Agricultural and Land Management Using AI: A Case Study of Rice Plot Identification in Senegal

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Abstract. Agricultural yield improvement is important to handle food insecurity mostly for developing countries. Indeed accurate knowledge of the distribution of crops in the landscape is crucial for better management and monitoring of the agricultural sector. In recent years the combination of artificial intelligence (AI) and remote sensing data has been widely used for crop type mapping. Given the essential place of rice in the Senegalese diet, increasing its production can positively impact food security. Thus, having an estimate of its harvests can be useful to stakeholders for better management of the rice sector in Senegal. In this work, we aim to build an AI system with remote sensing data for rice crop mapping in Senegal. We exploit two AI models with Sentinel-2 images for rice mapping. The first model is based on Support Vector Machine (SVM) and a second model based on deep learning using the Deeplab V3+ model. Both models shows promising results even if they still very low. The results reveals that the deep learning model provides better performance at identifying rice crop than the SVM model which has a lower accuracy.

Keywords: Agriculture · AI · Machine Learning · Remote sensing · Crop type mapping

1 Introduction

The world's population has been growing for years and, according to the United Nations (UN), it will reach 9.7 billion in 2050 and around 11 billion in 2100[1]. In addition, climate change is becoming more and more noticeable, with harmful impacts on agricultural production. Seasonal irregularities, excess heat and changes in rainfall patterns reduce yields. Thus, food security is very threatened and becomes a subject of great importance. Therefore, crop monitoring must be improved for better crop yield. The main component of crop monitoring is crop mapping which is included in land cover/land use mapping. Crop mapping

[1] https://www.un.org/fr/un75/shifting-demographics.

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K. Cheikh M. F. Kebe et al. (Eds.): InterSol 2024, LNICST 610, pp. 299–310, 2025.
https://doi.org/10.1007/978-3-031-86493-3_24

is crucial for providing accurate agricultural statistics [5], improving crop yield estimation and water management.

Remote sensing plays an important role in agriculture monitoring and management. It has emerged as a cost-effective tool for crop type mapping over space and time, repeatedly, and consistently at various spectral, spatial and temporal resolutions [1]. Today, satellite data is publicly and freely available. Among them, Moderate-resolution Imaging Spectroradiometer (MODIS)[2], Landsat(7, 8)[3], and Sentinel(1, 2, 3, 5)[4] are advancing methodologies to solve environmental and societal challenges. The lunch of Sentinel-2A and 2B satellites by the European Space Agency (ESA) provides a 5 days revised time data with high spatial resolution(10 m for visible bands and 20 m for the remaining bands) and has shown their potential in agricultural applications [4].

In the past decades, machine learning algorithms (MLA) have been widely used in remote sensing as an inductive approach for pattern recognition. They are used to extract reliable information related to crop health, distribution, and acreage estimation. Earlier works has investigated classical MLA including Support Vector Machine (SVM), Random Forest, Decision Trees (DT) and Maximum Likelihood Classifier (MLC). In a first work, Saini et al. [27] used SVM on Sentinel-2 images to classify crops. Later they studied a comparison between Sentinel-2 and Landsat-8 by using random forest and MLC [26]. In [19], the authors explored the identification of sugarcane plantations using Landsat-8 images and SVM. Random Forest has also been used in [32] for crop type mapping with Sentinel-2 data. [12] investigate DT models for land cover mapping. These works rely on different bands from satellite images [26,27] and/or vegetation indices such as Normalized Difference Vegetation Indices (NDVI) [12], Green Vegetation Index (VIgreen), Renormalized Difference VI (RDVI) [24].

In recent years, deep learning applications with satellites images for land cover/land use (crop type mapping) mapping has emerged. Most of them are based on transfer learning [22]. Wu et al. [33] opted for an ensemble of convolutional neural networks (CNN) models including Resnet [13], Inception V4 [30], Densenet [16], MobileNet [15] which is also used in [10] and ShuffleNet [36]. A majority voting approach is used to classify images. In [8], Chew et al. used VGG16 [28] as backbone and add a feed-forward network for the crop identification. Transfer learning [22] has also been explored for land cover/land use mapping in [20] where the authors used GoogleNet [31] and VGG16 [28]. In [3], Bah et al. has used the Segnet model [2] for mapping crops. Recurrent neural network has also been used for crop mapping as in [23], which used an LSTM (Long Short-term Memory) [14] and [11] which employed a recurrent CNN.

