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A probabilistic risk assessment for the vulnerability of the European carbon cycle to extreme events: the ecosystem perspective

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Abstract

Extreme meteorological events are most likely to occur more often with climate change, leading to a further acceleration of climate change through potentially devastating effects on terrestrial ecosystems. But not all extreme meteorological events lead to extreme ecosystem response. Unlike most current studies, we therefore focus on pre-defined hazardous ecosystem behaviour and the identification of coinciding meteorological conditions, instead of expected ecosystem damage for a pre-defined meteorological event. We use a simple probabilistic risk assessment based on time series of ecosystem behaviour and meteorological conditions. Given the risk assessment terminology, vulnerability and risk for the previously defined hazard are, thus, estimated on the basis of observed hazardous ecosystem behaviour.

We first adapt this generic approach to extreme responses of terrestrial ecosystems to drought and high temperatures, with defining the hazard as a negative net biome productivity over a 12 months period. Further, we show an instructive application for two selected sites using data for 1981–2010; and then apply the method on pan-European scale addressing the 1981–2010 period and future projections for 2071–2100, both based on numerical modelling results (LPJmL for ecosystem behaviour; REMO-SRES A1B for climate).

Our site-specific results demonstrate the applicability of the proposed method, using the SPEI index to describe the meteorological condition. They also provide examples for their interpretation in case of vulnerability to drought for Spain with the expected value of the SPEI being 0.4 lower for hazardous than for non-hazardous ecosystem behaviour, and of non-vulnerability for Northern Germany, where the expected drought index value for hazard observations relates to wetter conditions than for the non-hazard observations.

The pan-European assessment shows that significant results could be obtained for large areas within Europe. For 2071–2100 they indicate a shift towards vulnerability to drought, mainly in the central and north-eastern parts of Europe, where negative

net biome productivity was not used to be associated with drought. In Southern parts of Europe, considerable vulnerability and risk to drought have been identified already under current conditions; in future, the difference in SPEI between hazardous and non-hazardous ecosystem behaviour as well as the frequency of hazardous ecosystem behaviour will increase further. Vulnerability decreased only for the border region between Ukraine, Russia and Belarus, where a change in ecosystem types occurred with less vulnerable plant species in the future.

These first model-based applications indicate the conceptional advantages of the proposed method by focusing on the identification of critical meteorological conditions for which we observe hazardous ecosystem behaviour in the analysed dataset. Application of the method to empirical time series would be an important next step to test the methods.

1 Introduction

Climate change is expected to have negative impacts on the productivity and stability of ecosystems worldwide. Such ecosystem degradation can further enhance atmospheric CO_2 concentrations and thus reinforce climate change. Especially extreme meteorological events – expected to become more frequent and intense (Field et al., 2012; Coumou and Rahmstorf, 2012) – have been assessed to impact terrestrial ecosystems most (Reichstein et al., 2013). Investigations of impacts of various extreme meteorological events on ecosystems, including drought and heat waves, include individual observations on the basis of empirical data (e.g. Buentgen et al., 2011; Ciais et al., 2005), experiments (e.g. Eilmann et al., 2011; Misson et al., 2011) as well as model-based approaches (e.g. Cherwin and Knapp, 2012). However, not all meteorological extreme events lead to extreme responses in the ecosystem (Smith, 2011). Identifying those extreme meteorological conditions which lead to extreme ecosystem responses therefore is an imperative to better understand the feedbacks between ecosystems and climate change. On the contrary, average meteorological conditions can also lead

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to extreme ecosystem behaviour. Therefore, it is important to start looking from the ecosystem perspective: which meteorological conditions coincide with extreme or hazardous ecosystem behaviour.

To allow for this assessment, we use the concept of Probabilistic Risk Assessment (PRA) which has originally been used in engineering (e.g. Wall, 1969), but is also applied in ecological research, such as population ecology (e.g. Diez et al., 2012; Hope, 2000; Regan et al., 2003; Wilson et al., 2009). Van Oijen et al. (2013) adopt the PRA concept to quantify the "vulnerability" of an ecosystem in terms of the expected impact of meteorological extreme events on carbon storage in European spruce forest. They combine this with the probability of the occurence of such extremes to deduce the risk for the ecosystem. This means, they pre-define an extreme meteorological event as the underlying "hazard" and then investigate the related ecosystem response, regardless of how extreme the ecosystem responses are. Here, we build on the conceptional frame of PRA, but focus on extreme responses of the ecosystems, i.e. we define the "hazard" as extreme ecosystem response and identify the meteorological conditions that led to, or more strictly, co-occurred with the extreme ecosystem responses. Instead of using arbitrary definitions of extremeness in the distribution of the ecosystem variable (i.e. percentiles), we define a discrete and ecologically meaningful threshold for hazardous ecosystem behaviour.

In accordance to our focus on the feedback between the terrestrial ecosystem and the climate system, we define the hazard as carbon emissions from the ecosystem to the atmosphere. Our analysis then quantifies vulnerability of an ecosystem by indicating how far the expected meteorological conditions during hazardous ecosystem responses differ from values that are expected for non-hazardous responses, i.e. positive net carbon storage in the ecosystem. Building on this vulnerability, risk is quantified by taking into account the probability of occurrence of hazardous events (as in Van Oijen et al., 2013). Under future climatic conditions with probably increasing climate variability, vulnerability may increase e.g. due to an increasing range of values occurring. The

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respective risk may increase because of increasing vulnerability and of increasingly occurring extreme values.

Three challenges can thus be addressed in this contribution:

1. The adaptation of a probility-based vulnerability and risk assessment concept which focusses on hazards defined as extreme responses of an ecosystem (sensu Smith, 2011), will help us to understand critical meteorological conditions connected to hazardous ecosystem responses,

2. a first application of this new PRA serving as proof of concept, and

3. a second application that compares current ecosystem vulnerability and risk of European ecosystems with those in the future.

According to these challenges, we first adapt and present a general PRA focusing on the ecosystem response to derive vulnerability and risk towards meteorological conditions. Then we exemplify the application of this concept to single time series at two European sites towards drought defining the hazard as release of CO_2 from the ecosystem. Finally, we extend the application to a Pan-European vulnerability and risk assessment by identifying areas of increasing drought related emissions from terrestrial ecosystems in Europe under future climatic conditions.

