

Storm damages "VAIA" using multi-remote sensing data

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UNIVERSITÀ DEGLI STUDI FIRENZE

DAGRI DIPARTIMENTO DI SCIENZE E TECNOLOGIE AGRARIE, ALIMENTARI, AMBIENTALI E FORESTALI

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ForTech

Windstorm and strong rainfall

Extreme cyclones play an important. The increase create high-impact weather events may cause windstorms, storm surges, landslides and flooding that impact on Forests Ecosystems

can potentially hit any country in Europe

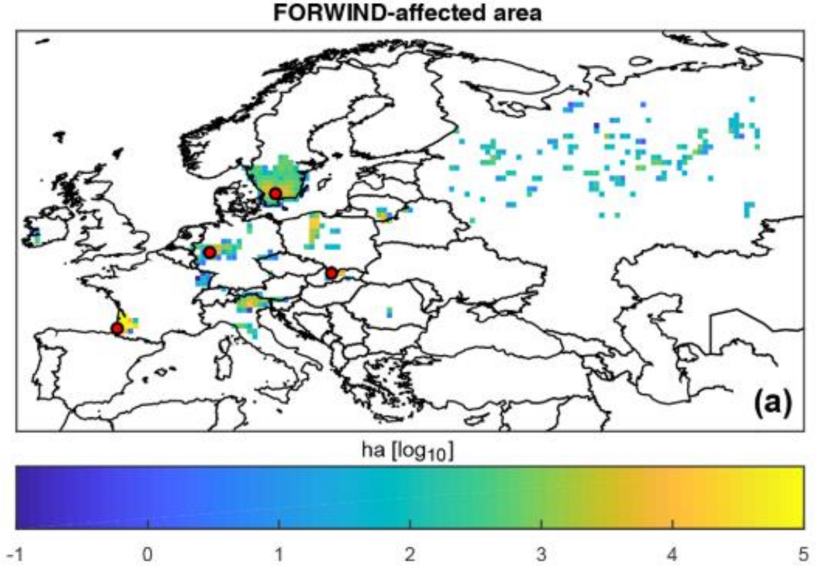
1999 Lothar 165 million m^3 of timer France, Germany Switzerland

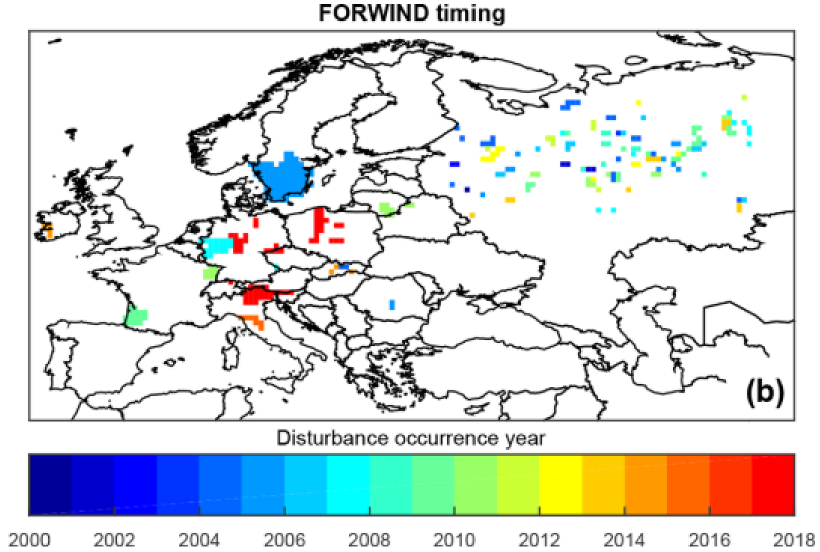
2005 Gudrun in swiden 75 million m^3 Sweeden

2007 Kyrill 49 million m^3 in Germany and Czech

2009 Klaus and 2010 Xynthia hit France and Spain 45 million m^3

2018 VAIA Italy





Forzieri, G., Pecchi, M., Girardello, M., Mauri, A., Klaus, M., Nikolov, C., Rüetschi, M., Gardiner, B., Tomaštík, J., Small, D., Nistor, C., Jonikavicius, D., Spinoni, J., Feyen, L., Giannetti, F., 2020. A spatially explicit database of wind disturbances in European forests over the period 2000 – 2018 257–276.

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Windstorm damage mapping

Forestry An International Journal of Forest Research
Institute of Chartered Foresters

Forestry 2017; 00, 1–11, doi:10.1093/forestry/cpx029

Assessing forest windthrow damage using single-date, post-event airborne laser scanning data

Gherardo Chirici[1,2], Francesca Bottalico[1], Francesca Giannetti[1*], Barbara Del Perugia[1], Davide Travaglini[1], Susanna Nocentini[1,2], Erico Kutchartt[3], Enrico Marchi[1], Cristiano Foderi[1], Marco Fioravanti[1], Lorenzo Fattorini[4], Lorenzo Bottai[5], Ronald E. McRoberts[6], Erik Næsset[7], Piermaria Corona[8] and Bernardo Gozzini[5]

Remote Sensing of Environment 143 (2014) 171–179

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

ELSEVIER

Landsat remote sensing of forest windfall disturbance

Matthias Baumann [a,*], Mutlu Ozdogan [a], Peter T. Wolter [b], Alexander Krylov [c], Nadezda Vladimirova [c], Volker C. Radeloff [a]

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remote sensing
MDPI

Article

Rapid Detection of Windthrows Using Sentinel-1 C-Band SAR Data

Marius Rüetschi [1,*], David Small [2] and Lars T. Waser [1]