This study constitute a first step towards our goal of building an AI system for rice crop management in Senegal which will include rice crop identification, rice yield estimation and disease detection on rice leaves. Here, we made a focus on crop type mapping in Senegal. We propose an ongoing work on identifying

[2] https://www.sciencedirect.com/topics/earth-and-planetary-sciences/modis.
[3] https://www.sciencedirect.com/topics/earth-and-planetary-sciences/landsat.
[4] https://www.sciencedirect.com/topics/earth-and-planetary-sciences/sentinel.

rice crops in Senegal using Sentinel-2 images and AI. We explore classical MLA such as SVM and deep learning model based on Deeplab V3+ [7] and Resnet [13]. The rest of this paper is structured as follow. We first will discuss about the study area in Senegal and explain why we are focusing on the rice culture. Then the data we used in this work will be explained. We will also talk about the models that we used in this work and finally we will discuss the results we obtained from these models.

2 Related Works

Land Use/Land Cover (LULC) based on remote sensing and machine learning (ML) has been an active topic of research for the last decades. First works have exploited classical ML algorithms including Random Forest (RF), Support Vector Machine (SVM), and Decision Trees(DT). Saini et al. [26] exploit the capabilities of RF and Maximum Likelihood Classifier (MLC) to classify different crop typ using Sentnel-2 and Landsat 8. They also investigated SVM on Sentinel-2 images. Their studies shows that RF performs better compared to SVM and MLC. Tran et al. [32] achieved higher accuracy with random forest and Sentinel-2 in South Dakota (94.24% against 90.05 in Roorkee city) and smaller accuracy in California (83.20%). More recent works such as [18] in 2020 has also explored the power of SVM and RF for LULC classification (with a focus on rice mapping). They made different combination of different features extracted from different satellite imagery (Sentinel-1, Sentinel-2, Landsat-8). SVM has provided higher accuracy on 2015 (90.16 against 88.6) dataset and RF gives better results in 2016 (95.0 and 92.7). DT algorithms have also been studied by Friedl et al. [12]. They presented a univariate DT, a multivariate DT and an hybrid DT. The latest gave higher accuracy on the different dataset they used. Zhang et al. [35] made a comparative study of several machine learning models included RF, XGBoost and SVM for rice mapping. Their experiment was carried out in two districts, and the XGBoost and SVM models performed best (0.7742 and 0.7538 F1 score). In 2022, [25] also used RF and XGBoost to identify rice type (Tarom-Hashemi and Shirodi) by combining Sentinel-1 and Sentinel-2 images, resulting in an overall accuracy of 84.0% and 80.8% respectively with XGBoost and RF. A study combining Sentinel-1 and Landsat images was also carried out by [21] for rice mapping in China using SVM and RF. In addition to these algorithms, [6] has also experimented with Naive Bayes (NB) and K Nearest Network (KNN) to map rice from Sentinel-1 images.

These works have achieved good results but requires tremendous work to manually extract multiple features that are then fit into the model for training. Therefore recent studies are mostly focused on using deep learning models that allow to extract deep and complex features from data and provides better results. Paris et al. [23] have used a Long Short Term Memory (LSTM) model for multiple crop classification and the highest accuracy they achieved was 85.87%. Attention with Recurrent Convolutional Neural Network (RCNN) was used by Feng et al. [11] for multi crops classification and achieved an OA (overall accuracy) of

92.8%. Attention with CNN has also been used in [25] for rice classification. The authors got an OA of 97.1% by combining Sentinel-1 and Sentinel6-2 datasets. CNN architecture is used in [10] for crop classification and achieved an F1 score of 88.1%. [20] has adopted two existing model (GoogleNet and VGG16) for crop mapping in Malawi and Mozambique and achieved an OA of 83% and 90% respectively in Malawi and in Mozambique. Likewise Chew et al. [8] used VGG16 for with a F1 score of 86%. Xu et al. [34] made a study where they compare different deep learning models (DeeplabV3, Unet and Swin Transformer [17]) for rice crop mapping using Sentinel-2 images. The highest accuracy is obtained from Swin Transforme with 95.47% followed by DeeplabV3 with 90.80% and Unet with 89.34%. However Unet and DeeplabV3 has lower number of parameters and inference time.

