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Fusion of Deep Learning Autoencoders with Random Forest for Wetland Classification Using Sentinel-2A Data: A Case Study on Sirpur Wetland

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Abstract

Present study analyzes the performance of deep learning algorithm-autoencoder to reduce data dimension as compared to conventional models. Classification accuracies of Sirpur wetland using Sentinel-2A dataset with different inputs have also been studied. These inputs sets comprise the reconstructed data through compression of original 13 bands into 4 bands using decoder algorithm, first four Principal Components, all spectral bands, and spectral indices. Random Forest classifier (RF) is used to classify Sentinel data. Findings revealed that reconstructed input data through decoder has R2 of 0.99 indicating a very good compression of the original 12 bands data into 4 nodes while Principal Component Analysis (PCA) had 94% of total variability in first four PCs. Classification results showed highest accuracy of 96.25% when nodes were used as input followed by the accuracy of 95% in case of PCs as input. Bands alone could classify with accuracy of 92.5% followed by spectral indices (90.0%). Finally, autoencoder can be a good choice to reduce the number of bands with maximum information especially for complex land surface features and to improve the accuracy. Notably this work is an inaugural step for Sirpur, and results are stepping stone to explore this wonderful ecosystem further.

Keywords: Autoencoder, PCA, R software, sentinel-2A, Sirpur

INTRODUCTION

Wetlands are versatile, complex, and dynamic natural ecosystems on Earth. Every wetland differs significantly from one another in terms of seasonal water dynamics, inland water capacity, flora-fauna, and soil conditions. Field studies to understand their water dynamics and health are restricted due to the challenges faced by researchers in visiting this ecosystem frequently. Satellite data plays a very crucial role in studying these parameters and hence participates in formatting policies and understanding their health deterioration/restoration. Spatiotemporal analysis using satellite images is a historic way to understand the pattern of various health parameters of wetlands. Since 1970, approximately 1200 research papers are published highlighting various models to classify wetlands [1]. In India, the first scientific wetland inventory was carried out by Space Applications Center ISRO, Ahmedabad in 1988 [2].

Availability of plethora of satellite images in different electromagnetic spectrum and various spatial resolution has opened a wide opportunity to use/develop models and methodologies to study, predict, and analyze these landscapes. With the availability of sensors collecting data in number of bands, it sometimes essential to compress the essential information in relatively lesser bands so that computing time can be saved. A few data dimension reduction models include band to band

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correlation, linear dimensionality reduction, nonlinear dimensionality reduction, group-wise band selection [3] and principal component analysis. Performances of several data dimensionality reduction models including PCA have been analyzed for hyperspectral data [4] and was observed that a smaller set is better to achieve higher accuracy. Another study reveals that deep learning model outperformed the conventional model for high dimensional data [5].

Further step is to classify a wetland in required number of classes using supervised or unsupervised classifiers. Despite of existing numerous methodologies of classifying wetlands using different satellite imageries [6–8] accurate classification still is a subject of understanding of the area. Number of dynamical models have been developed by researchers to meet the expectation in classification as per the wetland types and its dynamics.

A knowledge-based classifier [9] for Indian wetland inventory and further investigated [10] the role of spatial location in classification using three machine learning algorithms (SVM, CART, and mBACT). Literature is flooded with the authentication of improved performance of several ML models (like SVM, Decision trees, random forest) in land surface classification using multispectral satellite data [11, 12]. Recently, Digital Elevation Model (DEM) data is fused along with sentinel data and RF model is used to map Great Lakes wetlands with 93% accuracy [13]. Another enhanced version of RF model is developed to classify avalon area situated at the easter portion of Newfoundland Newfoundland [14].

Classification of a particular wetland using remote sensing is still a challenge despite of existing a broad spectrum of models due to its formation and complexity. Ensemble of optimum information in minimum variable is again a subject of deep understanding of land surface features and their spectral radiances to apply ML models. In view of these challenges, this study is planned to explore an untouched wetland of Indore (Sirpur) which is added to the list of “wetlands of importance” by Ramsar convention in 2022 using Sentinel-2a dataset. As it is new Ramsar site, there is lack of remote sensing study for this area so far.

First ever report on the wetland features of Sirpur is published in 2021 by Environment Research Laboratory, EPCO which studies the overall biodiversity based on samples collected and tests in laboratory. Present research attempts to compare the performances of some conventional and unconventional dimension reduction models to classify wetland in different scenarios using random forest classifier.

