Detecting changes in essential ecosystem and biodiversity properties- towards a Biosphere Atmosphere Change Index: BACI

Deliverable 6.3: Synthesis paper on suitability and limitation of BACI for monitoring ecosystem changes

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Abbreviations

ARMA	Autoregressive Moving Average
BACIndex	Biosphere Atmosphere Change Index
CL	Cropland
ESDC	Earth System Data Cube
ESS	Earth System Science
FAO	Food and Agriculture Organization
FO	Forest
GL	Grazingland
GPP	Gross Primary Productivity
HANPP	Human Appropriation of Net Primary Production
LE	Latent Energy
LSS	Land System Science
NEE	Net Ecosystem Exchange
NPP	Net Primary Production
SH	Sensible Heat
TER	Terrestrial Ecosystem Respiration

1. Summary

Deliverable 6.3 presents results of a data-driven assessment of extreme events in biosphere and land use dynamics that is a joint collaboration across a number of BACI WPs and strongly builds upon BACI developments and innovations. This work provides an interdisciplinary effort to study processes and extremes in the biosphere and land use sector jointly, which in the past has been tackled by different research communities separately (Earth System Science vs. Land System Science). We integrate biospheric (WP2) and land use data streams (WP7), and adopt a data-driven (machine learning based) approach developed in WP5 to detect biospheric and land use extreme events across Europe and Africa. We characterise detected extreme events by using approaches developed in WP6 and synthesize the results. We will expand the work to global scale and submit the results as a scientific paper in mid/late-2019.

2. Introduction

Biospheric processes and land use are key components of the Earth system and its dynamics. Extreme events in both, the biosphere and land use, system can strongly alter the functioning of the Earth system and affect humans as much as the natural environment. Such events are often related to climatic extremes (e.g. droughts, heatwaves and floods); but also to direct human-induced dynamics. Human-induced dynamics include large scale changes in the extent of land-use, like forest conversion (Hansen et al., 2013), or alterations in the intensity of land use, like harvest changes, triggered by e.g. changes in land use policies, humanitarian crises or political dynamics (Lesk et al., 2016, Seidl et al., 2017).

While extreme events are often key archetypes (syndromes) of ongoing changes, their characteristics and impact are not well understood. In particular, tackling sustainability challenges that relate to different areas, including climate change, land-use, as well as loss of biodiversity and challenges to food security, is intricate and requires understanding of the complexity of extreme events and their interrelation among the different Earth system components. Such an understanding is only slowly emerging in the last decades.

Traditionally, the study of processes and extremes in the biosphere and land use sector have been tackled by different research communities. Earth system science (ESS) and related efforts in climate and vegetation modelling has put its major efforts to better understand the functioning of system Earth and its natural processes. While the impact of human societies as part of the Earth system Science is only recently staring to be implemented as direct links with land use and land management processes (Pongratz et al., 2018). Land system science (LSS), in contrast, is an interdisciplinary endeavour that aims at understanding the drivers and impacts of land use and its change over time (Rindfuss et al., 2004, Turner et al., 2007, Verburg et al., 2016). It originates in studies of land change processes and social-environmental relationships, as either a driver or a consequence of changes in the Earth system.

The study of extreme events is an important strand in both research communities. The communities mostly operated on distinct terms and focus on certain types of events from their specific and selective perspective. While this has the advantage of detailed, in depth understanding of specifics, the from either a LSS or ESS perspective, the risk of omitting or under representation of critical events is high. In particular, it does not allow to understand the entirety or complexity of the interrelations between socioeconomic and natural dynamics in relation to extreme events. Currently, mostly hypothesis or theory-driven approaches prevail, that try to understand the impact of certain changes in climate on land use and vice versa (Meyfroidt et al., 2018). Such approaches have allowed us to gain important knowledge about the Earth systems and evolved LSS and ESS to where it is now. The major drawback of such approaches, however, is that the view is restricted to the hypothesis and can be biased by presumptions. It is also unlikely to identify events that are so far unknown.

Recently, ESS is exploring new avenues by moving away from physical process models to more data-driven approaches that are able to digest and make use of the increasing amount and diversity of available data (Reichstein et al., 2019). Such data science developments allow to analyse new multivariate data sources and to take a more independent perspective on dynamics of the Earth System. This should allow to take a new look into extreme events, their drivers and interrelations in both the biosphere and land use system, and help to explore some of the unknown unknowns we might have missed so far in that context.

Data science opportunities are grounded in new and more rich data sources from various disciplines and methods emerged recently (Erb et al., 2016, Erb et al., 2017, Kuemmerle et al., 2013, Reichstein et al., 2019). The biosphere has been continuously monitored at a high temporal resolution by a set of variables based on the integration of remote sensing and in situ information (Beer et al., 2011, Jung et al., 2010) for the last decade. Now new global high spatial-temporal resolution and harmonised earth system data increasingly become available. These datasets, when systematically combined with census data on land use (Erb et al., 2007, Goldewijk et al., 2017) allow for the reconstruction of annual spatially explicit time series of changes in the extent individual land uses.