2 Material and methods

2.1 Vulnerability concept from the ecosystem perspective

Recently Van Oijen et al. (2013) developed the PRA method further to quantify a hazard as the potentially damaging phenomenon and the probability of the hazard occurring for terrestrial ecosystems using PRA to quantify environmental stress probabilistically integrating climate and simulated vegetation data. Van Oijen et al. (2013) quantify the probability of hazardous weather conditions which cause a loss in net

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primary production. We adopt the approach but define hazardous conditions from an ecosystem perspective and quantify the probability of specific weather conditions being the drivers. For calculating vulnerability from the ecosystem perspective, we define an ecosystem variable *sys* and an environmental variable *env* (Fig. 1a). Here, thresholds of the ecosystem variable *sys* define the hazard and divide the data set into hazardous (haz) and non-hazardous conditions (nonhaz) (Fig. 1b). Ecosystem vulnerability (V_E) is determined by conditional probabilities, i.e. the expectation value (E) of *env* under non-hazardous and hazardous conditions of *sys* (Eq. 1, Fig. 1c)

$$V_E = E(env\,|\,sys\ \text{nonhaz}) - E(env\,|\,sys\ \text{haz}) \tag{1}$$

based on conditional expectation values

$$E(env\,|^{\circ}) = \int env\ P(env\,|^{\circ})\,\mathrm{d}\,env \tag{2}$$

with probability P of *env* under the specified condition. Ecosystem vulnerability V_E (Eq. 1) in our assessment is the average deviation of the environmental variable under hazardous ecosystem conditions from values under non-hazardous ecosystem conditions (Fig. 1d). V_E and R_E are therefore expressed in the unit of the environmental variable and describe the deviations in the climatic conditions co-occurring with hazards in the ecosystem. The probability of the hazard occurrence is given by the relative size of the hazard group, i.e. the number of data points for hazardous conditions N_{haz} in relation to the total number of values N with $P(sys = \text{haz}) = N_{\text{haz}}/N$. The resulting risk ($R_E$) is then defined as the product of the vulnerability of the ecosystem and the probability ($P(sys = \text{haz})$) that such disturbing events would occur (Eq. 3, Fig. 1e),

$$R_E = V_E \cdot P(sys = \text{haz}) = E(env\,|sys\ \text{nonhaz}) - E(env) \tag{3}$$

which can be replaced by the respective expectation values for non-hazardous and non-hazardous conditions combining Eqs. (1) and (2). On the one hand, R_E reflects

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the usual perception of risk as the realized vulnerability but on the other hand, it cannot be interpreted as expected damage.

In the ecosystem vulnerability approach, high values of V_E and R_E denote high vulnerability and risk towards the respective environmental variable because the ecosystem hazard (e.g. carbon loss) occurs when *env* differs considerably to situations when the ecosystem accumulates carbon (see discussion in Sect. 4.1). The distance between the expectation values reveals the potential impact of *env* on the ecosystem.

Our approach is completely general in the sense that we can choose any ecosystem variable to describe the vulnerability of that variable (see Sect. 2.2.1) and any threshold as the criterion for hazardous conditions. It can be applied to measured data as well as to simulation results from ecosystem models.

2.2 Application to European ecosystems

In order to demonstrate the applicability of the concept, first we calculate ecosystem vulnerability and risk for two sites in Germany and Spain and secondly quantify V_E and R_E on the European scale for two time periods. For both, we used meteorological data as environmental variables *env* (Sect. 2.2.1) and the results of a dynamic vegetation model as system variables *sys* (Sect. 2.2.3) with a spatial resolution of $0.25^\circ \times 0.25^\circ$ across Europe ($\sim$ 17 800 grid cells). This approach enables a consistent analysis since the meteorological data were used as forcing for the vegetation model and as *env*. We analyzed a current period (1981 to 2010) and compare to potential future conditions (2071 to 2100) using the European regions defined by SREX (IPCC, 2012) for regional aggregation (Table 1).

2.2.1 Data sources for environmental variable *env*

Examples of environmental variables (*env*), which can be chosen for the probabilistic risk assessment are monthly values of the Standardized Precipitation Evapotranspiration Index (–) (SPEI as defined in Vicente-Serrano et al., 2010) but also monthly precip-

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itation (mm month^{-1}), monthly mean temperature (°C), monthly values of Consecutive Dry Days (CDD) with precipitation below 1 mm (days). The SPEI is a recent extension of the Standardized Precipitation Index by the influence of temperature on the potential evapotranspiration and was calculated with function spei of R-package SPEI (Vicente-Serrano et al., 2010; R Development Core Team, 2009) with a 3-monthly averaging interval. SPEI values have an average of 0 and are regarded as indicator of drought below −1.0 or water surplus above 1.0.

The decision for the application of a certain *env* is always coupled with an expectation in which value ranges of *env* the ecosystem could be affected negatively. For temperature and CDD, high values are expected to be problematic, whereas for precipitation and SPEI, hazardeous conditions of *sys* are expected at low values. In order to provide a common framework, the choice of *env* is combined with the definition of a factor δ (Eq. 4).

$$\delta = \begin{cases} 1: & \text{low values of } env \text{ expected to be damaging} \\ -1: & \text{high values of } env \text{ expected to be damaging} \end{cases} \tag{4}$$

For the current analysis, we choose S as monthly SPEI values ($\delta = 1$) and give results in Appendix Figs. A1–A3 for P as monthly precipitation ($\delta = 1$), T as monthly temperature ($\delta = -1$) and C as monthly CDD ($\delta = -1$). We use meteorological variables from 1901 to 2100 (see Sect. 2.2.2).

2.2.2 Input data

We use WATCH-ERA-Interim daily climate data at 0.25° × 0.25° grid cell resolution to the European spatial domain (29.125° N to 71.375° N and −23.875° E to 45.375° E). This data set is based on down-scaled WATCH climate data (Weedon et al., 2011) for the years 1901–2001 and extended to 2010 using downscaled ERA-Interim climate data (Dee et al., 2011) (see also Beer et al., 2014). For future climate, the MPI-Remo regional climate model was applied for the A1B SRES emission scenario (provided by

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the ENSEMBLES project). MPI-REMO results have been bias corrected by applying the 1970–2010 mean and standard deviation of the WATCH-ERA-Interim climate data. Annual atmospheric CO_2 concentrations for 1901–2010 are based on data from ice-core records and NOAA atmospheric observations.

2.2.3 Choice of ecosystem variable *sys*

For deriving the system variable *sys*, we use results of the global, dynamic process-based vegetation model LPJmL (see Sect. 2.2.4). For the analysis, meteorological data described in Sect. 2.2.1 are used as forcing data for the simulations with LPJmL. All processes, including fire, are simulated at a daily resolution in this study, so that extreme weather conditions contained in the climate input data set will have an impact on the simulated ecosystem variables. For deriving *sys*, we select monthly values of net primary production (NPP), heterotrophic respiration (RH) and burned biomass (BB) (all given in $\mathrm{g\,C\,m^{-2}\,month^{-1}}$) from which net biome production (NBP) is derived (Eq. 5).

$$\mathrm{NBP} = \mathrm{NPP} - \mathrm{RH} - \mathrm{BB} \tag{5}$$

A detailed protocol of the model set up is given in Sect. 2.2.5. In order to detect hazardous conditions outside their average seasonal dynamics and to include the reaction of the ecosystem over the next year, NBP values were considered over a longer time period than one month. The system variable *sys* for month *i* in the period of *ny* years is chosen as the sum of NBP over a 12 month moving window including month *i* and the following 11 months (Eq. 6).

$$sys_i = \sum_{k=i}^{i+11} \mathrm{NBP}_k \quad \text{for} \quad i \in (1, \ldots, ny \times 12). \tag{6}$$

With this definition, sys_i integrates over a 12 month period but is not fixed to the calendar year. The *env* variable SPEI with an averaging interval of 3 month represents

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a medium-term situation on the subseasonal scale. The combination with the ecosystem condition over a cycle of 12 month allows for the identification of responses which exceed seasonal variations.