STUDY AREA

Indore city is centrally located in the Indore district, positioned on the fertile Malwa Plateau at the coordinates of 23° 43’N latitude and 76°42’E longitude. The city is elevated at an average of 550 meters above mean sea level, with a gentle slope extending northward. Located on the outskirts of Indore city, the sirpur wetland (Figure 1), consists of two connected water bodies: the small lake (chota talab) and the large lake (bada talab). This man-made biodiversity rich wetland is a home various species of terrestrial plants, birds, macrophytes, fish, reptiles, and amphibians. It offers an ideal winter habitat for waterbirds.

MATERIALS AND METHODS

Satellite and Training Data

High resolution Sentinel-2A product of February 25, 2025, has been downloaded from Copernicus land monitoring service. It is derived from level-1C products and provides atmospherically corrected Bottom of Reflectance (BOA) values. L-2A product is also orthorectified as it is corrected for geometric distortion. Sentinel’s multispectral instrument provides land coverage in 13 spectral bands ranging from visible, near infrared and short-wave infrared region of thermal spectrum. with 5 days revisit frequency globally. Detailed specifications of spectral bands along with spatial resolution are provided in Table 1.

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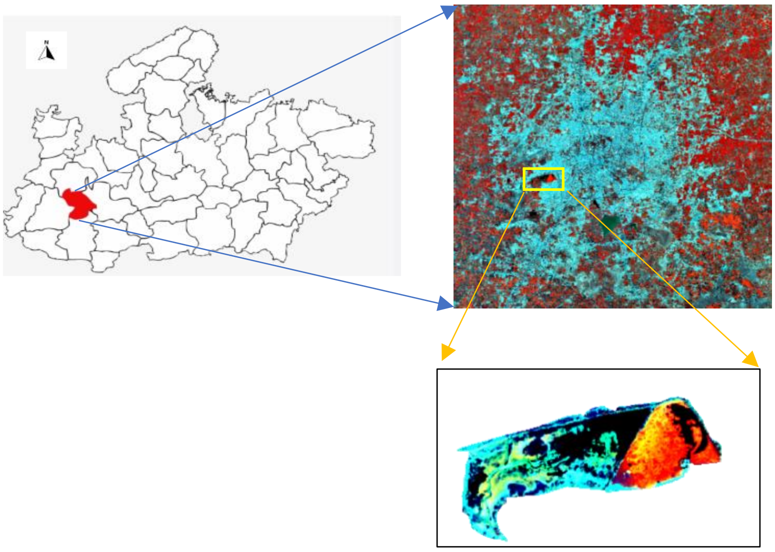

Figure 1. Study area - Sirpur Wetland.

Table 1. Bands specification of Sentinel-2A product.

Bands	Resolution	Central wavelength	Application
B1	60 m	443 nm	Aerosol detection
B2	10 m	490 nm (Blue)	Soil-vegetation discrimination, forest type mapping
B3	10 m	560 nm (Green)	Excellent contrast between clean and turbid water
B4	10 m	665 nm (red)	Vegetation types, soil and urban areas detection
B5	20 m	705 nm (VNIR)	Vegetation types
B6	20 m	740 nm (VNIR)	Vegetation types
B7	20 m	783 nm (VNIR)	Vegetation types
B8	10 m	842 nm (VNIR)	Biomass content, Vegetation types
B8a	20 m	865 nm (VNIR)	Vegetation types
B9	60 m	940 nm (SWIR)	Detect water vapour
B10	60 m	1375 nm (SWIR)	Cirrus cloud detection
B11	20 m	1610 nm (SWIR)	Moisture content of soil and vegetation
B12	20 m	2190 nm (SWIR)	Moisture content of soil and vegetation

https://custom-scripts.sentinel-hub.com/custom-scripts/sentinel-2/bands/

As the study area is a highly adaptable ecosystem and has recently been recognized as a Ramsar site, the use of satellite imagery to label such a diverse wetland is quite innovative. This paper categorizes the wetland features into eight classes viz- grass land (GL), deep water (DW), healthy vegetation (HV), shallow water (SW), submerged aquatic vegetation (SAV), moist sparse vegetation (MSV), built-up (BU) and wetland agriculture (WA)). A total of 251 training points (33 from GL, 33 from DW, 33 from HV, 33 from SW, 36 from SAV, 31 from MSV, 27 from BU, and 25 from WA) has been collected and identified as one of the above classes. These training dataset forms the foundation of supervised classifier and later produces the feature map of the wetland.

