commonly used to retrieve LST from single-band Landsat TIR data—the radiative transfer equation (RTE), the mono-window algorithm, and the generalized single-channel method [18]. Some results show that three algorithms have consistency and the LST has the closest retrieval results with MODIS LST product when RTE is used [19]. In this article, the RTE method is used to calculate the LST from Landsat 8 OLI images. The spatiotemporal resolution of LST data is consistent with that of Landsat 8 OLI sensor.

## III. Methods

In nature, any feature has unique spectral characteristics. In spectral feature space, each pixel corresponds to a multi-dimensional spectral vector. Change vectors are measured by subtracting vectors pixelwise as image differencing. The main characteristics of the change vectors, such as magnitude and direction, are indicative of the change type and degree [20].

### A. Euclidean Distance

The Euclidean distance (ED) of the spectrum is the measurement of the difference in the length between the two spectral vectors [20]. As shown in Fig. 2, the number of bands is the dimension of the coordinate system. The difference degree of

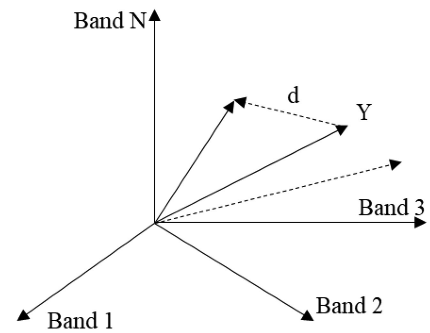


Fig. 2. ED sketch.

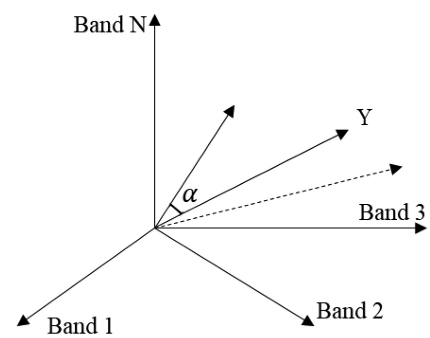


Fig. 3. SAD sketch.

two pixels can be obtained by calculating the distance between two pixels in spectral space, and the change of the same pixel at different times can be measured. Since the spectral distance is mainly calculated on the basis of the spectral characteristics of two vectors, it is more sensitive to brightness [21]. In this study, ED is used to calculate the spectral differences of the same samples in two years and the average spectral distance of different types. The spectral information of samples in 2020 are used as reference spectrum, and the spectral information of migrated samples in 2015 is the target spectrum. ED is Euclidean distance between reference spectrum and target spectrum. The smaller the distance, the smaller the difference between the two, and if the reference spectrum and target spectrum are the same, ED is 0. Specifically expressed as the square root of the square sum of the difference

$$\mathrm{ED} = \sqrt{\sum_{i=1}^{N} \left(X_{i(t1)} - Y_{i(t2)}\right)^2}$$

where $i$ is the band, $N$ is the total number of bands, and $X_{i(t1)}$ and $X_{i(t2)}$ are the pixel brightness values corresponding to *X* and *Y* samples at $t1$ and $t2$, respectively.

### B. Spectral Angle Distance

Spectral angle distance (SAD) is a common index to measure the similarity between two spectra, which was proposed by Kruse *et al.* [22]. Similar to ED, in spectral space, each pixel corresponds to a multidimensional spectral vector, and the angle between the two vectors is defined as spectral angle (Fig. 3) [23].The smaller the spectral angle is, the more similar the two spectra are and the more likely they are to belong to the same kind

TABLE I
WETLAND CLASSIFICATION SYSTEM

| Level 1 | Level 2 | Coding | Definition and description |
|---|---|---|---|
| Permanent water | | 10 | Natural complex in water covered area, including rivers, lakes, lagoons, reservoirs, etc. |
| Non-wetlands | | 20 | Including artificial cover type, bare land, forest land and other types of features that are not underwater |
| Wetlands | Marshlands | 30 | Including inland and coastal herbaceous marshlands, which are in wetland state for a long time in a year cycle or regularly exists in the growing season or specific season |
| | Flooding wetlands | 40 | Periodically flooded supersaturated soil near estuaries or inland lakes and rivers, with low vegetation coverage and no open water coverage |
| | Paddy fields | 50 | Often grow water-dependent crops, such as rice |
| | Ponds | 60 | Artificial water storage facilities built for irrigation, hydropower, flood control, and other purposes |
| | Irrigation canals and ditches | 70 | A channel dug by hand for irrigation or drainage |

