Earth's Future

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Key Points:
- We aim to assess whether the probability of flood losses occurring can be estimated by indices of atmospheric oscillations in Europe
- We show that the probability of flood losses occurring can change by 100% depending on the phase of the index of the atmospheric oscillation
- Some of the flood losses can be predicted one season ahead because a lagged relationship may exist between the variables investigated

Supporting Information:
- Supporting Information S1

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What Will the Weather Do? Forecasting Flood Losses Based on Oscillation Indices

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Abstract Atmospheric oscillations are known to drive the large-scale variability of hydrometeorological extremes in Europe, which can trigger flood events and losses. However, to date there are no studies that have assessed the combined influence of different large-scale atmospheric oscillations on the probabilities of flood losses occurring. Therefore, in this study we examine the relationship between five indices of atmospheric oscillation and four classes of flood losses probabilities at subregional European scales. In doing so, we examine different combinations of atmospheric oscillations, both synchronous and seasonally lagged. By applying logistic regressions, we aim to identify regions and seasons where probabilities of flood losses occurring can be estimated by indices of atmospheric oscillation with higher skill than historical probabilities. We show that classes of flood losses can be predicted by synchronous indices of atmospheric oscillation and that in some seasons and regions lagged relationships may exist between the indices of atmospheric oscillation and the probability of flood losses. Furthermore, we find that some models generate increased (or decreased) probability of flood losses occurring when the indices are at their extreme positive or negative phases. A better understanding of the effects of atmospheric oscillations on the likelihood of flood losses occurring represents a step forward in achieving flood resilience in Europe. For instance, improved early predictions of the indices that represent such atmospheric oscillations, or the evidence of a lagged relationship between their teleconnections and floods, can significantly contribute to mitigating the socioeconomic burden of floods.

Plain Language Summary From season to season or year to year, the climate in Europe varies. Some years we see above (or below) average rainfall and river flows in different locations, resulting from atmospheric and oceanic circulations. Every year, such variability in the climate can cause extreme events such as flooding, which accounts for high economic losses in Europe. The impact of flooding can be reduced when reliable risk information is available to steer preventative risk reduction measures. However, to date, we have a limited understanding of the links between atmospheric oscillations and the impacts of floods. Therefore, we examine the relationship between multiple indices of atmospheric oscillations and flood losses. We show that the indices of atmospheric oscillations have links with flood losses in several seasons and that some of the flood losses can be predicted one season ahead. The results provide a better understanding of the combined effect of atmospheric oscillation on flood losses and show how impact-based information can be used to improve flood risk management practices.

1. Introduction

Globally, floods are the most frequent form of weather-related disaster (Emerton et al., 2016). The impact of floods can be reduced when reliable forecasted risk information is available. Currently, in Europe, there are two operational continental-scale flood forecasting systems: the European Flood Awareness System (EFAS) of the European Commission (Smith et al., 2016) and the European Hydrological Predictions for the Environment (E-HYPE) model of the Swedish Meteorological and Hydrological Institute (Lindström et al., 2010). While these systems have greatly improved our capability of forecasting hydrometeorological variables by producing predictions of flood magnitudes with increasing lead times (Emerton et al., 2016), there is still a gap in translating flood events into impact information, such as the economic damage of floods (Dottori et al., 2017). For instance, in Europe, while EFAS provides streamflow forecasts with a 7-month lead time (Arnal et al., 2018), flood impact forecasts are only available through this system with a lead time up to 10 days (Dottori et al., 2017). If impact-based forecasting information was available through such climate services at seasonal lead times, this could offer a great window of opportunity for implementing early action and risk transfer mechanisms (Michel-Kerjan & Kunreuther, 2011) to address emerging flood risks.

Flood impact forecasts can be produced using methods with different levels of complexity, ranging from models that combine hydrological and hydrodynamic processes with information on exposure and vulnerability to empirical models that use statistical models to derive relationships between weather variables and observed flood impacts (Carisi et al., 2018; Devia et al., 2015). Statistical models may neglect or simplify some of the underlying physical and socioeconomic processes, assuming that past interactions between various drivers of risk may propagate similarly in the future. However, such models can be useful in practice because they are simple and can provide a first rapid estimation of the impacts of flooding. Moreover, the chain of models connecting oscillations-precipitation-discharge-losses also introduces modeling errors and forecast biases, which may diminish the estimated value of the forecast (Giuliani et al., 2019).

Another potential way to forecast flood impacts is to develop forecasts based on large-scale atmospheric oscillations, such as the El Niño Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO). It is well known that these drive interannual and seasonal large-scale variability of hydrometeorological extremes (Casanueva et al., 2014; Emerton et al., 2017, 2019; Guimarães Nobre et al., 2017; Sun et al., 2015; Ward et al., 2010). Globally, ENSO is the most dominant mode of interannual climate variability and has been linked with changes in hydrometeorological extremes in past studies at different scales (Emerton et al., 2017; Ionita et al., 2015; Villafuerte et al., 2014; Ward, Eisner, et al., 2014; Ward, Jongman, et al., 2014). The influence of ENSO is relatively weak in the Euro-Atlantic region (Casanueva et al., 2014), where variability is mainly dominated by four northern hemisphere modes of atmospheric oscillations. In Europe, several studies have found relationships between atmospheric oscillations such as the East Atlantic/West Russian pattern (EAWR), the East Atlantic Pattern (EA), the Scandinavian Pattern (SCA), and NAO, and both seasonal precipitation (Álvarez-García et al., 2018; Casanueva et al., 2014; Cusinato et al., 2019; Rios-Cornejo et al., 2015) and river discharge (Bouwer et al., 2008; Markovic & Koch, 2014; Steirou et al., 2019; Struglia et al., 2004).

Only few studies have specifically addressed the direct relationship between these atmospheric oscillations and the socioeconomic impacts of flood disasters. Globally, an initial study assessed links between ENSO and the reported frequency of flood disasters (Dilley & Heyman, 1995). This study was followed by Goddard and Dilley (2005), which analyzed whether phases of ENSO could be linked with an increase in reported climate-related disasters. More recently, flood risk models were used to examine ENSO's relationship with river flood risk in terms of economic damage, exposed population, and gross domestic product at the global scale (Ward, Eisner, et al., 2014; Ward, Jongman, et al., 2014), while Muis et al. (2018) assessed the number of people potentially exposed to global coastal flooding during years in which ENSO extreme phases are observed (Muis et al., 2018). Recent studies have also found connections between NAO and flood losses in Europe (Guimarães Nobre et al., 2017; Zanardo et al., 2019). However, to the best of our knowledge, there is no study that assesses the combined influence of different large-scale atmospheric oscillations on the probability of flood losses occurring.

A better understanding of the effects of (combined) atmospheric oscillations on flood losses would represent a step forward in achieving flood resilience. For instance, ENSO's prediction is used to estimate the seasonal impacts of floods and to trigger early actions and risk transfer mechanisms in Peru, where an El Niño contingent insurance product was developed for the region of Piura to compensate firms for lost profits or extra costs likely to occur as a result of floods (as cited in Coughlan De Perez et al., 2015). In Europe, improved early predictions of the indices of atmospheric oscillations, or the evidence of a lagged relationship between such teleconnections and floods, can significantly contribute to guiding adequate adaptation measures. Therefore, in this study we examine the relationship between five indices of atmospheric oscillation (SOI, NAO, EA, EAWR, and SCA) and four classes of flood losses probabilities at subregional European scales. In doing so, we examine different combinations of atmospheric oscillations, both synchronous and seasonally lagged.

