

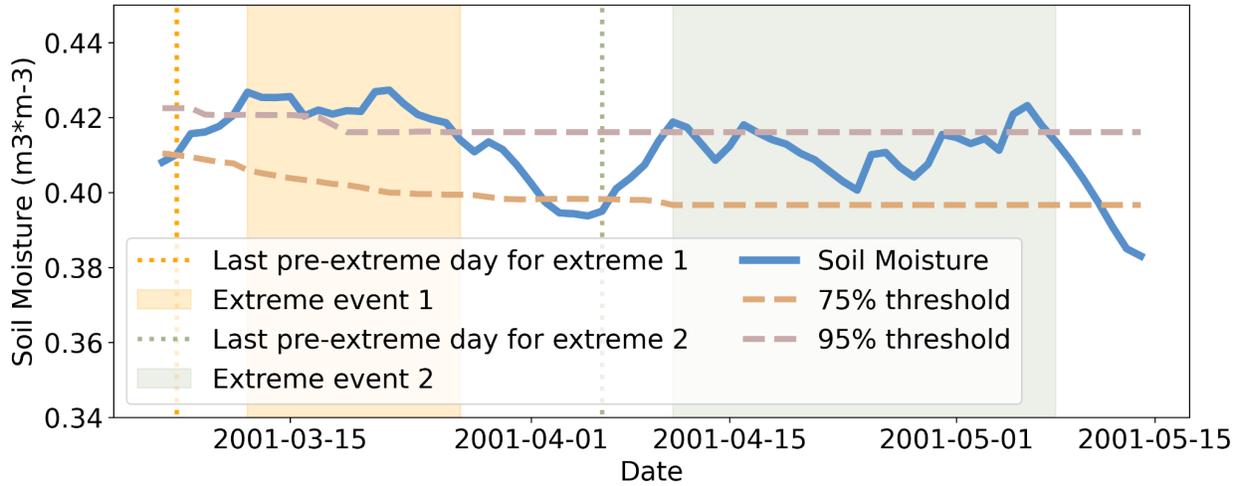
1 **Global vegetation responses to wet and dry soil moisture extremes**

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3 Supplementary information:

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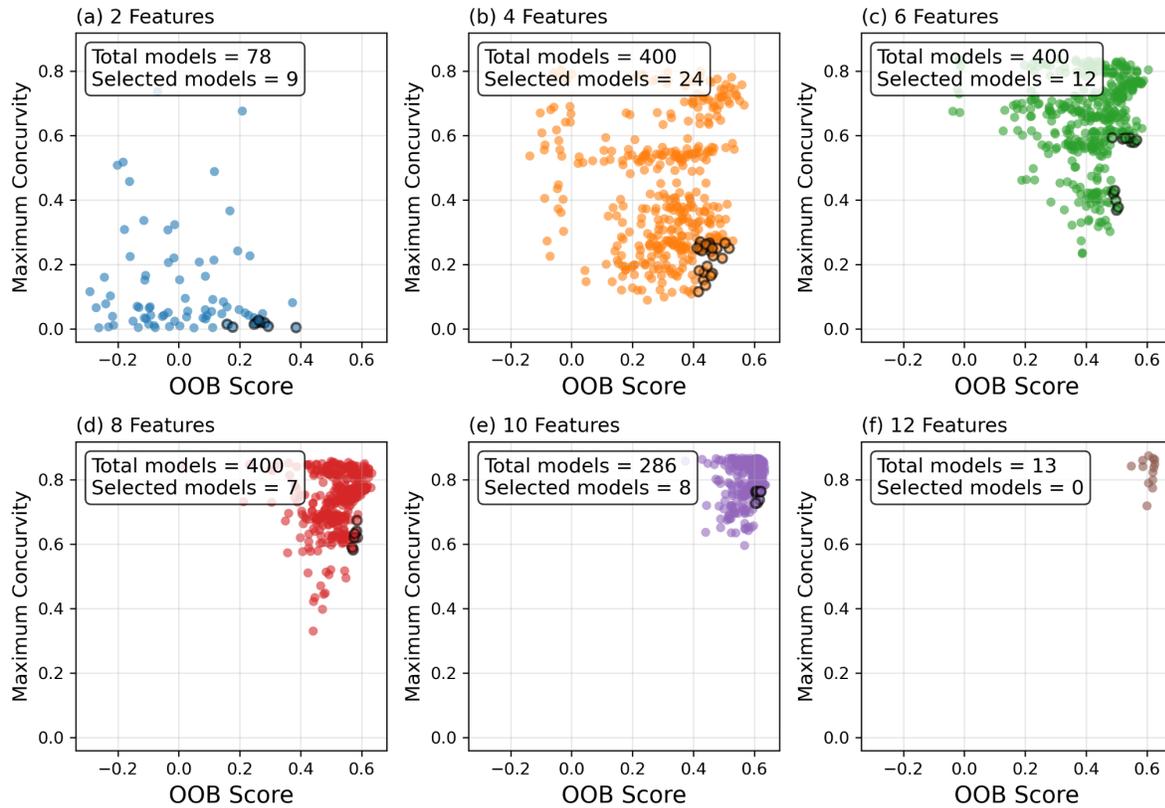
5 **Supplementary figures**