3 Study Area and Dataset

3.1 Study Area

Senegal is one of the most affected countries by the lack of food self-sufficiency and the rice constitutes the staple food. Indeed, to overcome the food insecurity problem, we are focusing on the monitoring and management of the rice crop in Senegal.

In this first part of our work, the study area is centered in the north of Senegal specifically at Dagana located between 16° 30′ 38.027″ North and 15° 30′ 12.524″ West. Rice cultivation is more developed in this area because of the Senegal River valley which allows cultivation throughout the year.

3.2 Dataset

Field Data: The ground truth data used in this study was provided by CERAAS (Centre d'Etude Régional pour l'Amélioration de l'Adaptation à la Sécheresse), a Senegalese organisation. They provided us 3 with shapefiles containing rice fields coordinates for February, March and April 2018. Figure 1 shows an examples from the ground truth data. The attribute *Dates_de_s* indicates the date on which the field was sown. The harvest date is scheduled two months after sowing. In overall 3133 field coordinates were collected (490 for February, 2074 for March and 569 for April).


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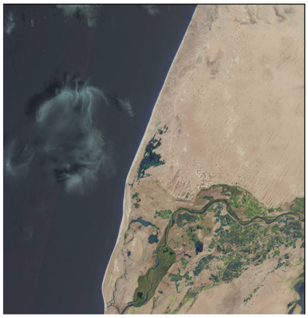
 'properties': OrderedDict([('Dates_de_s', '2018-02-25')]),
 'geometry': {'type': 'Polygon',
  'coordinates': [[(378964.5507067973, 1820096.2766705956),
    (378927.8651713524, 1820079.3011205588),
    (378889.9047981091, 1820150.408893695),
    (378919.33975281473, 1820162.3151675034),
    (378964.5507067973, 1820096.2766705956)]]}}
```


Fig. 1. Example of field coordinates from the ground truth data.

Band	Resolution	Central Wavelength	Description
B1	60 m	443 nm	Ultra Blue (Coastal and Aerosol)
B2	10 m	490 nm	Blue
B3	10 m	560 nm	Green
B4	10 m	665 nm	Red
B5	20 m	705 nm	Visible and Near Infrared (VNIR)
B6	20 m	740 nm	Visible and Near Infrared (VNIR)
B7	20 m	783 nm	Visible and Near Infrared (VNIR)
B8	10 m	842 nm	Visible and Near Infrared (VNIR)
B8a	20 m	865 nm	Visible and Near Infrared (VNIR)
B9	60 m	940 nm	Short Wave Infrared (SWIR)
B10	60 m	1375 nm	Short Wave Infrared (SWIR)
B11	20 m	1610 nm	Short Wave Infrared (SWIR)
B12	20 m	2190 nm	Short Wave Infrared (SWIR)

(a)



(b)

Fig. 2. (a) Sentinel-2 Bands specifications. (credit GisGeography). (b) Satellite images. (Color figure online)

Satellite Data: Sentinel-2 satellite images were used in this study. It provides medium resolution images for a revisit time of 5-days. Its specifications are given in Fig. 2a

We collected Sentinel-2 images using Earth Explorer[5] from April to June 2018 which correspond to the date on which the ground truth data were collected. Four images were collected in overall on the following dates: 03^{rd} April, 28^{th} April, 18^{th} May and 22^{nd} June. The original Sentinel-2 images were of size $5490 \times 5490 \times 3$ where 3 is the number of bands we considered (Red, Green and Blue). Figure 2b shows an examples of a Sentinel-2 satellite image that was collected

In order to be able to process these images through a neural network, we had to split them into smaller sizes. Each image was split into several images of size $256 \times 256 \times 3$. Given the original images extend were larger than the area of interest, we only kept images within this area after splitting. We ended up with a dataset of 203 images of size $256 \times 256 \times 3$. Crop type mapping can be seen as an image segmentation problem. Indeed, a segmented label is needed for each input image. Following the DeepGlobe dataset [9], we used the ground truth coordinates of rice field to map them into an RGB mask image with two classes: Rice and Not Rice. Figures 3a and 3b shows an illustration of an image and its corresponding mask label.