2. Methodology

The methodological framework used in this study involves three main steps (Figure 1). First, from a database of historical flood events recorded by Munich Re between 1980 and 2016 (Munich Re, 2016), we derive time series of classes of flood losses based on four thresholds of seasonal losses at the subregional and seasonal

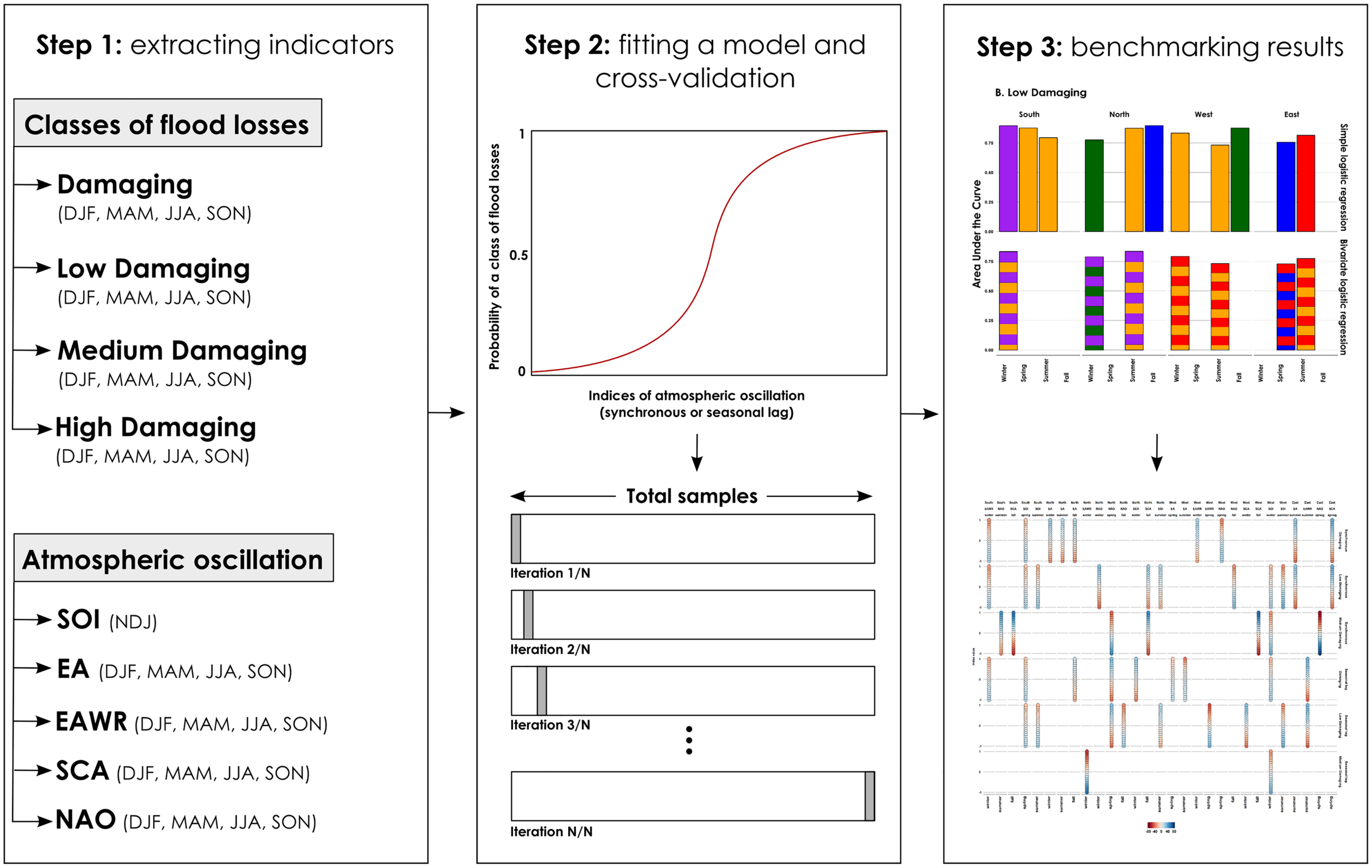

Figure 1. Flowchart representing the methodological framework applied in this study, handled in three steps: (1) extraction of datasets, (2) model fit and cross--validation, (3) benchmarking results.

scales, namely, winter (from December to February), spring (from March to May), summer (from June to August), and autumn (from September to November). For the same period, we obtained 3-month average values for the indices of atmospheric oscillation at the same seasonal scale (Figure 1, step 1). Second, we use logistic regression to estimate the probabilities of classes of flood losses based on five large-scale indices of climate variability: ENSO, NAO, SCA, EA, and EAWR. Logistic regression measures the relationship between the classes of flood losses and the indices of climate variability, by estimating probabilities using a primary logistic function. Subsequently, the results are cross-validated using leave-one-out cross-validation technique (step 2, Figure 1). Third, we benchmark our results against historical probabilities (step 3, Figure 1). The methods and datasets are described in detail in the following subsections.

2.1. Step 1: Extracting Indicators

2.1.1. Extracting Flood Losses Records and Classes

We use the NatCatSERVICE dataset of Munich Re (2016) to derive time-series of direct tangible flood losses. This dataset registers flood events in Europe, and their respective period, timing, location, and damages (in US$) since 1980, and has been widely used in previous studies (e.g., Bischiniotis et al., 2018; Guimarães Nobre et al., 2017; Hoeppe, 2016). We adjust the nominal flood losses value into 2016 US$ values according to the inflation rate obtained from the World Development indicators produced by the World Bank (available at https://data.worldbank.org/indicator/ny.gdp.defl.zs). To calculate seasonal flood losses, we extract the flood onset date and then sort these events into a corresponding season and subregion.

We aggregate seasonal flood losses of 35 countries into four European regions, namely, (1) southern Europe; (2) northern Europe; (3) western Europe; and (4) eastern Europe. The subregions are defined using the classification of the United Nations Statistics Division (see Figure S1 in the supporting information), which was already adopted in a previous study (Guimarães Nobre et al., 2017). We first develop a time-series over the period 1980–2016, showing damages for each season and subregion from the NatCatSERVICE dataset; if no damages are recorded, we insert a value of zero damage. We then convert these to binary time-series showing whether a "Damaging" event occurred in each season and subregion (1) or not (0). Based on this step, we extract the first class of flood losses, namely, "Damaging." In addition, we extract three other binary time-series based on the 33% ("Low Damaging"), 50% ("Medium Damaging"), and 66% ("High Damaging") percentile levels of all events in the NatCatSERVICE database. The seasonal distribution of flood losses is illustrated in Figure S2.

