A Sentinel-2 unsupervised forest mask for European sites

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ABSTRACT

Forests cover one third of Europe's land and significantly contribute to the regional economy. Moreover, they play an essential role in climate regulation. Traditional inventory-based forest data update is often much lower than required. Remote Sensing is a valuable source for forest monitoring, as it provides periodic data on vegetation status. In this context, EU Horizon-2020 MySustainableForest project (MSF, Grant Agreement nº 776045) aims at developing remote sensing-derived geo-information services for integrated forest management through a web service platform.

An unsupervised method to obtain a forest mask over European forests using optical Sentinel-2 data was implemented. K-means algorithm was used for segmenting the images in clusters, which were subsequently assigned to a forest class depending on its overlap with the forest classes of ancillary land cover data. The resulting classification was refined applying a filter and a vegetation mask. The algorithm was tested over 16 sites representing Europe's main biogeographic regions. A confusion matrix was built using points selected via photointerpretation. Validation metrics were computed from the confusion matrix.

The results showed that it is possible to develop an automatic forest mask for Europe, (overall accuracy above 90%). Accuracies varied depending on forest characteristics. Best results were achieved in Boreal and Continental forests. Although the algorithm was tuned to consider the diversity of European forests, there is scope for improving the adaptability of MSF Forest Mask, mainly in the southern Mediterranean region, where the mixed effect of tree-grass formations hindered a better forest discrimination. These results may be of interest to forest and land managers and climate modellers.

Keywords: Sentinel-2, forest mask, K-means, European forests, forest management, unsupervised classification.

INTRODUCTION

Forests cover one third of Europe's land and significantly contribute to the regional economy: more than 18,000 million € are generated yearly by the wood market, which implies a 0.9% sector contribution to the GDP, and at least 3 million employees work in the forestry sector[1]. Forest benefits include both tangible and intangible counts, the former linked to wood exploitation while the latter refer to other ecological, economic, social and aesthetic services, which are valuable for biodiversity maintenance, production of non-wood goods or ecosystem regulation[1,2,3]. Moreover, forests play an essential role in climate regulation[3], attenuating global warming through carbon sequestration[4,5,6]. In Europe, about 9% of total greenhouse gases emissions are absorbed by forests[1]. Although the forested area is currently growing, events such as storms[7], pests[8,9] or alien invasions, triggered by climate change, are increasingly threatening European forests[5,10,11,12,13,14]. Hence, forest monitoring has become a major concern for land managers and forest owners. Traditional inventory-based forest characterization from a dasometric perspective is expensive and the data update (5-10 years) is often much lower than required for planning commercial or recreational activities[15]. Forest change rates demand tools able to monitor, on annual basis, the forest extension, the attributes of available timber or the different ecosystem services emerged[15,16,17]. Remote Sensing is a valuable source for forest monitoring[17], as it provides periodic and spatially continuous data on vegetation status[18].

MySustainableForest (MSF)[19] in a EU-H2020 project which is developing remote sensing-derived geo-information services for integrated forest management, at pre-commercial stage, to be provided through a web service platform. MSF aims at integrating Earth Observation (EO) significantly further into forestry realm, by demonstrating the advantage of incorporating EO-based information into the daily decision making, protocols and operations of the different stakeholders

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across the silvicultural chain. It engages relevant European public and private forest stakeholders. It is expected that end-users will optimize their operations up to 10% and participating companies' headcounts increase up to 20%. MSF portfolio includes services on forest site characterisation, wood characterisation, biomass and CO2 stocking, forest condition, ecosystem vulnerabilities and forestry accounting. This study presents the development of the forest mask product, the first of the forest site characterisation service, on which most of the other services and products depend. MSF Forest Mask is an optical-based forest/no-forest binary classification map at 10 m spatial resolution which uses Sentinel-2 (S2) data as main input.

Different approaches have been used to carry out forest/non-forest classifications based on satellite data. The first studies focused on the development of forest maps for Europe used supervised methods (i.e., they needed ground truth data in order to train a classifier). Schuck et al.[20] used AVHRR 1 km resolution images, while Pekkarinen et al.[21] used ETM+ 30 m resolution images, yielding an Overall Accuracy of 88.37%, with significant differences depending on the country. Global forest maps have been developed using radar data and supervised methods, yielding accuracies of 84% with PALSAR 10 m data[22], and between 85 and 95% for North-American broadleaved forests with TanDEM-X 50 m data[23]. One of the main issues found in these studies is the relatively low accuracy of forest classifications in Mediterranean countries[20,21], where extensive areas are covered by tree-grass ecosystems. These areas are known by the difficulty of integrating the spectral response of different types of vegetation, what makes them challenging for Remote Sensing-based characterization[24,25].