of features. Similarly, the SAD makes full use of the information of the pixel in the spectral dimension, but different from the ED, the SAD is not affected by the light, shadow, and other conditions, that is, when the brightness value increases or decreases, its angular direction will remain unchanged. Therefore, the SAD method is not sensitive to the changes of shadow and light and can highlight the spectral shape characteristics of the target [24]. The higher the similarity between the reference spectrum and the target spectrum is, the greater the SAD. If the reference spectrum is the same as the target spectrum, the SAD is 1. The calculation formula is as follows:

$$\theta = \cos^{-1}\frac{\sum_{i=1}^{N} X_{i(t1)}Y_{i(t2)}}{\sqrt{\sum_{i=1}^{N} {X_{i(t1)}}^2 \sum_{i=1}^{N} {Y_{i(t2)}}^2}}$$

$$\mathrm{SAD} = \cos\theta \,.$$

## IV. Reliability Evaluation of Historical Samples

### A. Wetland Classification Scheme

Since there is no unified wetland classification system at present, considering that the research object of this part is mainly the national scale wetland types, the water body and nonwetland types are not subdivided. Starting from the perspective of wetland occurrence, combining the characteristics of wetland attributes and remote sensing technology, and considering the existing wetland classification results, we propose a multilevel dynamic composite wetland remote sensing classification system (Table I). The wetland type in this study is a narrow sense, which does not include open water body. The classification system includes both constructed and natural wetlands, which has been applied in many areas such as Baiyangdian basin, Northeast Plain, and other areas, and has good versatility [25], [26]. Each type is represented by a specific code.

### B. Wetland Type Identification

To obtain wetlands and water, the HSWDC monthly water data is accumulated at the sample locations. The sum is from 0 to 12, where 0 means the earth's surface is not underwater throughout the year, 12 means that it is always underwater throughout the year, i.e., permanent water, and 1–11 represent the feature that belongs to the wetland type. Similarly, the value of the Seasonality map from JRC surface water product map is discrete from 0 to 12, too.

Since both evaluation datasets are water datasets, they are sensitive to the occurrence of water, but not sensitive to the types of wetlands. Therefore, in this article, we first use two evaluation datasets to determine the types of water, wetlands, and nonwetlands and then further determine wetland subclass based on the values and trends of NDVI and NDWI time series data. It is worth noting that since the two evaluation datasets are from optical sensors and SAR sensors, respectively, the determination of water frequency at the same point may be inconsistent. In order to ensure the accuracy of the results, only samples with the same type in the two evaluation data sets are retained.

Samples without phenological characteristics cannot be unquestionably used to verify dynamic wetland products [7]. Trends in the time series of NDVI and NDWI can reflect the periodic changes of wetland types [27]. The 16-day Landsat NDVI time series values and NDWI time series values with 30-m spatial resolution are extracted from the year 2018 at the sample locations. The NDWI value reflects whether the feature is underwater or not. If the NDWI of the sample is always greater than 0 in a year, it indicates that the sample is water or wetland type; if the NDWI of the sample is greater than 0 or less than 0 with time, it indicates that the wetland is seasonal, such as paddy fields or flooding wetlands. The specific types of wetlands can be judged from NDVI values [28].

Since the surface of the marshland is covered with herbaceous plants, which affects the reflection signal transmission of water to the sensor, its NDWI value is low. Paddy field and flooding wetlands have seasonal characteristics, for example, before the flood season (January to June), flooding wetlands are in the state of not being flooded and exposed to the surface; so their NDWI values are low. During this period, paddy fields have no vegetation growth and more water, and their NDWI values are in a state of greater than 0. For the needs of classification, the study focuses on the index change characteristics of wetland

TABLE II
NUMBER OF DIFFERENT TYPES

| Types /dataset | Initial | CHSWD | JRC | CHSWD +JRC | Initial+ CHSWD +JRC |
|---|---|---|---|---|---|
| Water | 35431 | 15243 | 17302 | 10311 | 8109 |
| Wetlands | 25230 | 11735 | 13734 | 5063 | 2098 |
| Non-wetlands | 0 | 33683 | 29625 | 26860 | / |

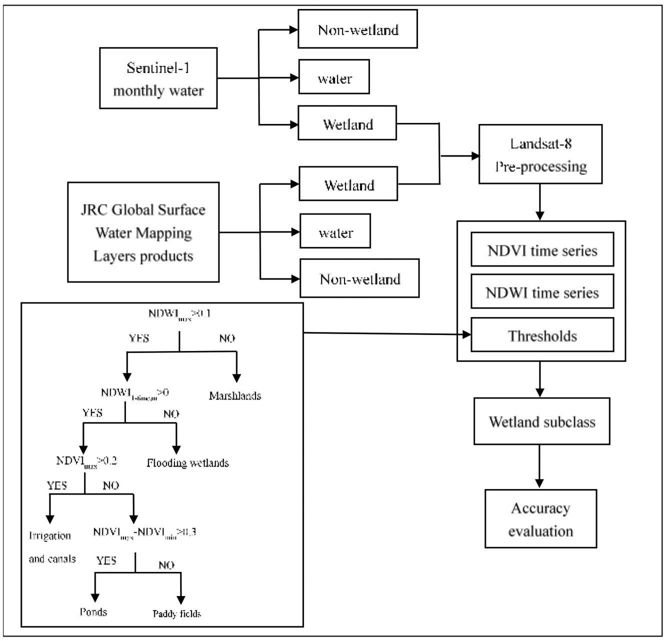


Fig. 4. Sample classification flow.

types and summarizes the change trends of NDVI and NDWI values of main wetland types (Fig. 4).