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2 Remote Sensing Laboratories (RSL), University of Zürich, Winterthurerstrasse 190, 8057 Zürich, Switzerland; david.small@geo.uzh.ch
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- Airbone LiDAR data, High spatial resolution images high costs

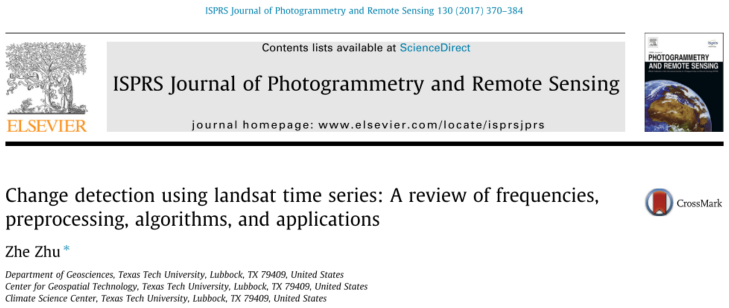
- Radar – not accurate border of the damaged area

We move to optical remote sensing data

Aims

- Map forest damage area quickly
- Area estimation with standard error of damaged area
- How many months we need using S2 data to map with high accuracy windstorm damaged area?

Tested algorithms - Continuous Change Detection


ISPRS Journal of Photogrammetry and Remote Sensing 130 (2017) 370–384

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

Change detection using landsat time series: A review of frequencies, preprocessing, algorithms, and applications

Zhe Zhu *

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Climate Science Center, Texas Tech University, Lubbock, TX 79409, United States

Detect interannual changes using trajectory analysis

- Breaks for Additive Seasonal and Trend Iterative Algorithm (BEAST)

  Wu, L.; Li, Z.; Liu, X.; Zhu, L.; Tang, Y.; Zhang, B.; Xu, B.; Liu, M.; Meng, Y.; Liu, B. Multi-type forest change detection using BFAST and monthly landsat time series for monitoring spatiotemporal dynamics of forests in subtropical wetland. *Remote Sens.* **2020**, *12*, 1–33, doi:10.3390/rs12020341.

- Continuous Change Detection and Classification Algorithm

  Zhu, Z.; Woodcock, C.E. Continuous change detection and classification of land cover using all available Landsat data. *Remote Sens. Environ.* **2014**, *144*, 152–171, doi:10.1016/j.rse.2014.01.011

These methods are able to split the time series into three adaptative components (i.e., trend, seasonal and remainder)

Tested algorithms - Continuous Change Detection

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Change detection using landsat time series: A review of frequencies, preprocessing, algorithms, and applications

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Those that are able to detect interannual changes using trajectory analysis appears to be adequate to detect interannual changes of forest area

- Breaks for Additive Seasonal and Trend Iterative Algorithm (BEAST)
- Continuous Change Detection and Classification Algorithm

The two algorithms use two different strategies to decompose the NBR TS (i.e., number of continues persistent deviation observation from seasonality to detect changes and classification)