Preprocessing

Sentinel-2A data of February 22, 2025. has been procured over the area of Indore, Madhya Pradesh, India, and processed in SNAP software. Since this product contains bands in 10 m, 20 m and 60 m resolution, the scene was resampled to spatial resolution of 10 m. Further, polygon boundary of Sirpur wetland has been procured from Ramsar website (https://rsis.ramsar.org/ris/2478) and region of interest (ROI) has been extracted. Further, essential bands of spectral indices (NDVI, NDWI, WMIa, WMIb) are generated and added as additional bands in the stack of available 12 bands (Table 2).

Principal Component Analysis (PCA)

PCA [15, 16] (Wold et al., 1987; Centeno et al., 2020) is a conventional data dimension reduction technique in remote sensing literature. It efficiently compresses the input information into compressed form called PCs and thus removes the redundancy and multicollinearity. First inter-bands variations are computed through covariance matrix and then direction along with amount of variation is found through eigen values and eigen vectors. These eigen vector construct principal components and compresses the optimum information in these bands. First PCs covers the most variation in the data and subsequent PCs explain the parts of the remaining variations. This work uses prcomp() functions from "stats" package [17] in R software to generate PCs from the sentinel data with all bands including four spectral indices (NDVI, NDWI, WMIa, WMIb).

Autoencoders

An autoencoder is a type of artificial neural network which is used for data dimension reduction under unsupervised domain [18]. It typically compresses the essential information into lower dimensional space. Finally, reconstruction of the output is performed to match the original input as closely as possible. An autoencoder has three key elements in its architecture namely encoder, latent space, and decoder. Encoder compresses the information in input data into lower dimensional space. This space holding the encoded representation is known as latent space. Finally, decoder reconstructs the original data from the compressed latent presentation from the latent space. Decoder attempts to reconstruct the compressed data to match the original data with highest accuracy possible (Figure 2). ANN2() package of R software has been utilized for data compression through autoencoder algorithm.

Table 2. Construction of spectral indices.

SN	Indices	Formula
1	Normalized Difference Vegetation Index (NDVI)	$NDVI = \frac{R_{NIR} - R_{Red}}{R_{NIR} + R_{Red}}$
2	Normalized Difference Water Index (NDVI)	$NDWI = \frac{R_{Green} - R_{NIR}}{R_{Green} + R_{NIR}}$
3	Wetland Index Model A (WMIa)	$WIMa = \frac{R_{SWIR-11} - R_{Green}}{R_{SWIR-11} + R_{Green}}$
4	Wetland Index Model B (WMIb)	$WIMa = \frac{R_{SWIR-12} - R_{Green}}{R_{SWIR-12} + R_{Green}}$

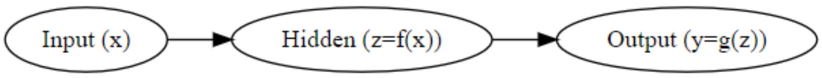

Figure 2. Basic architecture of autoencoder.

Random Forest

RF is a machine learning algorithm used for classification and regression. It has gained enough recognition in satellite data classification due to its higher accuracies [19] (Akar and Gungor, 2012). Primarily, it works on developing an ensemble of multiple decision trees where every tree is developed by using a random set of training data as well as variables. Typically, random forest works on the bagging principal where bagging starts by selecting a random set of training data. Iteratively, many such samples are collected from original dataset with replacement. These sample are bootstrap samples. Several models are developed based on these bootstrap samples. Finally, the output is generated by combining the results of all these models. Since it is an ensemble of several decision trees, mathematically it can be expressed as a concept rather than algorithm. Let us suppose that are individual developed decision trees from the training dataset. Also, for a given input, each tree predicts response i.e.. If the final predicted class label by random forest algorithm is denoted by, then:

$$RF(x_j) = mode\ (D_i(y_j), D_2(y_j), D_3(y_j), \ldots\ldots, D_n(y_j)\ ).$$

Present study uses built-in randomForest() in the R package "randomForest" [20] (Liaw and Wiener, 2002) to fit the random forest model for the study area. We used most of the default arguments in the function with number of trees 100.

RESULTS AND DISCUSSIONS

Loading of Spectral Indices

Importance of individual bands segregating wetland feature through RF is not significant wrt to other bands and hence not been reported. In case of spectral indices, it has been observed that WMI for is best for classifying GL, DW, HV, SW, and MSV. NDWI is the most important index for SAV and WA while NDVI is best for BU (Table 3).

PCA shows that first four PCs accounts for 94% variability in the dataset. Exact bifurcation of individual PC's contribution can be observed from table (Table 4).