2.1.2. Extracting Indices of Atmospheric Oscillation

In this study, we represent the northern atmospheric oscillations (NAO, EA, EAWR, and SCA) using a 3-month average of their indices from the Climate Prediction Center of the NOAA/National Weather Service (available at http://www.cpc. ncep.noaa.gov). We obtain monthly mean values of these four oscillation indices and derive the 3-month average value from 1979 to 2016 for each season. To represent ENSO, we obtain the standardized Southern Oscillation Index (SOI) records from the same source. We extract 3-month averages of the SOI when this oscillation is strongest, that is, during the boreal winter months (NDJ) (Trenberth, 1997). The time series of the 3-month average values of the five indices of atmospheric oscillations are shown in Figure S3. We test the autocorrelation and cross-correlation of the indices in order to understand the serial correlation and similarity of the two series. This step is required because unacceptably high correlations between predictors may increase errors when performing the logistic regressions (Figures S4 and S5). We observe that the autocorrelation and cross-correlation of the indices of atmospheric oscillation is mostly low, and therefore should not negatively affect the performance of the logistic regressions (see Figure S4).

2.2. Step 2: Fitting a Model and Cross-Validation

2.2.1. Fitting a Model Based on Oscillation Indices

To predict classes of flood losses based on indices of atmospheric oscillation, we fit logistic models to the derived binary time series of flood losses (Damaging, Low Damaging, Medium Damaging, and High Damaging), in which the output of the model indicates whether the indices of atmospheric oscillation are significantly associated with the probability of a certain class of flood losses occurring. The significance of the logistic model is assessed by calculating whether the model with predictors fits significantly better than a model with just an intercept and classified as significant when the p value ≤ 0.1. A p value ≤ 0.1 indicates that there is strong evidence in favor of a relationship between the indices of atmospheric oscillation and classes of flood losses and therefore is used for rejecting the null hypothesis of no association. We use two types of logistic models at two temporal scales: (i) synchronous season, in which we fit a logistic model over a class of flood losses using indices of atmospheric oscillations from the same season (equations 1a and 1b); and (ii) previous season, in which we fit a logistic model over a class of flood losses using indices of atmospheric oscillations from the previous season. We use different logistic regressions, named (a) simple logistic regression (equation 1a) and (b) bivariate logistic regression (equation 1b). By applying different types of regression, we aim to identify regions and seasons where the predictions of flood losses can be improved by a combination of different indices of atmospheric oscillation. Such a multivariate approach was suggested and adopted in previous studies (Bouwer et al., 2008; Giuliani et al., 2019; Guimarães Nobre et al., 2017; Heino et al., 2018). We limit the assessment to a maximum of two pairs of indices of atmospheric oscillation per equation in order to avoid overfitting the relatively small samples of flood losses. For instance, when examining the influence of the indices of atmospheric oscillation I_1 and I_2, the probability of a given class of flood losses (p_F) is estimated as follows:

$$p_{F,s,r} = \frac{1}{1 + \exp(-\beta_1 \times I_1 + \beta_0)}, \quad p_{F,s,r} = \frac{1}{1 + \exp(-\beta_2 \times I_2 + \beta_0)}, \tag{1a}$$

$$p_{F,s,r} = \frac{1}{1 + \exp(-\beta_2 \times I_2 - \beta_1 \times I_1 + \beta_0)}, \tag{1b}$$

Table 1
Combination of Indices of Atmospheric Oscillations Used in Each Logistic Regression Model

Models	1	2	3	4	5	6	7	8	9	10
Simple regression	EA	EAWR	NAO	SCA	SOI					
Bivariate Regression	EA and EAWR	EA and NAO	EA and SCA	EA and SOI	EAWR and NAO	EAWR and SCA	EAWR and SOI	NAO and SCA	NAO and SOI	SCA and SOI

where p_F represents the probability of a class of flood loss (Damaging, Low Damaging, Medium Damaging, or High Damaging) for a given season (s) and subregion (r). β_0 is the log-odds when the predictors are equal to zero, and β_1 and β_2 measure the effect of the independent variables I_1 and I_2, respectively. Since we establish a maximum of two different indices of atmospheric oscillation per model, we fit a logistic regression with the following combination of independent variables (Table 1).

2.2.2. Cross-Validating Models

For each regression fitted over N samples in which the p value is $\leq$0.1, we test the predictive skill of the regression models using leave-one-out cross-validation to calculate the Area Under the Curve (AUC) index. The leave-one-out cross-validation is suitable to validate models obtained from small sample sizes (James et al., 2013), and the AUC measures how well the logistic regression can distinguish binary classes (Metz, 1978). The AUC index is calculated assessing the true positive rate against the false positive rate, where the higher the AUC, the better the model is at distinguishing a binary class. The AUC values can vary between 0 and 1, and predictions that are randomly drawn are presumed to provide an AUC = 0.5. For each season and subregion, we calculate the AUC of the cross-validated models by comparing the flood losses observations to the predicted values. We carry out the leave-one-out cross-validation as follows:

1. Fit a logistic model to N-1 samples of the flood losses for each season and region.
2. Predict whether the class of flood losses is 0 or 1 for the test sample.
3. Repeat step 1 N times.
4. Compare the binary class of flood losses observations to the predictions.
5. Calculate the AUC index and select models with AUC > 0.5.

2.3. Step 3: Benchmarking Results Against Historical Probabilities

The logistic models presented above can be used for estimating the probability of classes of flood losses based on indices of the atmospheric oscillations when they are statistically significant and have predictive skill. Therefore, we estimate the probabilities of classes of flood losses occurring when the indices of atmospheric oscillations are at their positive ($1 \geq I > 0$) and negative ($-1 \leq I < 0$) phases. Subsequently, we assess the increase or decrease in the probability of a given class of flood loss occurring in comparison to a historical probability. For example, the historical probability p_H of a Medium Damaging flood in season s and subregion r is approximately 41%, because there are 15 flood events above the threshold for Medium Damaging (percentile 50%) out of 37 seasons. When the probability obtained from the logistic model (based on a certain index of atmospheric oscillation) is higher than the historical probability, we calculate the percentage increase compared to the historical value, and we calculate the percentage decrease when the probability obtained from the logistic model is lower than the historical probability.

3. Results and Discussion

In this section, we firstly describe the performance of indices of atmospheric oscillations in predicting classes of flood losses both synchronously (section 3.1) and seasonally lagged (section 3.2), followed by the outcomes of a benchmarking analysis in light of previous literature in section 3.3. Subsequently, in section 3.4, we discuss the implications and limitations of our study.

3.1. Probability of Classes of Flood Losses Based on Synchronous Oscillation Indices

In Table 2, we show the descriptive statistics for all logistic models (simple and bivariate regression) that are found to have skill to predict classes of flood losses based on synchronous indices of atmospheric oscillation. We find that in total, 15, 15, and seven simple logistic models have skill in predicting classes of Damaging, Low Damaging, and Medium Damaging floods, respectively (out of 80 candidate models per class, i.e., five

Table 2
Descriptive Statistics for Models Based on Synchronous Oscillation Indices with AUC > 0.5

		Damaging	Low Damaging	Medium Damaging
Simple logistic	Number of models with AUC > 0.5	15	15	7
	Mean AUC	0.86	0.80	0.56
	Minimum AUC	0.62	0.62	0.54
	Maximum AUC	1	0.90	0.60
Bivariate logistic	Number of models with AUC > 0.5	37	25	10
	Mean AUC	0.82	0.72	0.54
	Minimum AUC	0.62	0.60	0.52
	Maximum AUC	0.98	0.86	0.57

indices, four seasons, and four regions) (Table 2). Furthermore, we find that in total, 37, 25, and 10 bivariate logistic models have skill in predicting classes of Damaging, Low Damaging, and Medium Damaging floods, respectively (out of 160 candidate models per class, i.e., 10 combination of indices, four seasons, and four regions). Both simple and bivariate logistic regressions are unable to classify cases of High Damaging floods based on synchronous oscillation indices. On average, higher AUC values are observed for models derived using simple logistic regression, especially for classifying cases of Damaging versus non-Damaging flood events. On average, the lowest AUC values are found for models derived using bivariate logistic regression to classify cases of Medium Damaging versus non-Low Damaging flood events.