6

7 Figure S1: Illustration for extreme identification, using wet extreme detection as an example. The  
8 last pre-extreme day for extreme is defined as the last day on which soil moisture remained below  
9 a 75% threshold. The threshold is the higher soil moisture values between overall threshold and  
10 seasonal threshold.

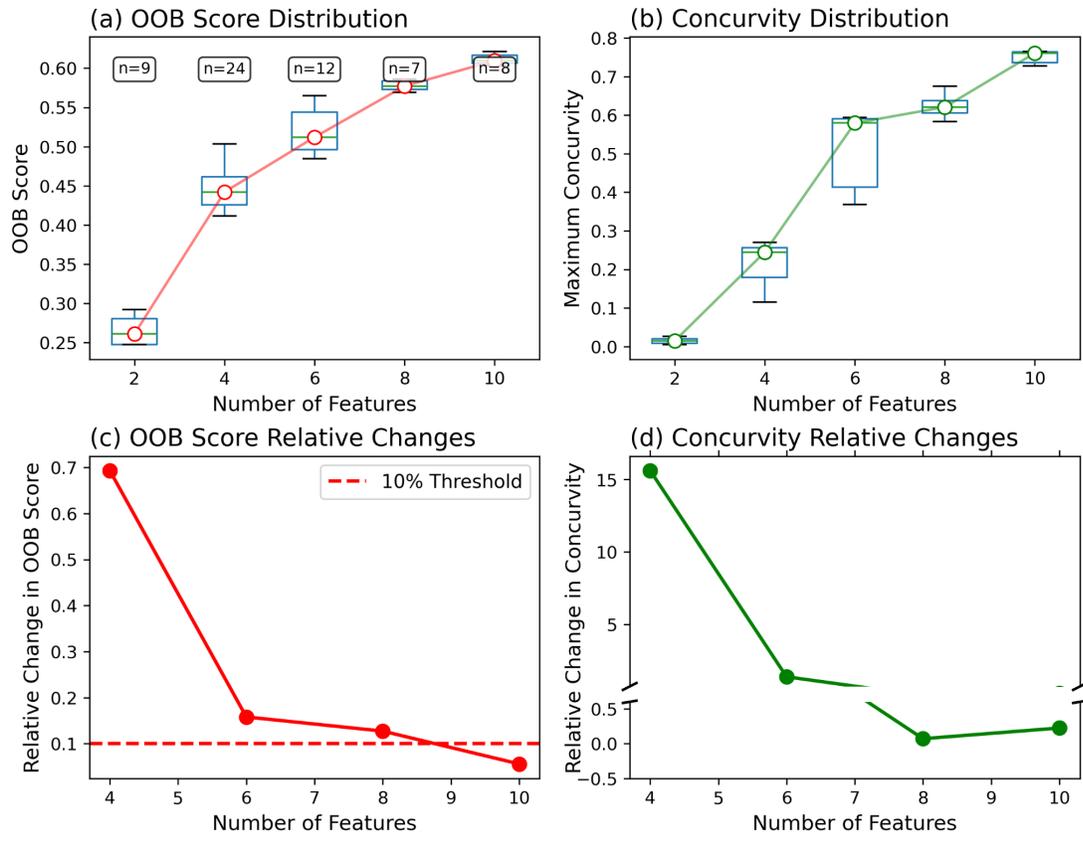
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13 Figure S2: Out-of-bag (OOB) score and maximum concurrency of Random Forest models with  
 14 varying numbers of predictor variables.

