COSMO-CLM

# Estimating uncertainties from high resolution simulations of extreme wind storms and consequences for impacts

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**Abstract**

A simple method is presented designed to assess uncertainties from dynamical downscaling of regional high impact weather. The approach makes use of the fact that the choice of the simulation domain for the regional model is to a certain degree arbitrary. Thus, a small ensemble of equally valid simulations can be produced from the same driving model output by shifting the domain by a few of grid cells. Applying the approach to extra-tropical storm systems the regional simulations differ with respect to the exact location and severity of extreme wind speeds. Based on an integrated storm severity measure, the individual ensemble members are found to vary by more than 25 % from the ensemble mean in the majority of episodes considered. Estimates of insured losses based on individual regional simulations and integrated over Germany even differ by more than 50 % from the ensemble mean in most cases. Based on a set of intense storm episodes, a quantification of winter storm losses under recent and future climate is made. Using this domain shift ensemble approach, uncertainty ranges are derived representing the uncertainty inherent to the used downscaling method.

**Keywords:** COSMO-CLM, uncertainty, ensemble, impact, Winter storm

## 1 Introduction

Quantitative estimates of the severity of high impact weather are needed in the context of applications such as weather forecasting, long range forecasting and climate simulations. At all scales, however, such estimates are subjected to uncertainties which must be taken into account and which are commonly adressed by means of generating ensembles of simulations. A range of potential developments of future weather is produced by introducing small deviations from the original initial conditions of a model (e.g. using singular vectors, see PALMER et al., 2007), or by introducing variations of the model's physical parameterizations FOREST et al. (2002). Another perturbation method commonly used for the ensemble generation (e.g. in the context of seasonal or decadal predictions) is to use lagged initial conditions BAEHR and PIONTEK (2014). A different approach is used in the COSMO-LEPS system run by the German Weather Service (DWD): here, variations of the particular large scale weather situation are generated by using different global analyses or forecast outputs to generate the boundary conditions for the COSMO regional model. Several studies confirmed a role of the domain size as well as of the location of lateral boundaries for the simulation results, particularly with respect to the small scale features produced (SUKLITSCH et al., 2011;

LEDUC and LAPRISE, 2009; SUKLITSCH et al., 2008). JACOB and PODZUN (1997) found a dominating role of variations in the boundary conditions over that of changing the physical parametrization or regional model's domain size. JONES et al. (1995) found that even though lateral boundary effects on resulting long term means (e.g. of precipitation) at individual grid-points are rather small, the character of day-by-day synoptic variations can be strongly influenced by lateral boundary forcing. Thus, variations of the lateral boundary conditions are an apparently suitable candidate for generating ensembles. However, physical consistency of the boundary conditions (after application of a perturbation) should be given, which precludes the possibility of directly modifying individual quantities of the forcing data at the boundaries.

Recently, SASSE and SCHÄDLER (2013) suggested a method to generate an ensemble of RCM simulations by applying a so called Atmospheric Forcing Shifting (AFS) method. In this method, the forcing GCM fields are shifted by 25 (or 50 km) with respect to the model orography. The authors find that for long term simulations the uncertainties generated by the AFS technique do not exceed uncertainties resulting from the use of different forcing data sets. However, particularly with regard to extremes the AFS technique is able to generate considerable ensemble spread. In this paper, a technique is described, which is similar to the AFS technique in terms of taking exactly the same RCM and exactly the same data source for the ensemble. In contrast, however, the relationship to the underlying orography and land-

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sea mask are kept fixed. Instead, the nest of the RCM into the driving model is shifted, resulting in a few more (or less) grid points at the individual boundaries. The choice of the location of the nesting domain for a simulation of events is arbitrary. Thus we regard such a shift as a simple approach to generate consistent realizations, as long as it is assured that lateral boundaries are far enough from the area of interest to allow for a sufficient relaxation at the boundaries. A similar methodology has been applied to investigate uncertainties in high-resolution quantitative precipitation forecasts for heavy convective precipitation events (REZACOVA et al., 2009). For five convective events, REZACOVA et al. (2009) studied the relationships between spread and skill of an ensemble forecast, generated using area shifting. Findings indicate that both lead time as well as spatial scale influence spread and forecast skill.

In this study, the usefulness of the presented method is investigated for the case of synoptic scale wind storms, analyzing European wind storm risks under present and future climate conditions. Since local impacts of wind storms are highly sensitive and non-linearly dependent on the near-surface gust wind speeds (compare e.g. KLAWA and ULBRICH, 2003), it is of great importance to address the uncertainties associated with local estimates of wind gusts and the resulting uncertainties on derived storm impacts. Ideally, this would require an ensemble of continuously driven RCM simulations to be able to assess the distributions of extreme winds and through applying a wind damage transfer function resulting damage distribution. However, continuous RCM simulations at high resolutions suitable for the modelling of local wind storm impacts are computationally costly. Thus, the idea in this study is to identify large scale winter storm events using an impact focused winter storm identification methodology (LECKE-BUSCH et al., 2008) in the continuous GCM simulations. To characterize the severity of a winter storm event, the so called storm severity index (SSI) is used (LECKE-BUSCH et al., 2008). For the most intense storm systems identified within a reference climate period as well as within future climate periods, the dynamic downscaling is then performed to investigate possible changes in future severe winter storm impacts. This approach is supported by the finding that few of the most intense storm systems contribute a major share to the total amount of storm damages (PRAHL et al., 2015). Using the presented ensemble generation method, we then aim to quantify the ensemble variations in terms of wind and in terms of impact to address the uncertainties arising from the introduced lateral boundary shifts.

Deriving such uncertainty information will enhance the usefulness of high resolution model simulations (WU et al., 2005), especially for improving the statistics of (rare) extreme values (SASSE and SCHÄDLER, 2013). It has been shown by HELD et al. (2013), that such uncertainty information can also be used for the estimation of return levels/return periods which can be included into

a general framework to assess and integrate uncertainty information of different sources.

The remainder of this paper is structured as follows. In Chapter 2, the driving forcing data is described as well as the used model configuration and the basic setup of the ensemble simulations. Chapter 3 presents the analysis methods to model and assess the impacts of winter storms. In Chapter 4 the applied ensemble technique is demonstrated for an example storm episode, and the quantification of impacts and their uncertainties is presented. Finally, the usage of the ensemble technique for the estimation of uncertainties in climate change impact studies is demonstrated.