In Figure 2, we display the indices of atmospheric oscillation whose logistic model maximizes the predictions of classes of Damaging (Figure 2a), Low Damaging (Figure 2b), and Medium Damaging (Figure 2c) floods per subregion and season. When a subregion and season has multiple models with predictive skill, we display the model with the highest AUC value. In Figure 2a, we observe that the indicator most frequently used for predicting Damaging flood events is the EA, with the SOI being the most frequent indicator for predicting Low Damaging flood events (Figure 2b), especially in summer seasons in southern, western, and northern Europe. The combination of EA and SOI is the most frequently used by the bivariate logistic regressions, also in summer. For predicting Medium Damaging flood events, the SCA index is the most used by both simple and bivariate regressions, especially in fall in both southern and western Europe (Figure 2c).

3.2. Seasonal Forecasting of Flood Losses Based on Oscillation Indices

In Table 3, we show the descriptive statistics for all logistic models (simple and bivariate regression) that are found to have skill in predicting classes of flood losses based on indices of atmospheric oscillation from the antecedent season. We find that in total, 10, 10 and two simple logistic models have skill in predicting classes of Damaging, Low Damaging, and Medium Damaging floods, respectively. Furthermore, we find that 17, 18, and nine bivariate logistic models have skill in predicting classes of Damaging, Low Damaging, and Medium Damaging floods, respectively. Similar to the results for the synchronous oscillations, both simple and bivariate logistic regressions are unable to classify cases of High Damaging floods based on indices from the antecedent season. On average, higher AUC values are observed for models derived using simple logistic regression compared to bivariate models. The lowest AUC values are attributed to bivariate models applied to Medium Damaging events, for which such a classification task becomes more challenging given the reduced number of flood events that fall above the 50% quantile.

In Figure 3, we display the indices of atmospheric oscillation that maximize the classification of Damaging (Figure 3a), Low Damaging (Figure 3b), and Medium Damaging (Figure 3c) floods per subregion and season, here based on a seasonal lag relationship between atmospheric oscillation and classes of flood losses. When interpreting the results from models derived using seasonally lagged relationships, one should notice that we assess the predictive skill of the antecedent season atmospheric oscillation in predicting classes of current season classes of flood losses. For instance, EAWR (in fall) has predictive skill to forecast classes of Damaging versus non-Damaging floods in southern Europe in winter. In terms of frequency, the SOI, the NAO, and EAWR indices are the most often used for classifying Low Damaging flood events (Figure 3b). In winter, for classifying Medium Damaging flood events in northern and western Europe, the EAWR (in fall) and SOI are most commonly used, respectively. Bivariate models using a combination of SCA and SOI in fall and spring are also found to produce skillful predictions of Medium Damaging floods in winter and summer in western Europe.

3.3. Benchmarking Results

In Figure 4, we display the percentage increase and decrease in the probability of classes of flood losses (compared to historical probabilities) of Damaging, Low Damaging, and Medium Damaging flood events based on predictions of simple logistic regressions (synchronous and seasonally lagged). Empty boxes in Figure 4 represent a season and subregion where a model with predictive skill could not be obtained.

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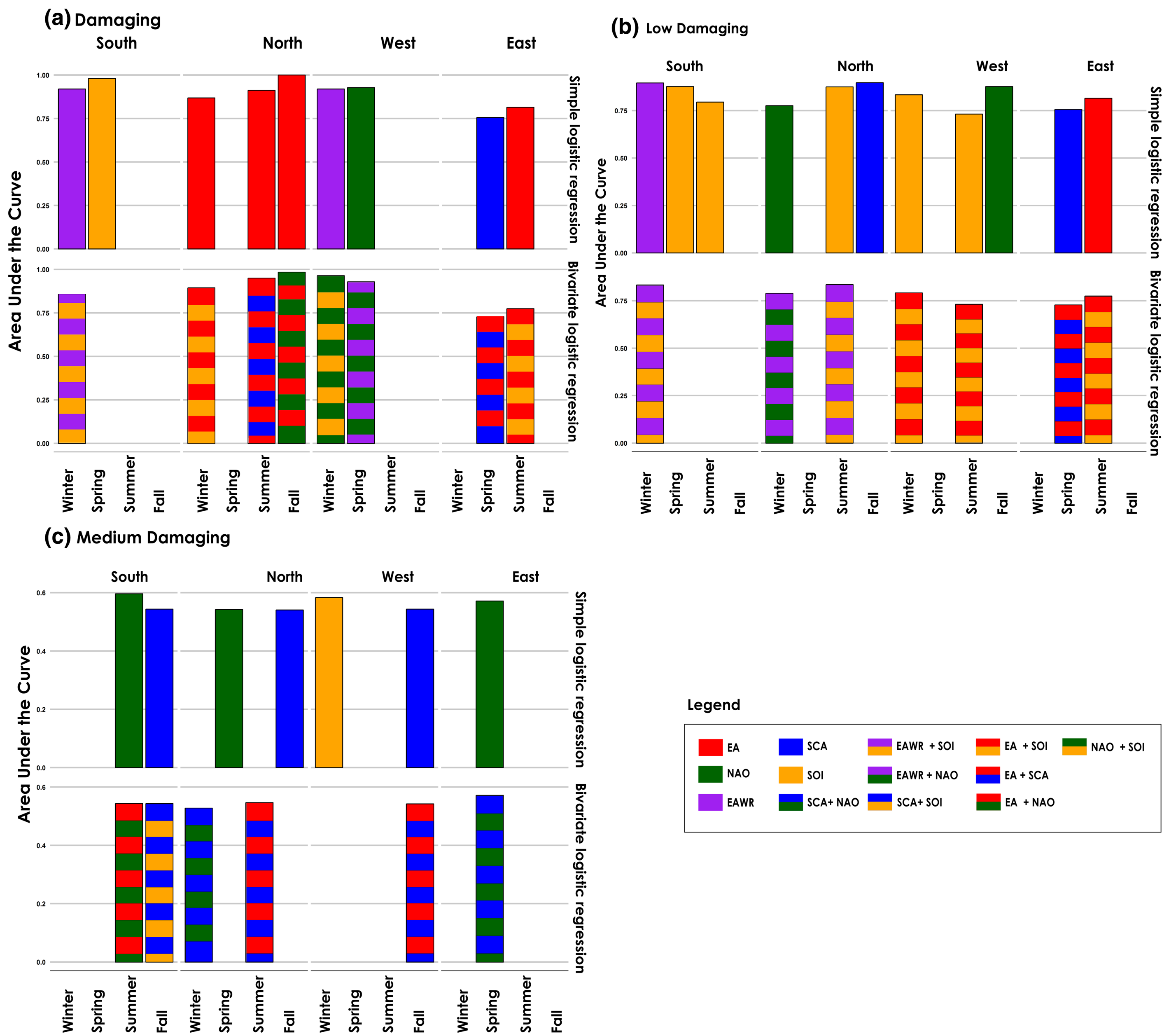

Figure 2. Best performing indices of atmospheric oscillation that maximize the predictions of classes of (a) Damaging, (b) Low Damaging, and (c) Medium Damaging floods per subregion and season based on simple and bivariate logistic regressions.