Remote Sensing time series

Google Earth Engine

sentinel-2

Cloud masking

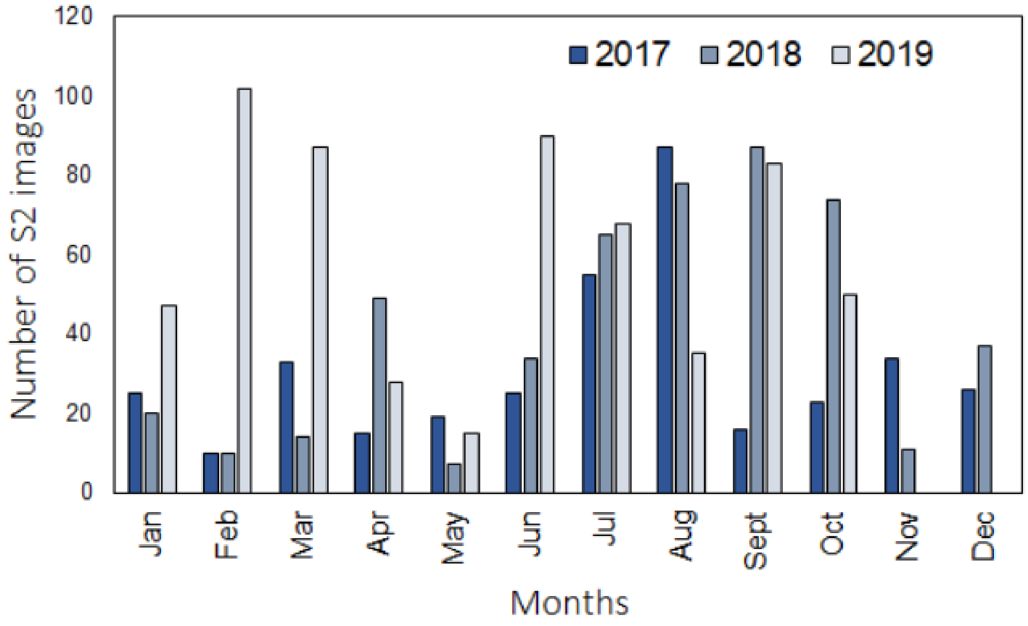
Normalized Burned Ratio

$$NBR = (NIR - SWIR)/(NIR + SWIR)$$

Despike apporch of NBR – snow cover mapping

NDSI > 0.1

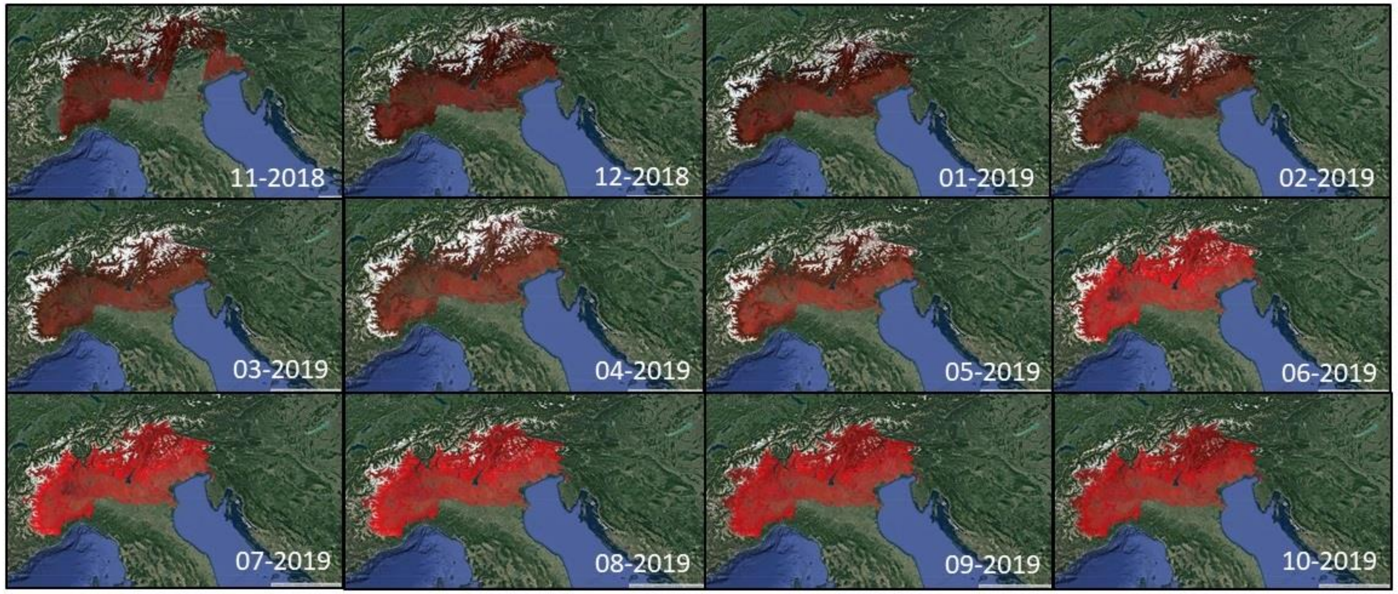
$$NDSI = (GREEN - SWIR)/(GREEN + SWIR)$$



Total 1360 images

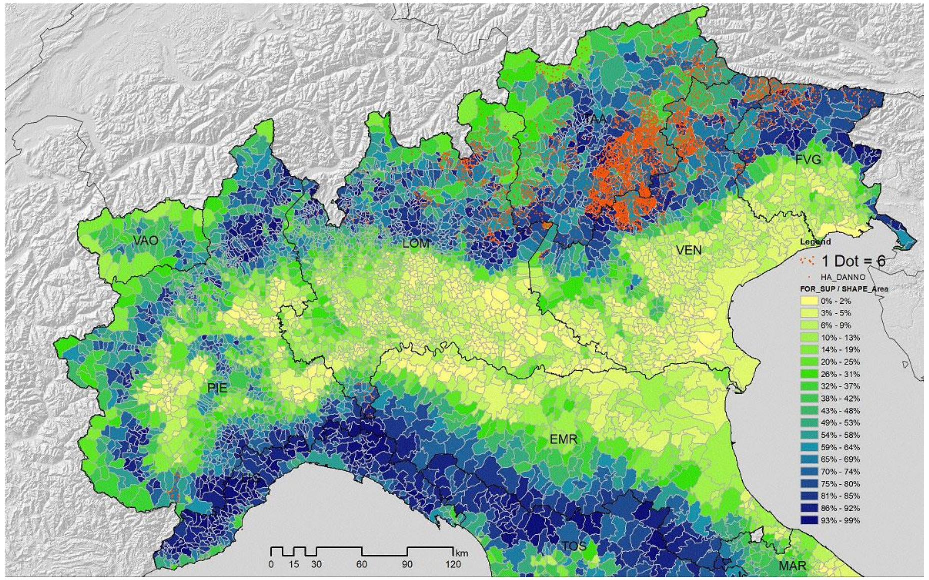
707 before storm

653 after the storm



Training dataset

- forest polygons covering both damaged and undamaged areas. Forzieri et al. (2020)
- extracted at least one damaged polygon for each cell of the grid of 30 km x 30 km.
- the same cell manually photointerpreted a total of 100 undamaged forest polygons