## 2    Data and dynamical downscaling

In this study we use data from the ECHAM5-MPIOM model runs conducted for the IPCC-AR4 (ROECKNER et al., 2006) as driving data for the regional model simulations. Each of the three transient climate simulations is forced with observed greenhouse gas (GHG) concentrations for the period 1860–2000 and with A1B scenario concentrations thereafter. Four 30-year time slices are considered: 1970–2000, 2011–2040, 2041–2070 and 2071–2100. ECHAM5-MPIOM is chosen for downscaling, since previous studies suggested a good agreement of this single model ensemble with a multi-model ensemble in terms of the climate change signals of winter storm impacts (DONAT et al., 2011a) and the mid-latitude synoptic scale variability (ULBRICH et al., 2009). The COSMO model in Climate Mode (COSMO-CLM, see DOMS, 2011) is the community regional climate model for German climate research. The COSMO model is used by several weather prediction centers across Europe for operational numerical weather prediction. Here, we used the COSMO-CLM version 4.0 (BÖHM et al., 2008). A description of the parameter setting used for the simulations can be found in BÖHM et al. (2008). The model is run on a rotated pole grid with a horizontal resolution of $0.165° × 0.165°$ degrees ($≈ 18\,km$) with 32 vertical levels, and the temporal discretization is performed using a leap-frog scheme with a internal time step of 150 seconds. The total extent of the entire domain is $257 × 271$ grid cells. Wind gusts in $10\,m$ height are calculated from wind speeds at levels above the boundary layer and static stability according to SCHULZ and HEISE (2003) and SCHULZ (2008). Maxima of wind gusts in 6 hourly intervals are used for the wind storm identification and quantification procedure as presented in Section 3.1, and daily maxima are used for the modeling of storm damages as described in Section 3.2. The nesting of the COSMO-CLM into the ECHAM5-MPIOM data for a domain covering all of Europe and parts of northern Africa (Figure 1) is repeated with four additional nesting domains which are shifted by 8 COSMO-CLM grid boxes to the north (dot-dashed), south (long dashed), east (dotted) or west (dashed). The shift by eight grid boxes is motivated by
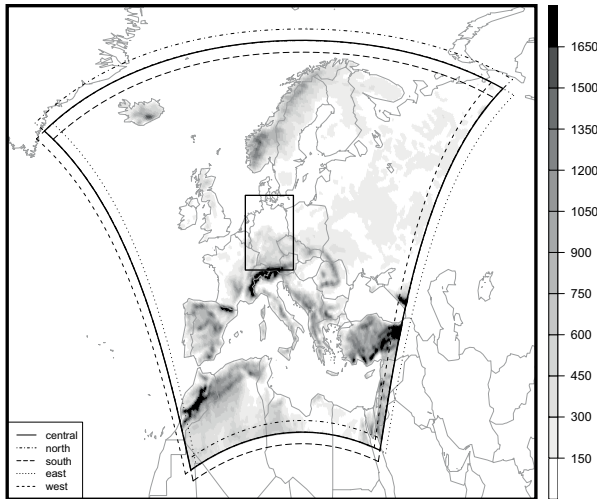
**Figure 1:** COSMO-CLM topography (shaded), domain location of five ensemble members (lines) and Germany box (rectangular).

the fact that this is the zone which is usually significantly affected by relaxation at the boundary (Doms, 2011). The region of Germany considered with respect to storm severity is far away from the models boundaries, so it is assured that results are not influenced by effects from the relaxation zone at the boundary. As noted in the introduction, the RCM is not nested continuously into the GCM, but for storm periods identified from the GCM only (see next section). Instead, the strongest 30 events affecting the German region within each of the four time slices were selected for downscaling. For these events, the COSMO-CLM simulations are initialized 5 days previous to the emergence of the identified storm events using the respective ECHAM5-MPIOM fields. This initialization time is chosen to allow for perturbations (introduced by means of the domain shift) to take effect already at the stage of cyclogenesis. The COSMO-CLM simulations are then continued for the whole lifetime of each of the selected winterstorm events which ranges from 5 to 7 days. Thus, in total 120 storm systems are selected and dynamically downscaled using COSMO-CLM, with each episode lasting 10–12 days depending on the duration of the storm event identified in the GCM. To evaluate the storm characteristics and to model local storm impacts, 6 hourly maxima of surface wind gusts are analyzed from the COSMO-CLM simulations.

## 3 Methodology

### 3.1 Wind storm identification and quantification

Both ECHAM5-MPIOM and COSMO-CLM model results are analyzed using a wind field tracking algorithm as described in Leckebusch et al. (2008). In the first step, the algorithm detects spatially contiguous clusters of wind speeds exceeding the local 98th percentile. Clusters must fulfill a certain size criterion (equivalent to

two $2.5° \times 2.5°$ grid boxes or an area of $400 \times 400\,\text{km}^2$) and are detected from 6 hourly maximum near surface wind fields. The resulting clusters are connected into a wind field track using a nearest neighbor method and any track lasting less than a minimum duration of 18 hours is discarded. The wind field tracking has been successfully used for the analysis of GCM model data (see e.g. Leckebusch et al., 2008), however, applying it to output of high resolution simulations is not trivial. For model output as used here (18 km grid) spatial structures such as atmospheric fronts lead to strong spatial variations in the wind fields, which complicates the tracking procedure. The rather homogenous single time step clusters from ECHAM5-MPIOM (with a horizontal resolution of T63) are often decomposed into sub clusters in COSMO-CLM leading to problems in the nearest neighbor matching and thus to a splitting of resulting wind field tracks. Of course this problem also exists in low resolved GCM simulations, however this leads to a splitting of wind field tracks only in few cases. To overcome this problem, the wind field tracking procedure has been slightly modified when applied to COSMO-CLM data. Instead of identifying single time step clusters at each time step (in the 2 dimensional wind fields), contiguous clusters of threshold exceedances are identified in the 3 dimensional longitude-latitude-time array of wind data directly.