In this study, a new unsupervised automatic method to create a forest/non-forest map across Europe is proposed. This method uses Sentinel-2 MSI multi-spectral data and ancillary land cover maps to generate a 10 m spatial resolution forest mask. The specific objectives of this study were to: i) develop an unsupervised automatic method to detect forest cover across different European regions, and ii) compare the effectiveness of the proposed method in environments characterized by different forest types and management practices. The results of this study can be used in carbon stock estimation, forest cover trend analysis and other forest management purposes.

METHODS

1.1 Study Area

Sixteen Areas of interest (AOI) were selected across Europe, representing the main biogeographical regions and forest types in the continent (Figure 1, Table 1), in order to test the accuracy of the methods in forests with different structure and composition. The total area masked accounts for 10,773 km^2.

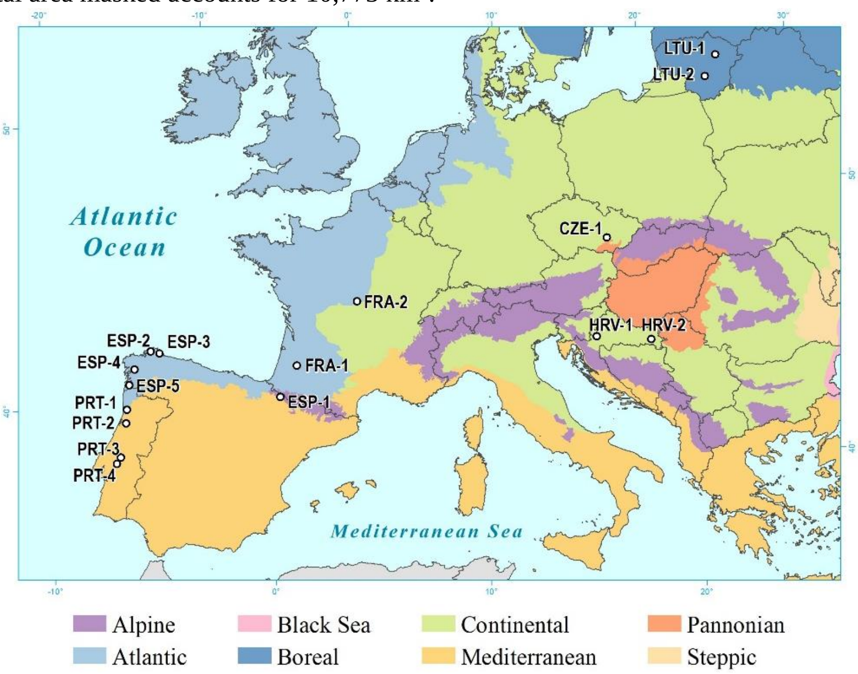

Figure 1: Areas of interest (AOIs) across European biogeographical regions according to the EEA (2016).

Table 1. Country, biogeographical region, dominant forest type and area of the 16 AOIs.

AOI	**Country**	**Biogeographical Region**	**Forest Type**	**Area km^2**
HRV-1	Croatia	Continental	Mixed	138
HRV-2	Croatia	Continental-Pannonian	Mixed	1103
CZE-1	Czech Republic	Continental-Pannonian	Mixed	150
FRA-1	France	Atlantic	Conifer and mixed	641
FRA-2	France	Atlantic-Continental	Broadleaf	275
LTU-1	Lithuania	Boreal	Mixed	1997
LTU-2	Lithuania	Boreal	Mixed	128
PRT-1	Portugal	Atlantic	Mixed	10
PRT-2	Portugal	Atlantic-Mediterranean	Mixed	610
PRT-3	Portugal	Mediterranean	Sclerophyllous and mixed	104
PRT-4	Portugal	Mediterranean	Sclerophyllous and mixed	165
ESP-1	Spain	Alpine-Mediterranean	Conifer and mixed	423
ESP-2	Spain	Atlantic	Mixed	725
ESP-3	Spain	Atlantic	Mixed	835
ESP-4	Spain	Atlantic	Mixed	2103
ESP-5	Spain	Atlantic	Mixed	1366

1.2 Datasets

Two Sentinel-2 (S2) images (i.e., winter and summer) were used for each AOI. S2 images were retrieved in Level-2A (i.e., surface reflectance) from Copernicus Open Access Hub. Green, Red, NIR and SWIR bands were selected to generate the forest/non-forest classification.