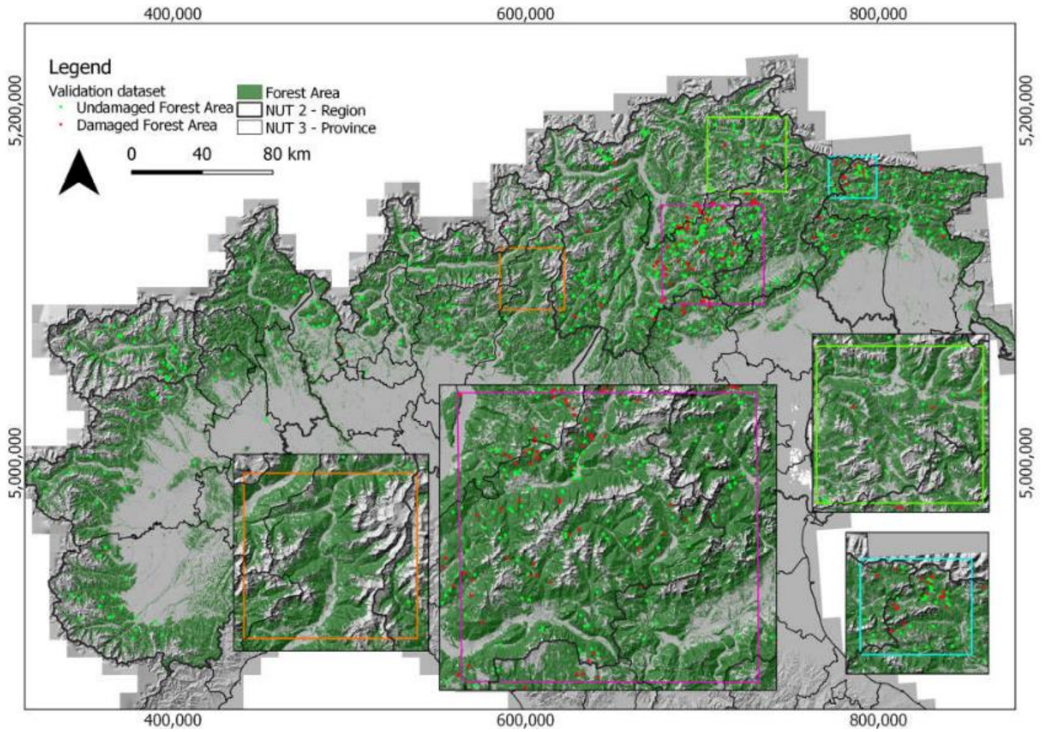
Validation dataset

-the Italian Inventory of Land Use (IUTI - Inventario dell'Uso delle Terre d'Italia

128.548 IUTI Point in the area

-we extracted a sub-sample of 700 points on the basis of a stratified random sampling

- For each Province we extracted a different number of point of the hectares of damage reported by local authorities (minimum point for province 10)



Probability-Based stratified estimators

the estimate of the total proportion of the area in the damaged class can be derived from the confusion matrix using the validation dataset as reference (Table 1), and is given by:

$$\hat{p} = \sum_{j=1}^{2} w_j \cdot \hat{p}_j$$

where w_j is the proportion of the map in each map classes (i.e., w_1 damaged and w_2 undamaged forest), while the variance of esteems of the total proportion of the area in damaged class is:

$$\widehat{\mathrm{Var}}(\hat{\mathrm{p}}) = \sum_{\mathrm{j}=1}^{3} \mathrm{w}_{\mathrm{j}}^{2} \cdot \widehat{\mathrm{Var}}(\hat{\mathrm{p}}_{\mathrm{j}})$$

On the basis of the confusion matrix we can produce a formal estimation of the damaged area as:

$$\hat{\mathrm{A}}_{\mathrm{damaged}} = \mathrm{A}_{\mathrm{tot}}\, \hat{p}$$

Moreover, based on $\hat{p}$ and $\widehat{Var}(\hat{p})$ it is possible to calculate a 95% confidence interval for damaged area estimation, that is

$$\hat{\mathrm{A}}_{\mathrm{damaged}} \cdot \hat{\mathrm{p}} \pm 2 \cdot \hat{\mathrm{A}}_{\mathrm{damaged}} \cdot \sqrt{\widehat{\mathrm{Var}}(\hat{\mathrm{p}})}$$

where $\mathrm{A}_{\mathrm{damaged}}$ is the mapped damaged forest area.