The intensity of a storm system is assessed using the so called Storm Severity Index (SSI, compare Leckebusch et al., 2008)

$$SSI = \frac{1}{A_0} \cdot \sum_t \sum_x A(x) \cdot \left( \max\left[ \frac{v(t,x)}{v_{98}(x)} - 1, 0 \right] \right)^3 \quad (3.1)$$

where $A(x)$ is the area of a grid cell $x$ (in $\text{km}^2$) normalized with a reference area $A_0$ chosen as $1000\,\text{km} \cdot 1000\,\text{km}$, ensuring the SSI to be dimensionless. $v(t,x)$ is the 6 hourly maximum surface wind at a certain grid point which is normalized onto the corresponding 98th percentile $v_{98}(x)$ of 6 hourly maximum surface winds. Summation is done over all time steps $t$ and all grid cells affected by a certain wind field track. To identify potential high impact situations in Germany, the summation is restricted to a rectangular box around Germany, with resulting SSI denoted with $SSI_{\text{GER}}$. The SSI is thus a measure of the system strength including its horizontal and temporal extent. Furthermore the cube of local wind exceedances is used as it has been found that the amount of damages are best described using this term (see Klawa and Ulbrich, 2003; Leckebusch et al., 2008; Donat et al., 2011b). Since SSI values from ECHAM5-MPIOM shall be compared to values from COSMO-CLM simulations, SSIs from ECHAM5-MPIOM are calculated for the area covered by the COSMO-CLM simulation domain (see Figure 1) only. Next, potential damage related wind storm events over Germany (due to strong winds over this region) are selected and dynamically downscaled. Thus for the selection of events to be simulated with COSMO-CLM, the $SSI_{\text{GER}}$ values are cal-
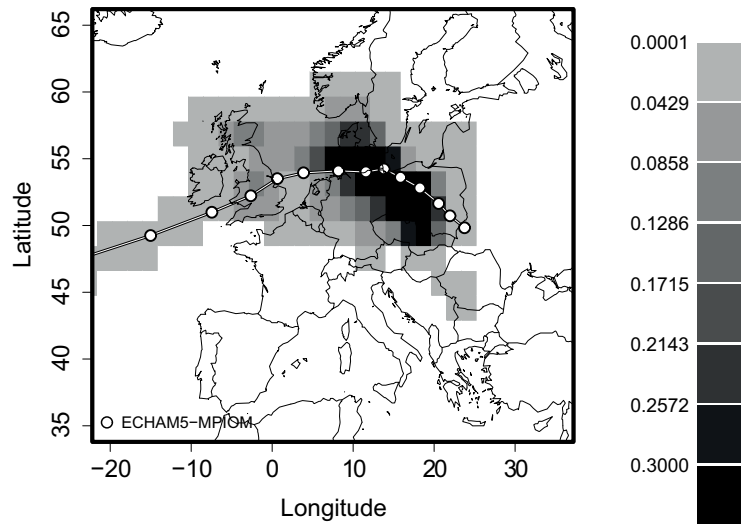
**Figure 2:** Example storm system from ECHAM5-MPIOM (run 1). Identified wind field track is lasting from 1997-11-11 18:00 till 1997-11-18 12:00. Total *SSI* value is 0.55, *SSI* inside the COSMO-CLM domain is 0.46. Shading shows the spatial distribution of the *SSI* (see eq. (3.1)). The wind field track (corresponding to the consecutive wind field centers) is shown as connected white points.

culated from ECHAM5-MPIOM according to Equation 3.1 and restricted to a rectangular region (5 °–16 ° W and 47 °–55.5 ° N) around Germany.

## 3.2   Storm damage modeling

The *SSI* describes the hazard strength which can be considered as the potential impact of a wind storm event. A damage or loss to be realized, however, requires the presence of an exposure to such a hazard. Considering the large local variations in population density (by a factor of 100 on district basis), it becomes obvious that impacts will largely depend on the areas affected by the storm. Also vulnerabilities might differ locally due to differences in architecture, coping capacities and other socio-economic factors. In Donat et al. (2011b) a storm damage model was presented based on high-resolution insurance records, which comprise daily occurred losses on private housing resolved for 439 German administrative districts. The approach presented in Donat et al. (2011b) and Klawa and Ulbrich (2003), is based on the assumption that losses depend on a product of *exposure*, *vulnerability* and *hazard*. In this framework, the *exposure* is assessed through the insured sum of values (*IS*), while the *vulnerability* is estimated from empirical analysis of hazard strength and observed losses for historical events. The model is set up assuming a linear relation between the local meteorological hazard strength (described by the cube mean excess of wind speeds over the local 98th percentile) and actually realized losses in a certain district. This linear regression, which is performed per district, results in estimates for the parameters *a* and *b*, which can be used to model losses according to

$$loss = IS \cdot \left( a + b \cdot \left( \max\left[ \frac{v}{v_{98}} - 1, 0 \right] \right)^3 \right). \quad (3.2)$$

where the sum of insured values is abbreviated with *IS*. Often the loss ratio rather than the actual loss is specified, which is the amount of losses divided by *IS*. Similar to the calculation of the *SSI* as an integrative measure for a storms hazard strength, the total impact is calculated by summation over all districts with weighting according to the *IS* (see Donat et al., 2011b for details). The refined loss model presented by Donat et al. (2011b), compared to the original formulation of the storm loss model (Klawa and Ulbrich, 2003), is able to model locally varying vulnerabilities by taking into account differences in the regression coefficients on a county level. The model has been tested for its ability to model historical winter storm losses (see Donat et al., 2011b), and shall be applied to the storm events simulated with COSMO-CLM in this study.