CORINE Land Cover (CLC) 2018 maps were used as ancillary information. Forest and transitional woodland-shrub classes were selected for the statistical analysis of S2 images.

1.3 Forest/non-forest classification

All S2 bands were clipped to the AOI extent and resampled to 10 m. For each season, Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI)[26] and NDVI texture indices (homogeneity and entropy) were computed. A first threshold was applied to the summer NDVI image in order to remove all the non-vegetation pixels. A second threshold was subsequently computed from the summer NDVI image based on the mean and standard deviation of vegetated pixels within CLC forest and transitional woodland classes, obtaining a vegetation mask. This mask was applied to all the bands, indices and textures in summer and winter, which were stacked into a single multi-band image, containing the bands and indices for both seasons but only with those pixels with vegetation with an NDVI close to that of CLC forest and woodland classes. It was assumed that, even if CLC is updated every 6 years, forest changes in that time are not large enough to produce significant changes in the NDVI threshold used to obtain the vegetation mask.

The stacked image with S2 bands, indices and textures was segmented in five classes using K-means clustering algorithm. K-means assigns each pixel to a cluster by minimizing the squared distance between points in the same cluster through an iterative process starting from random centroids[27].

In order to assign each cluster to forest or non-forest, a cross tabulation was carried out between clusters and CLC forest class. A cluster was assigned to the forest class when its overlap with CLC forest was greater than 45%. Otherwise, the cluster was assigned to non-forest. A filter was applied to refine the classification, removing all the polygons with less than 0.1 ha (i.e., 10 pixels), which define the minimum mapping unit of the forest mask. Finally, the vegetation mask generated in previous steps was applied to the forest mask to ensure that no non-vegetation pixel was assigned to forest.

The methods explained are summed up by the flow diagram in Figure 2.

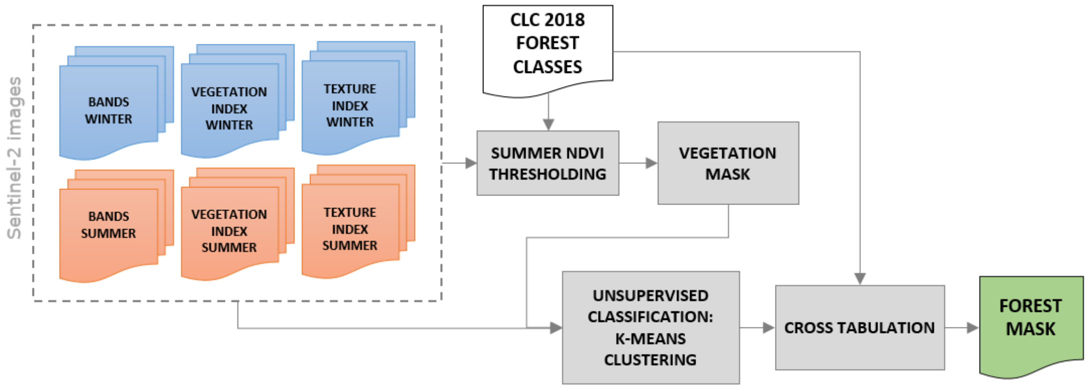

Figure 2. Flow diagram of the methods processed for the S2 forest/non-forest classification.

1.4 Forest mask validation

A reference dataset was created to validate the forest mask. A sample of 2500 random points was generated, allocating the number of points proportional to the size of each AOI using binomial distribution. Points were manually assigned to forest or non-forest via photointerpretation, based on the summer S2 image used for the automatic classification (i.e., date of the forest mask) and the very high resolution aerial image closest to the S2 image.

Confusion matrices (Table 2) between forest mask and reference dataset were built for each AOI. A total confusion matrix was built pooling all the AOIs. Overall accuracy (OA, Eq. 1), commission error (CE, Eq. 2), omission error (OE, Eq. 3) Dice similarity coefficient (DC, Eq. 4) and relative bias (relB, Eq. 5) were computed from confusion matrix to analyse the classification accuracy.

Table 2. Confusion matrix for a sample case.