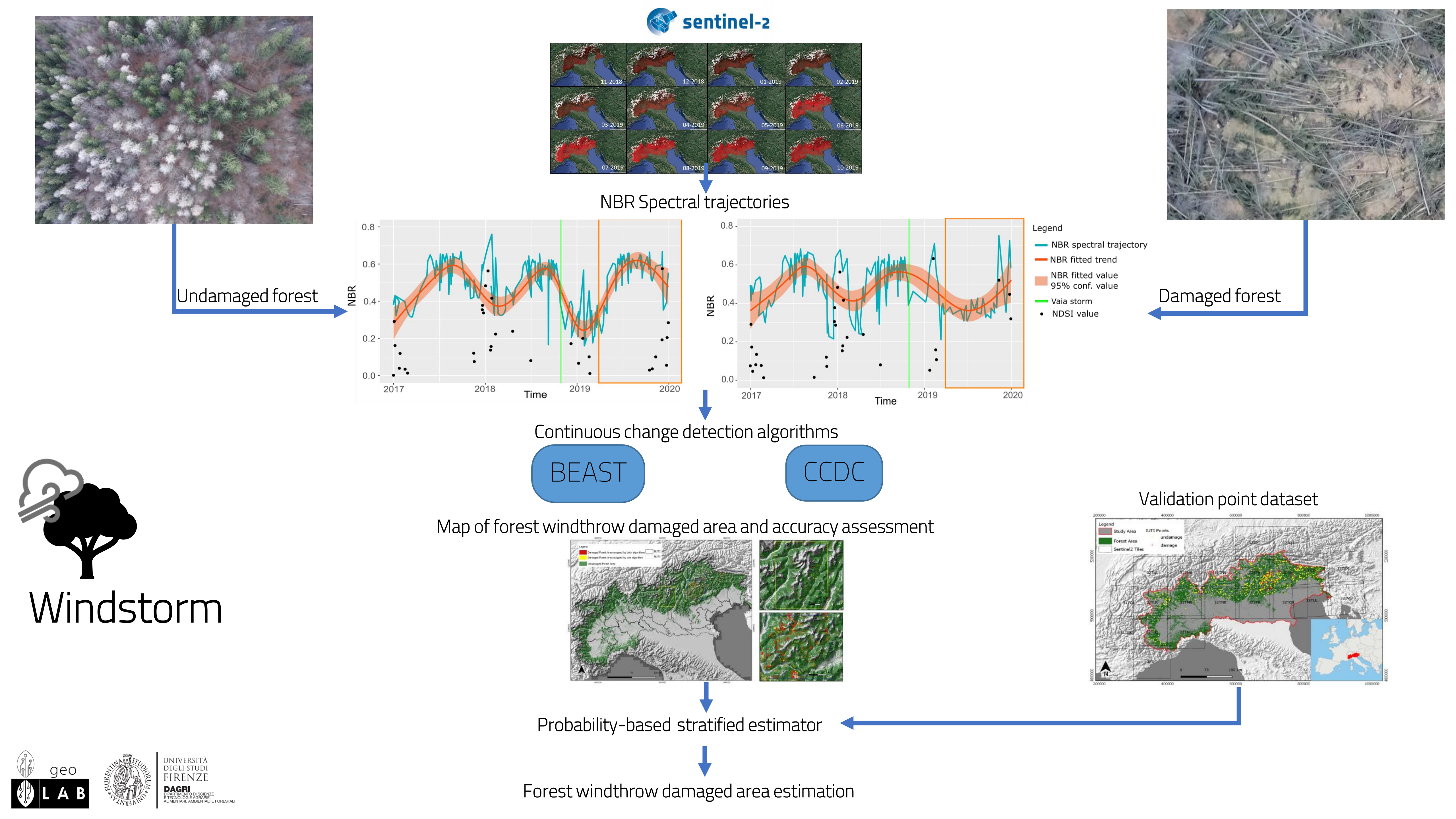
In addition, we calculated the standard error (SE) and the percentage SE ($\mathrm{SE}_{\%}$) of the area estimates as:

$$SE(\hat{\mathrm{A}}_{\mathrm{damage}}) = \mathrm{A}_{\mathrm{tot}}\sqrt{(w_1{}^2 \cdot \widehat{\mathrm{Var}}(\hat{\mathrm{p}}_1) + w_2{}^2 \cdot \widehat{\mathrm{Var}}(\hat{\mathrm{p}}_2)}$$

$$SE\% = \frac{SE(\hat{\mathrm{A}}_{\mathrm{damage}})}{\hat{\mathrm{A}}_{\mathrm{damage}}} x100$$

Table 1. Confusion matrix and estimators

Map Class	Reference Class		Total	Stratum Weight $\mathbf{w_j}$	$\hat{\mathbf{p}}_{\mathbf{j}} = \frac{\mathbf{n_{j1}}}{\mathbf{n_{j\bullet}}}$	$\mathbf{w_j} \cdot \hat{\mathbf{p}}_{\mathbf{j}}$	$\widehat{\mathbf{Var}}(\hat{\mathbf{p}}_{\mathbf{j}})$	$\mathbf{w_j^2} \cdot \widehat{\mathbf{Var}}(\hat{\mathbf{p}}_{\mathbf{j}})$
	Damaged	**Undamaged**						
Damaged	TP	FP	$n_{1\bullet}$ =TP+FP	w_1	$\hat{p}_1 = \frac{TP}{n_{1\bullet}}$	$w_1 \cdot \hat{p}_1$	$\widehat{Var}(\hat{p}_1) = \frac{\hat{p}_1 \cdot (1-\hat{p}_1)}{n_{1\bullet}}$	$w_1^2 \cdot \widehat{Var}(\hat{p}_1)$
Undamaged	FN	TN	n_2 =FN+FP	w_2	$\hat{p}_3 = \frac{FN}{n_{2\bullet}}$	$w_2 \cdot \hat{p}_2$	$\widehat{Var}(\hat{p}_2) = \frac{\hat{p}_2 \cdot (1-\hat{p}_2)}{n_{2\bullet}}$	$w_2^2 \cdot \widehat{Var}(\hat{p}_2)$


