Response to reviewer comments on "Predictive modeling of hourly probabilities for weather-related road accidents".

N. Becker, H.W. Rust, U. Ulbrich

July 31, 2020

Preliminaries

We would like to thank the three anonymous reviewers for their comments on our manuscript. We find the comments helpful and constructive. We think that they helped to improve the manuscript.

In the following pages we set out in detail our responses to the comments and how we acted on them.

Response to Anonymous Referee #1 (RC1)

Comment C 1.1 — Line 1 first word - use 'The' instead of 'An'

Reply: We used an alternative formulation using plural form.

Comment C 1.2 — Line 2 - suggest 'This study investigates hourly...' instead of 'We study hourly...'

Reply: We followed the reviewers suggestion.

Comment C 1.3 — Line 8 - suggest 'approximately' instead of 'about'

Reply: We followed the reviewers suggestion.

Comment C 1.4 — Line 16 - space needed between 2016 and (- Line 23 - add 'The' before 'aim'

Reply: We corrected the sentence following the reviewers suggestion.

Comment C 1.5 — Page 2, line 31 - check Mills et al reference

Reply: We corrected the reference.

Comment C 1.6 — Page 3, line 9 - add 'The' before 'aim'

Reply: We corrected the sentence following the reviewers suggestion.

Comment C 1.7 — Page 3, line 16 and 17 - change 'Sect.' to 'Section'

Reply: We followed the abbreviation rules as described in the NHESS manuscript preparation guidelines for authors.

Comment C 1.8 — Page 4, line 4/5 - suggest 'Radar reflectives cannot...' instead of 'As from radar reflectives we cannot...'

Reply: Radar reflectivity refers to the amount of radiation reflected back to the receiver by the precipitation particles

Comment C 1.9 — Page 4, line 9 - suggest 'projects aim to combine the...' instead of 'projects thus aims at combining the...'

Reply: We followed the reviewers suggestion.

Comment C 1.10 — Page 5, line 15 - check brackets in equation

Reply: The used mathematical interval notation refers to a half-open interval. A half-open interval includes only one of its endpoints, and is denoted by mixing the notations for open and closed intervals. $(0, 1]$ means greater than 0 and less than or equal to 1, while [0,1) means greater than or equal to 0 and less than 1.

Comment C 1.11 — Page 5, line 29 - is a comma needed at end of equation?

Reply: Yes, because the equation is part of the sentence.

Comment C 1.12 — Page 8, line 1/2 - suggest "This allows the performance of the model for different districts to be assessed."

Reply: We changed the sentence to "This allows us to compare the performance of the model in different districts.", because we want to emphasize that we are interested in the difference between the individual districts.

Comment C 1.13 — Page 9, line 4 - suggest 'P ranges from <0.001' instead of 'It ranges from below 0.001'

Reply: We reformulated the sentence to "It ranges from less than 0.001 ...".

Comment C 1.14 — Page 9, line 25 - remove comma and include 'and' after 0

Reply: We corrected the sentence following the reviewers suggestion.

Comment C 1.15 — Page 9, line 26 - clarify what 'they are' means

Reply: "They are" was replaced by "Probabilities are".

Comment C 1.16 — Page 9, line 32 - add 'a' after 'as'

Reply: We corrected the sentence following the reviewers suggestion.

Comment C 1.17 — Page 13, line 24 - add 'by' after 'increases'

Reply: We changed the sentence to "We found that the probability of weather-related accidents depends on hourly precipitation to the power of 0.2." for clarity.

Comment C 1.18 — Page 13, line 25 - add 'the' after 'of'

Reply: We corrected the sentence following the reviewers suggestion.

Comment C 1.19 — Page 13, line 33 - add 'a' after 'that'

Reply: We corrected the sentence following the reviewers suggestion.

Comment C 1.20 — - Page 14, line 3 - 'road user is rather interested in their individual...' instead of 'road used is rather interested in his individual...'

Reply: We corrected the sentence following the reviewers suggestion.

Tables and figures general comments

Comment C 1.21 — these should be able to stand on their own so acronyms need defining a much as possible.

Reply: We followed the reviewers suggestion and defined all relevant acronyms in the figure and table captions.

Comment C 1.22 — Table 2 - In caption refer to Table 1 for definitions of Formula variations

Reply: We followed the reviewers suggestion.

Comment C 1.23 — Table 3 - de-acronym

Reply: We defined the acronyms of the metrics displayed in table 3 as suggested.

Comment C 1.24 — Figure 4 - can the 3-hour variations in the AUCSS be explained in the body of the text?

Reply: The effect is explained in the second paragraph of section 4.2. The repetitive pattern occurs because hourly data is used for the analysis, but COSMO-DE-EPS is only initialized every three hours. Thus, the lead times 1, 4, 7, etc. include certain hours of the day, while the lead times 2, 5, 8, etc. include others. Consequently, there are three sets of lead times that are associated to different hours of the day, which causes differences in model performance for each set and leads to the observed three-hourly pattern.

Comment C 1.25 — Figure 6 - can the observed data be displayed to compare the model data to? This would be helpful to see to show that the models are a good representation and show which model set are better.

Reply: Unfortunately, the contractual obligations for the usage of the German accident data do not allow us to display information based on accident counts less than three to prevent the possibility of an identification of the drivers. Since in most districts one or two accidents occurred, the figure would be largely empty.

Response to Anonymous Referee #2 (RC2)

Comment C 2.1 — Table 2. RAD_INT. Please specify the meaning of the symbol P (it is not specified in Table 1)

Reply: This was a mistake, we replaced P with $\overline{P}'$.

Comment C 2.2 — Page 2, line 30. "diving habits"

Reply: We corrected the sentence.

Comment C 2.3 — Page 9, line 26. mm/h is in italic

Reply: We changed the unit to normal font type.

Response to Anonymous Referee #3 (RC3)

Comment C 3.1 — On page 1, lines 17-18, it is mentioned that "weather is one of the most important factors contributing to road traffic safety". This is a strong statement that requires a corresponding reference. To the experience of the reviewer, there is a significant amount of studies where weather-related variables are not as significant for road crashes as others (such as behavioral variables), or not at all.
On page 2, lines 11-13, there is a very recent review on that point, and pertinent with the study in general, which the authors may want to consult:
Ziakopoulos, A., & Yannis, G. (2020). A review of spatial approaches in road safety. Accident Analysis & Prevention, 135, 105323.

Reply: We agree with the reviewer that the statement that "weather is one of the most important factors contributing to road traffic safety" might be too strong in the given context. We modified this part of the introduction. We also thank the reviewer for pointing us to the interesting review article of Ziakopoulos and Yannis (2020), which we took into account on page 1 line 17 of the revised version of the manuscript.

Comment C 3.2 — On page 3, lines 24-27, it is mentioned that "However, almost 8% of the accidents were indicated as being caused by adverse road conditions, which includes a wet, snowy or icy road, but also mud or dirt on the road. This class of accidents, which we refer to as weather-related accidents, is selected to generate the response variable used in the logistic regression models." Firstly, it would be informative if the total number of considered accidents is mentioned (a rough calculation suggests it is about 345,000?). Secondly, and more importantly, this approach introduces a bias inherent from the subjectivity of crash recording, as it relies on indicators by policemen. The authors are suggested to elaborate on this bias, its extents and any implications it might have had on the results.

Reply: Section 2.1 includes information about total accident numbers as well about numbers of time steps with at least one accident and their percentages. We reformulated the section in a more consistent way. Also, we corrected some numbers given in that section, which have been taken over by mistake from a previous version of the manuscript. Therefore, they did not correspond to the data used in the present form of the study. Furthermore, we agree with the reviewer that a discussion of the subjectivity of the police officers decision on the accident cause is an important aspect. We added a paragraph to the discussion section of the manuscript, where we address this issue.

Comment C 3.3 — For binary logistic models, the Hosmer-Lemeshow test is also customary to indicate the degree of correct predictions per population stratum. The authors can examine the HL for their best predictive models, or at least utilize it in future research.