### C. Accuracy Evaluation

More than 100 samples were randomly selected for each wetland type and were visually interpreted by wetland experts comparing with the Google Earth image with high spatial resolution. The overall accuracy is 86%. Among them, the accuracy of ditches is the lowest. The main reason is that the resolution of Landsat image is relatively coarse for irrigation canals and ditches type, and some narrow ditches could not be identified or there are mixed pixels, which affected the wetland type judgment. At the same time, due to the lack of cloudless images, there are fewer reference NDVI and NDWI values in some areas, which will partially affect the final results.

### D. Results

In this article, we first used Sentinel-1 SAR data to determine the monthly water inundation map, combined with JRC global surface water mapping layers product to make a first-class classification of 60 661 wetland samples in 2018 and then based on the phenology characteristics of different wetland types, combining the NDVI and NDWI time series trends to classify wetland subclasses by threshold method and, finally, random sampling of sample points combined with high spatial resolution Google Earth images for accuracy evaluation.

All original sample types are wetlands or water, of which the largest number is water, a total of 35 431. Among the wetland types, the type with the largest number belongs to marshlands, which is 10 205, followed by ponds, a total of 9816. The number of flood wetlands and ditches is less, i.e., 3299 and 1910, respectively. The assessment results of CHSWD and JRC global surface water mapping products (Table II) show that the number of wetlands determined by the two assessment datasets is only 5063. The type determined by an evaluation dataset shows that about half of the water and wetlands have degenerated into nonwetlands in the past decade.

For the 5063 samples that are identified as wetlands by the two evaluation datasets, the NDVI and NDWI time series trends are also classified by the threshold method for wetland subclass classification. The results show that the number of ditches is 2028. There are 1267 flood wetland samples, 854 pond samples, 455 paddy field samples, and 459 marshlands samples. It can be seen that the number of constructed wetlands has increased significantly in the past decade. In terms of spatial distribution, wetlands are mainly concentrated in the Central and Eastern China with flat terrain, and there are also a small number of wetland samples in the Tibetan Plateau and Northeast China.

## V. SAMPLE MIGRATION

In order to solve the problem that the samples cannot be used across time, this article selected three solutions. First, establish rule set to classify samples, extract the image reflectance and index characteristics of the samples during the study period, first classify the samples, and then classify the wetlands according to the samples. The second is to adopt the method of reclassification, assuming that the sample types of two adjacent years have little change, the samples that are different from the initial classification results are eliminated, and the samples that are the same in sample type and classification results are used for reclassification. The third method is to calculate the ED and SAD of the spectrum where the sample is located, combined with the threshold to judge whether the type of sample points has changed so as to achieve the purpose of discrimination.

In order to show the classification effect, the Tibetan Plateau is selected as the study area. As a unique wetland type in Tibetan Plateau, marsh meadow is a transitional zone between marsh wetland and meadow, which nourishes a lot of unique wetland vegetation of this type. It is of great significance in the field of soil organic carbon content and microbial community and is also one of the types that this study focuses on. Therefore, combined with the characteristics of land cover types in the Tibetan Plateau, this article added the marsh meadow type on