sentinel-2
11-2018
12-2018
01-2019
02-2019
03-2019
04-2019
05-2019
06-2019
07-2019
08-2019
09-2019
10-2019
NBR Spectral trajectories
Undamaged forest
Damaged forest
NBR
Time
0.8
0.6
0.4
0.2
0.0
2017
2018
2019
2020
Legend
NBR spectral trajectory
NBR fitted trend
NBR fitted value
95% conf. value
Vaia storm
NDSI value
Continuous change detection algorithms
BEAST
CCDC
Map of forest windthrow damaged area and accuracy assessment
Validation point dataset
Probability-based stratified estimator
Forest windthrow damaged area estimation
Windstorm
geo
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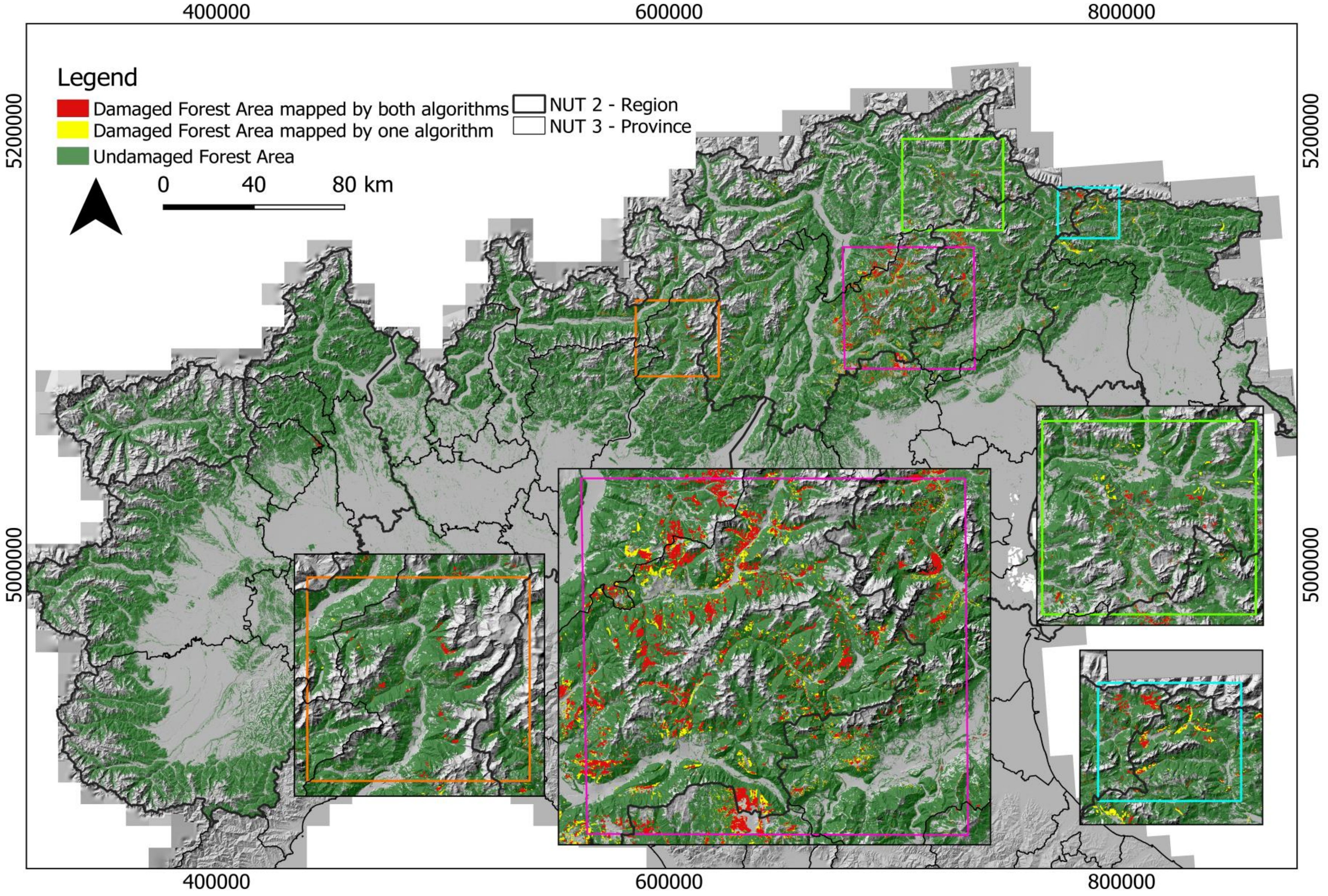
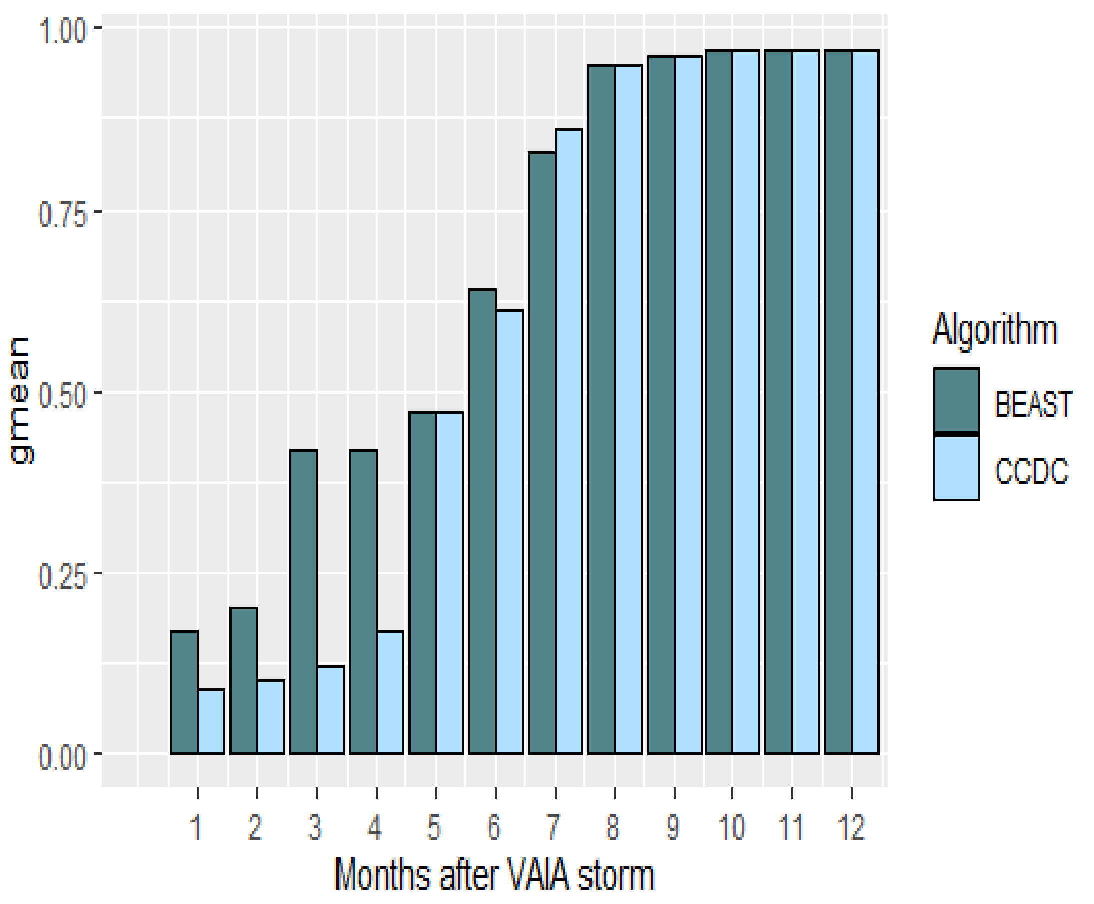
Results