Table 3. Importance of spectral indices in classification features identified by RF classifier:

Indices	GL	DW	HV	SW	SAV	MSV	BU	WA
NDVI	10.27	9.76	9.12	11.23	9.04	10.05	10.16	10.04
NDWI	9.29	6.40	9.12	11.24	26.89	9.05	8.18	10.64
WMIa	7.74	7.62	7.32	9.85	9.25	16.94	1.73	9.43
WMIb	12.26	12.11	9.96	12.17	13.78	10.02	5.19	9.29

Table 4. Contribution of bands in PCs.

Input Bands with First Five Loading Factors of First 3PCS								
Pcs	PC1		PC2		PC3		PC4	
Bands	Band 11	-0.2994	Band 1	0.3906	WMIb	0.6248	Band 2	-0.2619
	NDWI	0.2974	Band 4	0.3760	WMIa	0.4062	Band 4	-0.2351
	Band 6	-0.2972	Band 2	0.3750	Band 3	-0.3363	Band 3	-0.2124
	Band 8A	-0.2944	Band 12	0.2675	Band 12	0.2583	WMIa	0.1161
	Band 8	-0.2917	Band 3	0.2454	Band 5	-0.2317	Band 12	-0.0874
% variability explained	51%		29%		9%		5%	

As the number of PCs increases, there is a noticeable rise in speckle and noise, complicating the differentiation of features. Therefore, only the initial four PCs are considered (Figure 3). The PCA results indicate that PC1 is primarily influenced by bands in the SWIR, NDWI, and vegetation red edge wavelengths, although the separation is only clear in terms of direction. Conversely, PC2 highlights the significance of bands in the blue, green, red, and SWIR wavelengths. PC3 and PC4 reveal that the involvement of WMI in both SWIR bands is distinct, in addition to the bands that were also present in the first two PCs.

Autoencoders

An autoencoder is a deep learning algorithm to compress the original high dimensional data into low dimension latent space and then reconstructs the original input from this latent space. In this present study, all spectral bands along with four indices are defined as the input dataset with 16 variables (data dimension = 16). Using autoencoder () function from ANN2 package of R software, latent space has been generated using functions vector of tanh and linear. Overall and feature wise accuracies are calculated on how reconstructed data matches with the original input data. Overall mean square error of autoencoder is 8886.01 with root mean square error of 94.26. Overall R2 square is 0.996 which is an indication of highly good construction across all variables. Synchronization of original and reconstructed data (Figure 4) shows that our model reconstructed the input data perfectly in almost all bands except some variations in middle range bands.

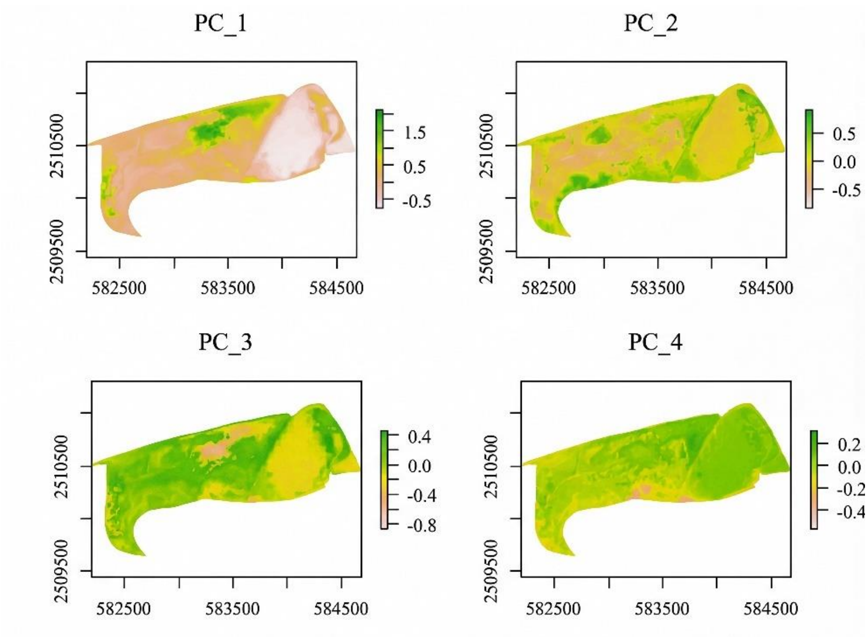

Figure 3. First four principal components.