Ground Truth	**Classification**		
	Non-Forest	Forest	Total
Non-Forest	TN	FP	CN
Forest	FN	TP	CP
Total	PCN	PCP	n

TN: True Positive; FP: False Positive, FN: False negative; TP: True Positive; CN: Condition Negative; CP: Condition Positive; PCN: Predicted Condition Negative; PCP: Predicted Condition Positive; n: sample size.

$$OA = \frac{TP + TN}{n} \tag{1}$$

$$CE = \frac{FP}{FP} \tag{2}$$

$$OE = \frac{FN}{CP} \tag{3}$$

$$DC = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} \tag{4}$$

$$relB = \frac{(FP - FN)}{CP} \tag{5}$$

RESULTS

1.5 Forest mask accuracy

The high accuracy of the forest mask was inferred from the pooled confusion matrix (Table 3) and the validation metrics (Table 4). For the pooled set of AOIs, accuracy metrics were high (OA = 94.2%; DC = 95.2%) and error metrics were low and balanced (OE = 4.8%; CE = 4.8; relB = 0%). OA ranged from 88% to 98.5% across AOIs, and DC ranged from 88% to 98.6%, thus confirming the good results.

Table 3. Confusion matrix for all the AOIs.

Ground Truth	**Classification**		
	Non-Forest	Forest	Total
Non-Forest	951	71	1022
Forest	71	1407	1478
Total	1022	1478	2500

The best metrics were obtained for Central and Northern Europe, (CZE-1, LTU-1), with OA and DC higher than 98%, OE and CE around 2% and low relative bias, which confirmed the good balance between both types of errors. The forest mask was less accurate for Portugal, with OA falling to 88% in PRT-2 and high OE. In these areas, errors were less balanced, as reflected by relB, especially in PRT-1 (OE = 21.7%; CE = 0%, relB = -21.7%).

Table 4. Validation metrics per AOI and total.

AOI	**OA**	**DC**	**OE**	**CE**	**relB**
LTU-1	98.5	98.1	1.3	2.6	1.3
CZE-1	98.0	98.6	1.4	1.4	0.0
ESP-4	97.5	98.0	2.4	1.6	-0.8
HRV-1	97.0	98.1	1.3	2.5	1.3
ESP-3	97.0	96.9	4.0	2.1	-2.0
FRA-2	97.0	96.7	4.3	2.2	-2.2
HRV-2	95.0	96.9	4.3	1.9	-2.4
ESP-2	95.0	95.3	3.8	5.6	1.9
LTU-2	95.0	95.1	0.0	9.3	10.2
ESP-1	94.5	96.5	2.0	4.9	3.0
FRA-1	94.5	95.5	4.1	4.8	0.8
PRT-4	92.0	95.2	4.8	4.8	0.0
PRT-3	90.0	88.9	13.0	9.1	-4.3
PRT-1	90.0	87.8	21.7	0.0	-21.7
ESP-5	88.5	88.0	8.7	15.2	7.6
PRT-2	88.0	87.8	15.7	8.5	-7.8
All AOIs	**94.2**	**95.2**	**4.8**	**4.8**	**0.0**

The forest mask clearly delimited forest areas in most of the AOIs. Figure 3 shows HRV-2 case, which is close to the average in terms of accuracy (OA = 95%; DC = 96.9%). Forest clearings, roads, dry channels, abandoned meanders and other features are clearly identified, thus highlighting the quality achieved.

