



HAL
open science

Deep convolutional neural network for mangrove mapping

Corina Iovan, Michel Kulbicki, Éric Mermet

► **To cite this version:**

Corina Iovan, Michel Kulbicki, Éric Mermet. Deep convolutional neural network for mangrove mapping. IGARSS 2020 International Geoscience and Remote Sensing Symposium, Sep 2020, Waikoloa, United States. pp.1969-1972, 10.1109/IGARSS39084.2020.9323802 . hal-03927567

HAL Id: hal-03927567

<https://hal.science/hal-03927567v1>

Submitted on 26 Sep 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, Waikoloa, HI, USA, 2020

Pages 1969-1972

<https://doi.org/10.1109/IGARSS39084.2020.9323802>

<https://archimer.ifremer.fr/doc/00816/92811/>

Archimer
<https://archimer.ifremer.fr>

Deep Convolutional Neural Network for Mangrove Mapping

Iovan Corina ¹, Kulbicki Michel ¹, Mermet Eric ²

¹ IRD - UMR Entropie, Laboratoire d'Excellence-CORAIL BPA5, Nouméa cedex, New Caledonia

² CAMS - UMR 8557, EHESS, Paris, France

Abstract :

Updated information on the spatial distribution of mangrove forests is of high importance for management plans. Yet, access to mangrove distribution maps is limited, even-though remote sensing data is currently freely available and deep learning algorithms score high performances in automatic classification tasks. The methodologies developed in this paper are based on a deep convolutional neural network and have been tested on WorldView 2 and Sentinel-2 images. The obtained results are highly satisfactory and open perspectives for automatically mapping mangrove distribution over large areas.

Keywords : CNN, mangroves, Sentinel-2, World-View2, remote sensing

1. INTRODUCTION

Updated spatial distribution of mangroves is of high importance for ecosystem conservation and management. However, this information is limited for many areas of the world where mangrove forests are present, such as countries of the South Pacific Ocean.

Remote sensing data plays a key role in determining the extent of mangrove forests and understanding its dynamics. The last few years have brought remarkable diversity in remote sensing sensors, as well as in the approaches to automatically classify this data.

The deployment of ESA's Sentinel-2 operational satellites has established a new paradigm for remote sensing applications, as it provides world wide coverage with multispectral, high spatial and temporal resolution, free of charge. In the same time, deep learning approaches have become the gold standard in image classification tasks.

The main contribution of this paper is to propose a deep convolution neural network approach to automatically detect mangroves in Sentinel-2 and WorldView 2 imagery. We tested the proposed architecture on data acquired over Fiji, in the South Pacific Ocean. The results obtained on both type

This work was funded by PEPS MANGROVES INEE CNRS-IRD program.

Study Area	Data description	Dates of acquisition
Fiji	WorldView 2, 50cm	2012, 2013, 2015
Fiji	Sentinel-2, 10m	2016

Table 1. Study areas and satellite data used in this study.

of data open promising perspectives to automatically generate updated maps of mangrove distribution over large areas.

2. STUDY AREA AND DATA

2.1. Study Area

The study areas are located in the South Pacific Ocean and extend over several areas of Fiji (see Table 1).

2.2. Remote Sensing Data

We used multispectral WorldView 2 and Sentinel-2 imagery for several sites in Fiji. The WorldView 2 imagery was acquired between 2012 and 2015 and has a spatial resolution of 50 cm. Sentinel-2 data was acquired in 2016 and has a spatial resolution of 10m.

2.3. Reference Data

The training and test data correspond to areas of the images containing mangroves and were generated through on-screen digitizing via visual interpretation of the images. The training and test datasets are independent, and each covers approximately half of the images.

3. METHODOLOGY

We have developed a supervised image classification algorithm based on a deep convolutional neural network.

The architecture of the network we have proposed is illustrated in Figure 1 and is composed of the following layers :

- One layer composed of 1000 convolutional filters with 8x8 kernel size with 50% stride. Non linearity: ReLU
- Two "dense-layer" type layers of respective dimensions 500 300 50. Non-linearity: ReLU
- One softmax output layer

The dropout is used for all layers except the first one. The implementation of the convolutional neural network is based on Keras with the backend of tensorflow. It runs on an Ubuntu OS platform with a core processor of i7, 64 GB memory and a GTX NVIDIA ZOTAC with 12 GB memory.

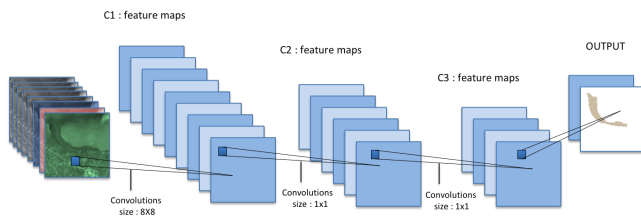


Fig. 1. Convolutional neural network architecture developed for supervised image classification of mangroves from Sentinel-2 and WorldView 2 data.