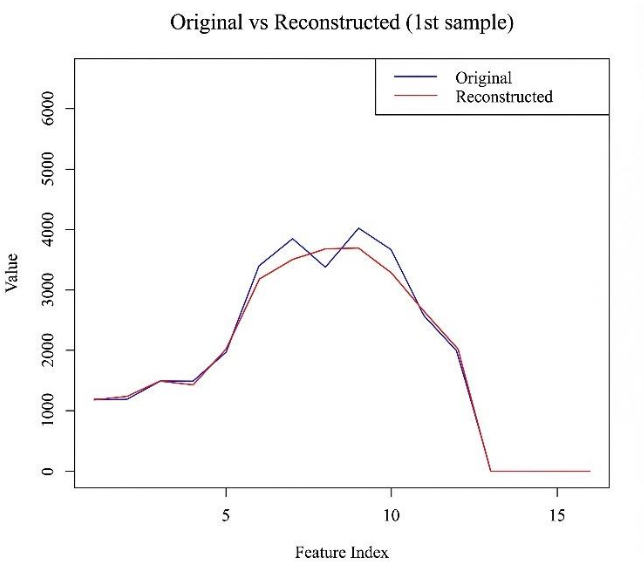

Figure 4. Comparison of original and reconstructed data by autoencoder.

Sample wise RMSE (Figure 5) shows that SWIR bands (Band 9, Band 8, Band 8A and one band from VNIR) have the compression in the hidden layer with higher RMSEs. WMIb has the best compression followed by WMIb, NDVI, and NDWI. This analysis show that these spectral indices have better influence in generating compressed data with no multicollinearity. Figure represents the R2 of all bands in constructing nodes through autoencoder. It can be observed that despite of having high RMSE, R2 of SWIR bands is not significantly lower than other bands with lower RMSE. Based on this, it can be concluded that all 16 bands are compressed highly accurately, and information extracted through reconstruction in the form of nodes. Finally, variations captured by four nodes in wetland features are shown in Figure 6.

Wetland Mapping Using RF for all Bands, Spectral Indices, PCs and Autoencoder Nodes

Random forest starts learning with building individual tree and then ensemble all trees to find the best combination of nodes to label the feature.

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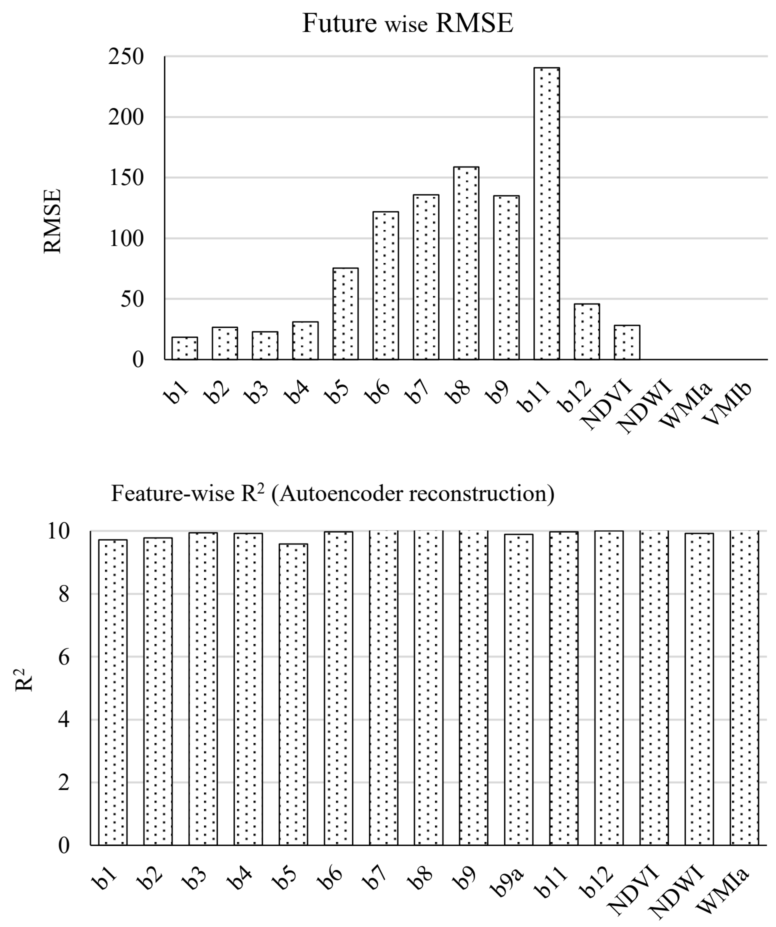

Figure 5. Feature wise RMSE and R^2 achieved through autoencoder.