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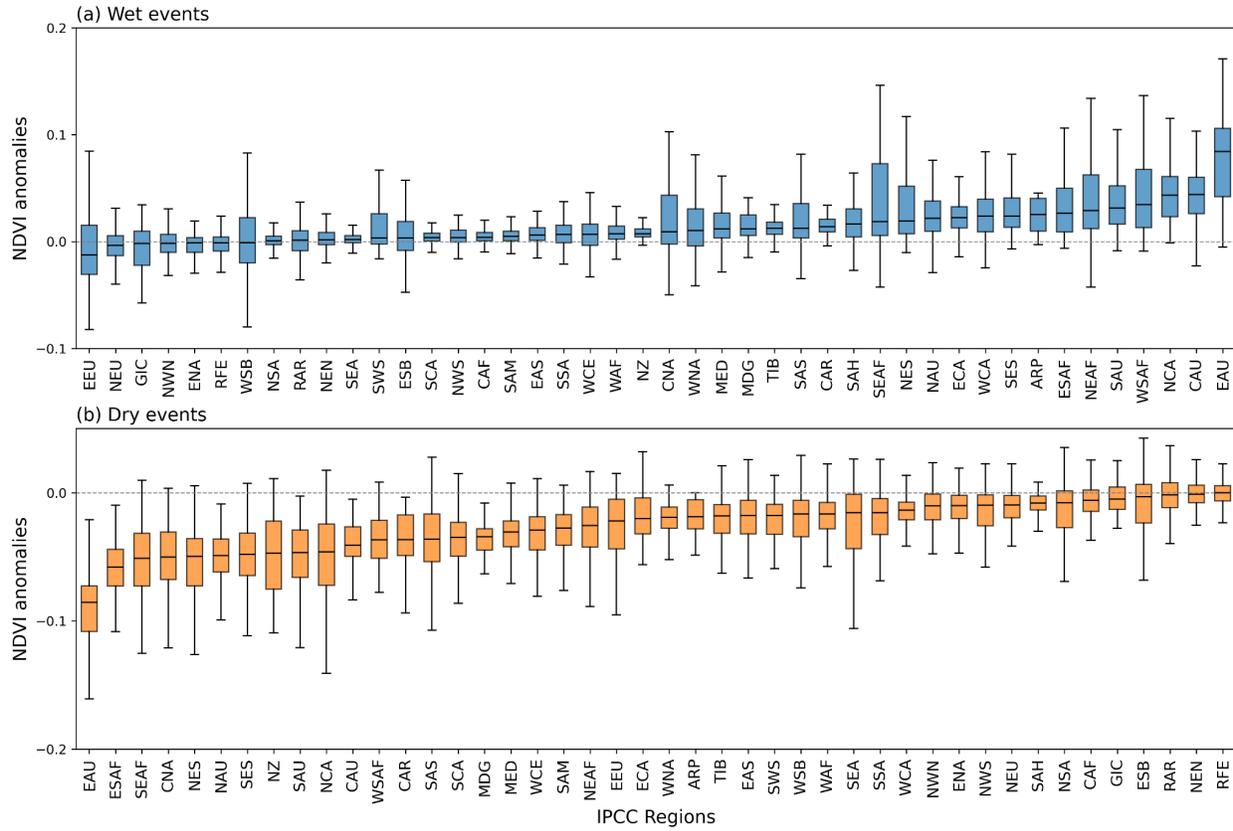


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17 Figure S3: OOB score and maximum concavity distributions across categories with varying  
 18 numbers of predictor variables (a-b), and their relative changes with additional variables (c-d).