We define a hazard as a month i for which the system variable sys_i is negative ($sys_i < 0$), i.e. the ecosystem is a net source of carbon for the following 12-month period.

2.2.4 Description of the vegetation model LPJmL

LPJmL simulates carbon and water cycles as well as vegetation growth dynamics. Natural vegetation is represented in LPJmL at the biome level by nine plant functional types (Sitch et al., 2003). The model calculates closed balances of carbon fluxes (gross primary production, auto- and heterotrophic respiration) and pools (in leaves, sapwood, heartwood, storage organs, roots, litter and soil), as well as water fluxes (interception, evaporation, transpiration, snowmelt, runoff, discharge) (Gerten et al., 2004; Rost et al., 2008). Photosynthesis is simulated following the Farquhar model approach (Farquhar et al., 1980; Farquhar and Von Caemmerer, 1982). Processes of carbon assimilation and water consumption are parameterized on the leaf level and scaled to the ecosystem level. Carbon and water dynamics are closely linked so that the effects of changing temperatures, declining water availability and rising CO_2 concentrations are accounted for and their net effect can be evaluated (Gerten et al., 2004, 2007). Physiological and structural plant responses determine water requirements and water consumption. Fire is simulated within the process-based submodule SPITFIRE (Thonicke et al., 2010). Vegetation re-growth on burnt areas, simulated by SPITFIRE, depends on respective tree seedling performance and grass establishment under given climate conditions and follows the algorithms as described in the LPJmL model. Biomass burnt (BB) result from dead and live fuel consumption in surface fires and from crown scorching (Thonicke et al., 2010) and are included in the carbon balance NBP (Eq. 5). The suitability of the LPJmL framework for vegetation and water studies has been demonstrated by validating simulated phenology (Bondeau et al., 2007), river discharge (Gerten et al., 2004; Biemans et al., 2009), soil moisture (Wagner et al., 2003) and evapotranspiration (Sitch et al., 2003; Gerten et al., 2004).

2.2.5 Modelling protocol

For deriving the system variable *sys*, LPJmL simulations were performed with natural vegetation and the SPITFIRE fire submodule (Thonicke et al., 2010). In order to derive equilibrium fluxes between soil and vegetation, 1000 years spinup were simulated by using the climatic forcing from 1901 to 1930 in repetitive loops. The transient run from 1901 to 2100 was started by a further spinup period of 30 years. Climate forcing consisted of the WATCH-ERA-Interim climate data with daily values from 1901 to 2100 for temperature (daily minimum and maximum values), precipitation, wind speed, long wave and short wave downward radiation flux. Data for the soil properties (Sitch et al., 2003) and for lightning, population density and human ignition (Thonicke et al., 2010) were regridded from a spatial resolution of $0.5^{\circ} \times 0.5^{\circ}$ to $0.25^{\circ} \times 0.25^{\circ}$.

3 Results

3.1 Determination of vulnerability and risk: two examples

We show the calculation of ecosystem vulnerability in detail for two sites in Europe which differ in climatic conditions. In site 1 in northern Germany (Fig. 2a) the probability for a hazardous ecosystem condition (i.e. $sys < 0$) for the period 1981 to 2010 is 0.25 (80 of 360 data points are in the hazard group). The expectation value of the chosen *env*, the drought index SPEI, is 0.34 for data points with $sys < 0$ whereas the average SPEI with positive *sys* (non-hazard case) is −0.09. The difference of both sets of SPEI values is significant ($p < 0.01$) and results in negative V_E and R_E (Fig. 2c). Thus, site 1 is not vulnerable to drought but to high SPEI values, i.e. the ecosystem hazard occurs under wetter conditions than usual. Due to the infrequent hazard occurrence, the corresponding risk is low.

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In the second site in Spain, the probability for $sys < 0$ in the period 1981 to 2010 is much higher (50 %, Fig. 2b). The average SPEI values in the hazard group (−0.19) and in the non-hazard group (0.22) are significantly different ($p < 0.001$). Here, V_E and R_E are positive (Fig. 2c). Site 2 is vulnerable to low SPEI meaning that carbon losses from the biosphere are connected to SPEI being 0.4 lower than compared to situations when the ecosystem is accumulating carbon. The corresponding risk values cannot be related directly to severity of drought conditions. However, they allow the spatial comparison of the damaging potential of environmental variables by combining the vulnerability with the hazard occurrence.

3.2 Spatial distribution of ecosystem vulnerability

Ecosystem vulnerability towards SPEI for the period 1981 to 2010 (Fig. 3a) maps predominantly areas in southern Europe with V_E values of more than 0.6. The border region of Ukraine, Belarus and Russia is most pronounced with positive V_E values of more than 0.4 where fire has a large impact on the carbon balance. However, V_E is negative in the boreal zone. The corresponding R_E towards SPEI (Fig. 3b) shows highest values in Northern Africa (0.4) and about 0.2 in the Mediterranean and Ukraine.

Spatial patterns of ecosystem vulnerability towards P, C and T (Figs. A1–A3) reveal similar patterns for water availability (i.e. drought (P), dry spells (C) and the drought indicator S) but not for temperatures (T). Ecosystem vulnerability towards drought for the period 1981 to 2010 (Fig. A1a) maps the Mediterranean, the Balkan, eastern Ukraine and a southern part of Russia with V_E values of more than 10 mm month^{-1}. For these regions, the risk towards drought is approximately 5 mm month^{-1} (Fig. A1b). For southern and eastern Norway as well as the mountainous regions of France, Belgium and Switzerland, V_E is mostly negative (below −10 mm month^{-1}), i.e. not vulnerable towards low precipitation but to wetter conditions. Due to rare hazard occurrence, R_E reaches values below −10 mm month^{-1} only in marginal areas in southern Norway. Ecosystem vulnerability towards temperatures (T, Fig. A2a) is mostly positive but only rarely ex-

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ceeds 1 K. The corresponding risk (Fig. A2b) is between 0.5 and 1 K and does not show a clear spatial pattern. However, it is only significant for less than 0.2 % of the grid cells.

The proportion of the European area, for which positive V_E values were found, can also be determined. Apart from positive values in Southern Europe, there are extensive areas in the temperate region with V_E values close to zero which are not significant (areas not marked by dots in Fig. 3) and in the northern ranges even negative values are widespread. For each of the analysed periods, for the majority of the area at least one of the environmental variables induced high positive V_E values indicating vulnerability towards drought or high temperatures. In the southern region, this holds for about 66 to 90 % of the grid cells whereas the percentages are smaller for the temperate (44 to 56 %) and the northern (53 to 61 %) regions. That implies, that in northern Europe about 39 to 47 % of the cells have near or below zero V_E values for all *env* considered indicating that the ecosystem hazard (NBP < 0) is occurring but not because of drought or high temperature. For each region and period, negligible V_E for each of the considered *env* variables are extremely rare (less than 0.2 % of the cells). When high negative V_E are calculated, there might be at least two reasons: (1) the cause for the ecosystem hazard is not explained by the selected *env* variable and a further *env* has to be considered, or (2) the expected value ranges chosen for the analysed *env* are not appropriate and e.g. high SPEI values are more damaging for the ecosystem than drought. This situation occurs nearly nowhere in the southern region (< 1.2 % of the area) where high temperatures and droughts are the major threats for the ecosystems, but frequently in the temperate (2 to 7 %) and northern (3 to 5 %) zone.