During the test phase, the network produces a classification image whose values are close to a probability of mangrove presence. A threshold is applied to this classification image in order to obtain a mask of mangrove presence. The mask obtained by classification is further processed to eliminate outliers (isolated detections of the order of one pixel in size).

4. RESULTS

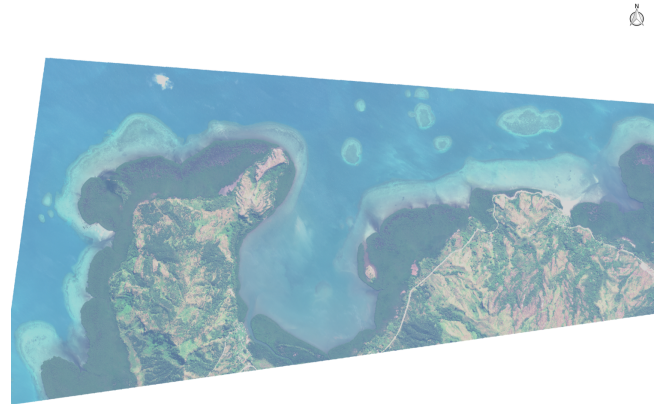
Figures 2 and 3 depict the results obtained by the convolutional neural network on WorldView 2 and Sentinel-2 images of two study areas in Fiji.

Overall accuracy for mangrove detection depends on the threshold chosen on the ROC curve. The ROC curve depicted in Figure 4 shows that detection rates are of 87.94% for a false positive rate of 1.00% and increases to 99.15% if we tolerate a false positive rate of 5.00% (see Table 2).

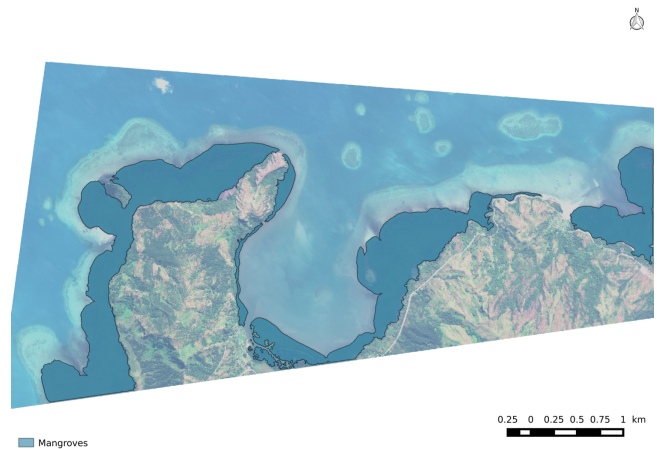
5. RELATED WORK

Several quality review papers focused on remote sensing of mangroves such as [1], [2], [3], [4], [5] and [6].

They discuss major contributions to this field highlighting different types of remote sensing sensors (optical imagery, synthetic aperture radar, LIDAR) and techniques developed to



(a) WorldView 2 (true color) image of Fiji.



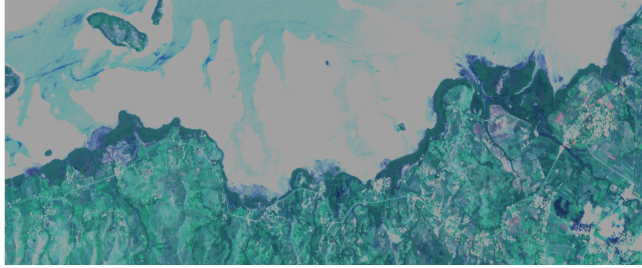
(b) Results for mangrove detection are depicted in green.

Fig. 2. WorldView 2 imagery of a study area in Fiji and mangrove regions.

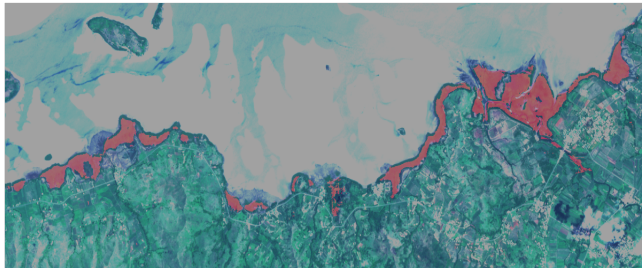
answer specific ecological needs such as land cover classification, ecosystem measurements or monitoring through time and different spatial scales.