The analytical framework Human Appropriation of Net Primary Production (HANPP) goes beyond accounts of changes in the extent of land uses, by systematically adding information on productivity in terms of net primary production and land-use intensity of agricultural and forestry production. HANPP is an accounting framework that allows to integrate and map information on the extent and land-use intensification of land-use categories such as forestry, cropland, grazing land, infrastructure and wilderness (Erb et al., 2009, Haberl et al., 2007, Haberl et al., 2014). It integrates data on biomass harvest from census statistics, at the global level mainly from Food and Agriculture Organization (FAO), with information on Net Primary Production (NPP) derived from dynamic vegetation models and, by systematically discerning NPP fluxes of the potential vegetation of the actual vegetation and the NPP remaining in land ecosystems after harvest, provides a metric for the human domination of ecosystems (Vitousek 1997). HANPP accounts in long time series allow to scrutinize and quantify the drivers of land use change (Gingrich et al., 2015, Krausmann et al., 2013). In particular, the HANPP framework allows for a systematic reconstruction and analytical separation of effects resulting from changes in land-use extent and of land-use intensity. The newly available, annual land cover datasets (ESA 2017) provide the opportunity to disentangle changes driven by natural changes (via NPPpot) and land use, and separates land use drivers in (i) land cover change and (ii) land management (intensity) change.

To detect extreme events anomaly detection algorithms are commonly used. We define extreme events as an anomaly in the multivariate dataset. An anomaly in the multivariate dataset is defined as a spatial-temporal part of the data cube that differs with respect to the mean and variance from the normal rest of the multivariate data cube. A number of algorithms for multivariate anomaly detection are available, but only a few have been applied in the context of ESS applications and even fewer in LSS (Flach et al, 2017). A review of related data driven methods is given in (Flach et al., 2017, Gauche Garcia et al., 2018, Reichstein et al., 2019)

Here we present a workflow to automatically detect extreme event patterns in multivariate Earth System data streams and Land System data streams. We analyse their distribution and drivers. We aim to answer following research questions:

1. Where are extreme events in the biosphere and land use system located in space and time and what drives them?
2. How to disentangle extreme events in the land system driven by natural processes and driven by socioeconomic processes?
3. Are there archetypes of the interrelation of biospheric and land use extreme event?

3. Data and methods

Figure 1 illustrates the proposed methodology detect and analyse biospheric and land use extreme events.

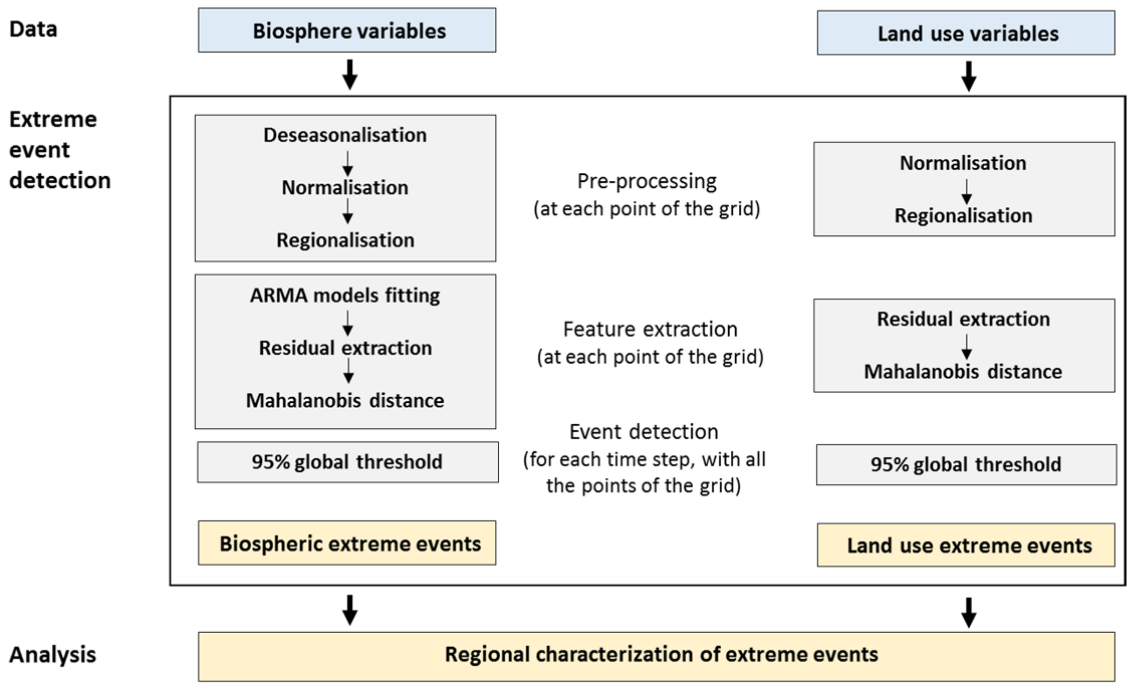

Figure 1. Flow chart of the proposed methodology to detect and analyse biospheric and land use extreme events.

3.1 Data

3.1.1 Biospheric variables

Data from the Earth System Data Cube (ESDC) developed within the ESDL project have been used as the primary source of ESS data for this study. The ESDC comprises spatiotemporal data consisting of: time, latitude, longitude and multivariate Earth Observations. The version used in this study covers the period from January 2002 to December 2010 with 8 daily observations and a spatial grid with a resolution of 0.25 degree. 5 variables measuring the terrestrial biosphere activities were used: Gross Primary Productivity (GPP), Latent Energy (LE), Net Ecosystem Exchange (NEE), Sensible Heat (SH) and Terrestrial Ecosystem Respiration (TER), which were kindly provided by the FLUXCOM initiative (Tramontana et al. 2016).