3.3 Future ecosystem vulnerability

We identify ecosystems in Southern Europe as being vulnerable towards water shortages (low precipitation, low SPEI) under current conditions (Figs. 3a, A1a). Vulnerability increases under future conditions (Fig. 3c) and the corresponding risk increases considerably due to more frequent hazard occurrence (Fig. 3d). This holds not only for

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vulnerability towards drought but also towards high temperature (see Figs. A1c and d, A2c and d, A3c and d). When comparing zonal averages of V_E according to the SREX regions (Table 1), vulnerability is higher under future conditions for all considered *env*. Ecosystem vulnerability in the Mediterranean (region MED) can be stated towards drought (S and P) under current conditions for the majority of grid cells with increasing intensity in the future (Table 2). For this region, V_E is positive for all *env* considered. Drought indicators S and C under future conditions are positive for most of central Europe (CEU) indicating widespread vulnerability towards water shortage. In contrast, high temperature and precipitation only affect limited areas. Northern Europe (region NEU), which is currently characterized by mostly negative V_E, will be impacted by high temperatures. V_E will reach values above 2 K for most of Finland and for large areas in northern Russia indicating that ecosystems adapted to colder climate will lose carbon because of increasing temperatures (Fig. A2c). Here, also risk values are relatively high because of more frequent hazard occurrence (Fig. A2d).

4 Discussion

4.1 The concept of ecosystem vulnerability determination

The proposed method allows for the quantification of the vulnerability and the associated risk of ecosystems to the loss of carbon. The definition of situations in which environmental drivers are associated with a hazard in the ecosystem represents a perception on ecosystem vulnerability seldom taken so far. From this ecosystem perspective, it is not necessary to assume a climatic hazard such as extreme temperature or precipitation that could have damaging effects on the ecosystem. The ecosystem, however, may be resilient or may react delayed in time. Therefore, precisely those conditions are of interest that are connected to ecosystem hazards.

The calculation of ecosystem vulnerability depends on the one hand on the chosen *sys* to define conditions that represent vulnerability of an ecosystem (e.g. high respiration or low net primary productivity). On the other hand, it is sensitive to the associated threshold that defines the hazard (e.g. $NPP < 0$). A careful selection is required of the appropriate metric, variable and threshold describing the hazard under consideration for the respective ecosystem. One option is to choose a variable for the hazard definition that is widely accepted and easy to interpret in the respective ecosystem process or status. The variable to be investigated and the threshold to define hazardous conditions are to be chosen with the goal of the study in mind. In this study, we selected carbon release to the atmosphere as hazard, i.e. negative net biome production (NBP). This variable is commonly used to interpret carbon fluxes of an ecosystem as net emittor through respiration and disturbances or net accumulator through photosynthesis (Schulze, 2006).

It can be debated whether this choice reflects the nature of a hazard for the ecosystem's carbon balance because under equilibrium conditions emissions equal more or less gains. Thus, the arbitrary occurrence of a month with negative NBP cannot be regarded as hazard. Only longer lasting net losses pose a problem to ecosystems and are suitable for the perception of a hazard when choosing carbon fluxes to express ecosystem vulnerability. We therefore sum NBP over 12 months in order to eliminate short-term fluctuations such as seasonal dynamics. This identifies situations, where on an annual time scale net carbon losses of an ecosystem to the atmosphere have been larger than net gains. And it avoids the unwanted detection of vulnerability in regions of regular seasonal drought where ecosystems are adapted and compensate losses usually during the vegetation period or rainy season.

In our opinion, NBP sums over 12 months are suitable to represent an ecosystem status that can be labelled as hazardous and non-hazardous in terms of being a source or sink of carbon to the atmosphere. It includes not only the effect of uptake processes such as photosynthesis but also those of losses such as heterotrophic respiration and fire. Choosing a much stronger condition for the hazard such as negative values for annual NPP, only 6.4 % of the European area in the current period is affected by vulnerability towards drought and 0.6 % is vulnerable towards high temperature (data not

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shown). A more severe hazard condition thus reduces the area for which vulnerability can be estimated. Defining the hazard depending on ecosystem specific conditions for different climatic regions would be another strategy. Such a flexible definition of a hazard, however, could cause statistical problems because of too small sample sizes, i.e. not enough samples in the hazard vs. non-hazard group. Additionally, definitions and thresholds would differ between grid cells and hinder comparability at the regional or continental scale. Nevertheless, this would be an interesting approach for assessing specific ecosystems on smaller spatial scales.

4.2 Context of ecosystem vulnerability

Our concept quantifies the long-term and combined impact of extreme meteorological events, and does not evaluate the effects of single events. By assigning each monthly value of *sys* to either the hazard or the non-hazard group, each individual ecosystem behaviour contributes to the assessment of our long-term ecosystem vulnerability and risk.

It links to Smith (2011) by directly addressing the ecosystem behaviours and relating it to the meteorological conditions under which it occurs. Exploring the connection between hazards and extremes (sensu Smith, 2011), both concepts define thresholds for hazardous or extreme conditions and both examine the physical and biological spheres independently. Different to Smith (2011), we apply not a distributional threshold (referring to extremeness) but a qualitative threshold (i.e. ecosystem as a source or sink of carbon). Applying the same logic to the environmental driver *env* (e.g. like Van Oijen et al., 2013), a meaningful threshold can be set for the environmental variable SPEI of -1 (as defined for drought in Vicente-Serrano et al., 2010). This allows deriving probabilities also for the transition of non-hazardous *env* events into hazardous and non-hazardous *sys* conditions. Following Smith (2011), it is then possible to quantify the probability of occurrence of all four combinations of the ecosystem variable *sys*, in our case NBP, and the environmental variable *env*, here SPEI (Fig. 4).

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We exemplarily quantified all four combinations for two sites (see Fig. 2) using the simulated 30 year time series (as described in Sect. 2.1). At both sites, hazardous *env* conditions occur in 16 % of the months but the responses of the ecosystems differ. At site 1, for which V_E is negative, about 22 % of the *env* data belong to the hazard group and less than 3 % of hazardous *sys* conditions are connected to hazardous *env* conditions (Fig. 4 left). At site 2 with positive V_E, about 50 % of the *env* time series belong to the hazard group and in about 11 % of the months, hazardous *env* conditions coincide with hazardous *sys* conditions (Fig. 4 right). Under current climate conditions, the Mediterranean site already experiences more hazardous (extreme) environmental condition that lead to carbon release.

This shows how the proposed PRA takes up the concern of Smith (2011) to include the ecosystem perspective into data driven probilitistic risk assessment.

4.3 Interpretation of ecosystem vulnerability values

The quantification of vulnerability and risk using the ecosystem vulnerability approach requires some careful interpretation of the obtained values. First of all, its unit is defined by the chosen *env* and, secondly, the interpretation of its sign and magnitude depends on our interpretation of the damaging effect of *env*. Therefore, we give both some consideration.