We observe that the probability of classes of flood losses may increase or decrease depending on the phase of the index of the atmospheric oscillations. For instance, we find that the negative (positive) phases of the best performing indices are often related to an increase (decrease) in the probability of Damaging and Low Damaging floods in comparison to the historical probability in southern and western Europe (Figure 4). The opposite is the case in northern and eastern Europe. Moreover, we find negative phases of NAO to be associated with an increased probability of Medium Damaging floods in northern and eastern Europe in spring, whereas positive phases of the SCA be associated with an increased probability of Medium Damaging floods in southern, northern, and western Europe in fall. Synchronous NAO (in spring) and SCA indices (in fall) are associated with large changes in the probability of Medium Damaging floods. In addition, we find that most of the models generate increased probability of flood losses when the indices

Table 3
Descriptive Statistics for Models Based on Previous Season Oscillation Indices with AUC > 0.5

		Damaging	Low Damaging	Medium Damaging
Simple logistic	Number of models with AUC > 0.5	10	10	2
	Mean AUC	0.94	0.82	0.56
	Minimum AUC	0.83	0.71	0.53
	Maximum AUC	1	0.88	0.58
Bivariate logistic	Number of models with AUC > 0.5	17	18	9
	Mean AUC	0.88	0.75	0.54
	Minimum AUC	0.71	0.67	0.52
	Maximum AUC	0.99	0.88	0.58

are at their extreme positive and negative phases. We display the 90% confidence interval of the probabilities of classes of flood losses in Figures S6–S11.

In Figure 5, we display the percentage increase and decrease in the probability of classes of flood losses (compared to historical probabilities) of Damaging, Low Damaging, and Medium Damaging flood events based on predictions of bivariate logistic regressions. Similar to the results for the simple logistic models, empty boxes in Figure 5 represent a season and subregion for which a model with predictive skill was not obtained. In comparison to simple logistic regressions, we find that most bivariate models produce increased or decreased probability of flood losses when a pair of indices are found to be in phase (e.g., pair is simultaneously at their extreme positive and negative phases). For instance, synchronous relationships between SCA and NAO, EA and SCA, and seasonally lagged relationships between SCA and SOI, yield large changes in the probability of Medium Damaging floods. However, for some models, the maximum differences in probabilities occur when the indices of atmospheric oscillations are with signals out-of-phase (i.e., only one index is at its extreme positive or negative phase).

In Southern Europe, we find that negative (positive) phases of the synchronous EAWR (in winter) and SOI (spring to summer) are related to an increase (decrease) in the probability of Damaging and Low Damaging Flood events, respectively (Figure 4), whereas positive (negative) phases of the NAO in summer and SCA in fall are related to an increase (decrease) in the probability of Medium Damaging flood events (Figure 4). In comparison with previous studies, negative EAWR in winter and negative SOI in summer, and positive phases of NAO in summer and SCA in fall, have been linked with wetter conditions in southern European regions (Casanueva et al., 2014; Ionita, 2014; Mariotti et al., 2002; Shaman, 2014), which may lead to higher chances of flood events and damages. Furthermore, we find that predictions using the combined extreme phases of the oscillation indices can yield an improvement in the estimation of the probability of flood events in southern Europe. For instance, the probability of Low Damaging flood events in southern Europe during winter months can increase when negative EAWR (EAWR = −1) and positive SOI (SOI = +1) are combined and synchronous (92%) relative to probabilities obtained from a simple logistic regression using only EAWR (EAWR = −1; 81%). In a similar fashion, the probability of Medium Damaging flood events in southern Europe during summer months is higher when positive NAO (NAO = +1) and negative EA (EA = −1) are synchronous (82%) relative to probabilities obtained from a simple logistic regression using NAO only (NAO = +1; 70%). We observe major increases/decreases in the probability of Medium Damaging floods (in summer and fall) in southern Europe associated with NAO, SCA, and SOI, while these differences are moderate for Damaging and Low Damaging floods.

In northern Europe, positive phases of the EA, NAO, SOI, and SCA are related to an increase in the probability of Damaging and Low Damaging flood events in different seasons. A lag-relationship may exist between positive phases of NAO (winter), EA (in summer), and SCA (in fall) and an increase in the probability of Damaging flood events in their subsequent seasons. Furthermore, positive NAO (in winter) and negative phases of NAO (in summer) and EAWR (in fall) are related to an increase in the probability of Low and Medium Damaging flood events. In northern Europe, during winter months rainfall variability is strongly modulated by the NAO and the EA, in which their positive phases are linked to higher than average and more intense extreme rainfall in the United Kingdom, Ireland, and in the Scandinavian countries (Casanueva et al., 2014; Guimarães Nobre et al., 2017). In addition, the combination of positive SOI and