## 4   Results

### 4.1   Comparison of *SSI* values from GCM and RCM

Due to the synoptic scale nature of the cyclonic systems generating large scale winter storms, with typical length scales ranging about 1000 km, it can be expected that large scale features of such systems (e.g. its track location) are largely prescribed from the driving GCM onto the RCM. Regarding small scale features, however, we expect to find differences when comparing the spatial distribution of *SSI* values from GCM and RCM which can be e.g. due to orographic effects or additional features such as land-sea contrasts at the coastlines due to the higher resolution. Spatial distribution of *SSI* for an example storm system identified in ECHAM5-MPIOM run 1 (start: 1997-11-11 18:00 UTC, end: 1997-11-18 12:00 UTC) are shown in Figure 2 (ECHAM5-MPIOM) and Figure 3 (COSMO-CLM). Besides the effects due
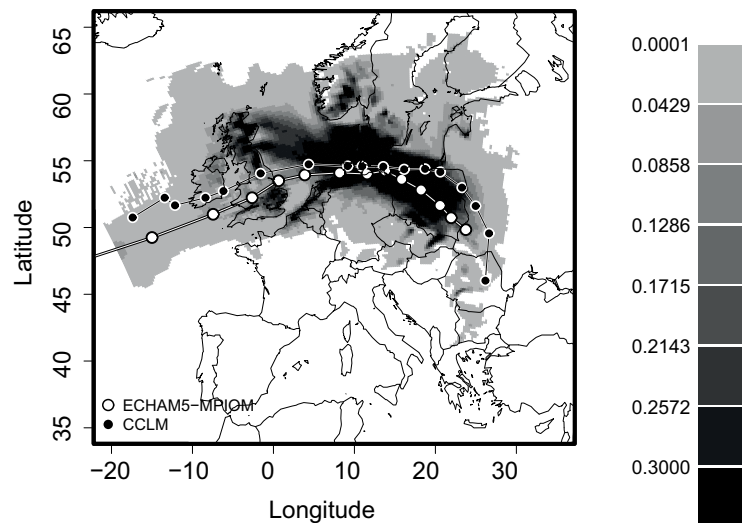
**Figure 3:** Spatial distribution of SSI for the central realisation of COSMO-CLM for the example in Figure 2. The wind field track from ECHAM5-MPIOM is shown in white connected points, comparing to the track from COSMO-CLM in black.
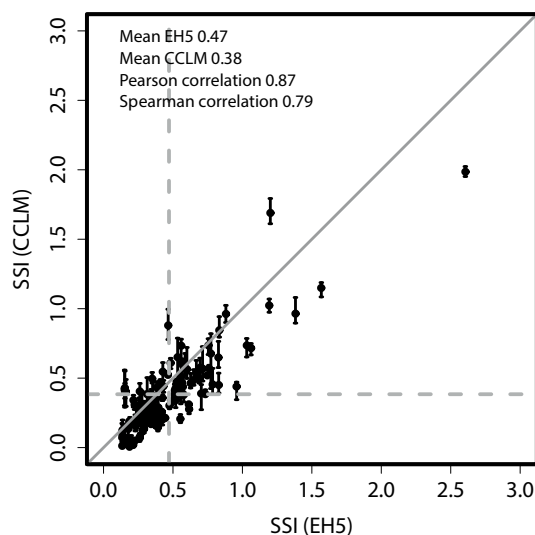


**Figure 4:** *SSI* calculated from ECHAM5-MPIOM versus COSMO-CLM. Points show COSMO-CLM ensemble mean and error bars indicate spread spanned by the 5 member ensemble.

to the higher resolution, spatial intensity characteristics of the RCM are in good agreement to the driving model. Resulting wind field tracks, which correspond to the location of highest *SSI* values at a specific time step, compare well as shown in Figure 3, the track however being slightly shifted northward in COSMO-CLM. Also, the resulting *SSI* value from ECHAM5-MPIOM within the COSMO-CLM domain (0.46), compares well to the *SSI* calculated for the central realization of the COSMO-CLM simulations (0.54). Figure 4 shows the scatter-plot between *SSI*'s from ECHAM5-MPIOM to the ones calculated from COSMO-CLM for all 120 storm episodes considered. Mean *SSI* values are biased in COSMO-CLM ($\overline{SSI}$ = 0.38) towards lower values compared to ECHAM5-MPIOM ($\overline{SSI}$ = 0.47). Besides possible model biases, this can partly be ex-

plained by the design of the *SSI*. The *SSI* is based on relative threshold exceedances, relating the wind extremes to the model's local climatology using the 98th percentile (Equation 3.1). Since absolute values of 10 m wind gusts as diagnosed from the RCM are considerably higher compared to maximum sustained wind speeds analyzed from the GCM, only through the scaling onto the model specific climatological 98th percentile *SSI* values become comparable. Such first order scaling onto model specific climatology, however, does not capture all differences in the surface wind pdf's which may lead to biases in the *SSI* characteristics as found here. In agreement with the assumption that large scale features of such systems are prescribed from the driving GCM onto the RCM, *SSI* values from COSMO-CLM and ECHAM5-MPIOM are found to be highly correlated (Pearson correlation of 0.87). However, in terms of the explained variation, this can also be interpreted that only about 75 % of variability in *SSI* values derived from the RCM is explained by considering *SSI* values from the forcing GCM.

## 4.2 Deriving uncertainties in storm severity and related losses

The uncertainty on storm severity as well as on resulting storm impacts is investigated by considering the ensemble of five realizations of the COSMO-CLM ensemble. In general the aim of generating an ensemble is to estimate the distribution characteristics, in particular the second moment or respective quantiles of the distribution, in order to quantify the uncertainty i.e. of local wind intensivies. Due to the limited number of five ensemble members generated for this study, we estimate the uncertainty by quantifying the ensemble spread spanned by the five individual ensemble realizations. This estimate can be interpreted as the range of possible realization of a storm's intensity under the given and fixed boundary forcing of the driving GCM.
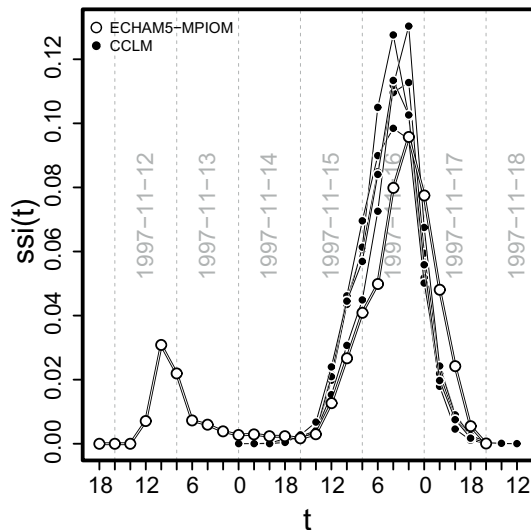
**Figure 5:** Time decomposition of SSI for the example in Figure 2. Shown in black circles is the *SSI(t)* from ECHAM5-MPIOM, single members from COSMO-CLM are shown in grey.

For the example shown in Figure 3, this spread in the *SSI* is found to be 0.032 (6 % of the mean). Considering the temporal evolution of the storm intensity (Figure 5) it can be found that the peak intensity differs amongst the individual simulations. Furthermore, the temporal development differs leading to different times of highest intensity. Considering the regional distribution of the *SSI*, largest spread is found in the regions of highest intensity (not shown). This can be understood considering the cubic dependence of wind speed exceedances in Equation 3.1. Small deviations in the threshold exceedances are amplified and thus contribute most to the generated spread in *SSI*.