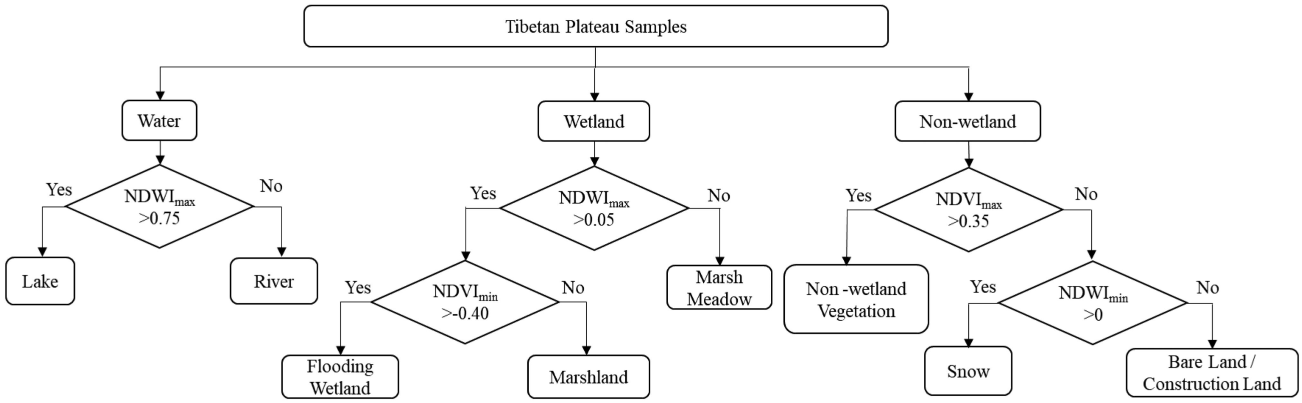


Fig. 5. Classification rule set of wetlands in Tibetan Plateau.

the basis of the national samples, including eight land cover types: lake, river, flooding wetland, marshland, marsh meadow, nonwetland vegetation, snow, and bare land/construction land.

## A. Sample Migration Method Based on Rule Set

Through lots of literature research and hundreds of experiments on land cover types and their images in the Tibetan Plateau in 2020, this article compared the differences of reflectance and characteristics of NDVI, NDWI, LSWI, MNDWI, and other indexes among different land cover types, especially different wetland types in time series, and established a set of fine wetland sample rule set in line with the Tibetan Plateau (Fig. 5).

However, there is a premise for applying the wetland sample rule set established in 2020 to other periods, that is, assuming that the annual change of reflectance of different land cover types is relatively small; so the NDVI and other indexes remain constant or change a little every year. In this case, the classification rule set based on Landsat 8 image in 2020 can be applied to other periods in theory.

A total of 1542 samples are selected to classify the wetlands in the Tibetan Plateau. After comparing the classification effect and accuracy of random forest (RF) classifier, classification regression tree classifier, support vector machine classifier, naive Bayes classifier, and minimum distance classifier in the early stage, the RF can obtain the highest classification accuracy and classification effect when inputting various classification features. Therefore, this article chooses RF as the research method. The data sources are Landsat 8 OLI median composite image, terrain data (slope), temperature data based on Landsat 8 OLI, NDVI, and other indexes. Finally, the wetland classification map of the Tibetan Plateau in 2020 (Fig. 6) is obtained, and the overall accuracy is 0.87, which can meet the research needs.

On the basis of the image of Landsat 8 in 2015 and NDVI and NDWI time series features, the same rule set is used. First, the sample set is classified, and the RF classification is carried out based on the generated samples. The wetland classification map in 2015 (Fig. 6) is obtained, and the final classification accuracy is only 0.77. From the 2015 wetland classification map based on the rule set, it can be seen that in the southeast

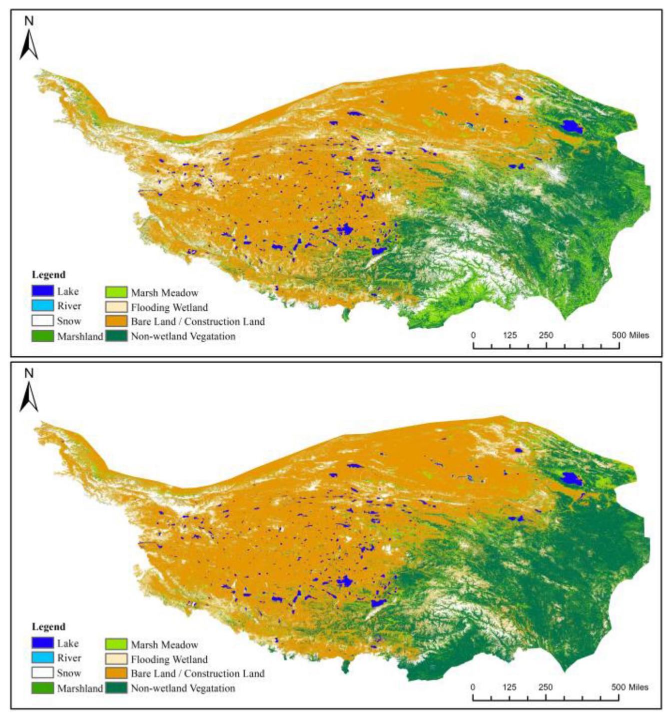


Fig. 6. Wetland classification map of Tibetan Plateau in 2020 (upper) and 2015 (lower) based on rule set.

of Tibetan Plateau, the marsh meadow is mistakenly divided into nonwetland vegetation types, and the recognition ability of flooding wetland is weak.

It can be seen that the basis of establishing the rule set is the similarity of reflectance and index of the image. Due to the change of climate conditions and other factors on the Tibetan Plateau every year, the reflectance of wetland types will naturally change when the time of studying changed to another year. The method of classifying the samples based on the same rule set and then classifying the study area based on the samples cannot meet the accuracy requirements. If we want to use the rule set sample classification method for time series wetland classification, we need to establish a new rule set for each period of image and index value.