3.1.2 Land use variables

Land use data have been compiled from the FAO dataset (FAOSTAT 2018) and comprise information for cropland, grazing land (permanent and non-permanent pastures as well as other grazed ecosystems (Erb et al., 2007), forests and infrastructure areas. Using a downscaling approach that builds upon data on land use (Hyde 3.2), anthromes (Ellis et al. 2011) and potential vegetation (FAO 2001, Olson et al., 2001, Ramankutty & Foley 1999), national data were allocated to a 5 arc minutes grid. For all these land use types, information is available on the extent (km^2 or percent per grid cell) as well as on carbon flows (gC/m2/yr). Harvest is, in line with the accounting framework HANPP, defined as the sum of annual harvested primary crops, secondary compartments and includes biomass fractions lost in the course of harvest (residues, felling losses, below ground biomass). The data has an annual temporal resolution and span the years 2002-2010. Figure 2 depicts the six land use varibles for the year 2002.

Table 1. Biospheric and land use variables available for the period 2002 – 2010.

Variables		**Temporal resolution**	**Spatial resolution**	**Definition & unit**
Biospheric	GPP	8 daily	0.25 degree	[gC m-2 day-1]; Carbon uptake by plants via photosynthesis
	NEE	8 daily	0.25 degree	[gC m-2 day-1]; Difference between amount of carbon uptake and release
	LE	8 daily	0.25 degree	[W m-2]; Amount of hidden heat energy which is supplied or extracted to change the state of a substance without changing its temperature
	SH	8 daily	0.25 degree	[W m-2]; Amount of heat energy exchanged by a body or thermodynamic system
	TER	8 daily	0.25 degree	[gC m-2 day-1]; Carbon release through autotrophic (plants) and heterotrophic (soil microorganisms, animals) respiration
Land use	Harvest cropland (CL)	annual	0.083 degree	[gC/m²]; cropland harvest including residues and below ground fractions killed during harvest
	Harvest forest (FO)	annual	0.083 degree	[gC/m²]; forest harvest including felling losses (branches, stumps) and below ground fractions (roots) killed during harvest
	Harvest grazingland (GL)	annual	0.083 degree	[gC/m²]; grass harvest by livestock or mowing
	Area CL	annual	0.083 degree	[% of gridcell] area of cropland, including arable land and permanent cropland
	Area FO	annual	0.083 degree	[% of gridcell] area of forests
	Area GL	annual	0.083 degree	[% of gridcell] area of grazing lands (sum of permanent and non-permanent pastures and meadows, rangelands and grazed (mainly open) woodlands).

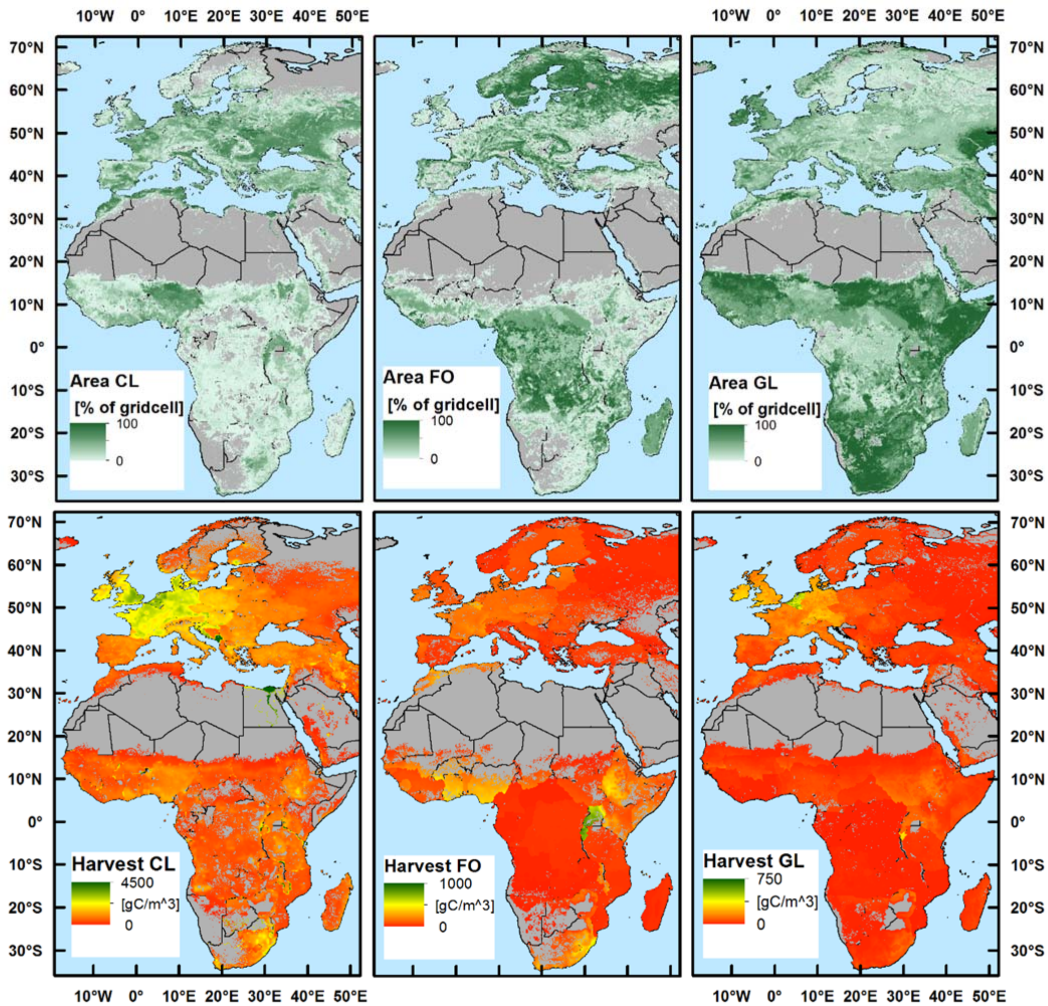

Figure 2. Land use variables used for the year 2002. See Table 1 for a description of the variables.