By choosing an environmental variable *env* that is supposed to potentially cause damages to the ecosystem, it is natural to formulate an expectation about the range of unfavourable values. When considering the impact of temperature in Europe, high values are expected to affect ecosystems negatively. The same holds for CDD. For precipitation and SPEI, problematic situations are expected in the low value ranges. In order to produce V_E values whose sign can be interpretated as described in the following paragraphs, the factor δ is defined (Eq. 4).

High values of ecosystem vulnerability indicate high vulnerability to lose carbon due to drier conditions than usual, i.e. the SPEI difference during ecosystem hazards is decisive for the vulnerability and not the absolute values of the drought indicator. This

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difference reflects the distance between two average conditions: on the one hand, the usually occurring climatic condition under which the ecosystem flourishes and accumulates carbon and, on the other hand, unfavourable climatic conditions under which the defined hazard is occurring and the ecosystem emits carbon to the atmosphere. Thus, the higher the difference and therefore V_E, the higher the distance between favourable meterological conditions (non-hazard) to those which coincide with the ecosystem hazard. Hence, high V_E values express that the environmental conditions to which the ecosystem is adapted differ strongly from those under which the ecosystem emits carbon. The vulnerability to these hazard inducing meteorological conditions conveys therefore not only that the ecosystem's net carbon uptake is connected to a certain range of SPEI values but also that during the investigation period much lower SPEI values appear when carbon is lost from the ecosystem. An increase in V_E in the future can have two reasons: SPEI values are low more often or more extremely low values occur. The latter also means that climate extremes, in our case droughts, are increasingly often causing hazardous conditions which result in lower mean values in the hazard group. Hence, the difference between the hazard and non-hazard groups increases. The approach does not specifically allow to identify the impact of single events but the long-term and general ecosystem status, which is interesting from an ecological and management point of view. Climate extremes, such as droughts causing negative NBP have been identified for past climate extremes (Ciais et al., 2005; Reichstein et al., 2007). Such events, which occur during the investigated 30 year period and lead to vulnerable conditions for the ecosystem's carbon balance, should fall into the hazard subset of data points. It is possible to identify the position of these hazard samples in the scatterplot (Fig. 2) and estimate the severity of this extreme event. However, the presented ecosystem vulnerability approach evaluates long-term effects that these climate extremes have on the affected ecosystem. It does not only look at short-term impacts, which occur immediately after the event, but captures long-term effects determining the capacity of the ecosystem to recover and stabilize. This is an important point as it refers to the ecosystem's resilience.

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Areas with ecosystem vulnerability values close to zero are those with similar mean *env* values in the hazard and non-hazard group. Thus, ecosystems are not or only marginally vulnerable to *env*, in our case drought. The proximity between both average values suggests that within the considered period any potential causal relationship between *sys* and *env* (in our case droughts causing negative NBP) did not materialize, i.e. from the occurring value ranges of both variables a relationship cannot be deduced and there is currently no effect of *env* on *sys*. The marginality of the impact of *env* was additionally evaluated by considering the statistical significance of the difference between hazard and non-hazard group.

Negative ecosystem vulnerability values indicate that the ecosystem is vulnerable (carbon losses do occur) but either not to the anticipated *env* values or not to the *env* under consideration. In the first situation, drought is not responsible for the ecosystem's carbon loss. Here, the expected value of SPEI for negative NBP (= hazard) is higher than that for positive NBP, i.e. under non-hazard conditions. In the second situation, other environmental variables, e.g. P or T, should be considered and evaluated for their potential impact on the ecosystem. Since V_E is based on a probabilistic approach, its values only indicate potential causalities which have to be evaluated subsequently.

There are two possibilities of failing V_E determination: when the hazard is not occurring at all in the study period, i.e. there is no vulnerability, or when there is no data point in the non-hazard group. The latter case can arise when due to changing environmental conditions each data point falls into the hazard group. In order not to misinterpret missing V_E values, the reason for the calculation failure should be reported. However, the ecological interpretation for the latter case is simple: the ecosystem has converted into a continuous carbon source and might undergo rapid and profound transitions to a new ecosystem state.

An interpretation of R_E values may reflect on the sign of the calculated value, i.e. whether a damaging effect of the regarded *env* can be stated, and on the likelihood of the quantified vulnerability. The ecosystem vulnerability approach does not assess the expected damage in terms of carbon loss as in Van Oijen et al. (2013) because it

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quantifies climate conditions that caused ecosystems to become a source of carbon to the atmosphere. Similar to other metric or model concepts, the presented approach reflects the impacts of currently known ecosystem hazards. For hazards emerging in the future, it can be modified accordingly.

With this concept, ecosystem vulnerability can be integrated into the framework proposed by Ionescu et al. (2009). For them, three main functions have to be fulfilled. First, there has to be an entity that is vulnerable which in our case is the property of an ecosystem to be a source or a sink for carbon. Secondly, a stimulus has to exist to which the entity is vulnerable, which here is exerted by the climatic variables. Thirdly, the interaction of entity and stimulus has to have a notion of worse or better which is given by assigning a hazard to an ecosystem when it is a carbon source. The perception of Ionescu et al. (2009) of the risk also matches well to formula Eq. (3) since they define risk as vulnerability weighted by the occurrence of the hazard. We go one step further in that we cannot only distinguish between vulnerable and non-vulnerable conditions, but quantify it along a continuum. This opens new ways to interpret ecosystem vulnerability in the context of ecological changes as well as implications on biogeochemical cycles.

4.4 Current and future pattern of vulnerability in Europe

Already under current climate conditions, hazard occurrence is frequent enough to calculate V_E and R_E values for different *env* variables at the European scale. Ecosystems in Southern Europe, i.e. in the Mediterranean basin, even stronger on the Balkan peninsula, in Turkey and the Ukraine, are known to experience severe drought stress (Bussotti and Ferretti, 1998; Piovesan et al., 2008; Anav and Mariotti, 2011). Highest V_E values, though, are found currently in eastern Europe. These regions are frequently exposed to conditions leading to ecosystem hazards ($sys < 0$), i.e. the ecosystem's carbon balance is already vulnerable to exceptional droughts and in a situation which is not beneficial for the ecosystem's carbon balance. Already today, these ecosystems are lacking water to compensate for drought stress in order to avoid carbon loss.

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Zscheischler et al. (2014) found most carbon losses in recent observational data on gross primary production (GPP) to be caused by drought. It is noteworthy that the majority of carbon loss is attributed to few and extreme situations.

Temperate regions in central and eastern Europe as well as boreal regions in northern Europe show vulnerability values close to zero, most of which are not significant. In these ecosystems, the hazard occurrence is rare and the difference between hazardous and non-hazardous conditions is small. Here, few periods during which carbon is emitted to the atmosphere are balanced by periods of carbon uptake so that the affected ecosystems are not vulnerable to drought under current climate.