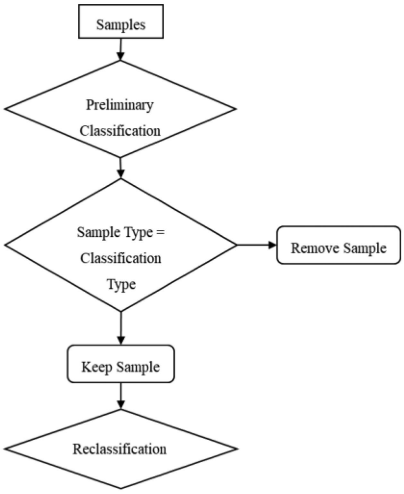


Fig. 7. Flowchart of reclassification sample migration.

## B. Sample Migration Method Based on Reclassification

In fact, nonwetland vegetation, bare land/construction land, snow, and other land cover types change a little from year to year. Only a few wetland types and water body types such as marshland will change due to the influence of climate. If the sample size is enough, as long as the changed types are removed, the labor cost can be reduced, but the optimal classification effect can be achieved.

In the process of classification, the classifier will make a comprehensive evaluation based on the reflectance data of all sample points. However, due to the serious deviation of individual samples from the reflectance of the same type of samples and closer to other types of reflectance, the classification result of the point is different from itself. In this case, the sample type is likely to have changed. In view of this, this article intends to remove the samples whose initial classification results are inconsistent with their own sample types by means of reclassification and use the remaining samples for reclassification to obtain the classification results with higher accuracy (Fig. 7).

Since the wetland classification results based on the samples in 2020 meet the needs of the study (the accuracy is 0.89), this study first extracts the type value of the samples in the classification results in 2020 and makes judgment, and retains the samples of same type as the original samples, a total of 1472 samples, which are applied to the image classification in 2015 for preliminary classification. The accuracy of the initial classification is 0.85. A total of 1402 samples of the same type are retained and reclassified (Fig. 8). The results show that the reclassification accuracy reaches 0.88, which can meet the research needs. And from the classification effect chart, it can be seen that the classification effect of preliminary classification and reclassification is basically the same, and the ability to identify various types is strong. The research shows that the use of reclassification method to optimize a sufficient number of samples can maintain a good balance between human time cost and classification accuracy and meet the research needs.

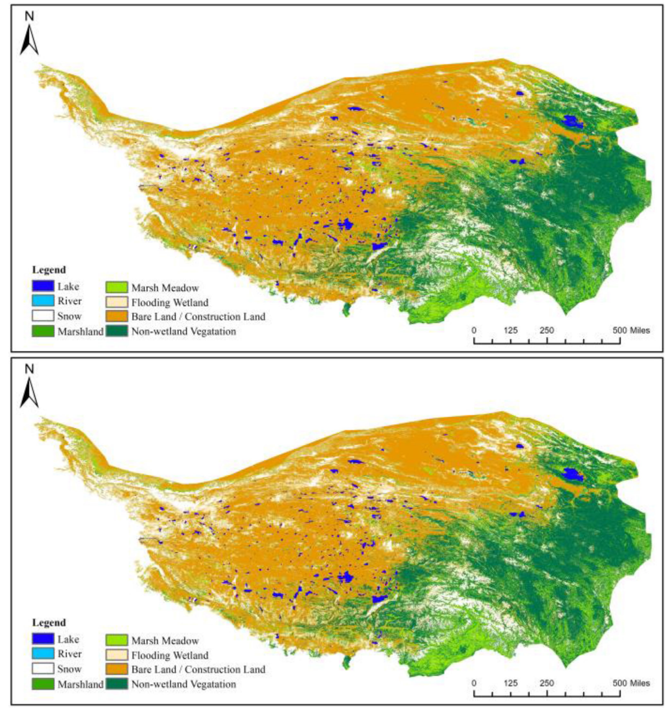


Fig. 8. Wetland distribution map of Tibetan Plateau based on reclassification samples in 2015 (the upper part is the preliminary classification, and the lower is the reclassification).

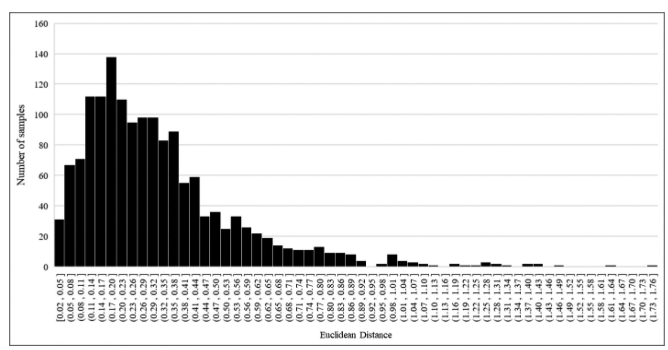


Fig. 9. ED of samples based on images in 2020 and 2015.