Reply: The Hosmer-Lemeshow test (HL) is an interesting test we have not been aware of. It is comparable to the reliability component of the Brier score (BS) decomposition (Murphy, 1973). In both cases it is tested, whether or not the observed event rates match modeled event rates in certain subgroups of the modeled probabilities. In addition to the reliability, the BS decomposition includes a second component called "resolution". The resolution measures the distance between the observed relative frequency and climatological frequency. Thus, it indicates the degree to which the forecast can separate different situations. BS is a proper

score which cannot be hedged (Wilks, 2011; Gneiting and Raftery, 2007; Jolliffe, 2008). HL instead cannot be proper as it can easily be hedged as the following example shows: A forecast always predicting the average probability is very reliable, but has a very low resolution, which is taken into account by the BS. The HL does not take resolution into account, but only tests for reliability. We tested the HL for our models and found that it is not suitable in our case. We find that our NULL model gets a perfect HL statistic of virtually 0, because it simply predicts the district average probabilities. The RAD_INT model, which includes meteorological predictor variables, gets a worse HL statistic and fails the significance test. We can assume that this corresponds to a reduction of reliability. However, since the HL does not take into account the resolution, it does not reward the RAD_INT model for "daring" to predict higher probabilities under adverse meteorological conditions. As suggested by the reviewer, we will consider the use of the HL in future studies, however, further research is necessary to test how the HL can be integrated into the concept of the BS decomposition for an improved consistency.

Comment C 3.4 — More importantly, a critical component of the study that is missing is a table with model coefficients (i.e. the influence of each variable) and their metrics (standard error, significance). The respective commentary of the effect of each variable is also critical. The authors should definitely add this part, at least for the best-performing models, as very useful knowledge and conclusions can be drawn, which are now left in the dark. After all, this is the main advantage of econometric models (such as logistic regression) vs. machine learning models, which are black boxes.

Reply: We agree with the reviewer that the model coefficients, standard errors and significances are important. However, since we use categorical variables and interaction terms the models in this study are relatively complex. For example, the best fitting model RAD_INT has 99 parameters, which are required to model the complex diurnal cycle based on 24 hourly coefficients and its interactions with the other parameters. Our idea was to base the description of the models in the results section of the article on the graphical representations in Figure 2, which are easier to read and interpret than a long table. The effect of each variable on the accident probability is displayed and the standard errors are reflected by the confidence intervals. Based on the reviewers comment, we decided to include the complete model coefficients, standard errors and significances of the main models NULL, HOUR, RAD and RAD_INT, which are described in section 4.1, as supplementary material in the revised version of the paper and comment on that in the results section of the manuscript. We provide the detailed model information in CSV format, which will enable the interested reader to look into the model details and easily reuse it for their own analyses. This enhances the reproducibility of this study.

Technical corrections

Comment C 3.5 — In the abstract, the authors mention "skillful" predictions, which is an unclear term. Do they mean informed predictions? Furthermore, there is mention of model hit rates. Is this a percentage of accurate predictions? Please clarify these points so that the abstract is more comprehensive.

Reply: With skillful we mean that the model has a positive skill score (see Eq. 5) and performs better than a reference model. We reformulated the abstract to make it more comprehensive.

Comment C 3.6 — On page 4, lines 25, it is stated that "τ is the difference between the time the model is initialized and the time the forecast is valid for". Shouldn't a more useful interval be between model finish and validity headway?

Reply: For the verification of meteorological forecasts the lead time τ is a standard parameter. It is used to assess how many hours/days ahead a forecast is useful. In contrast to a parameter that includes "model finish", as suggested by the reviewer, the lead time *tau* is independent of the wall-clock-time, that actually passes from the start of the computer program to the end. We added a sentence with an example to the manuscript to make the concept of lead time more comprehensible for the reader.

Comment C 3.7 — The English language needs minor revisions throughout the paper and in the abstract to avoid typographical mistakes (e.g. assess instead of asses). Also the authors are urged to select either "crash" (more widely used) or "accident" and use a single term consistently throughout the text.

Reply: We thoroughly checked the manuscript for typographical mistakes and use the term "accident" consistently throughout the text.

References

T. Gneiting and A. E. Raftery. Strictly proper scoring rules, prediction, and estimation. *Journal of the American statistical Association*, 102(477):359–378, 2007.

I. T. Jolliffe. The impenetrable hedge: A note on propriety, equitability and consistency. *Meteorological Applications: A journal of forecasting, practical applications, training techniques and modelling*, 15(1):25–29, 2008.

A. H. Murphy. A new vector partition of the probability score. *Journal of applied Meteorology*, 12(4):595–600, 1973.

D. S. Wilks. *Statistical methods in the atmospheric sciences*, volume 100. Academic press, 2011.

A. Ziakopoulos and G. Yannis. A review of spatial approaches in road safety. *Accident Analysis & Prevention*, 135:105323, 2020.

Predictive modeling of hourly probabilities for weather-related road accidents

Nico Becker[1,2], Henning W. Rust[1,2], and Uwe Ulbrich[1]

[1]Institut für Meteorologie, Freie Universität Berlin, Carl-Heinrich-Becker-Weg 6-10, 12165 Berlin, Germany
[2]Hans-Ertel-Centre for Weather Research, Berlin, Germany

Correspondence: Nico Becker (nico.becker@met.fu-berlin.de)

Abstract.

~~An impact~~ Impacts of weather on road accidents ~~has~~ have been identified in several studies with a focus mainly on monthly or daily accident counts. ~~We study~~ This study investigates hourly probabilities of road accidents caused by adverse weather conditions in Germany on the spatial scale of administrative districts ~~. Meteorological~~ using logistic regression models. Including meteorological predictor variables from radar-based precipitation estimates, high-resolution reanalysis and weather forecasts ~~are used in logistic regression models. Models taking into account temperature and hourly precipitation sums reach the best predictive skill according to different metrics. By introducing meteorological variables, the models hit rate~~improves the prediction of accident probability compared to models without weather information. For example, the percentage of correctly predicted accidents (hit rate) is increased from ~~0.3 to 0.7~~30% to 70%, while keeping the percentage of wrongly predicted accidents (false alarm rate~~constant at 0.2~~) constant at 20%. When using ensemble weather forecasts up to 21 h instead of radar and reanalysis data, the decline of model performance is negligible. Accident probability has a non-linear relationship with precipitation. Given an hourly precipitation sum of 1 mm, accident probabilities are ~~about~~ approximately 5 times larger at negative temperatures compared to positive temperatures. ~~Based on ensemble weather forecasts skilful predictions of accident probabilities of up to 21 hours are possible; the loss of skill compared to a model using radar and reanalysis data is negligible.~~ The findings are relevant in the context of ~~impact based warnings for both~~ impact-based warnings for road users, road maintenance~~and traffic managementauthorities~~, traffic management, as well as rescue forces.

1 Introduction

The road transport system is one of the most complex and dangerous systems that people have to deal with on a daily basis (Peden et al., 2004). In Germany, for example, road accidents lead to around 396,600 injuries and 3,200 fatalities per year in 2016 (BASt, 2017). Causes for road accidents can be of technical, ~~behavioral or~~ behavioural or of environmental nature. ~~Next to~~ According to a recent review paper on spatial approaches in road safety studies (Ziakopoulos and Yannis, 2020) , variables like traffic volume, ~~considered as the main cause for road accidents (e.g. Golob and Recker, 2003) , weather is one of the most important factors contributing to road traffic safety. The~~ speed limit or the number of lanes are frequently considered in accident analyses. Theofilatos and Yannis (2014) show that also the impact of weather on road accidents has been addressed in

several studies covering various temporal and spatial scales, ~~focussing~~ focusing on different weather parameters and applying different methods~~; for a review see Theofilatos and Yannis (2014)~~ . They find that the effect of precipitation is quite consistent and generally leads to an increased accident frequency. On the other hand, the impact of other weather parameters on road safety has not been found straightforward.