3.2 Extreme event detection

3.2.1 Biospheric extreme events

For detecting biospheric extreme events we applied the approach developed and described in Gauche Garcia et al., 2018. A brief summary is provided below. The proposed methodology is divided into three main steps: pre-processing, feature extraction and event detection.

Pre-processing: First, seasonality was removed from the 8-daily time series by subtracting the mean seasonal cycle and the remaining variables were normalised by subtracting its mean divided by its variance. This was done for all the 5 variables locally at each pixel of the grid. Next, the deseasonalized and normalised data was regionalized into 31 clusters of similar climate conditions defined by the Koppen Climate Classification (Chen & Chen 2013).

Feature extraction: To tackle the spatiotemporal dependencies of the biosphere variables, a feature extraction step was applied to each time series in the grid independently. The first step is based on the assumption that the time series of each variable can be represented by an autoregressive moving average (ARMA) process, and the anomalies are those time instances that are not well represented by the estimated ARMA model. The Mahalanobis distance (Hotelling 1947) of the ARMA models' multivariate residuals is used as a novelty score. At each pixel of the grid, we have combined the residuals of the 5 variables in a vector x and estimated its Mahalanobis distance (Hotelling, 1947, Mahalanobis, 1936). This distance measure compared to other metrics has the advantage of taking into account the shape of the joint distribution.

Event detection: Once the Mahalanobis distance for all the points of the grid has been estimated, a 95th percentile of the Mahalanobis distance distribution (all the Mahalanobis distance values along the entire region) was used as a threshold to detect extreme events and separate them from normal events. We further define extreme events as clusters with a minimum size of 5 pixel.

3.2.2 Land use extreme events

We adapted the methodology of Gauche Garcia et al., 2018 used to derive the biospheric events to detect land use extreme events from multivariate annual land use variables. We followed the three main steps: pre-processing, feature extraction and event detection.

Pre-processing: Since we deal with annual data, deseasonalization was not needed. We normalized the data by subtracting its mean divided by its variance. This was done for all the 6 variables locally at each pixel of the grid. Next, the normalised data was regionalized into 9 clusters of similar conditions by applying a K-means clustering to the multivariate land use data set.

Feature extraction: To tackle the spatiotemporal dependencies of the land use variables, a feature extraction step was applied to each time series in the grid independently. We first derived the residuals of the normalised time series and defined anomalies as those annual time instances that are not well represented by the distribution (in space and time) of the specific region (cluster). We calculated the Mahalanobis distance multivariate residuals as novelty score. At each pixel of the grid, we have combined the residuals of the 6 variables in a vector x and estimated its Mahalanobis distance.

Event detection: Land use events were detected in the same ways as described for the biospheric events. Once the Mahalanobis distance for all the points of the grid has been estimated, a 95th percentile of the Mahalanobis distance distribution (all the Mahalanobis distance values along the entire study area) was used as a threshold to detect extreme events and separate them from normal events. We further define extreme events as clusters with a minimum size of 5 pixel.

3.3 Analysis and validation

We separate three types of extreme events: (i) biospheric (ii) land use extreme events and (iii) extreme events where both, a biospheric and land use extreme co-locate. To do so, we first resampled the annual land use extreme event products from 0.083 degree to the 0.25 degree spatial resolution of the biospheric extreme event products.

3.3.1 Descriptive analysis

We analyse the distribution of detected extreme events in terms of their area coverage, and we examined the distribution of extreme events along the Europe-Africa transect.

3.3.2 Regional characterisation of extreme events

We characterised key detected biospheric and land use extreme events as well as co-located biospheric and land use extreme events. To characterise selected extreme events and analyse the underlying drivers we follow the procedure developed in Deliverable 6.2. We calculated the z-scores (Peters et al. 2002) for each of the biospheric and land use input variables, comparing the detected extreme event (pixel distribution) with the multi-year normal. The multi-year normal is defined as all pixels covering the detected area of the extreme event for all years (2002-2010). Excluded from this multi-year normal are (i) the year of the detected event itself, and (ii) all pixel of the remaining time period that were classified as biospheric or land use extreme event. This analysis enables us to identify anomalies of the different input variables.

A comprehensive validation of the model detection biospheric and land use extreme events is challenging as no well-defined ground-truth events exist.

4. Results

4.1 Detected biospheric and land use extreme events

Figure 3 shows the detected biospheric and land use extreme events and their spatial overlap for the period 2002-2010. In total, 1590 biospheric and 2025 land use events were detected, respectively. Figure 4 depicts the detected biospheric and land use extreme events ordered by size. Figure 5 shows the annual distribution of events. Figure 6 shows the spatial distribution and extent of extreme events averaged over the period 2002-2010 for latitudinal bands across the Europe-Africa transect.