This section presents a short review of mapping mangroves from satellite multispectral imagery through image classification and highlights the methodologies based on neural networks, as a forerunner of deep neural networks. For detailed information on the existing research, remote sensing sensors and methodologies used for mangrove mapping, we direct readers' attention to the aforementioned review papers.

Existing research on mapping the distribution of mangroves from satellite imagery was conducted on data such as IKONOS, QuickBird, GeoEye, Landsat, SPOT, Pleiades or WorldView and the methodologies developed to tackle the goal are various. They can be grouped into two categories. Traditional approaches rely mostly on low level features grouped according to continuity/homogeneity criteria based



(a) Sentinel-2 (true color) image of the study area in Fiji.



(b) Results for mangrove detection are depicted in red.

Fig. 3. Sentinel-2 imagery of a study area in Fiji and mangrove regions.

False positive Rate	True positive Rate
1.00%	87.94%
2.00%	92.97%
3.00%	96.85%
4.00%	98.41%
5.00%	99.15%

Table 2. True positive rates according to false negative rates for mangrove detection with deep convolutional neural network

on prior knowledge on mangrove distribution. They include visual interpretation of satellite imagery and manually delineating contours of mangrove areas [7, 8], pixel-based classification methods [9], object-based classification [10, 11] of hybrid methods [12, 13]. Conversely, machine learning approaches do not rely on any assumptions on data distribution and provide non-parametric classifications models. Such approaches include support vector machines [14], random forest [15] or neural networks [16, 17].

Deep convolutional neural networks (DCNN) have been used in the last years in image processing and computer vision tasks as this approach has a high ability of learning discriminative features in a hierarchical way. A typical DCNN consists of a number of convolution and pooling layers optionally followed by fully connected layers [18]. DCNNs are insensitive to rotation, affine transformation, scaling and have lately been exploited for remote sensing applications [19] due to their ability to exploit high-level features in images.

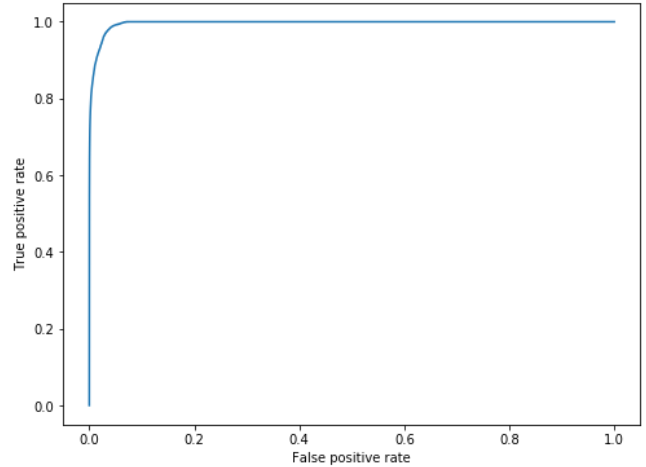


Fig. 4. Mangrove detection ROC curve on WorldView 2 imagery.

Recently, [20] proposed a small-patched convolutional neural network for mapping mangrove species, based on the inception architecture of GoogLeNet and applied it on WorldView 2 images. The results obtained were compared to an SVM using spectral and texture features and showed an improvement of 30% in overall accuracy.

6. CONCLUSIONS AND FURTHER WORK

This article proposes a deep convolutional neural network for automatically detecting mangroves in Sentinel-2 and WorldView 2 imagery. The architecture was tested on several areas of Fiji, in the South Pacific Ocean. The obtained results proved that the proposed method is pertinent for mangrove mapping. Future work will focus on species classification.

7. REFERENCES

- [1] Le Wang, Mingming Jia, Dameng Yin, and Jinyan Tian, "A review of remote sensing for mangrove forests: 1956–2018," *Remote Sensing of Environment*, vol. 231, no. 111223, pp. 15p, sep 2019.
- [2] B. W. Heumann, "Satellite remote sensing of mangrove forests: Recent advances and future opportunities," *Progress in Physical Geography*, vol. 35, no. 1, pp. 87–108, 2011.
- [3] C. Giri, E. Ochieng, L. L. Tieszen, Z. Zhu, A. Singh, T. Loveland, J. Masek, and N. Duke, "Status and distribution of mangrove forests of the world using earth observation satellite data," *Global Ecology and Biogeography*, vol. 20, no. 1, pp. 154–159, 2011.