Two types of studies can be distinguished regarding the temporal scales. One type of study aims at relating road accidents to weather on a monthly or seasonal time scale (e.g. Fridstrøm et al., 1995; Shankar et al., 1995; Eisenberg, 2004; Bergel-Hayat and Depireb, 2004; Stipdonk and Berends, 2008). ~~Aim~~ The aim of these studies is to gain insight into potential policy measures against the effects of adverse weather on road transport (Shankar et al., 1995). Due to the temporal variability of weather on monthly time scales, such studies can only account for ~~aggregate~~ aggregated effects by considering for example the number of days with precipitation or the number of days with temperatures below the point of freezing (e.g. Fridstrøm et al., 1995). Other studies focus on daily timescales (e.g. Eisenberg, 2004; Keay and Simmonds, 2005; Caliendo et al., 2007; Brijs et al., 2008). On such time scales, the link between accident counts and the actual weather conditions on a specific day can be established. However, the largest variability of traffic volume and accident rates is observed on sub-daily time scales, with peaks during the rush hours and low values during night time (Martin, 2002). Weather conditions may also change dramatically within hours. ~~For taking~~ To take into account the combined effect of weather and traffic volume, a sub-daily time scale is necessary. Nevertheless, only few studies focus on sub-daily time scales (e.g., Hermans et al., 2006a), possibly due to the lack of appropriate data sources. To establish robust relationships between accidents and weather parameters on an hourly time scale a sufficient amount of data is required at a high spatial resolution. However, the analysis of highly resolved accident data is often subject to restrictions due to data protection directives. The spatial scales covered by the different studies vary from the national or state level (Hermans et al., 2006a) down to the level of individual cities (Yannis and Karlaftis, 2010) or specific roads or road segments (Ahmed et al., 2012).

Meteorological data used in accident studies is often derived from measurement stations. Either individual stations are used (e.g. Knapp et al., 2000) or they are spatially aggregated for the area of interest (e.g. Eisenberg, 2004). In both cases, it ~~might happen~~ is possible that not all relevant weather events are captured, because they do not hit a station. Recent studies use radar data to estimate the impact of precipitation on accidents (e.g. Mills et al., 2019). Jaroszweski and McNamara (2014) argue that radar data offers significant advantages over traditional station-based analyses, namely a better representation of rainfall due to a high spatial and temporal resolution.

Different weather parameters with a significant impact on road accidents have been identified. Depending on the study's ~~modelling~~ modeling strategy and the specific formulation of variables characterising weather, magnitude and even the sign of the weather impact can vary between different studies. The most important weather parameter considered in most studies is precipitation. On wet roads the tire contact force is reduced (Hays, 2013), which increases the ~~stopping~~ braking distance starting at 100 km/h by about 20% compared to dry roads (Cho et al., 2007). Also glare caused by wet shining surfaces can lead to reduced visibility and increase accident probabilities (Brodsky and Hakkert, 1988). Hermans et al. (2006a) study hourly ~~crash~~ accident counts in the Netherlands within a one-year period and found precipitation to be the most important factor among 17 different variables characterising weather.

On a monthly basis, snowfall can lead to ~~reduced numbers of accidents~~the reduction of accident numbers, possibly due to indirect effects like reduced traffic ~~volumes or adaption of diving~~ volume or the adaption of driving habits (Fridstrøm and Ingebrigtsen, 1991). On the other hand, on a daily basis, ~~however,~~ the direct effect of snowfall was found to increase the accident risk. For example, Knapp et al. (2000) find that freeway ~~crash~~ accident rates increase by a factor of 13 in case of extreme ~~snow storms. (Mills et al., 2019)~~ snowstorms. Mills et al. (2019) find that injury and non-injury collisions increase by 66 and 137 percent, respectively, during winter ~~storms. Winter~~ storm events that were characterized by factors like precipitation and low visibility. The winter storm events were identified by using radar- and station-based observations. Malin et al. (2019) observe ~~an~~ a sharp increase of relative accident risk if road surface temperatures drop below the freezing point.

Since the first weather impact models for road accidents (Scott, 1986), various types of models have been used in this context. Most popular are generalized linear models (GLMs), e.g. Poisson regression for accident counts or logistic regression for accident probabilities (e.g. Fridstrøm et al., 1995; Caliendo et al., 2007; Keay and Simmonds, 2006), but also other methods like state-space (Hermans et al., 2006b) or autoregressive models (Brijs et al., 2008; Scott, 1986; Bergel-Hayat and Depireb, 2004) have been applied. Mostly, statistical models for weather impact on road accidents are used in an inferential way; they test hypotheses for variable relations by means of statistical hypothesis testing for parameters significance of prescribed predictor variables, also referred to as explanatory ~~modelling~~ modeling (Shmueli et al., 2010). This contrasts to predictive modeling, where statistical models are used for prediction of yet unobserved instances of the target variable (e.g., accident counts or probabilities). In practice, predictive models are built and assessed using cross-validation.

This study follows the predictive modeling approach: We build and ~~asses~~ assess the skill of logistic regression models for hourly probabilities of weather-related road accidents at the scale of administrative districts in Germany. ~~Aim is to asses~~ The aim is to assess model performance at small spatial and temporal scales, as well as identifying relevant meteorological predictor variables for optimizing the predictive skill. We thus seek an adequate functional relationship between hourly precipitation and accident probability under different temperature conditions and district characteristics. Instead of station-based observations, we use a gridded radar-based precipitation product and a new high-resolution regional reanalysis. Additionally, using ensemble weather forecasts, we assess the predictive skill of the accident model for ~~leadtimes~~ lead times of up to 21 hours.

Section 2 describes data and ~~preprocessing~~ pre-processing approaches. Statistical models and associated verification methods are described in Sect. 3. Results of model verification and the application of the models in a case study of a snowfall event are presented in Sect. 4, which is followed by a discussion and conclusions in Sect. 5.

2 Data

2.1 Accident data

A data set with anonymized information from police reports of all heavy road accidents in Germany from 2007 until 2012 is used (Source: Research Data Centre of the Federal Statistical Office and Statistical Offices of the Länder, *Statistik der Straßenverkehrsunfälle*, 2007-2012, own calculations). Heavy road accidents include all accidents with injuries, fatalities or write-offs. Minor accidents are not included in the data set. In total ~~4,313,069 complete accident reports are available for the~~

2,392,329 accidents were reported during the 6-year period under investigation. Most accidents were indicated by the police as being caused by driver behaviour. However, ~~almost 8~~7.7% (184,201) of the accidents were indicated as being caused by adverse road conditions, which includes a wet, snowy or icy road, but also mud or dirt on the road. This class of accidents, which we refer to as *weather-related accidents*, is selected to generate the response variable used in the logistic regression models. The location of the individual accidents is available on the level of administrative districts (*Landkreise*). Because of several territorial reforms during the study period, all accidents are assigned to boundaries of the 401 administrative districts as they existed in 2017. For each district an hourly time series is created~~for the dichotomous variable *accident* being zero if no~~ , which is one if at least one accident happened within ~~the hour considered and one~~ an hour and zero otherwise. In total this results in ~~16,775,572~~ 21,076,961 data points, of which ~~136,559~~ 0.80% (168,404) contain at least one weather-related accident.

2.2 Radar-based precipitation data

Gridded hourly precipitation sums derived from the RADOLAN data set (Bartels et al., 2004) are available from the German Meteorological Service at a spatial resolution of 1×1 km . The RADOLAN combines radar ~~reflectivities~~reflectivity, measured by the 16 C-band Doppler radars of the German weather radar network, and ground-based precipitation gauge measurements. As from radar ~~reflectivities~~ reflectivity we cannot directly infer the precipitation amount at the ground but only the amount of reflection in the lower troposphere, observations from rain gauges are used to calibrate the precipitation amounts estimated from the radar ~~reflectivities~~ reflectivity in an online-procedure typically used for nowcasting. Before calibration, a statistical clutter filtering is applied and orographic shadowing effects are corrected for. The RADOLAN ~~projects thus~~ project aims at combining the benefits of high spatial resolution of the radar network with the accuracy of gauge-based measurements.