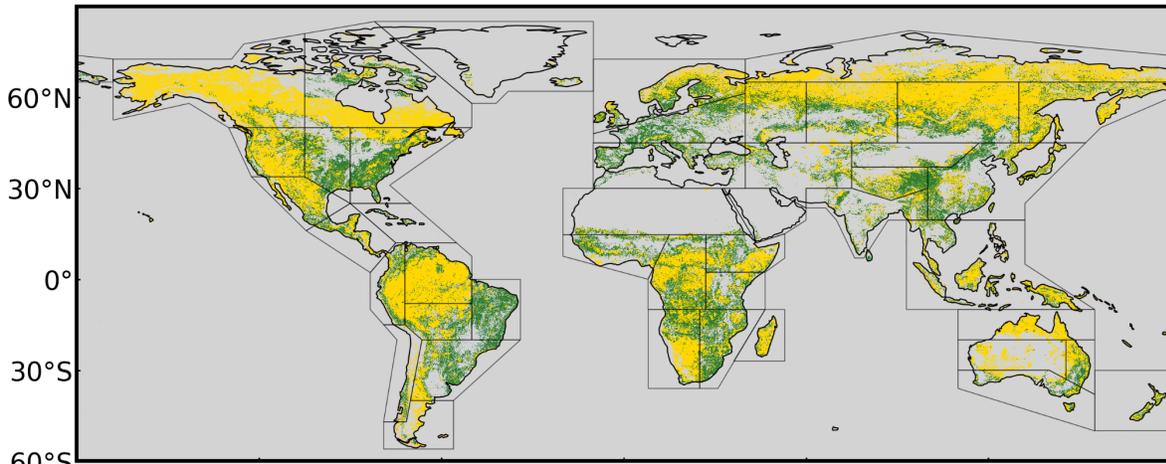




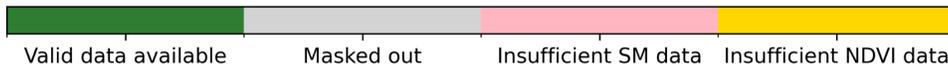
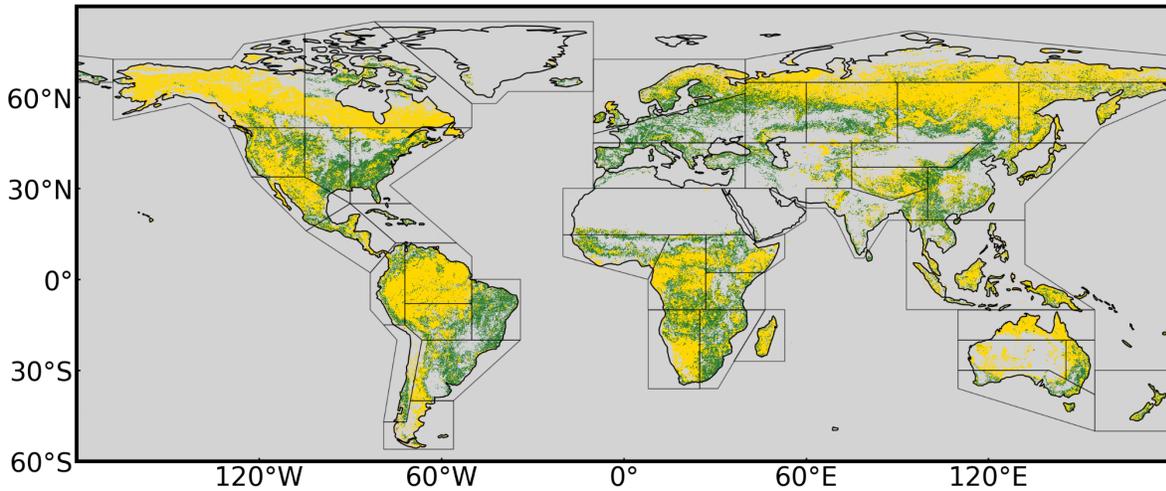
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Figure S6: NDVI anomalies during extremes in each IPCC region. The regions are ranked according to the median NDVI anomalies.