## C. Sample Migration Method Based on Spectral Similarity

Since the process of classification is mainly based on the spectral characteristics of the image, it can be considered that the type of the two samples has not changed when the spectral changes of the two samples are small. In this study, 2020 is taken as the reference year to extract the average values of all the images in 2020, and 2015 is taken as the target year. The average pixel values of the images in 2015 are taken as the target spectrum. The ED and SAD between the reference spectrum and the target spectrum are calculated, and the changes of spectral distance and spectral angular distance between the two years are analyzed. By setting the threshold and eliminating the sample with large changes, the samples with small spectral changes can be retained, and the sample migration between two years can be realized. In this study, 1542 sample points are selected to participate in the analysis. Figs. 9 and 10 are the statistical

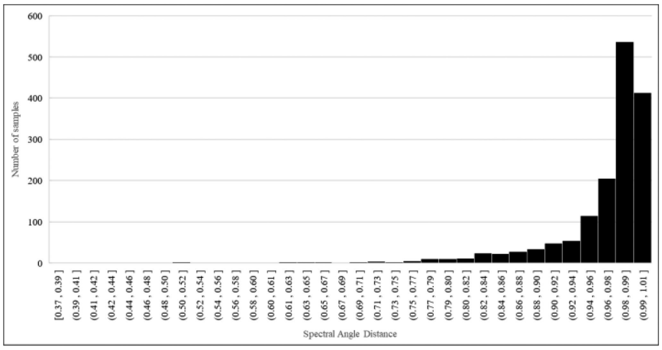


Fig. 10. SAD of samples based on images in 2020 and 2015.

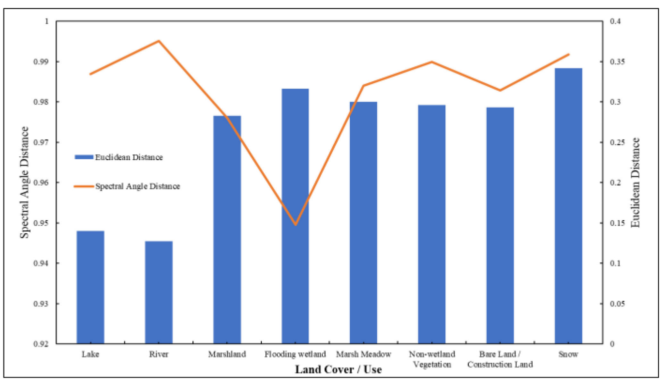


Fig. 11. Median of ED and SAD of different types.

values of ED and SAD of samples, respectively. Fig. 11 shows the median statistical values of ED and SAD for different land cover types.

Huang *et al.* extracted 100 samples of global land cover samples in their research and compared them in high-resolution Google Earth images. When ED is less than 0.2 and SAD is greater than 0.9, they can better retain the unchanged samples. Combined with the statistical values of the study area, and compared in the high-resolution image, this study selected the threshold suitable for the region, that is, ED is less than 0.4 and SAD is greater than 0.95, screened the samples, and found that the threshold can help to determine whether the sample changes. Among them, 1164 samples met ED $< 0.4$, 1194 samples met SAD $> 0.95$, and 905 samples met both conditions.

The wetland classification mapping is carried out on 905 samples with small spectral changes in 2015. The final classification accuracy is 0.82, which is slightly lower than the initial precision but could meet the research needs. Fig. 12 is a map of wetland classification of Tibetan Plateau based on the migration of spectral similarity samples. It can be seen from the western part of the Tibetan Plateau that the confusion between the two types of bare land and snow is serious, but the wetland types can be basically separated. From the classification accuracy and classification effect, this method can meet the requirements, but it needs to be improved in the detail of nonwetland classification.

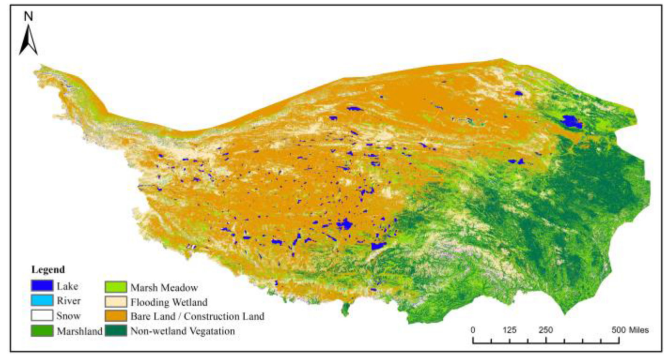


Fig. 12. Wetland classification map of Tibetan Plateau in 2015 based on the migration of spectral similarity samples.