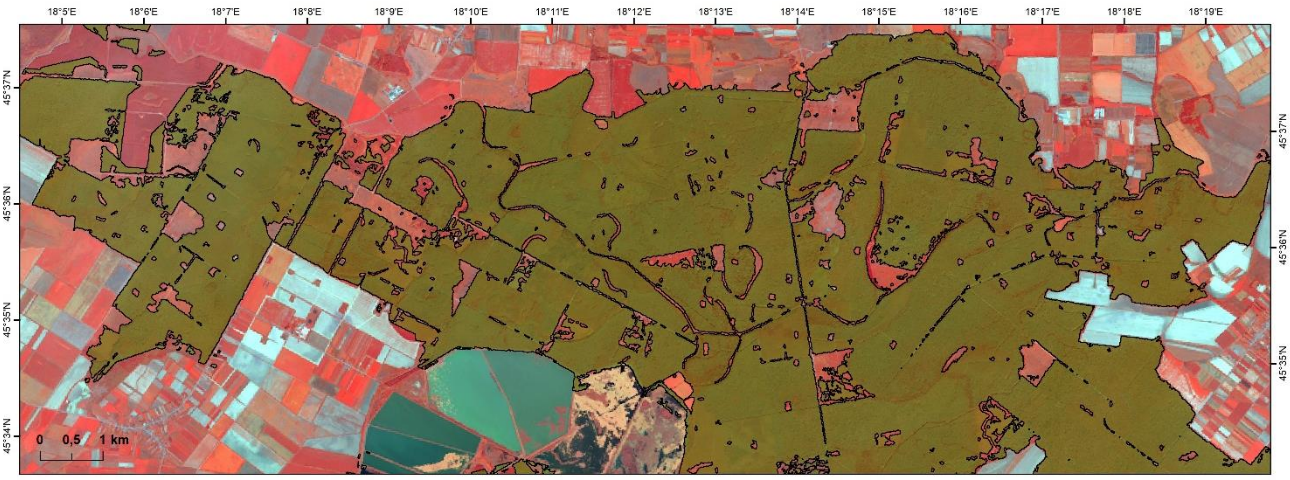

Figure 3. Forest mask for HRV-2 (Croatia). Background: S2 image 08/08/2018, false colour RGB composition: NIR (B08) / R (B04) / G (B03).

1.6 Influence of biogeographical regions on forest mask accuracy

The accuracy assessment grouped by biogeographical regions (Table 5) revealed significant contrasts. The difference between the best and worst region was around 10% for OA and DC. The best performance of the forest mask was achieved in Boreal (OA = 97.3%; DC = 96.9%) and Continental regions (OA = 97%; DC = 98.1%). Although OA was slightly better in Boreal region than in Continental, DC was better for Continental region due to the higher relB in Boreal (i.e., unbalanced errors, the low omission in Boreal might be explained by a relatively high commission)

Table 5. Validation metrics with AOIs grouped by biogeographical regions

Biogeographical Region	OA	DC	OE	CE	relB
Boreal *(LTU-1, LTU-2)*	97.3	96.9	0.8	5.3	4.8
Continental *(HRV-1)*	97.0	98.1	1.3	2.5	1.3
Atlantic-Continental *(FRA-2)*	97.0	96.7	4.3	2.2	-2.2
Continental-Pannonian *(CZE-1, HRV-2)*	96.0	97.4	3.4	1.7	-1.7
Alpine-Mediterranean *(ESP-1)*	94.4	96.4	2.1	5.0	3.1
Atlantic *(FRA-1, PRT-1, ESP-2, ESP-3, ESP-4, ESP-5)*	94.3	94.7	5.1	5.4	0.4
Mediterranean *(PRT-3, PRT-4)*	91.0	93.0	7.7	6.3	-1.5
Atlantic-Mediterranean *(PRT-2)*	88.0	87.8	15.7	8.5	-7.8

Mediterranean and Atlantic-Mediterranean regions yielded the worst metrics (OA = 88%; DC = 87.8% for Atlantic-Mediterranean). AOIs in these regions were generally characterised by higher omission than commission errors and a negative and relatively high relB, thus revealing some difficulty to identify low-density forests (Figure 4). This effect was attenuated in the Alpine-Mediterranean region by the contrast between Mediterranean forests at low altitudes and Alpine conifer forests at high altitude, where metrics should be closer to those of Boreal region. Validation metrics were close to the average in regions characterised by the dominance of broadleaf and deciduous forests (e.g., Atlantic, Continental-Pannonian, Atlantic-Continental).