(a) Data availability flags for wet extremes



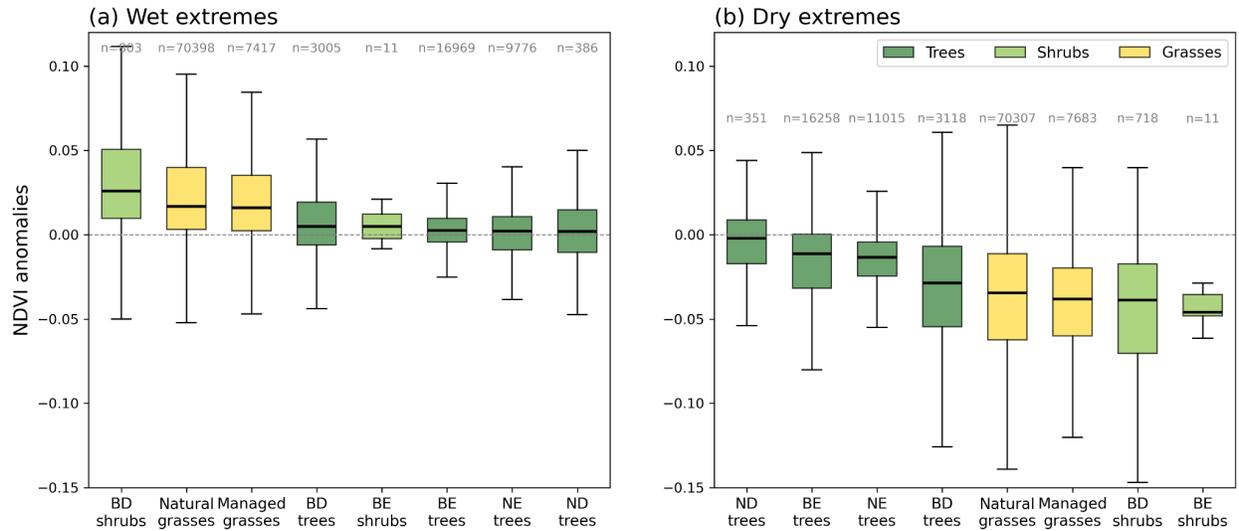
(b) Data availability flags for dry extremes