Considering the spread of the regional *SSI* values relative to the ensemble mean (Figure 6) values of up to 100 % can be found along the path of highest intensity of the storm system. The relative spread however is particularly high at the edges of the storms footprint. This points out the uncertainties of the exact area which is affected by the storm system, which differs slightly in all five COSMO-CLM members. Thus, differences can be analysed with respect to both the temporal as well as regional distribution of *SSI* contributing to the overall uncertainty.

There is a tendency towards higher spread for more intense storms as shown in Figure 7, which can be explained by the non linear amplification of uncertainties in gusts for the case of large threshold exceedances. However, this tendency is subjected to large variations showing that the uncertainties involved are obviously highly dependent on the particular storm situation. In about half of all events a spread (relative to the ensemble average) larger than 25 % is diagnosed. In a quarter of all cases this spread raises above 50 % and in few cases even above 100 % (Figure 10).

To assess the impact of the selected winter storm events, modeled loss ratios (Equation 3.2) for all COSMO-CLM simulations are calculated (see Figure 8 for the example storm system in Figure 3). The spatial distribution of modeled impacts (Figure 8) resembles the spatial distribution of *SSI* shown in Figure 3. However, due to differences in vulnerabilities (modeled through the coefficients *a* and *b* in equation 3.2) local differences become apparent. Integrating the estimated losses over Germany gives a German-wide loss ratio of 0.036 ‰ (ensemble mean) with an ensemble spread of 0.029 ‰ (82 %). To calculate German-wide loss ratios weighing with the local insured sum is needed. The local insured sum however, strongly varies locally, thus small changes i.e. in the location of high *SSI* values can lead to large differences in the German-wide loss ratio. In comparison to the relative spread of 82 % calculated for the German-wide loss ratio, the spread in $SSI_{GER}$ was found to be only 23 %. This shows that the inhomogeneous distribution of insured values as well as local variations in the coefficients *a* and *b* (modelling the vulnerability) lead to a strong amplification of uncertainties.

This increased uncertainty is affirmed when considering the spread for all 120 storm events shown in Figure 10 (gray histogram). In more than half of all simulations a spread larger than 50 % compared to the ensemble average is found. Compared to the spread analysed for $SSI_{GER}$ this implies an ensemble spread increased by a factor of 2. In terms of German-wide loss ratios, the spread raises above 100 % in nearly 25 % of the simulated events.

## 4.3 Implications for climate change assessment

To demonstrate the use of the presented technique in climate change impact studies, losses for the most severe winter storm events in future climate conditions (according to the SRES-A1B scenario (NAKICENOVIC et al., 2000)) are assessed, results are listed in Table 1. We focus on the 30 most severe wind storm events in the period 1971–2000 (recent climate conditions) as well as the 3 scenario periods 2011–2040, 2041–2070 and 2071–2100. Regarding the central realization of the COSMO-CLM simulations, total loss ratios for these periods are calculated to be 1.38 ‰, 1.91 ‰, 1.86 ‰, and 2.29 ‰, respectively. In comparison, the total loss ratio for the 30 most severe historical winter storm events accounted for a total loss ratio of 1.58 ‰, (compare Table 2 in DONAT et al., 2011b), which is higher than the value calculated from the COSMO-CLM simulations under recent climate conditions.

However from a deterministic simulation, uncertainties on the specified estimates are unknown. Each of the five realizations of a storm event is physically consistent with no one being preferred over the other. Thus any random set containing one out of the five COSMO-CLM realizations for each storm event represents one consistent and possible realization of the 30 winter storms
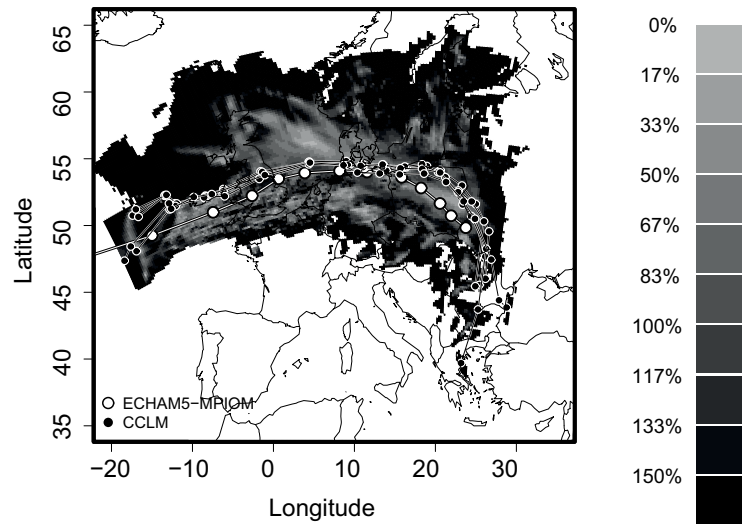
**Figure 6:** Relative spread of *SSI(x)*, given in %, spanned by the five member COSMO-CLM ensemble for the example from Figure 2. Besides the wind field track from ECHAM5-MPIOM (white connected points), resulting wind field tracks from the five simulations are shown in grey.

**Table 1:** Results for accumulated losses of 30 most severe winter storm episodes per each 30 year period. [*] For observed losses, the 30 most severe winter storms in the 25 year period 1984–2008 are considered (data source: GDV, compare DONAT et al., 2011b).