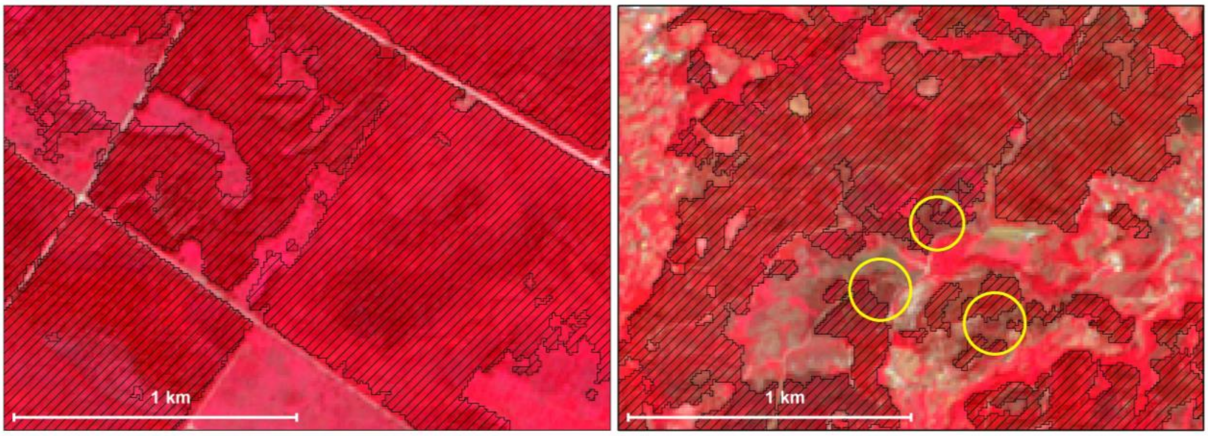

Figure 4. Comparison between two forest masks. Background: S2 image in summer 2018, false color composition, NIR (B08) / R (B04) / G (B03); vigorous vegetation appears in red; forest mask appears as striped polygons. Left: HRV-1 (Continental region), forest is delimited with high accuracy; right: PRT-2 (Atlantic-Mediterranean region), in yellow circles, areas with omission errors.

DISCUSSION

Some of the results of this study were similar to those of previous works. Pekkarinen et al. (2009)[21] used a method based on Landsat ETM+ images (multispectral at 30 m spatial resolution) and CLC to derive a Pan-European forest/non-forest map. The total accuracy of their forest map (OA = 90.8) was lower than MSF Forest Mask accuracy (OA = 94.2), which might be explained by the different spatial resolution (30 m vs 10 m), the refinement steps used in the present study and different validation strategies. Nevertheless, results found in both studies were similar regarding the accuracy grouped by regions. Pekkarinen et al. (2009)[21] found a high accuracy (OA > 96%) for Germany, Belgium, Luxembourg and the Netherlands, corresponding to Continental and Atlantic-Continental regions of MSF Forest Mask (OA = 97%), whereas in Portugal, Greece and Italy accuracy was lower (OA < 90 %), as found in this study for Mediterranean and Mediterranean-Atlantic regions (OA = 88% to 91%).

According to Martone et al., (2018)[23], most forest/non-forest classification maps show typical accuracies under 90%. In their work, they generate a global forest mask based on TanDEM-X interferometric SAR data at 50 m spatial resolution, achieving an accuracy of about 86% in Germany and Eastern Europe, validated with Copernicus High Resolution Layers (HRL). In comparison with previous studies, MSF Forest Mask improves the accuracy about 5% and provides higher spatial resolution (10 m). The spatial robustness of our forest mask is also higher than most of other similar products, with smaller differences across biogeographical regions and forest types.

The high accuracies achieved in Continental and Boreal forests might be due to forest characteristics in these regions (e.g., species, forest structure, high density), but also to surrounding land covers, mainly grasslands or crops with short vegetative phases, which can be easily distinguished from forests. Conversely, Mediterranean forests are often characterised by low-density stands (e.g., tree-grass formations that alternate almost isolated trees with pastures) and large transition areas with dominance of shrub stratum. The frontier between forest and non-forest classes becomes more diffuse in these areas, thus hindering the discrimination of forest (Figure 4). This assumption may be confirmed by examining the relatively high OE in Mediterranean region when compared to CE (OE = 15.7%; CE = 8.5%; relB = -7.8%).

One of the shortcomings of this study is its dependence on ancillary maps to turn the output of unsupervised K-means into forest and non-forest classes. Regarding the ancillary dataset used (CLC), other options are available at European level (e.g., Copernicus HRL). The use of other resources as OpenStreetMap (OSM) might be explored, but it will need an adjustment of the methods.

Some of the errors in the forest mask were caused by the confusion between forest and crops. This could be mitigated using more dates for the analysis (i.e., adding images as input), which will help to discriminate crops based on its more cyclic temporal behaviour.

Another limitation of the study is the number of AOIs used in some of the biogeographical regions, which might have biased the results (e.g., accuracy is high for Continental region, but the analysis included only one AOI). More locations and better distributed are needed to confirm the results found.