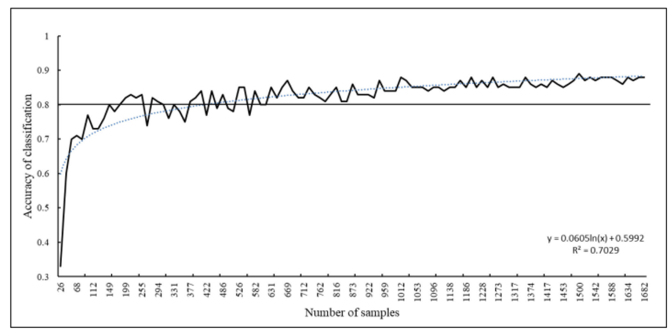


Fig. 13. Wetland classification map of Tibetan Plateau in 2015 based on the migration of spectral similarity samples.

## D. Relationship Between Sample Number and Classification Area

In the process of sample migration, the number of samples will decrease with the sample migration. However, the number of samples also means the richness of samples. Obviously, the classification accuracy is closely related to the number of samples. Therefore, in order to explore the relationship between the number of samples and the classification accuracy, this article aims at the 1542 samples in 2020 obtained from the above classification, increasing by about 30–40 step length, and explores the response relationship of different numbers of samples to the classification accuracy under the condition of the same data source and classification method.

In this article, the B1–B11 band and NDVI, NDWI, MNDWI, and LSWI indexes of Landsat 8 OLI are selected as the classification features for classification experiments. In order to study the impact of different number of samples on the classification accuracy, the RF classifier is conducted on the Tibetan Plateau wetland classification in 2020.

It can be seen from Fig. 13 that when the number of samples is less than 600, the overall classification accuracy is low, the variation range of classification accuracy is large, and the regularity is not obvious, which is greatly affected by the sample quality; when the number of samples is more than 600, the classification accuracy and the number of samples show a positive correlation trend, that is, the more the number of samples, the higher the classification accuracy. When the number of samples is more than 600, the classification accuracy can reach more than 0.8,

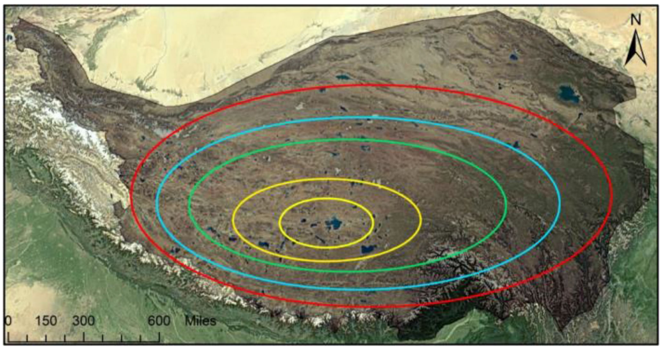


Fig. 14. Sketch map of different study areas.

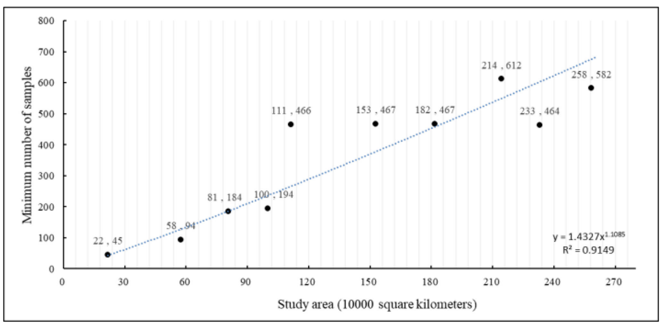


Fig. 15. Sketch map of different study areas.

which can meet the research needs; when the number of samples reaches 1500, the highest classification accuracy of 0.89 is obtained, but then the accuracy fluctuates and decreases. On the whole, the classification accuracy increases with the increase of the number of samples, but when the number of samples reaches a certain value, the classification accuracy no longer increases with the increase of the number of samples but shows a trend of oscillation. Through the function fitting of 109 pairs of samples and classification accuracy, it is found that they are in line with the logarithmic relationship ($R^2 = 0.70$).

We think that when the classification accuracy reaches 0.8, we can get a better classification effect, which can meet the needs of research and application. Therefore, when the sample number exceeds a certain threshold, the total accuracy is always greater than 0.8, and the corresponding sample number is defined as the minimum sample number required for wetland fine classification, such as the minimum sample number of the Tibetan Plateau study area is 582. At this time, the corresponding study area is 2 583 900 km$^2$. According to this criterion, the corresponding relationship between the classification area (Fig. 14) and the minimum number of samples is explored (Fig. 15). It can be seen from the figure that when the classification area is less than 1 million km$^2$, the minimum number of samples is almost twice of the classification area; when the classification area is between 1 and 2 million km$^2$, the minimum number of samples is around 466; when the classification area exceeds 2 million km$^2$, the minimum number of samples increases to about 600; on the whole, it meets the power relation, $R^2$ is 0.9149.