400000
600000
800000
Legend
Damaged Forest Area mapped by both algorithms
Damaged Forest Area mapped by one algorithm
Undamaged Forest Area
NUT 2 - Region
NUT 3 - Province
0
40
80 km
5200000
5000000
400000
600000
800000

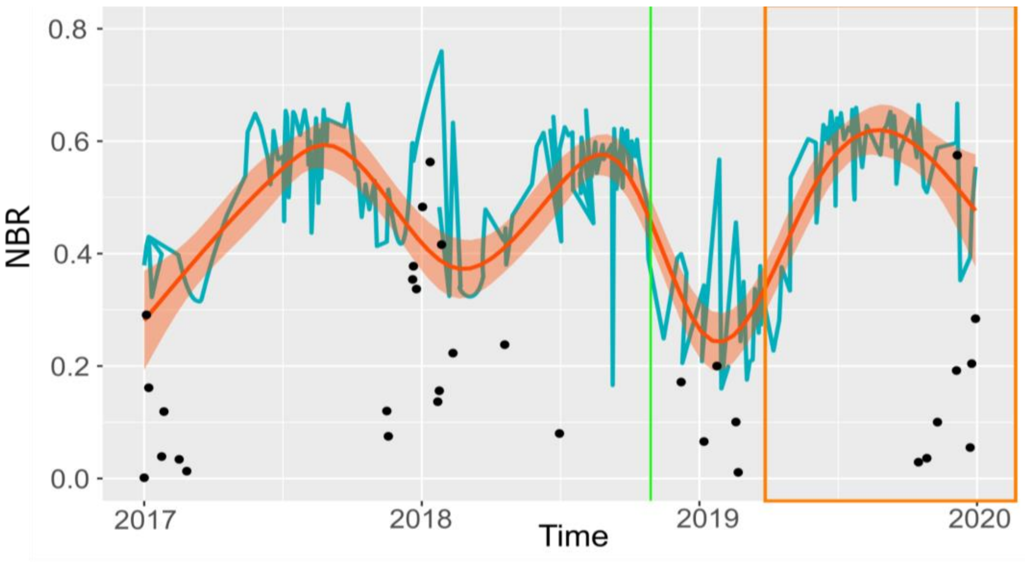
Results

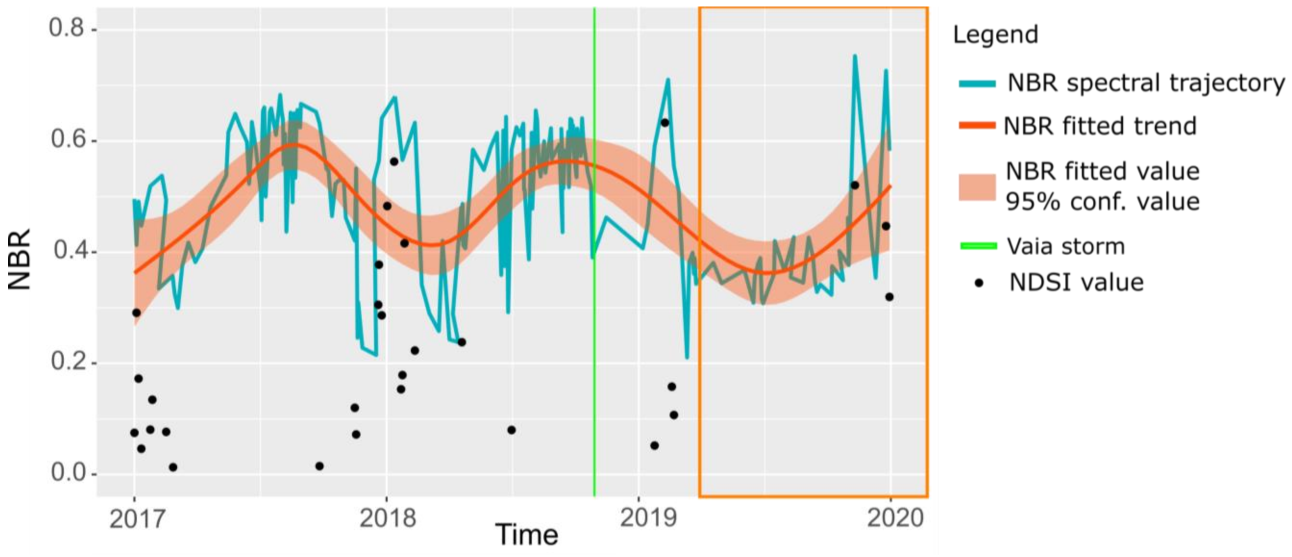
Algorithm	Month from the storm	$\hat{A}_{damage}$ [ha]	$SE(\hat{A}_{damage})$ [ha]	SE%	OA	PA	UA	g_{mean}
BEAST	1	11119	26345.6	236.93	48.2	0.15	0.18	0.17
	2	12369	23246.7	187.93	51.4	0.21	0.2	0.2
	3	20377	22354.1	109.7	60.2	0.37	0.46	0.42
	4	22614	199922.9	88	62.1	0.39	0.46	0.42
	5	27527	14802.1	53.77	67.2	0.46	0.49	0.47
	6	36766	13149.1	35.76	75.2	0.57	0.7	0.64
	7	38416	3725.3	9.69	89.7	0.87	0.87	0.83
	8	38819	405.4	1.04	97.1	0.95	0.95	0.95
	9	40018	402.1	1	97.8	0.95	0.97	0.96
	10	39931	346.5	0.87	98	0.95	0.97	0.97
	11	40126	346.5	0.86	98.1	0.96	0.98	0.97
	12	39954	238.2	0.6	98.4	0.97	0.98	0.97
CCDC	1	10203	28631	280.6	43.5	0.09	0.18	0.09
	2	11388	28099	246.7	44.3	0.1	0.1	0.1
	3	13160	26560	201.8	46.4	0.12	0.12	0.12
	4	14268	21110	148	52	0.18	0.16	0.17
	5	25349	12041	47.5	69	0.49	0.49	0.47
	6	32355	10295	31.8	75.5	0.59	0.63	0.61
	7	39204	3254.52	8.3	91.1	0.82	0.9	0.86
	8	38632	405.4	1.04	97	0.95	0.94	0.95
	9	40008	402.1	1	97.8	0.95	0.97	0.96
	10	39929	346.5	0.87	98	0.95	0.97	0.97
	11	40116	346.5	0.86	98.1	95.8	98.1	0.97
	12	39951	238.2	0.6	98.4	96.7	98.1	0.97