2.3 Reanalysis data

A reanalysis produced by a novel convective-scale regional reanalysis system for Central Europe (COSMO-REA2; Wahl et al., 2017) is used to generate meteorological predictor variables for the logistic regression models. The reanalysis results from the integration of COSMO-REA2 (a physical model for the atmosphere) with various heterogeneous observational data assimilated. COSMO-REA2 was developed within the framework of the Hans-Ertel Center for Weather Research (https://www.hans-ertel-zentrum.de). It contains different gridded atmospheric and surface variables for Central Europe at a spatial resolution of 2 km and at hourly time steps. Deep convection is explicitly resolved by the model, while shallow convection is parameterized using the Tiedke scheme (Tiedtke, 1989). In addition to conventional station-based observations, radar-derived rain rates are assimilated using latent heat nudging. On hourly to daily time scales, the assimilation of radar information substantially improves the parameterized precipitation compared to other reanalysis datasets (Wahl et al., 2017).

2.4 Ensemble weather forecasts

Weather forecasts are used to study the predictability of accident probabilities based on weather forecasts with an ensemble prediction system (EPS). We use the regional high-resolution ensemble forecasting system COSMO-DE-EPS, which run op-

erationally at the German Meteorological Service (DWD) before May 2018 with a spatial resolution of 2.8 km for the area of Germany. The COSMO-DE-EPS is initiated every 3 h with a ~~leadtime~~ lead time τ of ~~+~~up to 21 h. τ is the difference between the time the model simulation is initialized and the time the forecast is valid for. For example, if the model simulation is initialized at 0 UTC, $\tau = 21$ h corresponds to the forecast for 21 UTC. For each initialization time 20 ensemble members are available, generated using different global model forecasts as initial and lateral boundary conditions and variations of parameterizations for unresolved processes as described in detail in Gebhardt et al. (2011) and Peralta et al. (2012). The spread of the ensemble members allows an estimation of the forecast uncertainty. Similar to COSMO-REA2, precipitation rates derived from radar observations are assimilated at forecast initialization using latent heat nudging (Stephan et al., 2008).

For our study, a post-processed product of the archived COSMO-DE-EPS forecasts for the years 2011 and 2017 was provided by the DWD. Instead of archiving the forecast data on the original model grid, area averages of 21×21 grid boxes ($56 \times 56 km$) around 758 DWD owned gauge stations are stored. This drastically reduces the large amount of data, which facilitates their processing.

3 Methods

3.1 Data preparation

We aggregate the different meteorological variables to the level of administrative districts. For the station-based COSMO-DE-EPS forecasts a weighted mean of all available stations in the vicinity of the districts was calculated using the probability density function of a bi-variate circular symmetric normal distribution as the weighting function. A standard deviation of 25 km proved to be most appropriate, as it corresponds well to the average district area.

For a fair comparison of RADOLAN and COSMO-REA2 with COSMO-DE-EPS forecasts, the same aggregation is applied to the gridded RADOLAN and COSMO-REA2 products: the areal averages around the 758 gauge stations is computed as described in section 2.4 and the data is aggregated to the district level by applying the weighting function, as described above.

3.2 Logistic regression

Logistic regression models are used to model the probability of a certain event based on independent predictor variables (e.g. Menard, 2002). Here, we model hourly accident probabilities. If P_t is the probability that an accident occurs in a $1h$ time-interval $(t-1h, t]$, the logistic model equation is

$$P_t = 1/\{1 + \exp[-(\alpha + \mathbf{X_t}\,\boldsymbol{\beta})]\}, \tag{1}$$

where α is the intercept term, $\mathbf{X_t} = (X_{t1}, ...X_{tn})$ the set of n predictor variables, and $\boldsymbol{\beta} = (\beta_1, ..., \beta_n)$ are the corresponding parameters. α and the β_i are estimated using maximum likelihood. If the effects of the two predictor variables X_{ti} and X_{tj} are not additive (i. e. the effect of X_{ti} on P_t depends on the state of X_{tj}), interaction terms can be added to the model equation. If X_{ti} and X_{tj} are continuous variables, for example, this can be achieved by adding $\beta_{ij}\, X_{ti}\, X_{tj}$ to the linear term in Eq. 1, with β_{ij} quantifying the combined effect of X_{ti} and X_{tj}. For more detailed description of interactions, see Wood (2017).

The parameters of the logistic regression model can be easily converted to the odds ratio $\mathrm{OR} = \exp \beta_i$. The odds ratio for a given term X_{ti} describes the change of the odds of the event to occur in case of a unit change in X_{ti}.

3.3 Assessing model performance

Parameter estimates $\hat{\beta}_i$ associated to individual predictor variables X_{ti} can be tested for being significantly different from 0 using the p-values of a two-tailed z-test (Dobson and Barnett, 2008).

Different logistic models are compared with information criteria. The most popular is the Akaike Information Criterion (AIC; Akaike, 1974) defined as

$$\mathrm{AIC} = 2k - 2\log(\hat{L}), \tag{2}$$

where k is the number of parameters used in the model and $\hat{L}$ is value of the likelihood at its maximum. Fitted to the same data the model with lower AIC is to be preferred. The AIC penalizes models with more parameters to prevent overfitting.

The Brier Score (BS) is a proper score to measure accuracy of probabilistic forecasts for binary events, as they result from a logistic regression model. Based on Brier (1950) the BS can be defined as

$$\mathrm{BS} = \frac{1}{N}\sum_{t=1}^{N}(f_t - o_t)^2, \tag{3}$$

where f_t is the forecast probability, o_t is the observed outcome of the event ($o_t \in \{0,1\}$), t lables the events and N is the total number of events. However, Benedetti (2010) has shown that the Brier Score may not be suitable when forecasting very rare (or very frequent) events. He suggests the use of the logarithmic score (or *absolute score*)

$$\mathrm{LS} = a\frac{1}{N}\sum_{t=1}^{N}(o_t \ln f_t + (1-o_t)\ln(1-f_t)), \tag{4}$$

where $a = -(2\ln 2)^{-}1$ is simply a scaling factor, making LS comparable in size to BS. The LS is frequently used in the field of statistical mechanics and information theory and fulfills three basic desiderata (i.e. additivity, exclusive dependence on physical observations, and strictly proper ~~behavior~~behaviour).

By defining a threshold u, a probabilistic forecast ($0 \leq f_t \leq 1$) can be transformed into a binary forecast, which is either *positive* (accident) or *negative* (no accident) if the forecast probability falls above ($f \geq u$) or below the threshold ($f < u$) , respectively. The true positive rate (TPR, or hit rate) is the number of correctly predicted positive events divided by the total number of positive events. The false positive rate (FPR, or false alarm rate) is the number of incorrectly predicted negative events divided by the total number of negative events. The receiver operating characteristic (ROC) curve is a common way to illustrate the performance of a logistic regression model as a binary classifier, by plotting the TPR against the FPR for various thresholds $0 < u < 1$ (Hanley and McNeil, 1982). The area under the ROC curve (AUC) is frequently used for measuring the ability of a model to discriminate between positive and negative events. The AUC ranges between 0.5 and 1, which compares to random guessing and perfect discrimination, respectively. For a given FPR the corresponding TPR can be identified based

on the ROC curve. In this study, we compare the TPR of different models while selecting u so that the FPR is kept constant at 0.2.

A skill score SS is a relative measure of how much a forecast S_f outperforms a reference forecast S_r, defined as

$$SS = (S_f - S_r)(S_p - S_r)^{-1}, \tag{5}$$

where S_p is the score of a perfect forecast. In this study we use the BS to compute the Brier Skill Score (BSS, $S_{p,BS} = 0$), the LS to compute the Logarithmic Skill Score (LSS, $S_{p,LS} = 0$) and the AUC to compute a skill score based on the ROC curve (AUCSS, $S_{p,AUC} = 1$).