### E. Results

In order to solve the problem of sample acquisition difficulty in large-scale and long-time sequence wetland classification, this article attempts three methods for sample migration, which are as follows. First, establish wetland sample classification rule set, first use the rule set to classify the samples in different periods, and then use the classified samples for mapping. Second, the existing samples are used for classification mapping, and the samples whose classification types are inconsistent with the existing ones being removed and classified again so as to eliminate the samples whose types change or are quite different from the similar samples. Third, the ED and SAD between the reference sample and the target sample are calculated. It is considered that the type of the sample with large spectral change may change; so this part of the sample is removed.

From the perspective of classification accuracy, the accuracy of reclassification for sample migration can reach 0.88, which is the highest among the three sample migration methods; the classification accuracy of sample migration based on spectral similarity is 0.82, which initially meets the research needs, and the above two methods are confused in flooding wetland and snow; the overall classification accuracy of rule set based sample migration is 0.77, but it is easy to divide marsh meadow into nonwetland vegetation, which needs further verification in the actual classification. The theory and results of sample migration based on reclassification and spectral similarity can meet the research objectives and can be applied in large-scale wetland research.

In view of the reduction of sample number in the process of sample migration, this article discusses the relationship between sample number and classification area. Under a certain classification area, the number of samples and classification accuracy show a logarithmic growth trend. When the classification accuracy is greater than 80%, the number of samples is regarded as the minimum number of samples. It is found that the minimum number of samples and classification accuracy present a power trend.

## VI. Conclusion

### A. Discussion

Water, vegetation, and soil are the three main elements of wetland. Wetland identification from the perspective of water body is superior to the other two elements; for example, it is difficult to identify the types of flooding wetland by vegetation element. Although different water dataset are processed and obtained based on different spectral bands, which has different penetration abilities, the determination of wetland based on the water datasets obtained by satellite data has its limitations, such as the wetland type which is always covered by vegetation but saturated with soil, which is also the difficulty of wetland remote sensing monitoring at the same time. More experiments will be carried out in the future to solve this problem.

There are studies that show that texture and shape features are very helpful to identify wetland types, especially paddy fields, ponds, rivers, and other wetland types with obvious boundaries.

In the future, shape and texture features such as length, area, proportion, and correlation coefficient will be considered to determine the wetland type better.

In the part of sample size, we compared the relationship between sample size and classification area in different study areas of Tibetan Plateau. However, different classification areas correspond to different land cover compositions. On the premise that the proportion of land cover types remains unchanged, the relationship between sample number and classified area is discussed. However, this conclusion will be disturbed by the complexity of the surface. In the next step, we will consider further research in different research areas, such as tropical areas, which are different from the climate conditions of the Tibetan Plateau. If possible, the impact of different sample sizes on classification results will be further discussed on a global scale to make the results more representative.

## B. Conclusion

To sum up, aiming at the problem that the existing sample set cannot be reused and the acquisition of high-frequency sample set, this article uses optical and radar images to evaluate the reliability of wetland samples, compares three sample migration methods, and explores the relationship between the number of wetland samples and the classification accuracy. The results are as follows.

1) The combination of SAR image and optical image to analyze the reliability of historical samples can make up for the shortcomings of single sensor, such as low spatial and temporal resolution and affected by clouds and rain, and effectively ensure the accuracy of samples. For highly dynamic wetlands, seasonal variations must be considered when selecting samples or mapping. Only by adding phenological information can we get the accurate wetland type. The evaluation method proposed in this article comprehensively considers the NDVI and NDWI index characteristics of all high-quality images in the whole year and combines with the existing expert knowledge to make the wetland classification more accurate. Moreover, this method can also carry out large-scale automatic sample evaluation and obtain higher accuracy.
2) In order to realize the rapid collection of high-frequency samples in time series wetland classification, three sample migration schemes are proposed, which are based on rule set, reclassification, and spectral similarity. Through the migration of wetland samples from 2020 to 2015 and the study of wetland fine classification, it is found that the overall classification accuracy of sample migration methods based on reclassification and spectral similarity is more than 80%. The classification accuracy based on rule set is the lowest, which is 77%. The experiment of the relationship between the number of samples and the classification area shows that the relationship between sample number and classification accuracy is logarithmic, and the relationship between minimum sample number and research area is power. The study of sample migration and sample number provides an effective solution for the sample acquisition and updating of large-scale time series wetland remote sensing classification.

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