Discussion

- S2 imagery is adequate to map damaged forest area. The most accurate results can be obtained in spring-summer (i.e., after 7 months after the storm), independently of the CDC algorithm used
- was not possible to produce an accurate map 1-6 months after the storm (November 2018 – April 2019)
- Analyzing the seasonality and the remainder components of the NBR TS (Figure 3) we observed a persistent deviation of NBR trajectory from the seasonality between May 2019 and October 2019





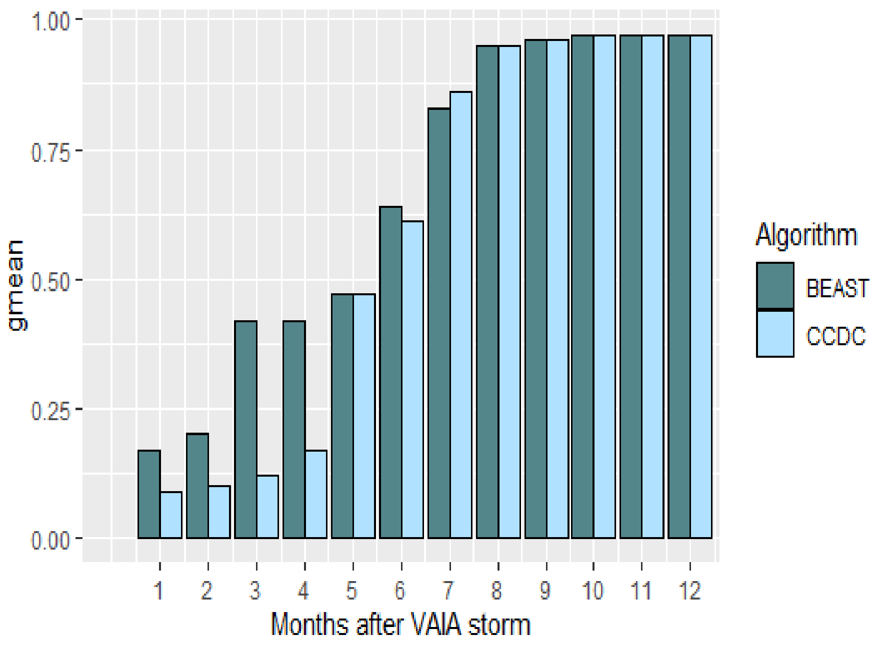
Limitation

- coniferous forests fallen trees remained green on the ground for a couple of months after the storm
- in broadleaves forests (i.e., mainly beech) differences in photosynthetic activities in winter between fallen trees and not damaged trees
- snow cover in Alpine regions introduced noise in spectral trajectories, also applying a despike approach in correspondence of NDSI high values
- optical images acquired in mountains regions shadows due to steep slopes which introduce large noises in NBR spectral trajectories that limit the accuracy of BEAST and CCDC methods

we found that 75% of errors are located in an area with steep terrains, while correctly classified areas are concentrated in the highlands or wide valleys where slope shadows are less present

Differences between the two tested algorithms

to decompose the NBR TS (i.e., number of continues persistent deviation observation from seasonality to detect changes and classification) and this can be the cause of the disagreement between the results obtained by BEAST and CCDC for the early months after the storm (K<0.3),



The estimates done by local authorities immediately after the storm is within the confidence intervals of the estimates we obtained with the two algorithms.

7 months after the storm (i.e., from May to October 2019) the area we estimate is slightly smaller than that one reported by local authorities

In fact, we found differences between 4109 ha and 2571 ha for BEAST and between 3321 ha and 2574 ha for CCDC

Thanks for your attention

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