While AIC penalizes large numbers of model parameters to avoid overfitting, in cross-validation techniques model parameter are estimated on a training data set and scores are computed on an independent testing data set. Here, we use a yearly cross-validation approach. Model parameters are estimated on a data set with one year of data left out and scores are calculated for this respective year. This is repeated several times until for all years a score has been estimated. The score is then averaged over all years and used for model comparison.

To understand the behaviour of the model, the predicted accident probabilities of the regression models can be compared to non-parametric estimates for accident frequencies within bins of specific parameter ranges. For example, a predicted accident probability for negative temperatures and a precipitation amount of 1 mm/h at 7:00 local time can be compared to the relative accident frequency for all time steps that showed negative temperatures and precipitation amounts in an interval of 1 ± 0.1 mm at 7:00. The uncertainty of model probability forecasts is estimated by computing the 95% confidence interval based on asymptotic standard errors. The uncertainty related to the ~~non-parameteric~~ non-parametric estimates of the accident frequency is estimated by using a bootstrapping approach. The observed accident frequency is computed 10,000 times after drawing random samples with replacement from the available data. The range between the 0.025 and 0.975 quantile of the resulting distribution of values can be used to construct a 95% confidence interval around the average observed accident frequency.

3.4 Model description

3.4.1 Models without weather information

The models NULL and HOUR predict the accident probabilities for each district without using weather information (see Table 1 and Table 2 for a detailed description of predictor variables and models, respectively). The simplest model is the NULL model, using only the intercept and the time average accident probability $\overline{P}$ for each district as a predictor. $\overline{P}$ is transformed into $\overline{P}'$ using the inverse logistic function. By using $\overline{P}'$ in the logistic regression equation, a linear relationship between $\overline{P}$ and the hourly accident probability is established. By introducing $\overline{P}'$ we can distinguish between different districts using a single model parameter. Alternatively, we could include an individual intercept parameter for each district. However, this would require the estimation of 401 parameters. By adding interaction terms, the number of parameters would increase even more, making the model inapplicable.

The model HOUR includes an additional categorical variable H specifying the time of day in hours (local time), which describes the diurnal cycle additionally to the average accident probability of each district. These two models are used as reference models to assess the benefit of adding weather information.

3.4.2 Models using radar and reanalysis data

Accident, radar and reanalysis data overlap in time for the years from 2007 to 2012. For this time period, a binary predictor variable with hourly resolution for the near surface temperature T_{REA} (temperature at 2 m height) is derived from COSMO-REA2, which distinguishes between temperatures above and below 0°C. Furthermore, a continuous variable Pr_{RAD} with the hourly precipitation sum in mm/h is used. In model RAD the model HOUR is extended by adding T_{REA} and $(Pr_{RAD})^{0.2}$ as direct effects. Different combinations of exponents have been tested to transform the precipitation, but 0.2 lead to the best results in terms of model skill. In the model RAD_INT the two-point interaction terms between $\overline{P}'$, H, T_{REA} and $(Pr_{RAD})^{0.2}$ are added to the model equation. Model parameter estimates result from using data from all districts simultaneously. However, the skill scores are calculated for each district individually within the ~~cross validation~~ cross-validation procedure. This allows ~~to asses~~ us to compare the performance of the model ~~for~~ in different districts.

Additionally, we fit the models to the individual districts, yielding models RAD_IND and RAD_INT_IND[1], respectively. On the one hand, these models capture the district specific characteristics; on the other hand, the amount of available data points for each model is strongly reduced, which complicates the estimation of model parameters, in particular for districts with low accident numbers. These models are used to quantify the benefit of having one model for all districts.

3.4.3 Models using weather forecast data

The overlapping time period of accident data and COSMO-DE-EPS data are the years 2011 and 2012. For this time period temperature and precipitation is aggregated to district level as before for all 20 ensemble members. This is done separately for all forecast ~~leadtimes~~ lead times τ, ranging between 1 h after forecast initialization and 21 h after initialization.

The COSMO-DE-EPS provides hourly forecast data, but is initialized only every three hours. Therefore, not all hours are available for all ~~leadtimes~~lead times. E.g. a ~~leadtime~~ lead time of 6 h is only available at 0, 3, 6, 9, 12, 15, 18, 21 UTC, while a ~~leadtime~~ lead time of 7 h is only available at 1, 4, 7, 10, 13, 16, 19, and 22 UTC. Furthermore, the logistics regression model uses local time, which has to take into account daylight savings time. Both effects complicate an explicit use of the hour as a predictor variable in combination with COSMO-DE-EPS data. Therefore, to facilitate the incorporation of a diurnal cycle in the model, a ~~two step~~ two-step procedure is applied. First, the model HOUR is used to forecast the average diurnal cycle of accident probabilities P_H for each district. Then P_H is transformed into P'_H using the inverse logistic function. Second, P'_H is used to replace the terms $\overline{P}' + H$ (compare HOUR and EPS_HOUR in Table 2, for example).

Three different ways to incorporate the ensemble information in the models are used.

[1]INT refers to the use of interaction terms in the model equation, while IND refers to estimating model parameters for each district individually.

1. *Deterministic forecasts:* In case of the model EPS_MEM$_i$_INT an individual set of parameters is estimated for each ensemble member and each ~~leadtime~~lead time. Skill scores are calculated for each of the resulting sets of parameters separately, thus treating the ensemble members as single deterministic forecasts.

2. *Meteorology-averaged ensemble:* In case of the model EPS_MEAN_INT the parameters are estimated using the ensemble mean of the meteorological variables, which results in a single set of parameters for each ~~leadtime~~lead time.

3. *Probability-averaged ensemble:* In case of the model EPS_PMEAN_INT accident probabilities are predicted using the models EPS_MEM$_i$_INT for the individual ensemble members, but the ensemble mean of the predicted probabilities is calculated before using it to compute the scores in the cross-validation procedure.

The models EPS_HOUR, EPS_RAD_INT correspond to the models HOUR, RAD_INT, but are fitted separately to the data available for each ~~leadtime~~ lead time, to allow a direct comparison to the models using COSMO-DE-EPS data.

4 Results

4.1 Models using radar and reanalysis data

The time average hourly probability that at least one weather-related accident occurs in an administrative district is referred to as $\overline{P}$. It ranges from ~~below~~ less than 0.001 for smaller districts with ~~less~~ few inhabitants to more than 0.05 for densely populated cities. The NULL model simply gives $\overline{P}$ for each district and serves as a reference model. As expected, the AUC is 0.5, indicating that the model is not able to distinguish between accident and non-accident cases (Table 3).

In model HOUR all parameters of the categorical variables H are significantly different from zero with p-values below 0.001, indicating that the diurnal cycle is an important aspect of the accident characteristics. The average AUC of all districts is 0.62, indicating that the introduction of the hour as a predictor improves the model.

The introduction of temperature and precipitation as direct effects in the model RAD leads to a further improvement of the scores, compared to NULL and HOUR. With an AUC of about 0.81 and an AUCSS of 0.49 (HOUR as reference) temperature and precipitation can be considered useful in terms of binary classification of accident events. The TPR increases from 0.3 for HOUR to 0.7 for RAD. The interaction terms in RAD_INT slightly improve all scores except for the TPR.

Fig. 1 shows that the variability of the AUCSS values of the different districts is relatively large, compared to the differences between the models. However, there is no evident systematic relationship between the skill of the model and the geographic location of the district or the district specific topography (not shown).

Fig. 2 shows the ~~modelled~~ modeled accident probabilities (solid lines) predicted by the RAD (left) and RAD_INT (right) versus precipitation (top), hour (middle) and $\overline{P}$ (bottom) together with the 95% confidence intervals estimated from the standard errors (shaded). Additionally, the accident probabilities estimated non-parametrically (number of time steps with accidents divided by total number of time steps) are shown (markers) together with the 95% confidence intervals estimated using a bootstrapping approach (vertical lines). Model and non-parametric probabilities are shown for positive (red) and negative (blue) temperatures.