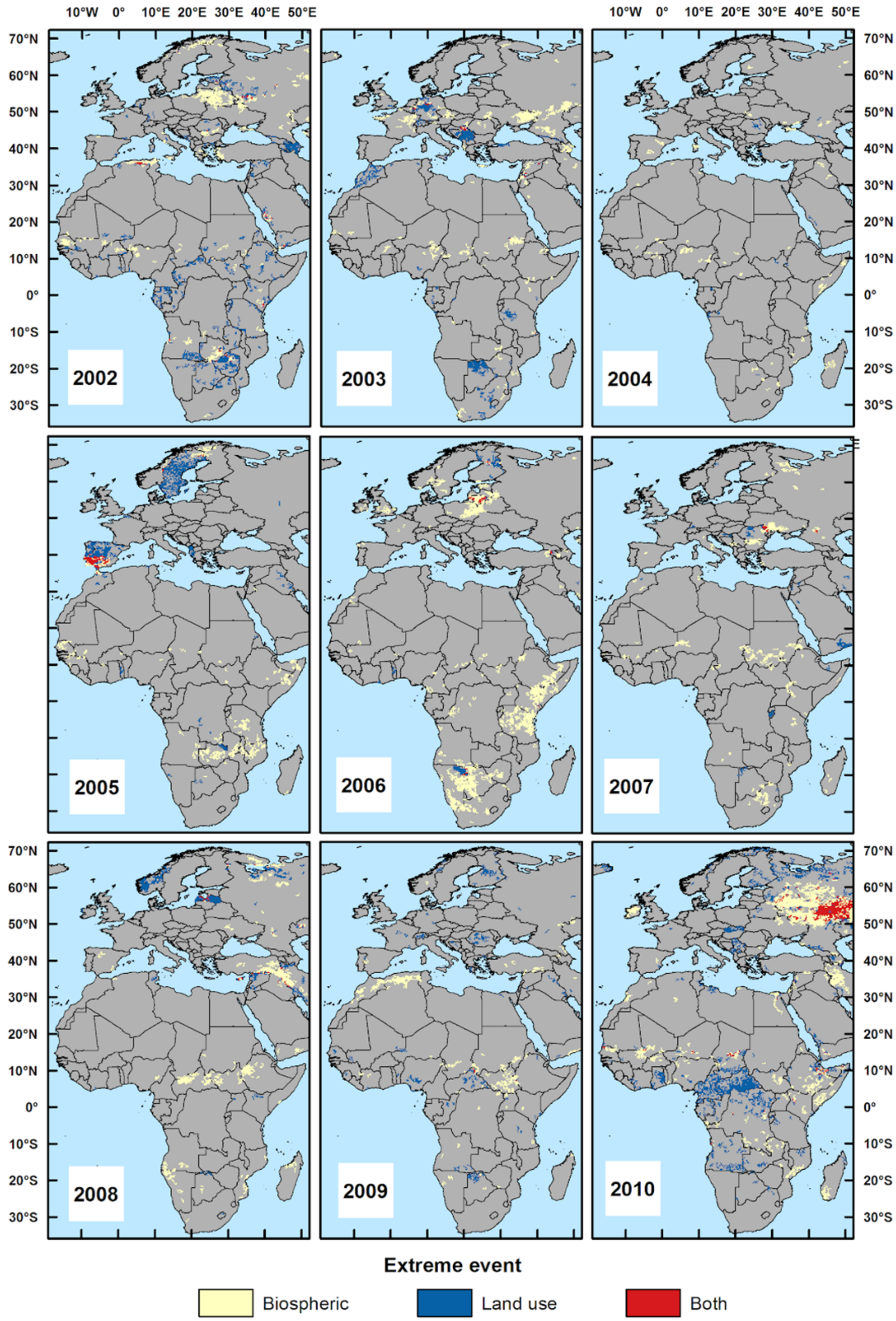

Figure 3. Detected biospheric (yellow) and land use (blue) and overlapping (red) extreme events for the period 2002-2010.

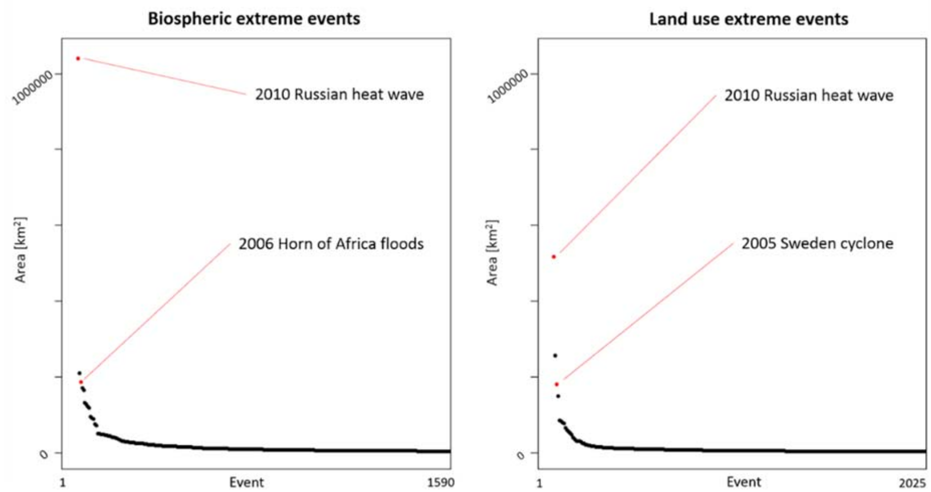

Figure 4. Detected biospheric (n = 1590) and land use (n = 2025) extreme events ordered by size.

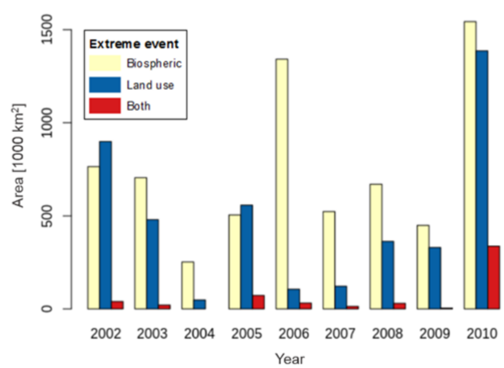

Figure 5. Annual distribution of biospheric, land use and co-locating events.