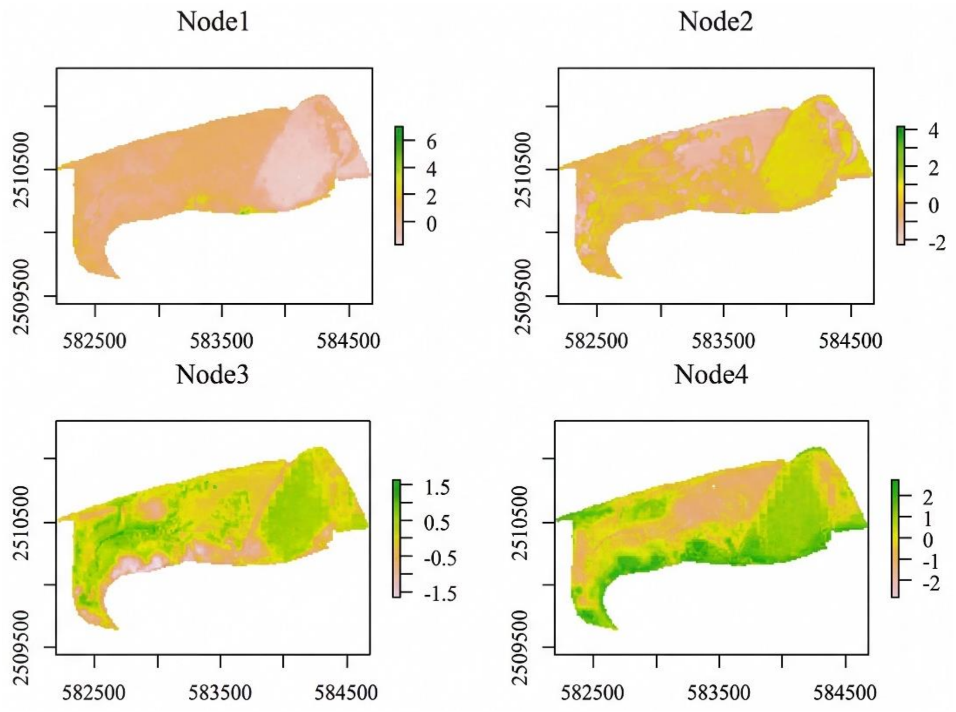

Figure 6. Nodes generated from autoencoder algorithm.

It's error map provides the number of optimum nodes for which the forest is built, and error stabilizes (Figure 7). As per this figure, it can be observed that in the first scenario where all bands are used as input, error is fluctuating and not stabilized even after 100 iterations. In the second case of using spectral indices, for most of the classes error stabilizes after 40 nodes and again started appearing after 80 nodes introducing some ambiguity.

As far as PCs are considered as input bands, overall trend of error is monotonic decreasing with some insignificant fluctuations. Finally, in the case of nodes as inputs, it is evident that error is decreasing and then stabilizes till 100th iteration. The most important observation is that all classes follow the same pattern in term of error stabilization which shows a first-hand positive sign of using autoencoders in data dimension reduction.

Finally, mapping of Sirpur wetland using RF is done in four scenarios i.e., using all bands, using four spectral indices, using four PCs and using four autoencoder nodes to find out the best one with maximum accuracy. Classified maps using in all scenarios are depicted in Figure 8.

Accuracy measures i.e., overall accuracy, kappa coefficient and consolidated F1 score (Table 5) have been calculated to rank the performance of random forest classifiers with 4 different input sets.

It is evident from the above table that classification using autoencoder nodes as an input has outperformed PCs which has usually shown its better performance for data dimension reduction in remote sensing literature. Kappa coefficient, a measure to show the degree of agreement between training and prediction has been calculated and it is found that nodes as an input provided the best agreement followed by PCs and then bands.