The ~~modelled~~ modeled accident probabilities as a function of Pr_{RAD} are shown for 7:00 local time for a district with an average probability for weather-related accidents of $\overline{P} = 0.01$ (Fig. 2, top row). Non-parametric probability estimates are calculated for precipitation bins with a width of 0.1 mm/h including only districts with $\overline{P} = 0.01 \pm 0.002$. In general, accident probabilities are lowest at $Pr_{RAD} = 0$ ~~,~~and show a steep increase with increasing precipitation with a decreasing slope at higher precipitation rates. Probabilities are higher at temperatures below 0°C. At ~~Pr_{RAD}1 mm/h they~~ Pr_{RAD}1 mm/h probabilities are about 5 times higher if temperatures are below 0°C. For RAD the ~~modelled~~ modeled probabilities fit well to the non-parametric probability estimates at $Pr_{RAD} < 0.5$ mm/h, but overestimate probabilities at higher precipitation rates. In contrast, the model RAD_INT shows reduced probabilities, which fit much better to the non-parametric probability estimates. The curved shape of the functional relationship between precipitation and probability is realized by taking precipitation to the power of 0.2. The value 0.2 was found to be the best choice after testing a series of different exponents, other functional relationships as $\log 1 + Pr$, as well as categories of precipitation.

The ~~modelled probabilities as~~ modeled probabilities as a function of H are shown for $Pr_{RAD} = 0$ mm/h (solid lines) and $Pr_{RAD} = 0.5$ mm/h (dashed lines) for $\overline{P} = 0.01$ (Fig. 2, middle row). Non-parametric probability estimates are calculated using time steps with $Pr_{RAD} = 0$ mm/h (circles) and $Pr_{RAD} = 0.5 \pm 0.25$ mm/h (triangles) including only districts with $\overline{P} = 0.01 \pm 0.002$. In general, accident probabilities show a pronounced diurnal cycle with maximum probabilities during morning and afternoon rush hours. RAD overestimates the observed probabilities in particular during the morning hours with precipitation at negative temperatures. The model RAD_INT is able to capture the observed diurnal cycle more precisely.

The ~~modelled~~ modeled probabilities as function of $\overline{P}$ are shown for $Pr_{RAD} = 0$ mm/h (solid lines) and $Pr_{RAD} = 0.5$ mm/h (dashed lines) at $H = 7$ h (Fig. 2, bottom row). Non-parametric probability estimates are calculated using time steps with $Pr_{RAD} = 0$ mm/h (circles) and $Pr_{RAD} = 0.5 \pm 0.25$ mm/h (triangles) including districts with $\overline{P} = 0.01 \pm 0.002$. In general, the probabilities show ~~an~~ a monotonic increase with $\overline{P}$, which justifies the introduction of $\overline{P}$ as a predictor to distinguish between different districts. The predictions of RAD and RAD_INT are relatively similar and lie mostly within the confidence intervals of the observed probabilities.

~~In a next step~~For a more detailed insight into the modeling results we provide the full model coefficients, standard errors and p-values of the models NULL, HOUR, RAD and RAD_INT as supplementary material to this article. In case of RAD, which hat 27 coefficients, almost all model coefficients have p-values below 0.001 and we can reject the null hypothesis that the coefficients are zero. Only one of the 23 coefficients of the categorical variable HOUR is not significant. In case of RAD_INT, which has 99 coefficients due to the introduction of interaction terms, 34 coefficients have p-values below 0.001. 29 have p-values greater than 0.1 and are thus not significantly different from zero. These non-significant coefficients all belong to the categorical variable HOUR or are included in an interaction term with this variable. This might indicate the diurnal cycle could be modeled sufficiently with less than the 23 coefficients used here. However, we do not expect a large impact of such a reduction on the metrics that have been discussed earlier.

Next, we compare the models RAD and RAD_INT, which are fitted to all districts simultaneously, to the models RAD_IND and RAD_INT_IND, which are fitted to all districts individually. Fig. 3 shows the difference of the AUCSS between RAD and RAD_IND (red) and between RAD_INT and RAD_INT_IND (black) as a function of $\overline{P}$. $\overline{P}$ provides ~~a~~ direct information about

how many accident cases were available in the time series used for training the models. In general, the AUCSS differences are mostly negative, indicating that the models fitted to each district individually perform poorer than the models including all districts. The AUCSS differences decrease with increasing $\overline{P}$, i.e. increasing accident numbers. Furthermore, the AUCSS differences are larger for the more complex models with interaction terms. The results are similar for the LSS (not shown).

Based on the results of this section, we can conclude that RAD_INT should be preferred over RAD, since it achieves the best scores and better represents the functional relationship between probability and precipitation as well as the diurnal cycle. Furthermore, RAD_INT preforms better than RAD_INT_IND, which is fitted to each district individually.

4.2 Models using weather forecast data

The model RAD_INT showed the best performance among the models predicting accident probability using radar and reanalysis data (Sect. 4.1). In this section the model formulation of RAD_INT is modified to allow the use of COSMO-DE-EPS ensemble weather forecasts. To facilitate the ~~modelling~~ modeling procedure, the variables H and $\overline{P}$ are combined into a single variable P'_H by using the model HOUR, which effectively results in a district-specific diurnal cycle of accident probabilities (see Sect. 3.4.3 for details). P'_H, precipitation and temperature are used as predictor variables, including their interaction terms. ~~In case of all of the following models, a new set of parameters is estimated for each leadtime~~ For each lead time from 1 to 21 h, a new set of model parameters is estimated using only those time steps, ~~which are~~ where COSMO-DE-EPS data is available for the specific ~~leadtime~~lead time. For a small number forecasts the COSMO-DE-EPS data is missing or incomplete.

The model EPS_RAD_INT uses T_{REA} and Pr_{RAD} and serves as ~~an upper limit~~a reference, representing the best available model based on reanalysis and radar data. The AUCSS of EPS_RAD_INT as a function of ~~leadtime shows a repetitive~~ lead time shows a three-hourly cyclic pattern with maximum values of around 0.5 at ~~leadtimes~~ lead times 1, 4, 7, etc. and 0.47 in between (Fig. 4, orange line). This ~~repetitive pattern can be explained by different data time steps that go into the model training and verification at the different leadtimes due to the three-hourly initialization of the~~ cyclic pattern occurs because hourly data is used in the statistical models, but COSMO-DE-EPS is only initialized every three hours (0 UTC, 3 UTC, 6 UTC, etc.). Consequently, EPS_RAD_INT for lead times of 1 h, 4 h, 7 h, etc. includes only data at 1 UTC, 4 UTC, 7 UTC, etc., the lead times 2 h, 5 h, 8 h, etc. include only 2 UTC, 5 UTC, 8 UTC, etc., and the lead times 3 h, 6 h, 9 h, etc. include only 0 UTC, 3 UTC, 6 UTC, etc. As a consequence, there are three sets of lead times that are associated to different sets of hours of the day, which correspond to the repetitive three-hourly pattern in the AUCSS. Apparently, the model performs differently for these three sets of hours, possibly due to different traffic characteristics during the specific hours.

The model EPS_MEMi_INT is estimated for each of the 20 ensemble members individually, which therefore results in 20 deterministic forecasts with 20 individual AUCSS values per ~~leadtime~~lead time. The AUCSS drops from 0.48 at ~~leadtime~~ lead time 1 h to below 0.45 at ~~leadtime~~ lead time 21 h (~~gray~~ grey lines). The spread between the AUCSS of the different ensemble members increases with increasing ~~leadtime~~lead time. The model EPS_MEAN_INT is based on the ensemble mean of the meteorological variables (meteorology-averaged ensemble) and shows a slightly higher AUCSS (black solid line) than all the deterministic forecasts.