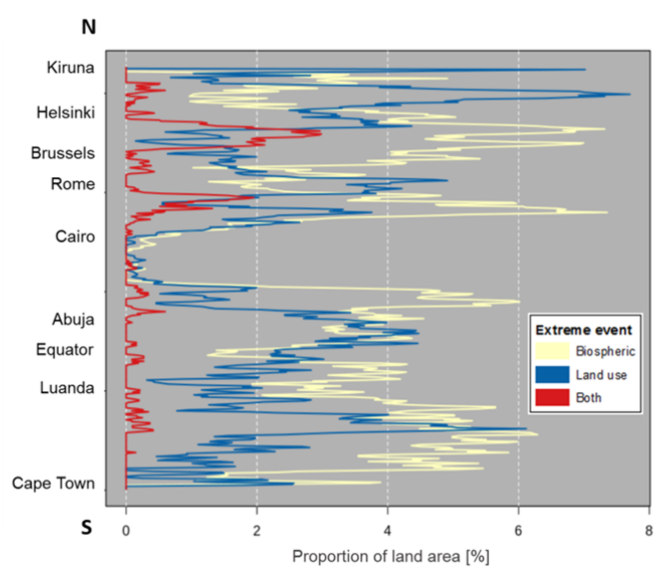

Figure 6. Spatial distribution and extent of extreme events averaged over the period 2002-2010 for latitudinal bands across transect.

4.2 Regional characterisation of selected extreme events

The characterisation of the following three detected extreme events is shown in Figure 7-10:

- 2006 Horn of Africa floods (biospheric)
- 2005 Sweden cyclone (land use)
- 2010 Russian heat wave (biospheric and land use)

The figures show the location and type of detected extreme event (detailed map) and the spider diagrams visualizing the anomalies of the various biospheric and land use variables.

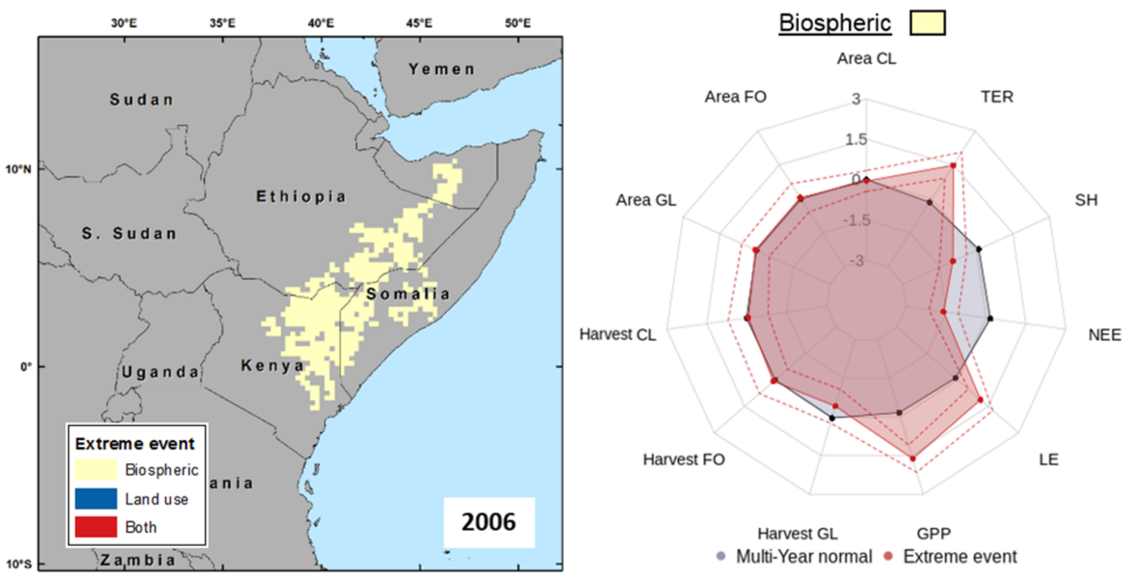

Figure 7. Detected biospheric extreme event "2006 Horn of Africa flooding's". In November and December 2006, heavy rains and severe flooding during the short rain season affected the Horn of Africa (Somalia, Djibouti and Ethiopia), as well as north-eastern Kenya. The observed positive GPP, TER and LE anomalies and related negative SH and NEE anomalies can be explained by an strong green up of the savannah vegetation that covers most of the region (NASA 2006). None of the land use variables show anomalies, which can be explained by the low and extensive land use in the region. Furthermore, it might be possible that the land systems prevailing in this area are adapted to such biospheric extreme events to a certain degree; thus strong reactions in terms of area or harvest changes are not occurring.