Northern Europe, in boreal forests as well as tundra ecosystems show negative vulnerability values. Belgium, the Netherlands, and northern Germany but also large areas in Scandinavia fall in this category (Figs. 2a, 3a, and A1–A3). In these ecosystems, moisture supply is higher than needed. When carbon loss is observed here, vegetation growth is limited by factors other than drought. That could either be caused by unfavourable temperature conditions or an excess supply of water.

The corresponding risk is negligible under current conditions. Even for the Mediterranean, water scarcity as expressed with R_E values for SPEI (Fig. 3b) and precipitation (Fig. A1b) is occurring rarely so that the significantly determined V_E values are reduced.

Under the considered future conditions, ecosystem vulnerability to drought increases substantially. Areas already vulnerable today become more vulnerable by the end of the century and the size of affected areas increases. Whereas parts of the Iberian peninsula are vulnerable today, the entire peninsula will be so in the future, except for Galicia. The same applies to the Balkan peninsula. The area most severely affected extends northward to include Hungary, Romania and the lowlands in Austria, Slovakia and the Czech Republic. New vulnerable regions emerge in the temperate zone such as the temperate forest in Poland. Also in the transition to the boreal zone increased vulnerability values occur by the end of the century.

The Benelux countries, northern Germany and boreal areas in Russia are not vulnerable to drought under current climate. They are becoming vulnerable in the future

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at a similar scale than the Mediterranean basin under current climate conditions. The regions in northern Europe showing negative vulnerability today are declining in size at the expense of more areas having vulnerability values close to zero. This points to the fact that even in high northern latitudes the ecosystems buffer to droughts is diminishing. It is interesting to note that the vulnerability in the Ukraine to drought is higher today than under future climate conditions, with future vulnerability values being closer to zero. Again, the risk shows that such vulnerabilities would occur less frequently than is the case under current climate conditions. The size of the regions affected by V_E and R_E is the same, but highlights potential hotspots where vulnerable conditions for carbon loss are more likely to be found. This refers to parts of the Iberian peninsula, mostly in central and southern parts and also some restricted areas on the Balkan peninsula.

5 Conclusions

From our ecosystem vulnerability and risk assessment, four main conclusions can be derived:

1. The quantification of ecosystem vulnerability by a probility-based concept allows to identify meteorological conditions that coincide with hazardous ecosystem responses.

2. Drought is a major threat to European ecosystems under current conditions and its impact will increase in the future especially in Southern Europe.

3. Ecosystems in northern Europe are vulnerable towards high precipitation and low temperatures currently but will be vulnerable to high temperatures in the future.

4. European ecosystem risk towards drought and high temperatures may be low now but will reach non-marginal values in the Mediterranean due to climate change.

In combination with the approach by Van Oijen et al. (2013), this concept from the ecosystem perspective allows to reconsider the connections between climatic conditions and ecosystem processes as proposed by Smith (2011). Both, the reaction of ecosystems to average and extreme climate as well as average and extreme ecosystem responses can be identified. Furthermore, their relative importance can be quantified and, by applying both concepts to different environmental and system variables, options for causal relations can be confined for the investigated ecosystem.

Though the application on net biome production in combination with drought and heat indicators is already an interesting study case, various extensions of the investigations seem worthwhile. On the one hand, ecosystem responses may be represented by carbon and water fluxes caused by single processes such as transpiration or autotrophic respiration. This enables to quantify the sensitivity of different ecosystem functions to climatic drivers. Also the defined hazard has to be reconsidered in relation to the focus of the respective study. On the other hand, the choice of the environmental variable *env* is under consideration. In addition to precipitation and temperature, not only drought indicators but also flooding periods, cold spells or management activities could be integrated. A natural next step in our efforts to assess European ecosystem vulnerability using observed data.

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Table 1. Coordinates of European geographical zones (latitudes, longitudes) according to the SREX classification (NEU: Northern Europe, CEU: Central Europe, MED: Mediterranean) (IPCC, 2012).

	NEU (11)		CEU (12)		MED (13)	
SW	(48° N,	10° W)	(45° N,	10° W)	(30° N,	10° W)
NW	(75° N,	10° W)	(48° N,	10° W)	(45° N,	10° W)
NE	(75° N,	40° E)	(61.32° N,	40° E)	(45° N,	40° E)
SE	(61.32° N,	40° E)	(45° N,	40° E)	(30° N,	40° E)

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Table 2. Ecosystem vulnerability V_E in northern Europe (NEU), central Europe (CEU) and the Mediterranean (MED) according to the SREX regions (Table 1) of yearly carbon loss (NBP < 0) towards the *env* variables SPEI S (–), precipitation P (mm month^{-1}), temperature T (K) and consecutive dry days C (days month^{-1}) for 2 periods of analysis for significant cells. Bold numbers denote high positive V_E values (mean value ± standard deviation > 0).

Region	*env*	1981–2010	2071–2100
NEU	S	−0.3 ± 0.1	−0.2 ± 0.3
CEU	S	0.1 ± 0.3	**0.4** ± 0.2
MED	S	**0.3** ± 0.2	**0.5** ± 0.2
NEU	P	−9.4 ± 4.8	−11.5 ± 6.2
CEU	P	−3.6 ± 10.2	7.5 ± 9.8
MED	P	**9.7** ± 5.3	**12.8** ± 5.5
NEU	T	1.0 ± 1.7	**2.7** ± 2.1
CEU	T	0.3 ± 2.2	1.4 ± 1.8
MED	T	1.1 ± 1.5	**1.9** ± 0.6
NEU	C	−1.3 ± 0.3	−1.2 ± 1.0
CEU	C	0.4 ± 1.8	**2.1** ± 1.1
MED	C	4.8 ± 10.1	**7.1** ± 5.9

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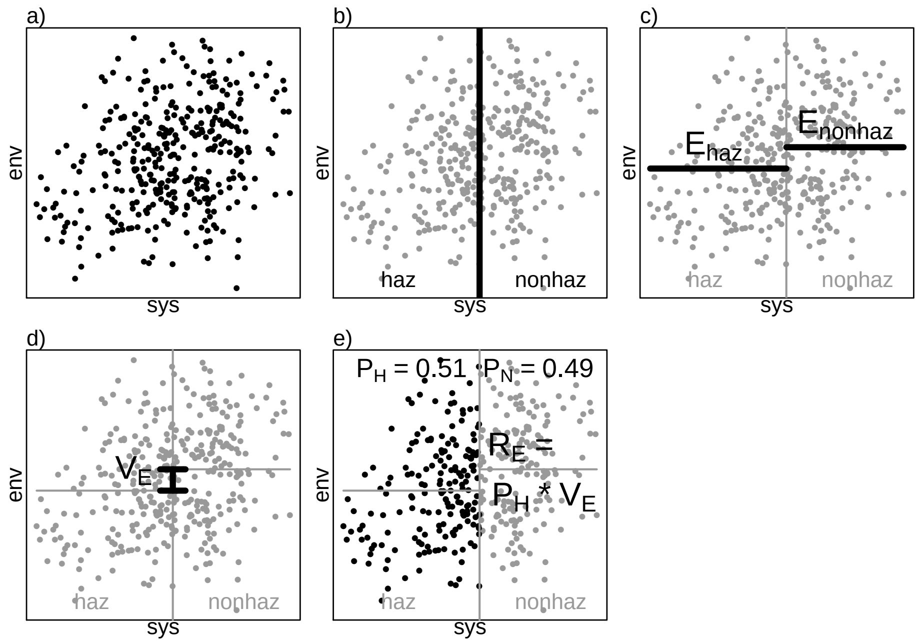

Figure 1. Schematic representation of ecosystem vulnerability determination. **(a)** Regarding *sys* as independent and *env* as depending variable, **(b)** dividing the data set according to the defined hazard for *sys* into hazardous and non-hazardous subsets, **(c)** calculating expectation values E_{haz} and E_{nonhaz} of *env* for the two data subsets, **(d)** determining V_{E} as the difference of the expectation values (Eq. 1), **(e)** determining R_{E} as the product of V_{E} and the probability of the hazard occurrence $P(sys = \mathrm{haz})$ (Eq. 3).