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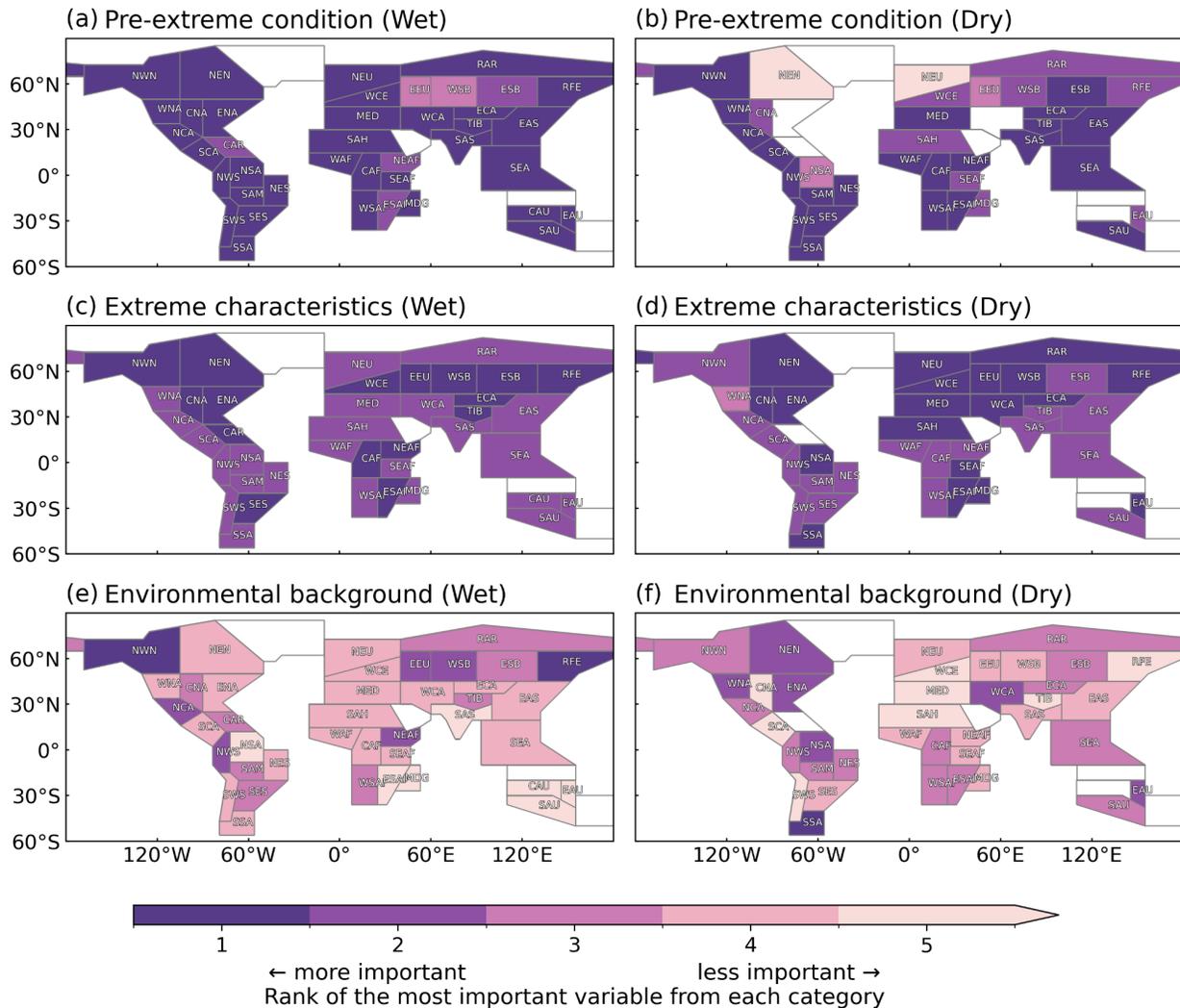
35 Figure S7: Dominant case of identified extremes in each grid cell, showing the most common

36 condition across all events.