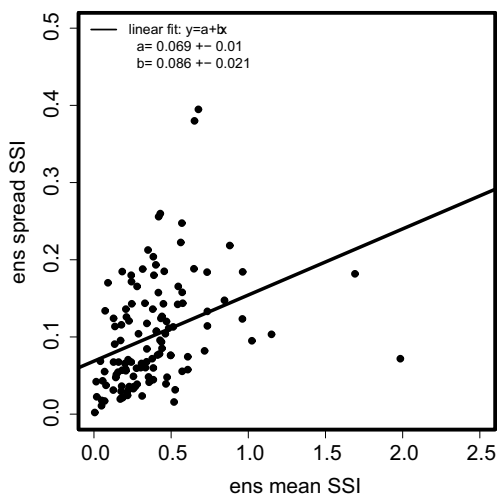|  | 1971–2000 | 2011–2040 | 2041–2070 | 2071–2100 |
|---|---|---|---|---|
| observed | 1.58[*] | – | – | – |
| central | 1.38 | 1.91 (+39 %) | 1.86 (+35 %) | 2.29 (+66 %) |
| north | 1.71 | 1.88 (+9 %) | 1.69 (−1 %) | 2.26 (+32 %) |
| south | 1.42 | 1.97 (+39 %) | 1.85 (+30 %) | 2.26 (+59 %) |
| east | 1.22 | 1.75 (+43 %) | 1.94 (+58 %) | 2.04 (+66 %) |
| west | 1.32 | 1.77 (+34 %) | 1.88 (+43 %) | 2.31 (+75 %) |
| mean | 1.41 | 1.86 (+32 %) | 1.84 (+31 %) | 2.23 (+58 %) |
| 66 % conf. int. | 1.30/1.53 (−8 %/+8 %) | 1.73/1.99 (+23 %/+40 %) | 1.74/1.95 (+24 %/+38 %) | 2.12/2.34 (+51 %/+66 %) |
| 90 % conf. int. | 1.21/1.61 (−14 %/+14 %) | 1.66/2.09 (+18 %/+48 %) | 1.67/2.01 (+18 %/+43 %) | 2.04/2.40 (+45 %/+70 %) |



**Figure 7:** Ensemble mean *SSI* versus *SSI* spread spanned by COSMO-CLM ensemble.

identified in the GCM. From this assumption, a bootstrap method (EFRON and TIBSHIRANI, 1986) can be constructed. As an alternative to statistical inference based on theoretical considerations a bootstrap approach offers the possibility to derive confidence intervals particularly in case of unkown or skewed distributions, which is certainly the case in the given application. In each bootstrap step, the sum of losses for the 30 events is calculated choosing a random realization for each of event. To estimate the downscaling uncertainty this random sampling is repeated 10000 time, resulting in a distribution of the total loss. From this distribution quantiles, i.e. uncertainty ranges on the total losses can be derived (Figure 11).

By this procedure, instead of specifying single estimates for each period, a range can be given using e.g. the quantiles including 90 % of all sampled total losses. This can be calculated to be 1.21–1.61 ‰ in 1971–2000, 1.73–1.99 ‰ in 2011–2040, 1.74–1.95 ‰ in 2041–2070 and 2.12–2.34 ‰ in 2071–2100. Within the derived uncertainty range (1.21–1.61 ‰), the results for recent climate are in agreement to observed losses (1.58 ‰). However mean losses (1.41 ‰) are found to be underestimated by about 11 %. For future climate conditions, total loss ratios are found significantly higher in all future scenario periods, with relative increases of +18 % to +48 % in 2011–2040, +18 % to +43 % in 2041–2070 and +45 % to +70 % in 2071–2100 compared to recent climate conditions.
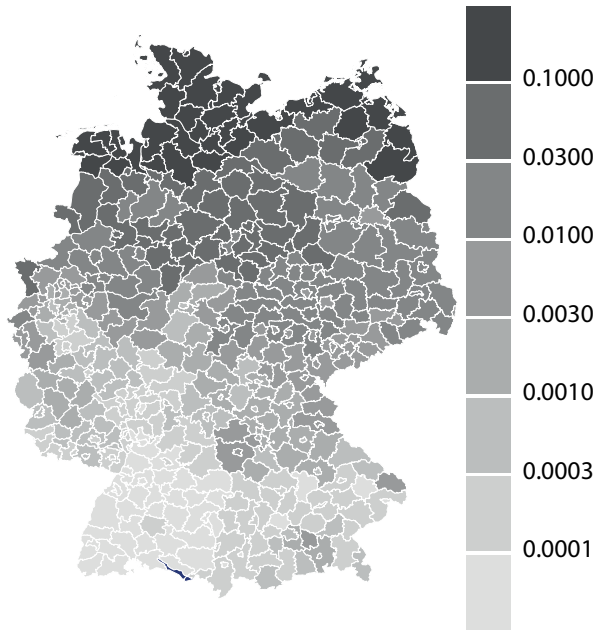
**Figure 8:** Ensemble mean of modelled losses [‰] for the example in Figure 2. Shown is the sum of daily losses for the days 15–17 November 1997.
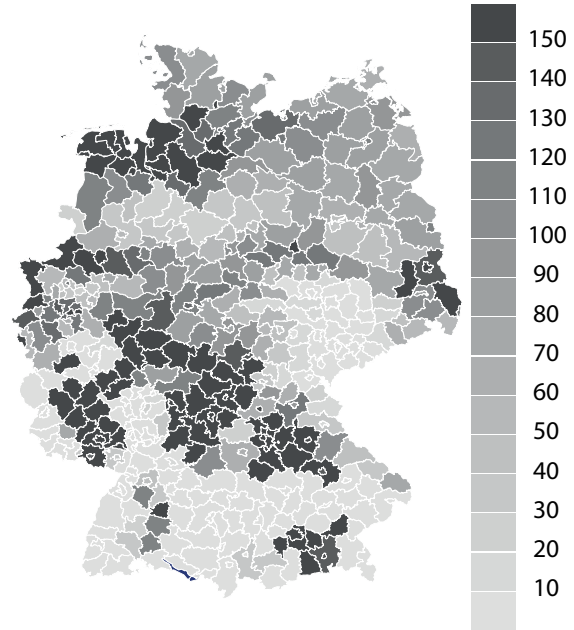


**Figure 9:** Relative ensemble spread $100 \cdot (max - min)/mean$ % of modelled losses on the days 15th–17th of November 1997 for the example in Figure 2.

It can be argued that the episode selection might bias the resulting estimates of storm losses. The choice of episodes is based on the GCM output only and thus might not reflect the most intense systems from a continuous RCM simulation, as less intense storm systems in the GCM may evolve to more intense situations within the RCM. These situations, however, cannot be considered using the proposed approach which can lead to an underestimation of the accumulated storm losses modelled for the set of 30 storm events. To estimate the magnitude of such a bias, a continuously forced COSMO-CLM simulation (first of two consortial runs as described in ROCKEL et al. (2008), analysed for the period 1971–2000) has been compared with the original forcing GCM. In both data GCM and RCM, storm episodes were identified using the storm identification method (Section 3.1). Within the list of the 30 strongest storms (according to their SSI) identified in GCM and RCM, 15 events coincided within both datasets, amongst which the ten most intense systems are found. Thus with respect to the most intense and thus loss producing storm events, the method of episode selection can be considered to be capable of capturing the relevant events.