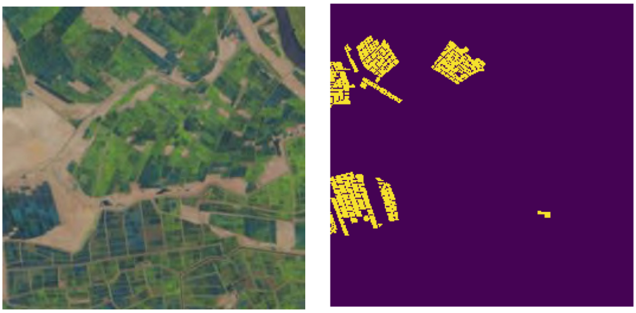
4 Modeling

Several classical machine learning (including SVM, Random Forest and decision trees) and deep learning (Unet, Deeplab V3 and Deeplab V3+) models were trained. The best results was obtained with SVM for classical ML models and DeepLab V3+ for deep learning models. In the following parts, we will present those models and the results we obtained.

[5] https://earthexplorer.usgs.gov/.

Model	Accuracy
Random Forest	49.73%
Decision Trees	47.51%
SVM	50.64%

Model	IOU
Unet	66.03
DeeplabV3 +	67.87



(a) (b)

Fig. 3. (a) Original Satellite images. (b) Mask: rice with yellow color and not rice purple (Color figure online)

4.1 SVM

To be able to train SVM on our data, we converted our image segmentation problem into a pixel wise classification problem. For each pixel in the satellite images, we associate a label (Rice = 1, Not Rice = 0) based on its color on the masks image. Figure 4 gives an illustration of the final dataset we used to train the SVM model.

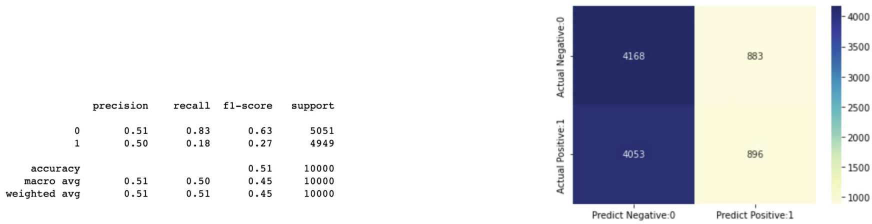
R	G	B	class
62	70	73	0
69	75	87	0
87	109	88	1
59	66	74	0
61	69	72	0

Fig. 4. Tabular pixel data

The original dataset was too large (over 1 million data points) and unbalanced with more than not rice than rice pixels. To overcome this, we randomly sampled

50 000 pixels. The final dataset contains 25561 of not rice pixels and 24439 rice. 80% of the data was used for training and 20% for testing. We used SVM from Sklearn and trained multiple models with different kernels (Linear and polynomial) and C values (from 1.0 to 200). The best results was obtained with a linear kernel with 100.0 as C value.

SVM Results: The overall accuracy of the SVM model is 50.64% on the test set. Figure 5a and 5b give details of the evaluation results. They show that the precision and recall for the class 0 (not rice) are higher than those for the class 1 (rice) which has a very low recall. This can be explained by the fact that the model is better at identifying not rice pixels (4168 over 5051 correct prediction) than rice pixels (only 896 over 4949 pixels). Figures 6a, 6b and 6c show a predicted image from our SVM model.



	precision	recall	f1-score	support
0	0.51	0.83	0.63	5051
1	0.50	0.18	0.27	4949
accuracy			0.51	10000
macro avg	0.51	0.50	0.45	10000
weighted avg	0.51	0.51	0.45	10000

(a) (b)

Fig. 5. (a) Classification report. (b) Confusion matrix

(a) (b) (c)

Fig. 6. (a) Original image, (b) Original mask and (c) Predicted image

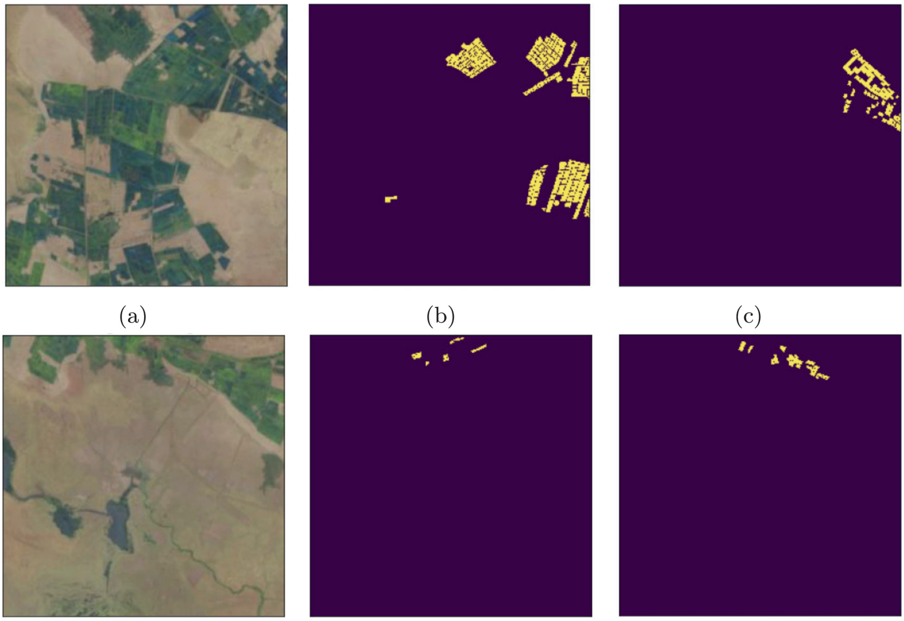
4.2 DeepLab V3

DeepLab V3+ [7] is a convolutional neural network made of an encoder and a decoder for image segmentation. Given the size of our dataset (203 images) and the computation power that we have, we were not able to retrain the model from scratch. We did a transfer learning by considering Resnet [13] as backbone in the encoder part and retrain the decoder. Adam optimizer is used for training with a learning rate of 0.00008. Learning rate scheduler is also applied using the cosine annealing with a minimum learning rate of $5e^{-5}$. The model was trained for 10 epochs. DiceLoss [29] and Intersection over Union (IOU) were used to evaluate the model. The IoU is calculated by dividing the overlap between the predicted and ground truth annotation by the union of these.