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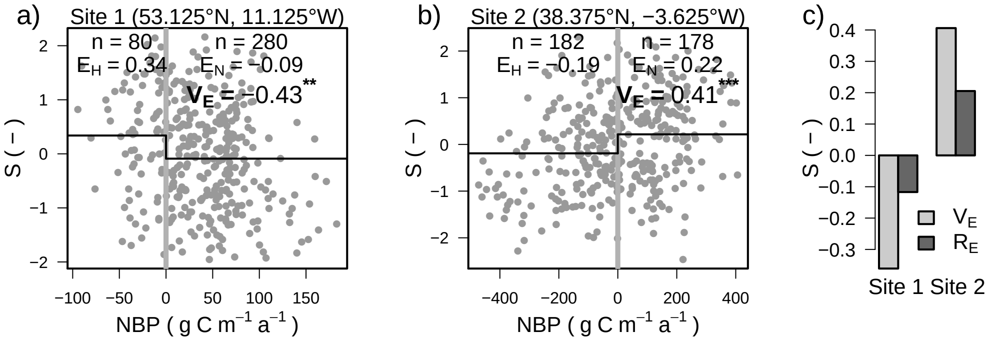

Figure 2. Scatterplots of *sys* variable NBP ($\mathrm{g\,C\,m^{-2}\,a^{-1}}$) against *env* variable SPEI (dimensionless) with monthly values from 1981 to 2010 for 2 sample grid cells in Europe: **(a)** northern Germany (53.125° N, 11.125° W) and **(b)** Spain (38.375° N, 3.625° E). Vertical lines denote the threshold value for the hazard and horizontal lines the expectation values for the respective *env* variable in the hazard (E_H) and the non-hazard case (E_N). Resulting expectation values, V_E and the frequency of data points in both groups are given (dimensionless numbers). Significance level of the Welch t test between both groups is indicated for V_E. **(c)** Calculated V_E and R_E values with negative sign for site 1 (vulnerable towards wet conditions) and positive for site 2 (vulnerable towards drought).

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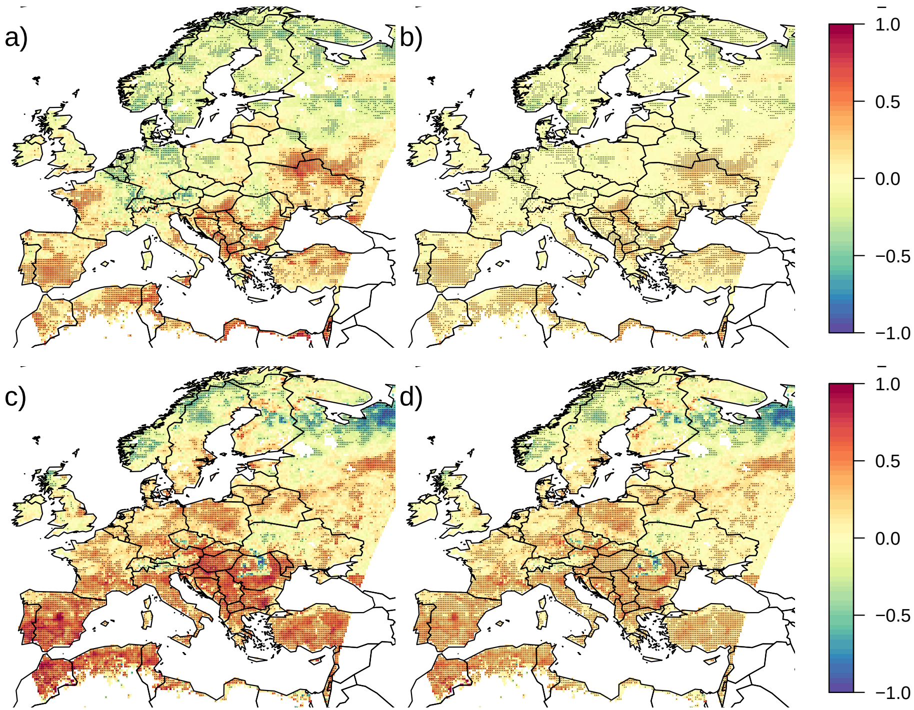

Figure 3. Ecosystem vulnerability (left, **a**, **c**) and risk (right, **b**, **d**) of carbon losses (negative NBP) towards SPEI for the period 1981 to 2010 (upper, **a**, **b**) and 2071 to 2100 (lower, **c**, **d**). Reddish colors indicate high vulnerability towards drought; significant cells are marked with black dots.

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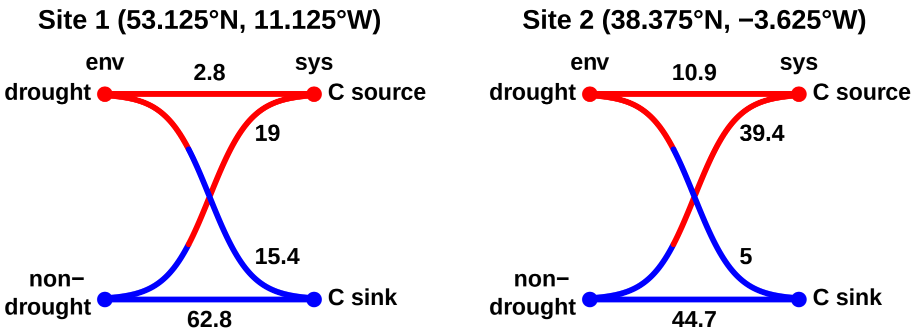

Figure 4. Probabilities (in percent) after Smith (2011) for all four combinations of non-hazardous and hazardous *env* and hazardous and non-hazardous *sys* conditions. Data are the same as in Fig. 2 for site 1 in Germany and site 2 in Spain for the period 1981–2010.