CONCLUSIONS

In this study, a Sentinel-2-based method to create a forest mask for European forests was proposed. The method was validated in 16 locations across Europe, characterized by the main dominant biogeographical regions in the continent. The accuracy of the forest/non-forest classification was high (OA = 94.2%; DC = 95.2%), varying for different biogeographical regions (maximum 10%). For Boreal, Continental, Atlantic-Continental, Continental-Pannonian, Alpine-Mediterranean and Atlantic regions, accuracy was higher than 94% and errors and biases were low. Some problems were found in Mediterranean region, although accuracy was still high (88%). The proposed method is suitable for its use in different forest types and regions across Europe, and it might help to save costs in forest identification and improve the current forest/non-forest maps used by managers and stakeholders in the forestry sector. MSF Forest Mask might also be used by scientists and decision makers in environmental matters, such as ecological and climate modelling. Future research should be carried out to generalize the method presented to be used in other regions of the world, exploring alternative ancillary data which may replace CLC maps.

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REFERENCES

[1] Forest Europe, Unece and F.A.O., "State of Europe's Forests 2015 FOREST EUROPE, Liaison Unit Madrid" (2015).

[2] Köhl, M., Lasco, R., Cifuentes, M., Jonsson, Ö., Korhonen, K. T., Mundhenk, P., de Jesus Navar, J. and Stinson, G., "Changes in forest production, biomass and carbon: Results from the 2015 UN FAO Global Forest Resource Assessment," For. Ecol. Manage. 352(September), 21–34 (2015).

[3] Schröter, D., Cramer, W., Leemans, R., Prentice, I. C., Araújo, M. B., Arnell, N. W., Bondeau, A., Bugmann, H., Carter, T. R., Gracia, C. A., De La Vega-Leinert, A. C., Erhard, M., Ewert, F., Glendining, M., House, J. I., Kankaanpää, S., Klein, R. J. T., Lavorel, S., Lindner, M., et al., "Ecology: Ecosystem service supply and vulnerability to global change in Europe," Science (80-.). 310(5752), 1333–1337 (2005).

[4] Bonan, G. B., "Forests and climate change: Forcings, feedbacks, and the climate benefits of forests," Science (80-.). 320(5882), 1444–1449 (2008).

[5] Trumbore, S., Brando, P. and Hartmann, H., "Forest health and global change" (2016).

[6] Pan, Y., Birdsey, R. A., Fang, J., Houghton, R., Kauppi, P. E., Kurz, W. A., Phillips, O. L., Shvidenko, A., Lewis, S. L., Canadell, J. G., Ciais, P., Jackson, R. B., Pacala, S. W., McGuire, A. D., Piao, S., Rautiainen, A., Sitch, S. and Hayes, D., "A Large and Persistent Carbon Sink in the World's Forests," Science (80-.). 333(6045), 988 LP – 993 (2011).

[7] Gardiner, B., Marzano, M., Nicoll, B., Blennow, K., Carnus, J.-M., Fleischer, P., Ingemarson, F., Lindner, M., Orazio, C., Reviron, M.-P., Landmann, G., Peyron, J.-L., Schelhaas, M.-J., Schuck, A., Spielmann, M. and Usbeck, T., "Storms - An increasing threat to Europe's forests," EFI News 19(1), 10–12 (2011).

[8] Hall, R. J., Castilla, G., White, J. C., Cooke, B. J. and Skakun, R. S., "Remote sensing of forest pest damage: A review and lessons learned from a Canadian perspective ∗," Can. Entomol. 148(S1), S296–S356 (2016).

[9] Tanase, M. A., Aponte, C., Mermoz, S., Bouvet, A., Le Toan, T. and Heurich, M., "Detection of windthrows and insect outbreaks by L-band SAR: A case study in the Bavarian Forest National Park," Remote Sens. Environ.