To complement the former analysis, we additionally perform the same analysis as before, restricting only on the ten most severe events for which any systematic bias resulting from an undersampling described above can be neglected. While the sum of historical losses for the top ten events accounts for 1.1 ‰ the sum of modelled losses accounts for 1.02 ‰, in the ensemble mean of five realizations (Table 2). Thus an underestimation of about 7 % can be found which is only slightly smaller
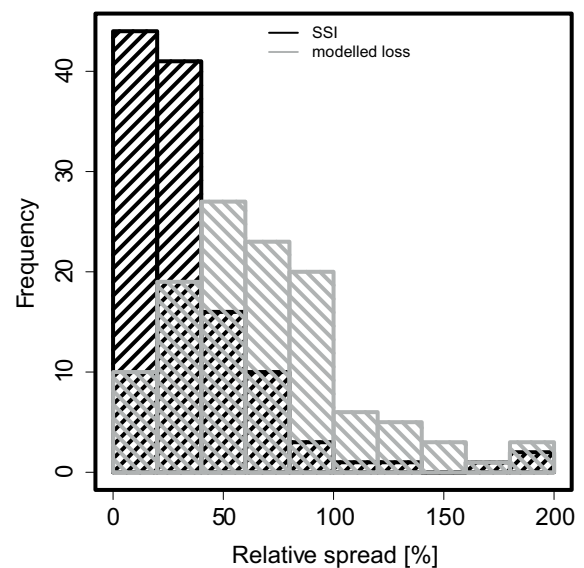


**Figure 10:** Histograms of relative spread for the *SSI* values (black) as well as for the modelled germanwide losses (grey).

compared to the analysis using all 30 storm events. This shows that only a small part of the identified underestimation of losses can be attributed to a systematic bias due to the episode selection. Since observed losses are found to be within the uncertainty range derived from the ensemble simulations for recent climate conditions (0.92–1.13 ‰), we conclude that random variability (which is represented by the generated ensemble simulation) can account for the identified underestima-

**Table 2:** Results for accumulated losses of ten most severe winter storm episodes per each 30 year period. * For observed losses, the ten most severe winter storms in the 25 year period 1984–2008 are considered (data source: GDV, compare DONAT et al., 2011b).

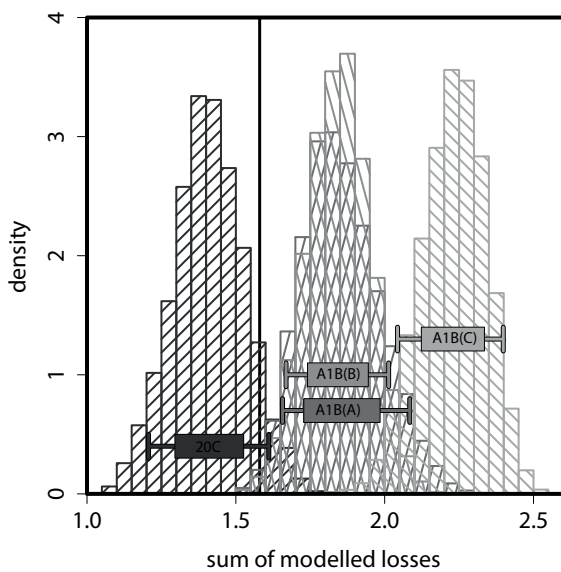|  | 1971–2000 | 2011–2040 | 2041–2070 | 2071–2100 |
|---|---|---|---|---|
| observed | 1.10[*] | – | – | – |
| central | 1.03 | 1.29 (+25 %) | 1.29 (+26 %) | 1.73 (+68 %) |
| north | 1.30 | 1.33 (+3 %) | 1.16 (−11 %) | 1.71 (+32 %) |
| south | 1.04 | 1.36 (+32 %) | 1.27 (+23 %) | 1.77 (+71 %) |
| east | 0.84 | 1.25 (+50 %) | 1.36 (+61 %) | 1.49 (+78 %) |
| west | 1.03 | 1.20 (+17 %) | 1.30 (+27 %) | 1.79 (+74 %) |
| mean | 1.02 | 1.22 (+19 %) | 1.26 (+23 %) | 1.68 (+64 %) |
| 66 % conf. int. | 0.92/1.13 (−10 %/+10 %) | 1.11/1.27 (+ 9 %/+25 %) | 1.16/1.34 (+14 %/+31 %) | 1.58/1.78 (+55 %/+75 %) |
| 90 % conf. int. | 0.83/1.21 (−19 %/+19 %) | 1.05/1.33 (+ 3 %/+30 %) | 1.09/1.40 (+ 7 %/+37 %) | 1.50/1.84 (+47 %/+80 %) |





**Figure 11:** Uncertainties in derived climate change signals. Histograms show density of sampled total sum of modelled losses of the 30 storms of each period. Each sampling is selecting one out of five realisations of each of the 30 storm systems. Sampling is repeated 10000 times. Box plots indicate the 66.7 % and the 90 % ranges for each of the periods 20C (1971–2000), A1B(A) (2011–2040), A1B(B) (2041–2070), A1B(C) (2071–2100). The vertical line indicates the accumulated loss ratio for the 30 most severe historical winter storms in the 25 year period 1984–2008.

**Figure 12:** Same as Figure 11 evaluating the ten most intense storm systems in each of the periods 20C (1971–2000), A1B(A) (2011–2040), A1B(B) (2041–2070), A1B(C) (2071–2100).

tion of historical losses. Resulting climate change signals analyzing the top ten storm events of each climate period (Table 2) are found in good agreement with the previous analysis using all 30 storm events.