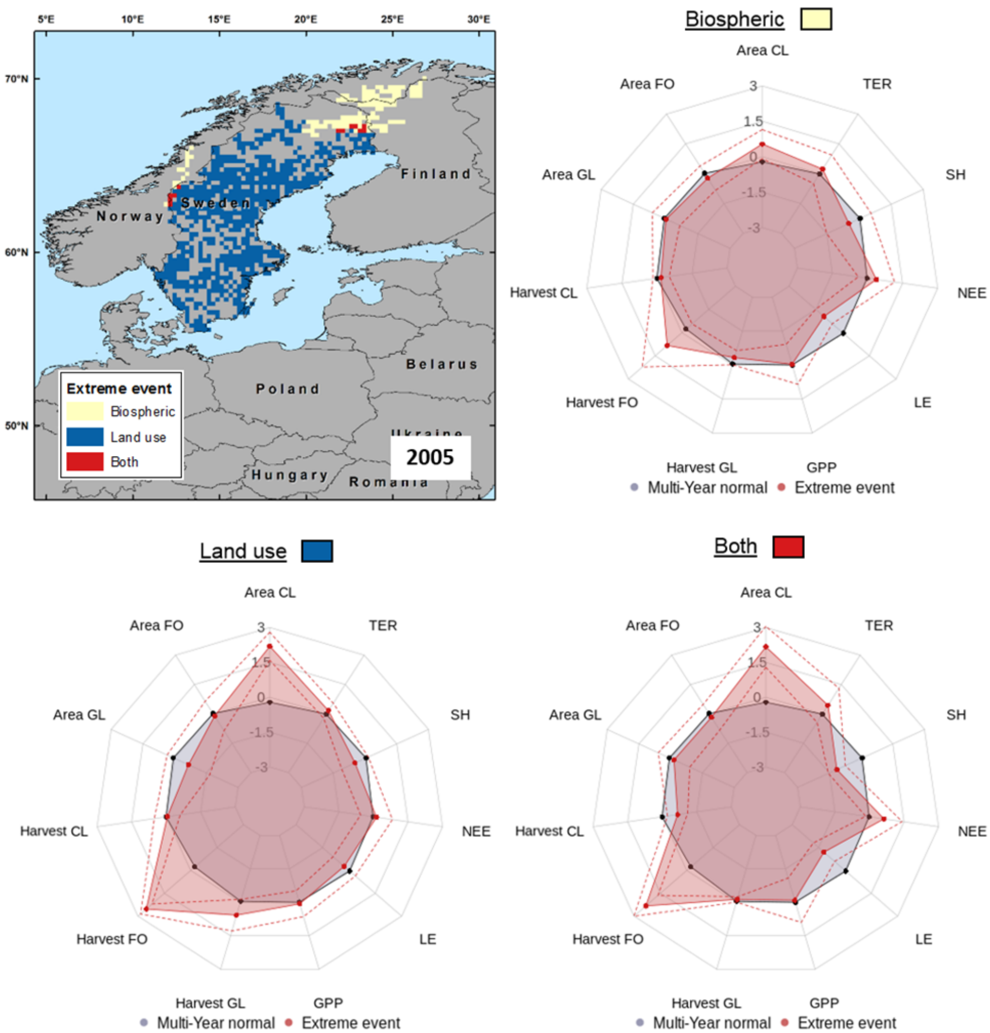

Figure 8. Detected land use extreme event “2005 Sweden Cyclone”. In the year 2005, a land-use extreme event in Sweden was detected. This event was induced by an increase of wood biomass harvested and an increase of cropland area, combined with a decrease of grazing land area. The gain in forest harvest can be explained by the cyclone Gudrun, which hit Sweden on January 8th 2005. The deadfall resulting from this storm event can be clearly identified in the FAO harvest statistics (FAO 2019), as well as the cropland increase. While round wood harvest shows a more or less stable trend in the shown period with a significant peak in 2005, cropland areas shows a decline in these years (negative anomaly), with a strong opposite direction in 2005 (and a weaker peak in 2009, not indicated by the outlier analysis). Note: the results for co-occurring events (bottom right, “both”) may not be meaningful due to the low amount of pixel represented.

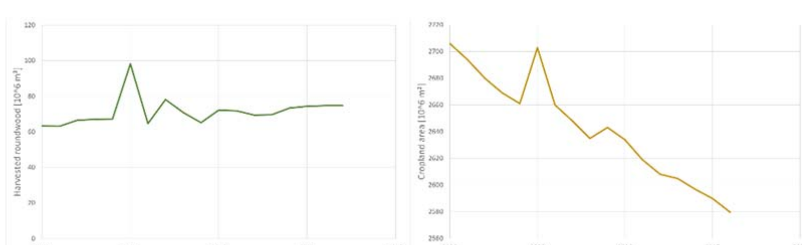

Figure 9. Harvested round wood and cropland area in Sweden (2000-2016) (FAO, 2019)