The model EPS_PMEAN_INT, which is based on the ensemble mean of the accident probabilities of the 20 versions of EPS_MEMi_INT (probability-averaged ensemble), shows again a slightly higher AUCSS (black dashed line) than the meteorology-averaged ensemble. As expected, the AUCSS values of all models based on weather forecast data are lower than the AUCSS of EPS_RAD_INT based on radar and reanalysis data. However, the differences are relatively small. The LSS shows a similar behaviour regarding the ~~leadtime~~ lead time dependence as the AUCSS (not shown).

4.3 Case study

The models RAD_INT and EPS_PMEAN_INT are used in a case study with adverse winter weather conditions on Dec. 3rd, 2012. At temperatures below the freezing point the fronts of a low pressure system lead to snowfall in large parts of Germany. These weather conditions lead to a total number of 280 accidents classified by the police as caused by road condition. The majority of the accidents occurred in southern and western Germany[2].

For the district of Stuttgart, which was located within the affected area, the RADOLAN data shows low precipitation amounts in the early morning and higher precipitation amounts of up to 0.3 mm/h in the afternoon (Fig. 5a). The COSMO-DE-EPS forecast, which was initialized on Dec. 3rd, 2012 at 00:00 UTC (02:00 h local time), shows ensemble mean precipitation amounts of more than 0.6 mm/h in the afternoon and a large spread between the ensemble members.

The temperature in COSMO-REA2 is below 0°C until 19:00 h and then changes to warmer conditions (Fig. 5b). All ensemble members of COSMO-DE-EPS predict the change to positive temperatures two hours earlier than observed.

The accident probability of EPS_RAD_INT shows the combined effect of the average diurnal cycle, RADOLAN precipitation and COSMO-REA2 temperature (Fig. 5c). It shows a peak of 0.07 in the morning during rush hour at low precipitation amounts at freezing temperatures, a drop to 0.02 at noon when RADOLAN shows no precipitation, a maximum peak of 0.22 in the afternoon, when precipitation is strongest. In general, the accident probability of EPS_PMEAN_INT matches well with EPS_RAD_INT. However, it slightly overestimates the morning peak and overestimates the afternoon peak due to the too intense and persistent precipitation.

The hourly accident probability P is useful for authorities to assess how likely the ~~occurence~~ occurrence of an accident is in a certain district at a certain point in time. However, it does not reflect the risk of an individual road user, as it does not distinguish whether P changes due to weather-related effects, due to a change in traffic density along the diurnal cycle, or due to the district characteristic. For example, a road user ~~travelling~~ traveling from a district with a high average accident probability $\overline{P}$ to a district with a low $\overline{P}$ would observe a decrease of P, also if the weather conditions remain the same. Therefore, to estimate the impact on an individual road user, we compare P to P_0, the probability under conditions without precipitation and positive temperatures (Fig. 5c, dotted line). The fraction P/P_0 gives the amplification of the actual predicted probability P compared to warm and dry conditions (Fig. 5d). In case of the forecast for Dec. 3rd, 2012, the amplification factor ranges between 50 in the afternoon when the precipitation amount is high and 5 around noon when precipitation amount is low. This factor could be a potential weather impact forecast product.

[2]Due to regulations regarding anonymization and data protection we are not allowed to show accident counts less than three, which prevents us from showing accident counts for single hours or days at the district level.

On Dec. 3rd, 2012 at 17:00 h local time, the COSMO-DE-EPS overestimates the precipitation amount in large parts of western and southern Germany, compared to RADOLAN (Fig. 6). The area with temperatures below 0°C is captured relatively well, compared to COSMO-REA2. The accident probability P is largest where high precipitation amounts and freezing temperatures occur. Spatially, P is relatively inhomogeneous, which reflects the large differences in average accident probability between the individual districts. P/P_0, representing the increase in accident probability of individual drivers, is spatially more homogeneous.

5 Summary, discussion and conclusions

Police reports of heavy road accidents in Germany were used to construct hourly time series based on weather-related accidents caused by adverse road conditions for German administrative districts. Different meteorological datasets aggregated to district level were used in logistic regression models to predict hourly accident probabilities. Models of different complexity were compared after calculating different skill scores using a yearly cross-validation approach. The best model with respect to these scores included district-specific average accident probability, the hour of the day, hourly precipitation and temperature, as well as their interaction terms. ~~By introducing meteorological variables to the model , the~~ The model reached a hit rate (TPR) ~~could be increased from 0.3 to~~ of 0.7, ~~while~~ when the false alarm rate (FPR) was ~~kept constant~~ fixed at 0.2. With the same false alarm rate, a model without meteorological parameters only reached a hit rate of 0.3. It was shown that the probability of weather-related accidents increases non-linearly with increasing hourly precipitation. Given an hourly precipitation of 1 mm, the accident probability is approximately 5 times higher at negative temperatures, compared to positive temperatures. In a case study it was shown that the model is able to reasonably capture the spatial and temporal development of accident probabilities during adverse winter weather conditions. When using ensemble weather forecasts to predict accident probabilities, the skill of the logistic regression model remains almost constant for a forecast ~~leadtime~~ lead time of up to 21 h. Furthermore, the use of ensemble forecasts leads to a higher skill compared to a setting, where ensemble members are treated as individual deterministic forecasts. These findings are in line with the results of Pardowitz et al. (2016), who show that the use of ensemble information improves predictions of storm damage probabilities.

The target variable of this study were weather-related road accidents. The accidents included in the analysis were indicated by the police as being caused by adverse road conditions, which includes a wet, snowy or icy road, but also mud or dirt on the road. Thus, the categorization of the accident cause is based on the subjective decision of the police at the location of the accident. This might introduce a bias to the results whose direction or extent is hard to estimate. For example, a large number of accidents that occur during adverse weather conditions are likely to be unrelated to the weather but are caused only by inattention of the driver. Police officers might still categorize these accidents as being weather-related in unclear situations. It should be kept in mind that this could lead to an overestimation of weather-related accident probabilities in the models developed in this study.

It is known that the main parameters affecting accident probability are traffic flow and density. In an optimal case one would ~~used~~ use measurements of these variables as a model predictor for accident probability. However, traffic measurements

are not continuously available for all administrative districts. Additionally, measurements of traffic flow are mainly available for highways and federal roads and might not be representative for municipal roads, where the majority of the accidents occur. Furthermore, in an operational setting, where the model is applied for predicting future accident probabilities, traffic measurements are not available. Therefore, we decided not to directly include traffic measurements in the models. Instead, the hour of the day was used as a categorical predictor variable to capture the average diurnal cycle of accident probability. It was shown ~~,~~ that this approach is able to reasonably represent the inner-day variability of accident probability. The introduction of additional factors like ~~a~~ at weekends or holidays did not lead to a significant improvement of the model.

It is a challenging task to combine accident data, which is available for the area of administrative districts, with meteorological data, which is usually available in the form of point observations or gridded data. Different ways of aggregating meteorological data to district level were tested and the approach based on distance-weighted averaging, which is presented in this study, showed the best results.

The temperature at 2 m height was used in this study to include the effect of negative temperatures in the statistical model in a relatively simple approach. It has the benefit, that the temperature at 2 m height is a ~~well established~~ well-established meteorological parameter, which is measured at most stations and available in all weather forecasting models. However, it might not reflect the conditions at the road surface, which can deviate from the conditions at 2 m height. Also, the choice of 0°C as a fixed threshold is a simplified approach, since ground frost or snowfall could also occur at higher 2 m temperatures. By using non-linear approaches like generalized additive models (Wood, 2017) a smooth transition between positive and negative temperatures could be established in future studies. Furthermore, it might be detrimental that area averaged temperatures are used, which does not fully represent topographic variations within the area of a certain district. A more complex approach could make use of a road surface model, which includes the combined effects of precipitation, evaporation, and road surface temperatures in a more sophisticated way (e.g. Juga et al., 2013).