It needs to be noted that these results are derived using a fixed GCM/RCM model combination and a fixed set of 30 winter storm episodes identified in ECHAM5-MPIOM GCM data for the four investigated 30 year periods. This fixed set of episodes predetermine the climate change signal derived in this study. The analysis of (multi-model) global and regional ensemble projections however reveal a high range of possible change signals derived for future winter storm losses (PINTO et al., 2007; SCHWIERZ et al., 2009; DONAT et al., 2011a). These results depend on the con-
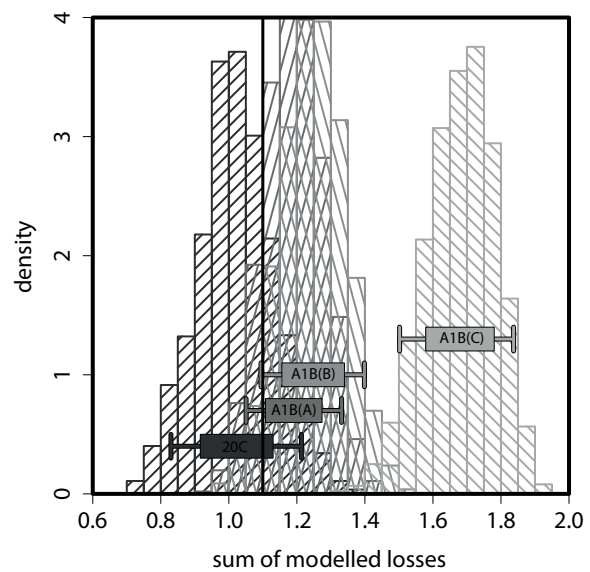
sidered model simulation, the methodology used to infer winter storm losses from climate model output and on the considered emission scenario. The afore mentioned studies derive change rates in mean annual winter storm losses for Germany in the period 2071–2100 compared to 1971–2000 ranging from +37,7 % (DONAT et al., 2011a) to +114 % (derived for the SRES-A2 scenario, (SCHWIERZ et al., 2009)). As shown by DONAT et al. (2011a), for individual GCM (RCM) model simulations possible change rates exhibit an even larger spread ranging from −6,2 % to +87,1 % (−4.5 % to +54.8 %), with change rates of +30,5 % derived from the three runs of ECHAM5-MPIOM ranging close to the multi-model ensemble mean.

## 5   Summary and conclusions

This paper presents a simple method to estimate uncertainties of high impact weather situations by using a regional climate model ensemble. Different simulation

domains are chosen, each shifted by a small number of eight grid cells in each direction with respect to a reference domain. This approach is justified by the fact that the model domain is to a certain degree a random choice. The proposed ensemble method is particularly appealing, since it is easily implementable and since it is generating physically consistent ensemble members. SASSE and SCHÄDLER (2013) presented a similar yet different approach, called the Atmospheric Forcing Shifting (AFS) method, where the atmospheric forcing fields are shifted with respect to the model orography by an amount of 25 (50) km. Even though SASSE and SCHÄDLER (2013) do not find systematic differences which may result from systematically shifted weather patterns, the physical consistency of ensemble members is not strictly given for the AFS method over orography. However, similar to the method presented in this study, the AFS method presents a way to assess the high sensitivity to slight modifications in the boundary conditions. Of course, as in any dynamic downscaling, physical inconsistencies arise due to the necessity of interpolating forcing data at the boundaries. However, we consider the approach of the ensemble generation method as consistent, since no additional inconsistencies are introduced to generate the disturbances at the lateral boundaries. This is different from the AFS technique in which the land-sea mask is shifted relative to the forcing fields, which might give raise to inconsistencies particularly at locations of steep orography gradients.

For a set of winter storm episodes it was shown that the small changes in the lateral boundary conditions introduced by shifting of the simulation domain lead to changes in the areas affected by high wind speeds as well as changes in the intensity of individual storm systems simulated by the regional model. It was demonstrated that this can lead to considerable ensemble spread in a storms potential impact due to the high sensitivity of impacts with extreme wind speeds. In more than half of the conducted winter storm episode simulations the spread exceeds 25 % compared to the ensemble mean. These changes in the synoptic development of the storm systems amplify to large variability in estimated losses which has been demonstrated by applying a winter storm loss model to the regional model output. The spread in estimated losses rises above 50 % compared to the ensemble mean for half of the simulated wind storm systems. The increased ensemble spread of estimated losses compared to spread in *SSI* values can be attributed to high spatial variations in the distribution of values as well as local variations in vulnerabilities to high winds.

The method's applicability for climate change impact studies was demonstrated on the example of winter storm damages. For a fixed GCM/RCM model combination (in this study ECHAM5-MPIOM and COSMO-CLM) the method enables the quantification of the inherent downscaling uncertainties. For recent climate conditions (20C), the total loss ratio of the 30 most severe storm systems is estimated to range between 1.2‰, and 1.6‰, (90 % confidence interval, compare Table 1), which embraces the observed total loss of 1.58‰, realized through the 30 most severe historical winter storms (compare Table 2 in DONAT et al., 2011b). For future scenario periods, increases are found to range between +18 % to +48 %, +18 % to +43 % and +45 % to +70 % for the periods 2011–2040, 2041–2070 and 2071–2100, respectively compared to recent climate conditions (1971–2000). Regarding climate change signals results are found to be similar when focusing on the ten most intense systems.

The episode approach has the large advantage of being computationally cheap, since in total for each of the 30 year periods less than 300 days need to be simulated using the RCM. Thus, computational effort is reduced to about 3 % compared to continuous RCM simulations. However, the approach yields the disadvantage that it is not possible to derive distribution characteristics or pdf's of meteorological quantities which may be necessary in many applications.

In the application presented in this study we focus on the impacts of severe winter storm events for which it has been found that they are strongly dominated by few of the most severe storm events (compare PRAHL et al., 2015). This justifies to focus on the 30 most intense winter storm systems identified in the GCM for each of the climate periods to address the impacts of major storm events. However as discussed in Section 4.3, the choice of episodes is based on the GCM output only and thus might not reflect the most intense systems from a continuous RCM simulation, as less intense storm systems in the GCM may evolve to more intense situations within the RCM. This applies particularly to strongly diffluenced lay correction events, which the selection method based on GCM output will not be able to capture appropriately. By means of a continuously forced COSMO-CLM simulation this effect was tested. The analysis showed that amongst the 30 events identified within the GCM, the ten most intense events produced within the RCM are found. Thus, regarding the potentially most loss producing events, the method of episode selection can be considered to be capable of capturing the relevant events.

Even though the results are not directly comparable to the results of this study due to differences in their methodology and used model combinations, the results show that compared to the multi-model spread derived for change rates the downscaling uncertainty for a fixed GCM/RCM model combination is considerable and should be kept in mind when interpreting estimates based on single model output.

The findings of the present study indicate the usefulness of such an approach, especially for extreme weather impact studies involving high sensitivities to precise local meteorological conditions. The method can be easily applied to other impact studies where small changes in the location and intensity of low pressure systems might strongly influence the events' impact (e.g. coastal flooding investigations).

# Acknowledgments

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