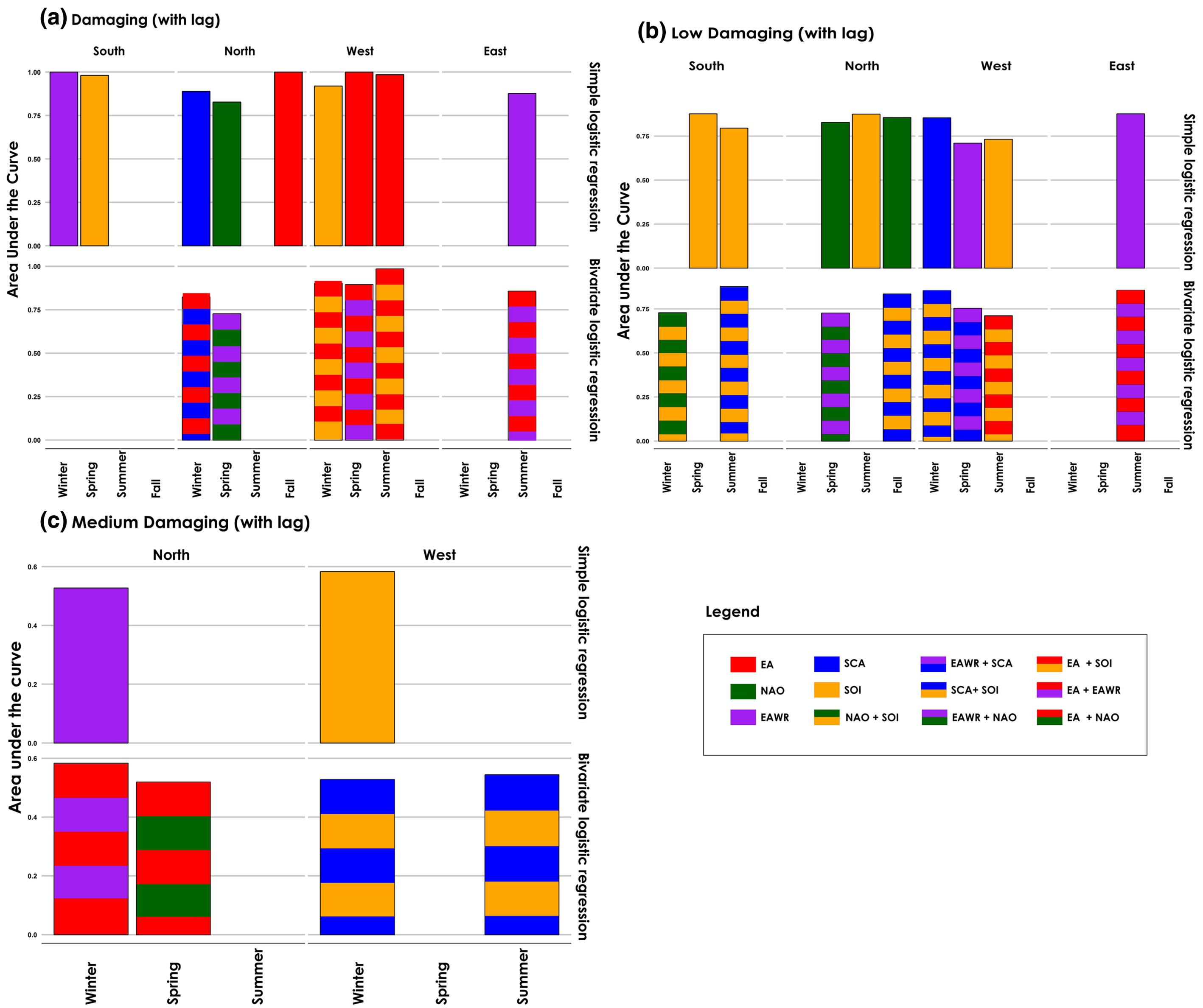

Figure 3. Best performing indices of atmospheric oscillation that maximize the predictions of classes of (a) Damaging, (b) Low Damaging, and (c) Medium Damaging floods per subregion and season based on simple and bivariate logistic regressions. Results are based on indices of atmospheric oscillation from antecedent season.

negative NAO has previously been linked with increased precipitation and high peak discharges in northern European regions in summer (Shaman, 2014; Zanardo et al., 2019), whereas negative EAWR is related to wetter autumns in the latter regions (Casanueva et al., 2014). Similarly, we also observe that the likelihood of Low Damaging floods may increase when indices of atmospheric oscillations are at their extreme phases, which indicates that some of the oscillations may intensify each other influence on flood damages. For instance, the chance of a Low Damaging event increases from 80% (NAO = +1) to 89% when positive NAO is synchronous with positive EAWR (NAO = +1; EAWR = +1). The study of Krichak et al. (2002) also found links between positive phases of NAO and EAWR and increased precipitation during winter in parts of northern Europe. We observe the largest differences in the probability of Medium Damaging floods in northern Europe in connection with NAO, SCA, and EA. These differences are moderate to low for models predicting classes of Damaging and Low Damaging floods. The NAO signal in winter and spring/summer is associated with different outcomes regarding the likelihood of flood losses.

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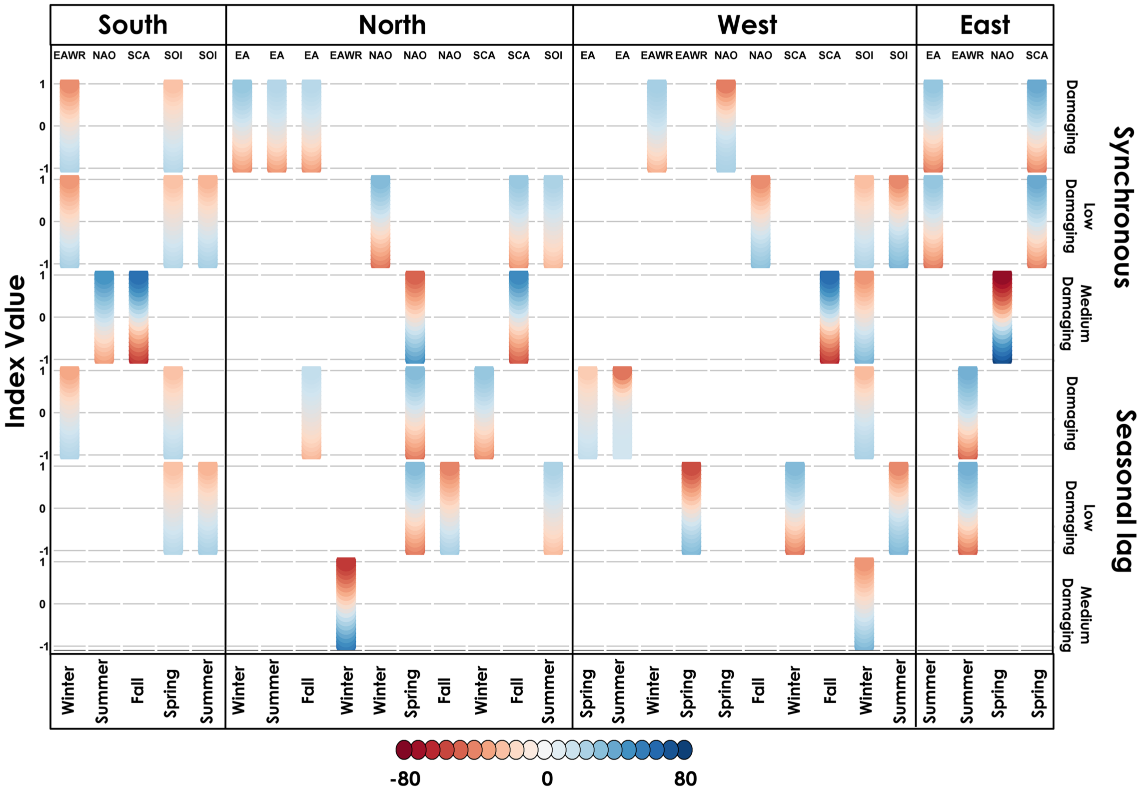

Figure 4. Increase and decrease (in % compared to historical probabilities) in the probability of a Damaging, Low Damaging, and Medium Damaging flood events based on outputs of best performing simple logistic regressions.

The NAO positive phase is associated with an increase in the probability of Low Damaging floods in winter, whereas the NAO negative phase is associated with an increased likelihood of Low and Medium Damaging floods in spring and summer. These differences in signal between winter and summer can be explained by changes in spatial configuration of the NAO pattern (Bladé et al., 2012; Casanueva et al., 2014). Furthermore, Brown (2018) shows that positive NAO is related to a reduction in the likelihood of extreme rainfall from spring to autumn in the United Kingdom, but an increase in winter.