- [4] Claudia Kuenzer, Andrea Bluemel, Steffen Gebhardt, Tuan Vo Quoc, and Stefan Dech, "Remote sensing of mangrove ecosystems: A review," *Remote Sensing*, vol. 3, no. 5, pp. 878–928, may 2011.
- [5] Tien Dat Pham, Junshi Xia, Nam Thang Ha, Dieu Tien Bui, Nga Nhu Le, and Wataru Tekeuchi, "A review of remote sensing approaches for monitoring blue carbon ecosystems: Mangroves, sea grasses and salt marshes during 2010–2018," *Sensors (Switzerland)*, vol. 19, no. 8, apr 2019.
- [6] Tien Dat Pham, Naoto Yokoya, Dieu Tien Bui, Kuni-hiko Yoshino, and Daniel A. Friess, "Remote sensing approaches for monitoring mangrove species, structure, and biomass: Opportunities and challenges," feb 2019.
- [7] G. Neukermans, F. Dahdouh-Guebas, J. G. Kairo, and N. Koedam, "Mangrove species and stand mapping in gazi bay (kenya) using quickbird satellite imagery," *Journal of Spatial Science*, vol. 53, no. 1, pp. 75–86, 2008.
- [8] Wilfrid Rodriguez and Ilka C. Feller, "Mangrove landscape characterization and change in Twin Cays, Belize using aerial photography and IKONOS satellite data," *Atoll Research Bulletin*, , no. 509-530, pp. 1–22, 2004.
- [9] L. Valderrama-Landeros, F. Flores-de Santiago, J. M. Kovacs, and F. Flores-Verdugo, "An assessment of commonly employed satellite-based remote sensors for mapping mangrove species in Mexico using an NDVI-based classification scheme," *Environmental Monitoring and Assessment*, vol. 190, no. 1, 2018.
- [10] Soe W. Myint, Chandra P. Giri, Le Wang, Zhiliang Zhu, and Shana C. Gillette, "Identifying Mangrove Species and Their Surrounding Land Use and Land Cover Classes Using an Object-Oriented Approach with a Lacunarity Spatial Measure," *GIScience & Remote Sensing*, vol. 45, no. 2, pp. 188–208, apr 2008.
- [11] Y. Maeda, A. Fukushima, Y. Imai, Y. Tanahashi, E. Nakama, S. Ohta, K. Kawazoe, and N. Akune, "Estimating carbon stock changes of mangrove forests using satellite imagery and airborne LiDAR data in the South Sumatra state, Indonesia," *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, vol. 41, no. July, pp. 705–709, 2016.
- [12] Claudia Giardino, Mariano Bresciani, Francesco Fava, Erica Matta, Vittorio E. Brando, and Roberto Colombo, "Mapping submerged habitats and mangroves of Lampi Island Marine National Park (Myanmar) from in situ and satellite observations," *Remote Sensing*, vol. 8, no. 1, pp. 1–13, 2016.
- [13] Dezhi Wang, Bo Wan, Penghua Qiu, Yanjun Su, Qinghua Guo, and Xincai Wu, "Artificial mangrove species mapping using Pléiades-1: An evaluation of pixel-based and object-based classifications with selected machine learning algorithms," *Remote Sensing*, vol. 10, no. 2, pp. 294, feb 2018.
- [14] Benjamin W. Heumann, "An object-based classification of mangroves using a hybrid decision tree-support vector machine approach," *Remote Sensing*, vol. 3, no. 11, pp. 2440–2460, 2011.
- [15] Dezhi Wang, Bo Wan, Penghua Qiu, Yanjun Su, Qinghua Guo, Run Wang, Fei Sun, and Xincai Wu, "Evaluating the Performance of Sentinel-2, Landsat 8 and Pléiades-1 in Mapping Mangrove Extent and Species," *Remote Sensing*, vol. 10, no. 9, pp. 1468, sep 2018.
- [16] Xiang Yu, Hong Bo Shao, Xiang Hua Liu, and Dong Zhi Zhao, "Applying neural network classification to obtain mangrove landscape characteristics for monitoring the travel environment quality on the Beihai Coast of Guangxi, P. R. China," *Clean - Soil, Air, Water*, vol. 38, no. 3, pp. 289–295, 2010.
- [17] Beh Boon Chun, Mohd Zubir Mat Jafri, and Lim Hwee San, "Mangrove mapping in Penang Island by using artificial neural network technique," *2011 IEEE Conference on Open Systems, ICOS 2011*, pp. 251–255, 2011.
- [18] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," in *In Advances in neural information processing systems*, 2012, pp. 1097–1105.
- [19] Zhengzheng Fang, Wei Li, Jinyi Zou, and Qian Du, "Using CNN-based high-level features for remote sensing scene classification," *International Geoscience and Remote Sensing Symposium (IGARSS)*, vol. 2016-Novem, pp. 2610–2613, 2016.
- [20] Luoma Wan, Hongsheng Zhang, Guanghui Lin, and Hui Lin, "A small-patched convolutional neural network for mangrove mapping at species level using high-resolution remote-sensing image," *Annals of GIS*, vol. 25, no. 1, pp. 45–55, jan 2019.