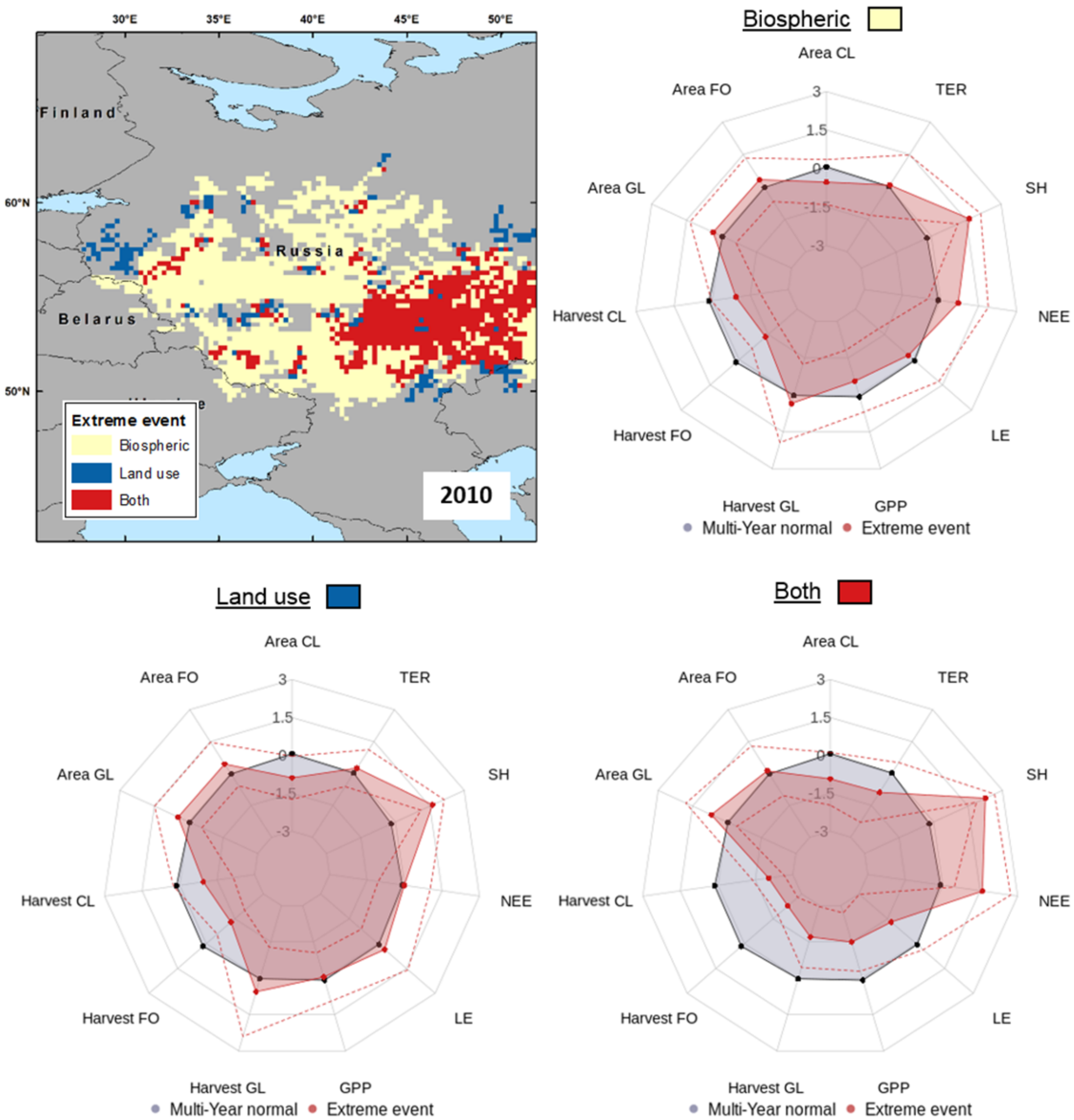

Figure 10: In the year 2010 several parts of the northern hemisphere were hit by a summer heat wave, including large areas of Russia. The area detected shows a distinction between large areas showing only a biospheric signal (yellow areas in Fig. 8, mainly in the western parts) and areas indicating also a land-use signal (red areas in Fig. 8, mainly in the eastern parts). Some areas at the fringes of the extreme event are dominated by land-use anomalies (blue areas). Biospheric extreme events are driven by anomalies of SH, NEE, LE and GPP. These areas also show a decrease of harvest in cropland and forest (negative anomalies). Red areas, indicating the co-occurrence of biospheric and land-use extreme events show noticeable deviations in all variables but forest area changes. All affected land-use related variables (but area of grazing land area) present obvious reductions, harvest declines in all land-use categories. Also GPP, LE and TER decrease, while SH and LE show distinct increases.

5.Summary and next steps

5.1 Preliminary results

Here we, for the first time, assess land use and ecosystem extreme events at the same time in combination using a consistent methodology. The proposed framework follows a data science approach and perspective (not hypothesis-driven), and was applied to detect bioshperic and land use extreme events at continental scale (Europe and Africa) for the years 2002 – 2010. By jointly assessing extreme events in land use and biosphere allows for a more comprehensive understanding of the complex Earth system and its dynamics.

The size of detected extreme events follows a typical logarithmic distribution with few large events and many small ones. The large majority of detect extreme events are either biospheric or land use and only few are co-occurring. Most large extreme events can be characterised well and linked to known climatic (e.g. floods, heatwave, cyclone) and socio-economic events (e.g. harvest decrease).

Our study shows first insights on how biospheric and land use extreme events are related and provides a tool to explore the unknown unknowns in linking ecosystem and land use change (archetypes of change). At the moment the study is conducted at annual scale which may prohibits the detection of some events.

5.2 Next steps

We aim to expand the study to global scale and submit the results as a scientific paper in mid/late 2019.

As part of this a number of key methodological improvements and assessments will be done. First, we will improve the anomaly detection method for the land use extreme events and decompose the temporal signal of the land use data into trends and anomalies (see D7.4). Second, we will conduct a comprehensive assessment of detected events using the validation framework developed in WP6 (D6.1/D6.2). This will include an detailed assessment of the time lag of ecosystem and land use changes and vice versa. Third, we will study which extreme events prevail (natural, land use driven) and try to understand whether we can observe regional differences. Also a major part will focus on identifying key archetypes (syndromes) of changes.

Beyond that study next steps should focus on producing the BACIndex globally at near real-time (see MS16 for pathways) to make the information actionable i.e. to address SDG objectives. Hereby the provision of near-real time data essential. While satellite data are available in near real-time, higher-level products (e.g. GPP) are not yet fully available. In this context, the link to the Copernicus climate and land service is important and should be further developed. Further, the land use data is only available at annual scale and the products used in this study are not yet fully mature and being improved (see D7.4).

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