$$IOU(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{TP}{TP + FP + FN} \tag{1}$$

- TP: True Positive
- FP: False Positive
- FN: False Negative

Given the size of our dataset only 20 images were kept for model evaluation and the IOU was 67.87%. Figures 7c and 7f shows an example of predicted image using our deeplab V3+ model along with their corresponding images and ground truth masks.



(a) (b) (c)

(d) (e) (f)

Fig. 7.

5 Discussion

The study reveals interesting results with both models (SVM and Deeplab V3+). They were able to identify some rice pixels even if there is a large room for improvement. The experiences we made show that Deeplab V3+ is more accurate and provide better results than the SVM model for which IOU is around 15 % on the test set. In both cases the performance still low. This can be due to two facts:

The Image Resolution. Sentinel-2 provides one of the free highest resolution for satellite images. However, this resolution still low for high performance images segmentation. To be convinced of this, we trained the same Deeplab V3+ model with the same hyperparameters on the DeepGlobe land cover classification dataset [9] which is 50 cm resolution. We sampled the same number of examples (203 images) and the IOU was about 80%.

Pixel Color Overlapping. Considering a binary classification(rice and not rice) can create more confusion for the model and make the pixels identification very hard. In fact, there is a lot of green pixels with very close values. Therefore, using multi-class instead of binary-class classification by differentiating other types of crop and vegetation to the rice crop may improve model performance on rice field mapping.

6 Conclusion

The development of AI and the availability of free satellite images have been widely used in the service of agriculture for a better yield management. In this study, we explored them for rice crop in Senegal. The first part of this work which is presented here shows that we can use AI and Sentinel-2 images to map rice field in the North of Senegal (Dagana). Two experiences have been conducted with an SVM model and a CNN model using Deeplab V3+. The outputs from these experiences show that the later model gives better results with 67.87% of IOU score. However, this still very low and leaves room for improvement. The main cause that might lead to this low performance are the resolution of the satellite images we considered here (Sentinel-2) and the pixel color overlapping. Indeed, for future work we first plane to handle the later problem by considering a multi-class problem instead of binary. We plan to collect data about other types of crops and vegetation in order to help the model to better map rice field. Then we will also build our own models that will fit better the data. If the outputs of this setting still low, we will consider collecting higher resolution satellite images which may requires some cost.

References

1. Atzberger, C.: Advances in remote sensing of agriculture: context description, existing operational monitoring systems and major information needs. Remote Sens. **5**(2), 949–981 (2013). https://doi.org/10.3390/rs5020949. https://www.mdpi.com/2072-4292/5/2/949
2. Badrinarayanan, V., Kendall, A., Cipolla, R.: Segnet: a deep convolutional encoder-decoder architecture for image segmentation. CoRR abs/1511.00561 (2015). http://arxiv.org/abs/1511.00561
3. Bah, M.D., Hafiane, A., Canals, R.: Crownet: deep network for crop row detection in UAV images. IEEE Access **8**, 5189–5200 (2020). https://doi.org/10.1109/ACCESS.2019.2960873