In western Europe, negative phases of SOI and NAO and positive phase of SCA and EAWR are related to an increase in the probability of the three classes of flood losses, whereas a lag-relationship may exist in all seasons. For instance, the positive phase of the SCA (in fall) and negative phase of EA (in winter and spring) and EAWR (in winter) are related to an increase in the probability of Low Damaging flood events. Negative EAWR has previously been associated with wetter winters (Casanueva et al., 2014; Ionita, 2014) in western Europe, whereas little influence has been found with the SOI during winter months (Shaman, 2014). However, in summer, positive SOI has been linked to reduced precipitation over the Netherlands and Germany (Shaman, 2014), and negative SCA has been linked with increased precipitation over southwestern Europe (Casanueva et al., 2014). Furthermore, bivariate models based on both synchronous and seasonally lagged oscillations mostly generate an increased probability of flood classes of flood events when indices are at their extremes. For instance, the chance of a Medium Damaging event in winter increases from 67% (SOI = −1) to 81% when negative SOI interacts with positive SCA in fall (SOI = −1; SCA = +1). Both indices and respective phases have previously been associated with increases in precipitation over large areas in western Europe in fall (Casanueva et al., 2014; Shaman, 2014). We observe major differences in the probability of Medium Damaging floods (in summer) in western Europe associated with SCA and SOI.

In eastern Europe, SCA positive and NAO negative phases in spring and positive EA in summer are linked to an increase in the probability of the three classes of flood losses. Furthermore, we observe a lag relationship between the positive phase of the EA in spring and an increase in the probability of Low Damaging flood

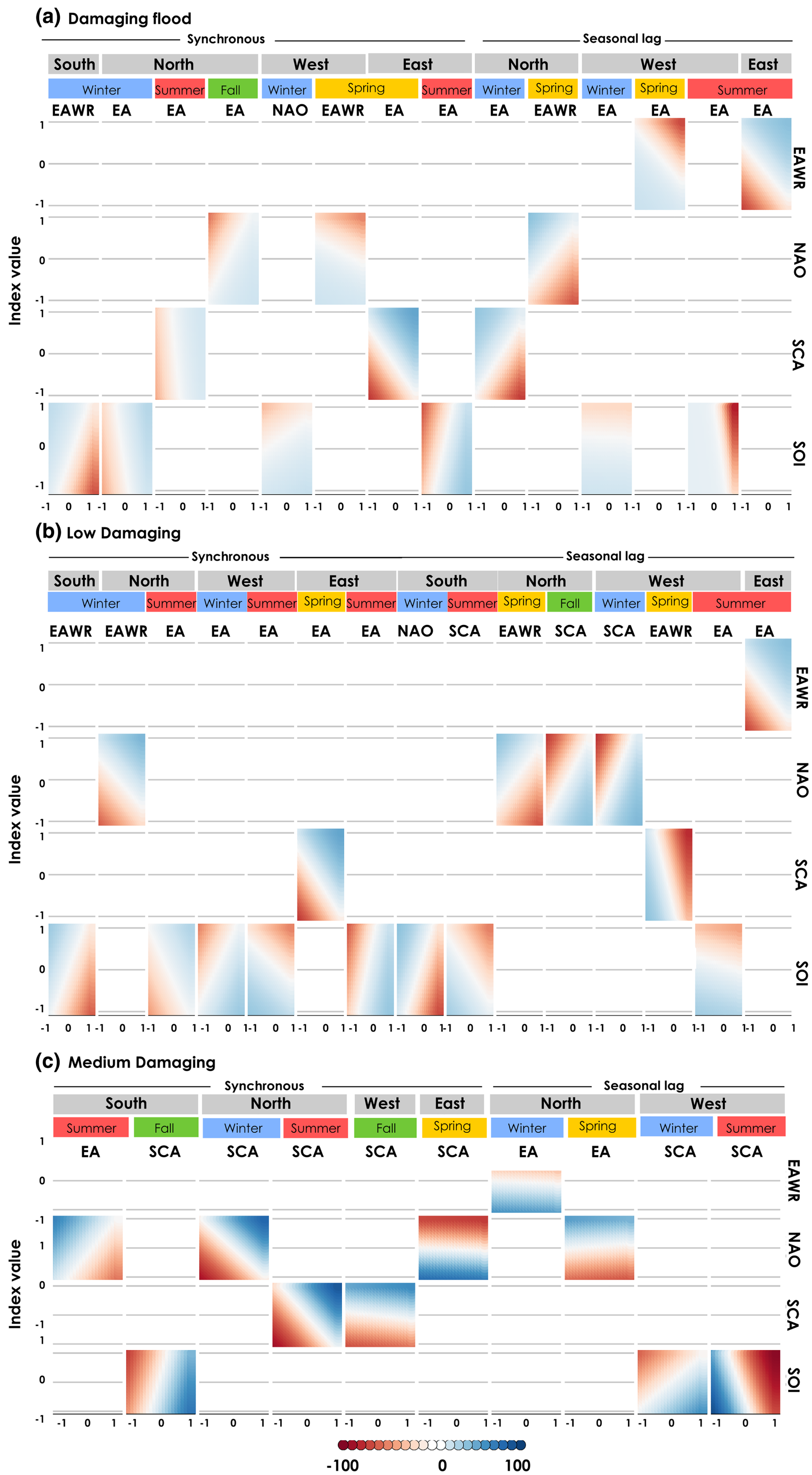

Figure 5. Increase and decrease (in % compared to historical probabilities) in the probability of (a) Damaging, (b) Low Damaging, and (c) Medium Damaging flood events based on outputs of best performing bivariate logistic regressions.

events in summer. In eastern Europe, floods and snowmelt are often observed in spring and summer (Blöschl et al., 2017), and previous studies found significant links between positive EA and more frequent and intense extreme precipitation in scattered areas over eastern European countries in spring (Casanueva et al., 2014; Guimarães Nobre et al., 2017). These conditions may lead to increased soil moisture and discharge in the region, which can increase the likelihood of damaging floods. We find that a seasonal lag relationship may exist between EA and EAWR (in spring) and the probability of Damaging and Low Damaging floods in summer. These indices of atmospheric oscillations, when at their positive phases, may be associated with an increase in the likelihood of Damaging and Low Damaging floods. For instance, the chance of a Low Damaging event in summer increases from 90% (EA = +1) to 96% when positive EA interacts with positive EAWR in spring (EA = +1; EAWR = +1). Lastly, despite the significant relationship between NAO and SCA in winter with Medium Damaging floods in spring, NAO is the main dominant indicator for increasing (decreasing) the likelihood of a Medium Damaging event. A slight increase in the probability of Medium Damaging floods is found when NAO and SCA are at their negative phases. Comas-Bru and McDermott (2014) also found increased and extended winter precipitation in northern and eastern regions when both indices are simultaneously negative. We find major differences in the probability of Medium Damaging floods in eastern Europe in connection with NAO and large changes in the likelihood of Damaging and Low Damaging floods in combination with EA and EAWR.

3.4. Implications and Limitations

The results of this study show that various classes of flood losses have a relationship with synchronous indices of atmospheric oscillation in at least one season in all regions of Europe. Furthermore, we observe that a seasonally lagged relationship exists between the indices of atmospheric oscillation and the classes of flood losses for some regions/seasons. However, there are also many regions and seasons in which we do not find significant relationships, especially in eastern Europe in winter and fall, even though flood protection levels are relatively low (Scussolini et al., 2015). This indicates that large-scale climate variability does not necessarily unfold into flood losses and that this relationship varies depending on the mutual interactions and feedbacks between social and physical systems (Di Baldassarre et al., 2015). This may also indicate that flood losses may be more associated with hydrometeorological changes at the regional-to-local scales, which is not represented by such indices of atmospheric oscillations. Further disconnections may also occur due to limitations in the flood losses datasets themselves, as well as the aggregations that we performed on them.