209(April 2017), 700–711 (2018).
[10] Bolte, A., Ammer, C., Löf, M., Madsen, P., Nabuurs, G.-J., Schall, P., Spathelf, P. and Rock, J., “Adaptive forest management in central Europe: Climate change impacts, strategies and integrative concept,” Scand. J. For. Res. 24(6), 473–482 (2009).
[11] Crabbe, R. A., Dash, J., Rodriguez-Galiano, V. F., Janous, D., Pavelka, M. and Marek, M. V., “Extreme warm temperatures alter forest phenology and productivity in Europe,” Sci. Total Environ. 563–564, 486–495 (2016).
[12] van Lierop, P., Lindquist, E., Sathyapala, S. and Franceschini, G., “Global forest area disturbance from fire, insect pests, diseases and severe weather events,” For. Ecol. Manage. 352, 78–88 (2015).
[13] Seidl, R., Klonner, G., Rammer, W., Essl, F., Moreno, A., Neumann, M. and Dullinger, S., “Invasive alien pests threaten the carbon stored in Europe’s forests,” Nat. Commun. 9(1), 1626 (2018).
[14] Senf, C., Pflugmacher, D., Zhiqiang, Y., Sebald, J., Knorn, J., Neumann, M., Hostert, P. and Seidl, R., “Canopy mortality has doubled in Europe’s temperate forests over the last three decades,” Nat. Commun. 9(1), 4978 (2018).
[15] White, J. C., Coops, N. C., Wulder, M. A., Vastaranta, M., Hilker, T. and Tompalski, P., “Remote Sensing Technologies for Enhancing Forest Inventories: A Review,” Can. J. Remote Sens. 42(5), 619–641 (2016).
[16] Lutz, D. A., Washington-Allen, R. A. and Shugart, H. H., “Remote sensing of boreal forest biophysical and inventory parameters: a review,” Can. J. Remote Sens. 34(sup2), S286–S313 (2008).
[17] Pause, M., Schweitzer, C., Rosenthal, M., Keuck, V., Bumberger, J., Dietrich, P., Heurich, M., Jung, A. and Lausch, A., “In situ/remote sensing integration to assess forest health-a review,” Remote Sens. 8(6), 1–21 (2016).
[18] Fernandez-Carrillo, A., Rodriguez-Galiano, V. F. and Sanchez-Rodriguez, E., “Characterisation of macrophyte phenology in the Doñana marshland using MODIS NDVI time series from 2000 to 2015,” Proc. SPIE - Int. Soc. Opt. Eng. 10428 (2017).
[19] MySustainableForest, “My Sustainable Forest. Earth Observation services for silviculture,” 2018, <https://mysustainableforest.com/> (29 May 2019).
[20] Schuck, A., Päivinen, R., Häme, T., Van Brusselen, J., Kennedy, P. and Folving, S., “Compilation of a European forest map from Portugal to the Ural mountains based on earth observation data and forest statistics,” For. Policy Econ. 5(2), 187–202 (2003).
[21] Pekkarinen, A., Reithmaier, L. and Strobl, P., “Pan-European forest/non-forest mapping with Landsat ETM+ and CORINE Land Cover 2000 data,” ISPRS J. Photogramm. Remote Sens. 64(2), 171–183 (2009).
[22] Shimada, M., Isoguchi, O., Motooka, T., Shiraishi, T., Mukaida, A., Okumura, H., Otaki, T. and Itoh, T., “Generation of 10m resolution PALSAR and JERS-SAR mosaic and forest/non-forest maps for forest carbon tracking,” 2011 IEEE Int. Geosci. Remote Sens. Symp., 3510–3513 (2011).
[23] Martone, M., Rizzoli, P., Wecklich, C., González, C., Bueso-Bello, J. L., Valdo, P., Schulze, D., Zink, M., Krieger, G. and Moreira, A., “The global forest/non-forest map from TanDEM-X interferometric SAR data,” Remote Sens. Environ. 205(August 2017), 352–373 (2018).
[24] Pacheco-Labrador, J., El-Madany, T. S., Martín, M. P., Migliavacca, M., Rossini, M., Carrara, A. and Zarco-Tejada, P. J., “Spatio-temporal relationships between optical information and carbon fluxes in a mediterranean tree-grass ecosystem,” Remote Sens. 9(6), 1–25 (2017).
[25] Hill, M. J., Hanan, N. P., Hoffmann, W., Scholes, R., Prince, S., Ferwerda, J., Lucas, R. M., Baker, I., Arneth, A., Higgins, S. I., Barrett, D. J., Disney, M. and Hutley, L., “Remote Sensing and Modeling of Savannas: The State of the Dis-Union,” 34th Int. Symp. Remote Sens. Environ. (2011).
[26] Huete, A. R., “A soil-adjusted vegetation index (SAVI),” Remote Sens. Environ. 25(3), 295–309 (1988).
[27] David, A. and Sergei, V., “k-means++: The advantages of careful seeding,” Proc. eighteenth Annu. ACM-SIAM Symp. Discret. algorithms (2007).