4. Bontemps, S., et al.: Building a data set over 12 globally distributed sites to support the development of agriculture monitoring applications with sentinel-2. Remote Sens. **7**(12), 16062–16090 (2015). https://doi.org/10.3390/rs71215815. https://www.mdpi.com/2072-4292/7/12/15815
5. Boryan, C., Yang, Z., Mueller, R., Craig, M.: Monitoring us agriculture: the US department of agriculture, national agricultural statistics service, cropland data layer program. Geocarto Int. **26**, 341–358 (2011). https://doi.org/10.1080/10106049.2011.562309
6. Crisóstomo de Castro Filho, H., et al.: Rice crop detection using LSTM, Bi-LSTM, and machine learning models from sentinel-1 time series. Remote Sens. **12**(16) (2020). https://doi.org/10.3390/rs12162655. https://www.mdpi.com/2072-4292/12/16/2655
7. Chen, L., Zhu, Y., Papandreou, G., Schroff, F., Adam, H.: Encoder-decoder with atrous separable convolution for semantic image segmentation. CoRR abs/1802.02611 (2018). http://arxiv.org/abs/1802.02611
8. Chew, R., et al.: Deep neural networks and transfer learning for food crop identification in UAV images. Drones **4**(1) (2020). https://doi.org/10.3390/drones4010007. https://www.mdpi.com/2504-446X/4/1/7
9. Demir, I., et al.: Deepglobe 2018: a challenge to parse the earth through satellite images. CoRR abs/1805.06561 (2018). http://arxiv.org/abs/1805.06561
10. d'Andrimont, R., Yordanov, M., Martinez-Sanchez, L., van der Velde, M.: Monitoring crop phenology with street-level imagery using computer vision. Comput. Electron. Agric. **196**, 106866 (2022). https://doi.org/10.1016/j.compag.2022.106866. https://www.sciencedirect.com/science/article/pii/S0168169922001831
11. Feng, Q., et al.: Multi-temporal unmanned aerial vehicle remote sensing for vegetable mapping using an attention-based recurrent convolutional neural network. Remote Sens. **12**(10) (2020). https://doi.org/10.3390/rs12101668. https://www.mdpi.com/2072-4292/12/10/1668
12. Friedl, M., Brodley, C.: Decision tree classification of land cover from remotely sensed data. Remote Sens. Environ. **61**(3), 399–409 (1997). https://doi.org/10.1016/S0034-4257(97)00049-7. https://www.sciencedirect.com/science/article/pii/S0034425797000497
13. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. CoRR abs/1512.03385 (2015). http://arxiv.org/abs/1512.03385
14. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural Comput. **9**, 1735–1780 (1997). https://doi.org/10.1162/neco.1997.9.8.1735
15. Howard, A.G., et al.: Mobilenets: efficient convolutional neural networks for mobile vision applications. CoRR abs/1704.04861 (2017). http://arxiv.org/abs/1704.04861

16. Huang, G., Liu, Z., Weinberger, K.Q.: Densely connected convolutional networks. CoRR abs/1608.06993 (2016). http://arxiv.org/abs/1608.06993
17. Liu, Z., et al.: Swin transformer: hierarchical vision transformer using shifted windows. CoRR abs/2103.14030 (2021). https://arxiv.org/abs/2103.14030
18. Mansaray, L., Wang, F., Huang, J., Yang, L., Kanu, A.: Accuracies of support vector machine and random forest in rice mapping with sentinel-1a, landsat-8 and sentinel-2a datasets. Geocarto Int. (2019). https://doi.org/10.1080/10106049.2019.1568586
19. Mulyono, S., Nadirah: Identifying sugarcane plantation using landsat-8 images with support vector machines. In: IOP Conference Series: Earth and Environmental Science, vol. 47, p. 012008 (2016). https://doi.org/10.1088/1755-1315/47/1/012008
20. Nowakowski, A., et al.: Crop type mapping by using transfer learning. Int. J. Appl. Earth Obs. Geoinf. **98**, 102313 (2021). https://doi.org/10.1016/j.jag.2021.102313. https://www.sciencedirect.com/science/article/pii/S0303243421000209