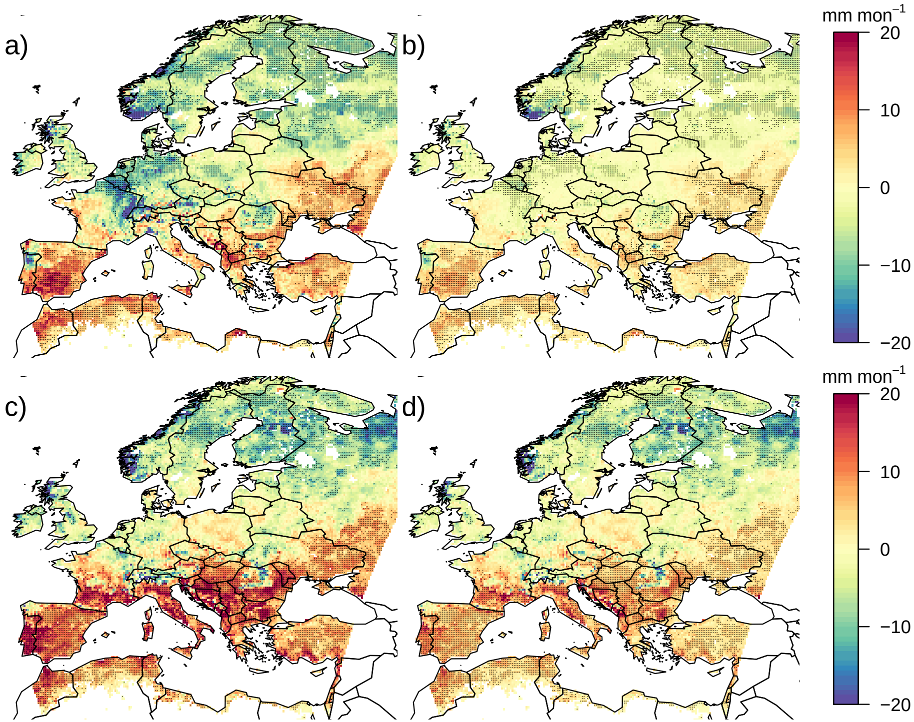

Figure A1. Ecosystem vulnerability (left, **a**, **c**) and risk (right, **b**, **d**) of carbon losses (negative NBP) towards *P* for the period 1981 to 2010 (upper, **a**, **b**) and 2071 to 2100 (lower, **c**, **d**). Reddish colors indicate high vulnerability towards water shortage; significant cells are marked with black dots.

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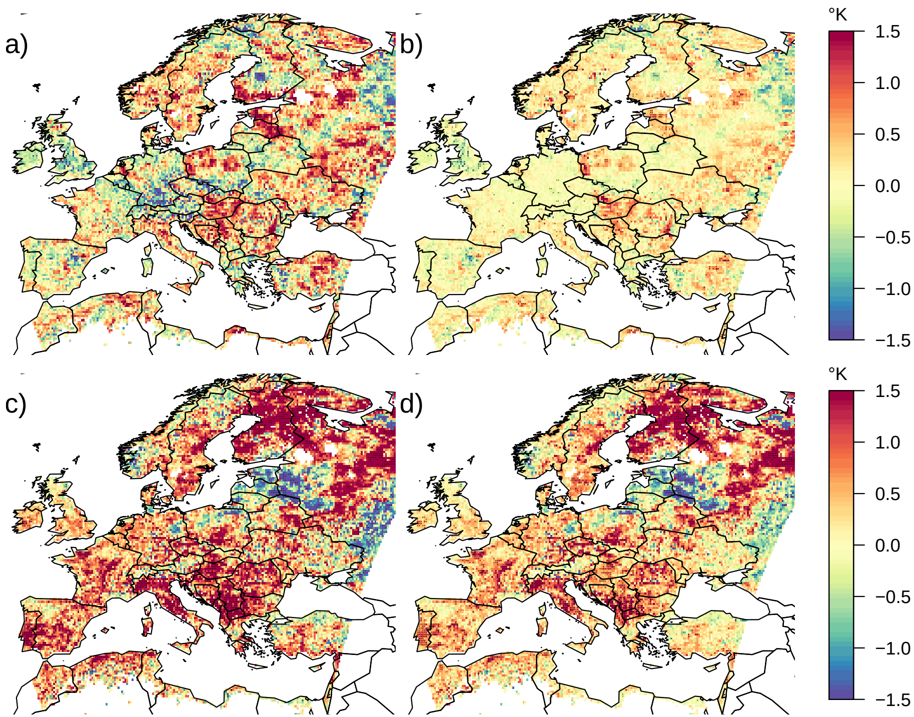

Figure A2. Ecosystem vulnerability (left, **a**, **c**) and risk (right, **b**, **d**) of carbon losses (negative NBP) towards T for the period 1981 to 2010 (upper, **a**, **b**) and 2071 to 2100 (lower, **c**, **d**). Reddish colors indicate high vulnerability towards heat stress; significant cells are marked with black dots.

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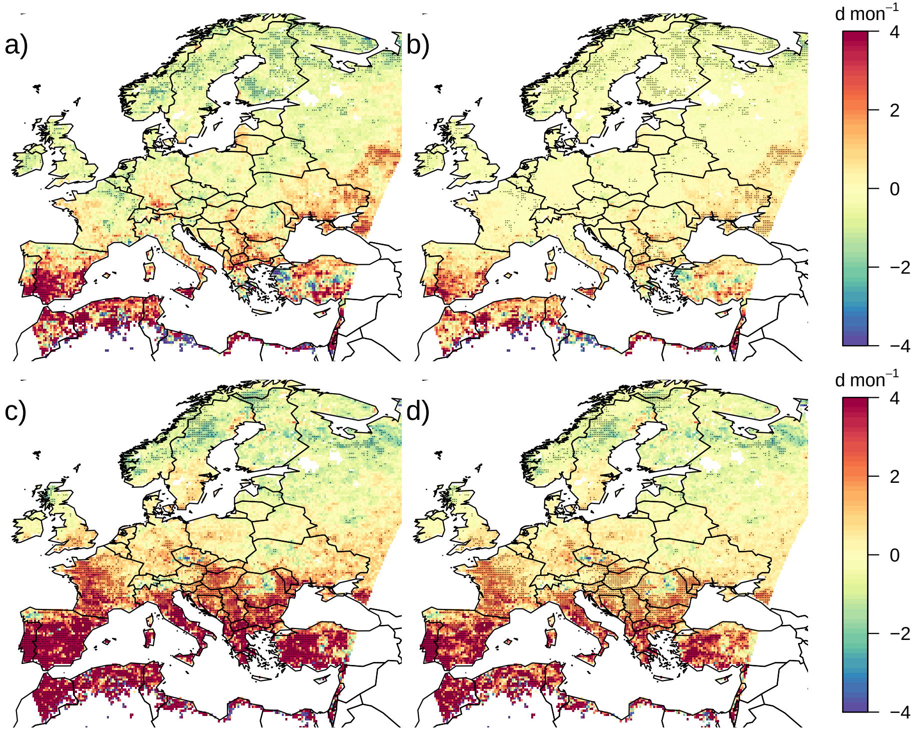

Figure A3. Ecosystem vulnerability (left, **a**, **c**) and risk (right, **b**, **d**) of carbon losses (negative NBP) towards *C* for the period 1981 to 2010 (upper, **a**, **b**) and 2071 to 2100 (lower, **c**, **d**). Reddish colors indicate high vulnerability towards drought periods; significant cells are marked with black dots.

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