Moreover, we show that the probability of various classes of flood losses increases or decreases depending on the phase of the index of atmospheric oscillations. In most cases, our models generate an increased (or decreased) probability of flood losses when the indices are at their extreme positive and negative phases. As observed, major floods can be driven by large-scale atmospheric oscillations (Wake, 2013; Ward, Eisner, et al., 2014; Ward, Jongman, et al., 2014), and as result, such flood events may increase the pressure on transnational risk reduction and risk transfer mechanisms (Jongman et al., 2014) due to the high interdependencies of flood hazard across European regions. For instance, we observe that summertime flood losses in western and southern Europe are synchronously linked with the SOI index and that mean flood losses are €1,296 m [25% quantile: €54 m; 75% quantile: €610 m] and €210 m [25%: €0.6 m; 75%: €47 m], respectively, in these regions when the SOI is in its negative phase.

These findings can provide decision makers with information on the average losses of flood events, which could be useful for flood disaster preparedness. For example, the European Union's Solidarity Fund holds €500 m per year to help member states finance disaster losses, and the EU may expect high pay-outs across large regions in Europe, and increased chances of fund depletion, when the SOI is negative. In addition, ex ante information regarding the spatial configuration of risk could support insurance or reinsurance companies to allocate and manage portfolios more efficiently in order to comply with the EU solvency requirements, which demands that (re)insurers have adequate reserves for 99.5% of potential loss events (European Parliament and Council, 2009). Although such disaster financing schemes are vital for sharing the abrupt financial burden of large floods (Jongman et al., 2014), improving flood protection standards may be a cost-effective alternative to reduce the magnitude of flood losses. Furthermore, different types of short-term early actions can be taken to reduce damages, such as evacuation and sand-bagging (Coughlan De Perez et al., 2015). Past studies have found that larger benefits can be yielded by early actions to reduce and avoid disaster impacts in comparison to ex post actions such as emergency response and reconstruction (Coughlan De Perez et al., 2015; Mechler, 2005).

There is a large uncertainty range in the flood losses associated with the atmospheric oscillations. For example, in western Europe, the Low Damaging flood class has an average of €1,296 m in summer, and the 25th and 75th percentiles correspond to €54 m and €610 m, respectively. Consequently, the usability of such risk-informed predictions will depend on the level of accuracy that the user of the information requires. Furthermore, we demonstrate that some of the classes of flood losses may be predictable one season ahead. Moreover, we show that some indices of atmospheric oscillations are more relevant for detecting the increased likelihood of flood losses than others, depending on the subregion and season. For instance, in southern Europe, Medium Damaging floods in summer can be better forecasted based on NAO averages, whereas Medium Damaging floods in fall based on SCA and SOI.

Some of the models presented in this study could potentially be transformed into impact-based flood forecasts if a relationship between the indices of atmospheric oscillations and flood losses are found either one season ahead, or when the indices of atmospheric oscillation can be predicted with some lead-time. For instance, with an improvement in stratosphere-troposphere coupling and atmospheric initial conditions in climate models, higher skill has been observed in predicting the Artic Oscillation, which is an important mode of circulation in the northern hemisphere winter circulation (Ceglar et al., 2017; Stockdale et al., 2015). Furthermore, improvements in seasonal forecasting systems have allowed skillful predictions of winter NAO and ENSO to be extended to more than a year ahead (Dunstone et al., 2016; Gonzalez & Goddard, 2016). EA summer and autumn anomalies have been forecasted with a lead time of 1 to 2 months (Iglesias et al., 2014). Given that the seasonal predictability of the indices of atmospheric oscillations is often higher than that of hydrometeorological variables such as rainfall (Dunstone et al., 2018) and streamflow (Arnal et al., 2018), seasonal flood risk outlooks could potentially be developed through the integration of statistical models with dynamical seasonal forecasts of large-scale atmospheric oscillations. Further value could be added to the forecasts of indices of climate variability by combining them with information on the resulting flood losses, thereby enabling the seasonal forecasting of those socioeconomic impacts of floods.

The current study is a statistical analysis of the relationship between large-scale atmospheric oscillations and seasonal flood losses. The primary limitation of this study is that we assume that flood losses and large-scale atmospheric oscillations follow a linear relationship and that large-scale atmospheric oscillations are linked among themselves via a linear process. However, past studies have found nonlinear relationships between NAO and ENSO (Matyasovszky, 2003), while other studies suggest that flood risk is shaped by a range of components such as risk perception, trust in authorities, awareness, and preparedness (Aerts et al., 2018; Di Baldassarre et al., 2018). Future studies would benefit from exploring relationships between large-scale atmospheric oscillations and seasonal flood losses through techniques that primarily focus on prediction skill, such as supervised machine learning algorithms. In addition, future studies could focus on constructing predictive models of precipitation and streamflow based on large-scale atmospheric oscillations or directly using sea surface temperatures. Furthermore, flood losses are only partially associated with atmospheric oscillations, and other aspects such as variation in exposure, vulnerability, and regional-to-local weather variability may strengthen this analysis.

Lastly, global disaster databases, such as the one used in this study, are also known to face major limitations, such as reporting errors and underreporting of small events (Kron et al., 2012). Therefore, to provide further insights into the strengths and limitations of our approach, the proposed method could be tested using other databases that register flood events such as the Dartmouth Flood Observatory.

4. Conclusions

In this study, we aimed to identify regions and seasons where probabilities of classes of flood losses can be estimated and predicted by five indices of atmospheric oscillation (NAO, EA, EAWR, SCA, and SOI) with higher skill than historical probabilities. We find that:

1. While logistic regressions are unable to predict High Damaging floods based on indices of atmospheric oscillation, they can be used to predict classes of Damaging, Low Damaging, and Medium Damaging floods, mostly in at least two out of four seasons in all subregions.

2. On average, higher predictive skills are found for models derived using simple logistic regression for classifying cases of Damaging versus non-Damaging flood events. In contrast, lowest predictive skills are observed for models derived using bivariate logistic regression for classifying cases of Medium Damaging versus non-Medium Damaging flood events;
3. The probability of flood losses occurring in a given class may increase or decrease (±100%) depending on the phase of the index of atmospheric oscillation, and most of our models generate increased probability of flood losses when the indices are at their extreme phases;
4. The negative (positive) phases of the best performing indices are often related to an increase (decrease) in the probability of Damaging and Low Damaging floods in comparison to the historical probability in southern and western Europe; the opposite is found for northern and eastern Europe;
5. Some of the classes of flood losses can be predicted one season ahead because a lagged relationship exists between the indices of atmospheric oscillation and the flood losses in all subregions.

As observed previously, major floods can be driven by large-scale atmospheric oscillations, and as a result, such flood events may increase the pressure on transnational risk reduction and risk transfer mechanisms due to the high interdependencies of flood hazard across European regions. Information regarding the spatial configuration of flood losses has the potential to be further developed into impact-based flood forecasts when coupled with the dynamical seasonal forecast of atmospheric oscillations. In addition, the seasonal predictions of flood losses could be used to guide ex ante investments in flood risk reduction strategies and risk financing schemes in Europe.

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