21. Onojeghuo, A., Blackburn, G., Wang, Q., Atkinson, P., Kindred, D., Miao, Y.: Mapping paddy rice fields by applying machine learning algorithms to multi-temporal sentinel-1a and landsat data. Int. J. Remote Sens. **39**, 1042–1067 (2018). https://doi.org/10.1080/01431161.2017.1395969
22. Pan, S.J., Yang, Q.: A survey on transfer learning. IEEE Trans. Knowl. Data Eng. **22**, 1345–1359 (2010)
23. Paris, C., Weikmann, G., Bruzzone, L.: Monitoring of agricultural areas by using sentinel 2 image time series and deep learning techniques, p. 18 (2020). https://doi.org/10.1117/12.2574745
24. Peña-Barragán, J.M., Ngugi, M., Plant, R., Six, J.: Object-based crop identification using multiple vegetation indices, textural features and crop phenology. Remote Sens. Environ. **115**, 1301–1316 (2011). https://doi.org/10.1016/j.rse.2011.01.009
25. Saadat, M., Seydi, S.T., Hasanlou, M., Homayouni, S.: A convolutional neural network method for rice mapping using time-series of sentinel-1 and sentinel-2 imagery. Agriculture **12**(12) (2022). https://doi.org/10.3390/agriculture12122083. https://www.mdpi.com/2077-0472/12/12/2083
26. Saini, R., Ghosh, S.: Exploring capabilities of sentinel-2 for vegetation mapping using random forest. ISPRS - Int. Arch. Photogrammetry Remote Sens. Spatial Inf. Sci. **XLII-3**, 1499–1502 (2018). https://doi.org/10.5194/isprs-archives-XLII-3-1499-2018
27. Saini, R., Ghosh, S.K.: Crop classification on single date sentinel-2 imagery using random forest and support vector machine. Int. Arch. Photogram. Remote Sens. Spatial Inf. Sci. (2018)
28. Simonyan, K., Zisserman, A.: Very deep convolutional networks for large-scale image recognition (2014). https://doi.org/10.48550/ARXIV.1409.1556
29. Sudre, C.H., Li, W., Vercauteren, T., Ourselin, S., Cardoso, M.J.: Generalised dice overlap as a deep learning loss function for highly unbalanced segmentations. CoRR abs/1707.03237 (2017). http://arxiv.org/abs/1707.03237
30. Szegedy, C., Ioffe, S., Vanhoucke, V.: Inception-v4, inception-resnet and the impact of residual connections on learning. CoRR abs/1602.07261 (2016). http://arxiv.org/abs/1602.07261
31. Szegedy, C., et al.: Going deeper with convolutions. CoRR abs/1409.4842 (2014). http://arxiv.org/abs/1409.4842
32. Tran, K.H., Zhang, H.K., McMaine, J.T., Zhang, X., Luo, D.: 10 m crop type mapping using sentinel-2 reflectance and 30 m cropland data layer product. Int. J. Appl. Earth Obs. Geoinf. **107**, 102692 (2022). https://doi.org/10.1016/j.jag.2022.102692. https://www.sciencedirect.com/science/article/pii/S0303243422000186

33. Wu, F., Wu, B., Zhang, M., Zeng, H., Tian, F.: Identification of crop type in crowdsourced road view photos with deep convolutional neural network. Sensors **21**, 1165 (2021). https://doi.org/10.3390/s21041165
34. Xu, H., Song, J., Zhu, Y.: Evaluation and comparison of semantic segmentation networks for rice identification based on sentinel-2 imagery. Remote Sens. **15**(6) (2023). https://doi.org/10.3390/rs15061499. https://www.mdpi.com/2072-4292/15/6/1499
35. Zhang, W., Liu, H., Wu, W., Zhan, L., Wei, J.: Mapping rice paddy based on machine learning with sentinel-2 multi-temporal data: model comparison and transferability. Remote Sens. **12**(10) (2020). https://doi.org/10.3390/rs12101620. https://www.mdpi.com/2072-4292/12/10/1620
36. Zhang, X., Zhou, X., Lin, M., Sun, J.: Shufflenet: an extremely efficient convolutional neural network for mobile devices. CoRR abs/1707.01083 (2017). http://arxiv.org/abs/1707.01083