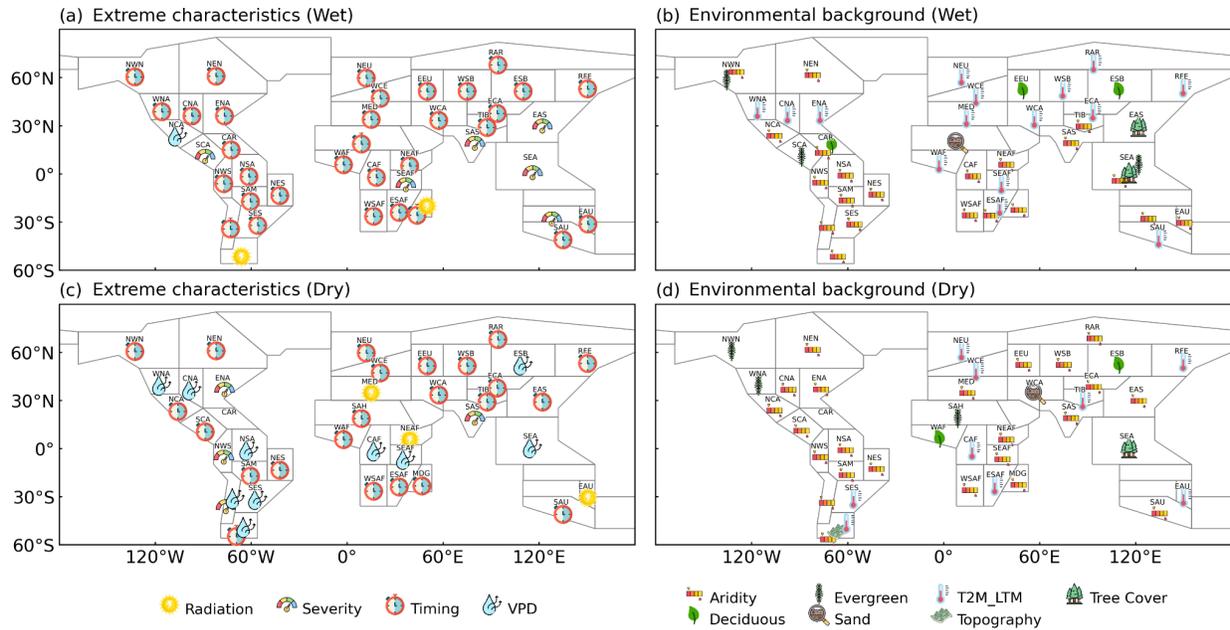


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38 Figure S8: Average NDVI anomalies during (a) wet extremes and (b) dry extremes in different  
 39 plant functional types. The dominant plant functional types are used to represent the major plant  
 40 type in each grid cell and only grid cells with the majority larger than 50% are included in the  
 41 boxplot. B is short for broadleaf, N is short for needleleaf, D is short for deciduous and E is short  
 42 for evergreen. n indicates the number of grid cells in each category.



43  
 44 Figure S9: Relevance of pre-extreme vegetation condition, extreme characteristics and  
 45 environmental background for negative vegetation responses to (a,c,e) wet and (b,d,f) dry events.  
 46 Relevance is expressed as the rank of the most important variable for explaining vegetation  
 47 greenness anomalies during extremes from each category. The top variables are ranked across  
 48 categories. Note that each category contains a different number of variables and the attribution is  
 49 based on extremes with both positive and negative NDVI anomalies (see Data and Methods 2.3).  
 50



51  
 52 Figure S10: Most relevant variables for both negative and positive vegetation responses during  
 53 wet (a,b) and dry (c,d) extremes in terms of extreme characteristics and environmental  
 54 background. Multiple variables are shown in case their relevance is the same according to the  
 55 ranking. Note that the results here are based on all extremes with both negative or positive NDVI  
 56 anomalies.

57  
 58 **Supplementary texts**

59 **Text T1. Predictor variable selection and importance ranking**

60 As an example, we illustrate our attribution analysis using the identification of dominant  
 61 variables associated with NDVI loss during wet extremes in Eastern Europe (EEU).

62 Random subsets of predictor variables (from the 13 candidates) were used to build  
 63 Random Forest (RF) models. For each model, we recorded the out-of-bag (OOB) score and the  
 64 maximum concurrency among predictors. The relationship between OOB score and concurrency was  
 65 visualized for each category (Figure S2). Models with relatively high predictive performance (OOB  
 66 score > 70th percentile) and low multicollinearity (concurrency < 30th percentile) were highlighted  
 67 with black-edged dots and retained for determining the optimal number of predictors (Figure S3a-  
 68 b). The optimal number was defined as the point where adding more predictors increased the  
 69 OOB score by less than 10% (Figure S3c).

70 The corresponding models (black-edged dots in Figure S2 with the optimal number of  
 71 predictors, in this case, the optimal number of predictors is 8) were then used for variable  
 72 importance ranking. For all retained models, we identified the variables that ranked in the top half

73 by permutation importance and calculated the frequency that they were ranked top half, which  
74 was used as an indicator of variable importance.

75 The average OOB score and concavity of the models chosen according to our algorithm  
76 for each IPCC climate reference region were shown in [Figure S4](#) and [S5](#).

#### 77 **Text T2. Filter for considered extremes**

78 To ensure data reliability, we applied a quality filter to the identified extremes. Although  
79 gaps exist in the NDVI dataset, we did not perform gap filling to preserve the observational  
80 vegetation signals. Instead, we verified that NDVI observations during each extreme were  
81 sufficiently representative. For each extreme, we defined a 40-day window centered on the  
82 extreme peak and divided it into three equal periods. An extreme was retained only if NDVI data  
83 were available for more than one-third of the days in each of the three periods. This approach  
84 ensured that the NDVI observations captured the developing, peak, and recovery phases of each  
85 extreme without involving artificial signals.