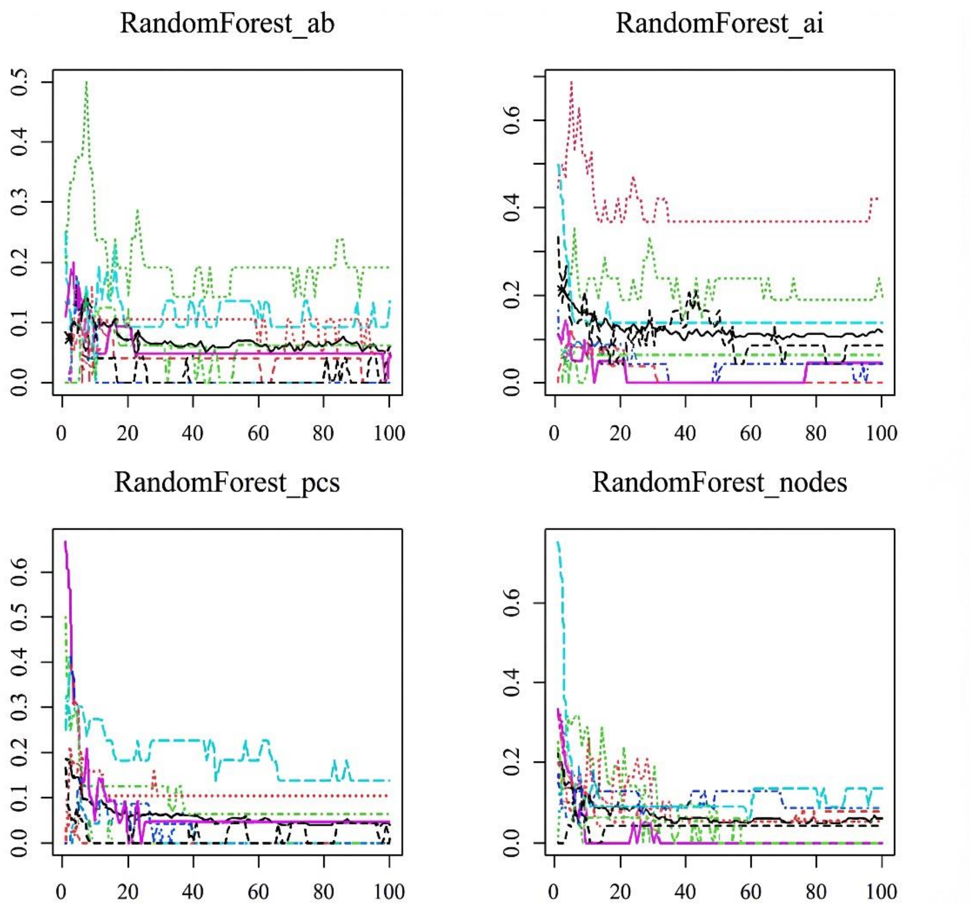

Figure 7. Error stabilization of Random Forest classifier for all four scenarios

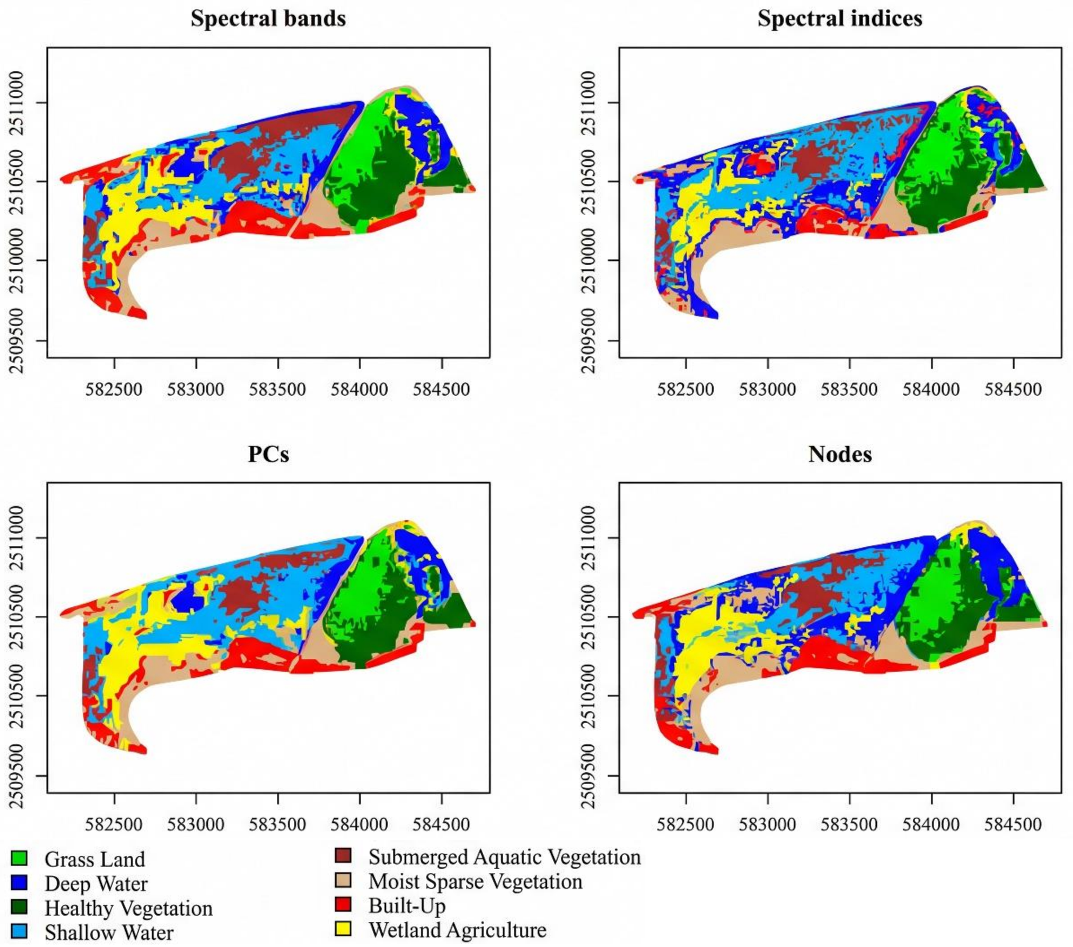

Figure 8. Wetland classification using Spectral bands, spectral indices, PCs and nodes through RF classifier.

Table 5. Overall accuracies.

	Bands	Indices	PCs	Nodes
Overall Accuracy (%)	92.5	90.0	95.0	96.25
Kappa	0.91	0.88	0.94	0.96
F1-score	0.92	0.89	0.95	0.96

Another accuracy measure is F1 which is a harmonic mean of precision and recall. It provides the accuracy of multiclass classification model. In the present study (Figure 8), F1 score for nodes again secured the best place justifying its best performance in wetland class segregation. Overall, it can be concluded that random forest classifier performs better with input of nodes followed by PCs and then bands, Indices alone should not be considered as an input for multiclass classification in remote sensing. As far as class-wise accuracies are considered, user's accuracies, producer's accuracies and class-wise F1 scores have been calculated (Table 6).

It is observed from class wise accuracies that for all three measures, nodes perform either equally good or better than other sets of inputs. User's accuracies of PCs for GL, SW, SAV, and WA are same as bands and indices while it performs better for DW and MSV. Looking at the producer's accuracies, one can observe that indices have better accuracy than bands and PCs for SW. Through all the analysis, it can be concluded that autoencoder generated nodes as input for classification through RF performs better than other scenarios considered in this paper. Table 7 provides the area covered by each class in each scenario using RF classifier.

Table 6. Class- wise accuracies.

User's accuracy					**Producer's Accuracy**				**F1 Scores**			
Bands		***Indices***	***PCs***	***Nodes***	***Bands***	***Indices***	***PCs***	***Nodes***	***Bands***	***Indices***	***PCs***	***Nodes***
GL	87.50	87.50	87.50	**87.50**	100	100	100	**100**	0.93	0.93	0.93	**0.93**
DW	91.66	91.66	100	**100**	100	78.57	100	**100**	0.95	0.84	1.00	**1.00**
HV	100	100	100	**100**	90.90	90.90	90.90	**90.90**	0.95	0.95	0.95	**0.95**
SW	90.90	100	90.90	**90.90**	83.33	91.66	90.90	**100**	0.86	0.95	0.90	**0.95**
SAV	86.66	86.66	86.66	**93.33**	92.85	100	92.85	**93.33**	0.89	0.92	0.89	**0.93**
MSV	85.71	85.71	100	**100**	100	85.71	100	**100**	0.92	0.85	1.00	**1.00**
BU	100	62.50	100	**100**	80.00	71.42	88.88	**88.88**	0.88	0.66	0.94	**0.94**
WA	100	100	100	**100**	100	100	100	**100**	1.00	1.00	1.00	**1.00**

Table 7. Area (ha) covered by individual class.

Scenario Class	**All bands**	**Spectral Indices**	**PCs**	**Nodes**
Grass land	13.13	14.73	12.07	14.32
Deep water	25.90	34.81	14.54	32.24
Healthy vegetation	19.86	20.66	21.96	18.92
Shallow water	26.73	34.95	37.74	24.43
Submerged aquatic vegetation	16.34	9.00	12.98	13.42
Moist sparse vegetation	21.31	20.03	23.08	22.17
Buit-up	17.21	11.09	13.29	14.40
Wetland agriculture	24.41	19.62	29.23	24.99

Variations in the area covered by each class in different set of inputs are still a subject of further investigation as the total area reported by Ramsar is 161 ha and no other information is reported so far. These estimations are the first inventory on the wetland and its features. Nevertheless, based on the ground reality, built up area classified by all bands are very high as there is not such a big concrete area around the wetland.

CONCLUSION

Multispectral data from sentinel-2A has been utilized for feature extraction using RF classifier. Primarily, the study focuses on the essential information procurement serving as input data for classification. Four different input sets are used for classifying the wetland viz: available spectral bands, spectral indices alone, first 4 PCs and nodes developed by autoencoder algorithm. Finding of the study reveal that nodes as input for classifier achieved the highest classification accuracy in both the domains i.e., overall, and class-wise. It can be concluded that unlike for PCA which is good for linear spaces, Autoencoder works better for non-linear spaces.

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