In addition to the weather parameters presented in this study, other parameters like snow fall amount or combined measures of cloud cover and sun angle to describe the impact of sun glare were tested as potential predictor variables. Furthermore, advanced predictor selection techniques like genetic algorithms (Calcagno et al., 2010) and the least absolute shrinkage and selection operator (Tibshirani, 1996) were applied, to find optimal combinations of parameters. However, none of the results were able to significantly improve the skill of the best models presented in this study, as measured by the cross-validation approach.

We found that the probability of weather-related accidents ~~increases approximately~~ depends on hourly precipitation to the power of 0.2. This exponent should not be understood as a universal relationship. Instead, it is likely to depend on different aspects of the road system (e.g. how fast is the water able to leave the road surface) or the average car characteristics (e.g. the share of cars equipped with assistance systems, or the type tires). It may even change in time, as road and car qualities improve.

In this work we showed two ways of ~~modelling~~ modeling probabilities in different districts: first, by creating a model that distinguishes between different districts based on their average accident probability and, second, by creating a model for each district individually. We found that to first approach lead to higher skill scores, particularly for districts with low accident

numbers. Including additional district-specific parameters describing the characteristics of the road network or topographic conditions could help to further refine the model.

This study shows that a skillful relationship between meteorological parameters and weather-related road accidents can be established. Forecasts of probabilities of weather-related road accidents, as presented in this study, might be useful for authorities (traffic management, police or emergency services) on the one hand and road users on the other hand. However, it is reasonable to provide the information about accident risk in different, user specific formats, which were introduced in Sect. 4.3. Authorities might be primarily interested in aggregated risk information for their region of interest, e.g. the occurrence probability of accidents in an administrative district. On the other hand, a road ~~used~~ user is rather interested in his individual risk. The individual risk is better reflected through an amplification of risk compared to certain reference conditions (e.g. warm and dry weather).

It was shown that impact-based warning can lead to ~~a~~ better actions of the recipients (Weyrich et al., 2018). Furthermore, Hemingway and Robbins (2019) state that information about weather impacts can be helpful for operational meteorologists when issuing weather warnings. This was found using a prototype impact model for predicting the risk of road disruption due to the wind-induced overturning of vehicles. In this context, the accident model presented in this study can be considered a useful tool for reduction of road traffic risk.

Data availability. The accident data for Germany was obtained from the Research Data Centre of the Federal Statistical Office and Statistical Offices of the Länder. The RADOLAN and COSMO-REA2 data are publicly available from the Climate Data Center of the Deutscher Wetterdienst. The COSMO-DE-EPS data was provided by the Deutscher Wetterdienst upon request.

Author contributions. Data analysis and visualization was done by NB; All authors contributed to writing the manuskript.

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements. This research was carried out in the Hans-Ertel-Centre for Weather Research. This research network of universities, research institutes, and the Deutscher Wetterdienst is funded by the BMVI (Federal Ministry of Transport and Digital Infrastructures).

References

Ahmed, M. M., Abdel-Aty, M., and Yu, R.: Assessment of interaction of crash occurrence, mountainous freeway geometry, real-time weather, and traffic data, Transp. Res. Rec., 2280, 51–59, https://doi.org/10.3141/2280-06, 2012.

Akaike, H.: A new look at the statistical model identification, IEEE Trans. Autom. Control, 19, 716–723, https://doi.org/10.1007/978-1-4612-1694-0_16, 1974.

Bartels, H., Weigl, E., Reich, T., Lang, P., Wagner, A., Kohler, O., Gerlach, N., et al.: Projekt RADOLAN–Routineverfahren zur Online-Aneichung der Radarniederschlagsdaten mit Hilfe von automatischen Bodenniederschlagsstationen (Ombrometer), Deutscher Wetterdienst, Hydrometeorologie, 5, 2004.

BASt: Verkehrs- und Unfalldaten - Kurzzusammenstellung der Entwicklung in Deutschland, Tech. rep., Bundesanstalt für Straßenwesen, Bergisch Gladbach, Germany, 2017.

Benedetti, R.: Scoring rules for forecast verification, Mon. Weather Rev., 138, 203–211, https://doi.org/10.1175/2009MWR2945.1, 2010.

Bergel-Hayat, R. and Depireb, A.: Climate, Road Traffic and Road Risk: An Aggregate Approach, in: 10th World Conference on Transport Research, https://trid.trb.org/view/843834, 2004.

Brier, G. W.: Verification of forecasts expressed in terms of probability, Mon. Weather Rev., 78, 1–3, https://doi.org/10.1175/1520-0493(1950)078<0001:VOFEIT>2.0.CO;2, 1950.

Brijs, T., Karlis, D., and Wets, G.: Studying the effect of weather conditions on daily crash counts using a discrete time-series model, Accident Anal. Prev., 40, 1180–1190, https://doi.org/10.1016/j.aap.2008.01.001, 2008.

Brodsky, H. and Hakkert, A. S.: Risk of a road accident in rainy weather, Accident Anal. Prev., 20, 161–176, https://doi.org/10.1016/0001-4575(88)90001-2, 1988.

Calcagno, V., de Mazancourt, C., et al.: glmulti: an R package for easy automated model selection with (generalized) linear models, J. Stat. Softw., 34, 1–29, https://doi.org/10.18637/jss.v034.i12, 2010.

Caliendo, C., Guida, M., and Parisi, A.: A crash-prediction model for multilane roads, Accident Anal. Prev., 39, 657–670, https://doi.org/10.1016/j.aap.2006.10.012, 2007.

Cho, J., Lee, H., and Yoo, W.: A wet-road braking distance estimate utilizing the hydroplaning analysis of patterned tire, Int. J. Num. Methods Eng., 69, 1423–1445, https://doi.org/10.1002/nme.1813, 2007.

Dobson, A. J. and Barnett, A. G.: An introduction to generalized linear models, Chapman and Hall/CRC, 2008.

Eisenberg, D.: The mixed effects of precipitation on traffic crashes, Accident Anal. Prev., 36, 637–647, https://doi.org/10.1016/S0001-4575(03)00085-X, 2004.

Fridstrøm, L. and Ingebrigtsen, S.: An aggregate accident model based on pooled, regional time-series data, Accident Anal. Prev., 23, 363–378, https://doi.org/10.1016/0001-4575(91)90057-C, 1991.

Fridstrøm, L., Ifver, J., Ingebrigtsen, S., Kulmala, R., and Thomsen, L. K.: Measuring the contribution of randomness, exposure, weather, and daylight to the variation in road accident counts, Accident Anal. Prev., 27, 1–20, https://doi.org/10.1016/0001-4575(94)E0023-E, 1995.

Gebhardt, C., Theis, S., Paulat, M., and Bouallègue, Z. B.: Uncertainties in COSMO-DE precipitation forecasts introduced by model perturbations and variation of lateral boundaries, Atmos. Res., 100, 168–177, https://doi.org/10.1016/j.atmosres.2010.12.008, 2011.

Golob, T. F. and Recker, W. W.: Relationships among urban freeway accidents, traffic flow, weather, and lighting conditions, J. Transp. Eng., 129, 342–353, https://doi.org/10.1061/(ASCE)0733-947X(2003)129:4(342), 2003.

Hanley, J. A. and McNeil, B. J.: The meaning and use of the area under a receiver operating characteristic (ROC) curve., Radiology, 143, 29–36, https://doi.org/10.1148/radiology.143.1.7063747, 1982.

Hays, D.: The physics of tire traction: theory and experiment, Springer Science & Business Media, 2013.

Hemingway, R. and Robbins, J.: Developing a hazard impact model to support impact-based forecasts and warnings: The Vehicle OverTurning Model, Meteorol. Appl., https://doi.org/10.1002/met.1819, 2019.

Hermans, E., Brijs, T., Stiers, T., and Offermans, C.: The impact of weather conditions on road safety investigated on an hourly basis, in: TRB 85th Annual Meeting Compendium of Papers, pp. 1–16, Transportation Research Board, http://hdl.handle.net/1942/1365, 2006a.

Hermans, E., Wets, G., and Van den Bossche, F.: Frequency and severity of Belgian road traffic accidents studied by state-space methods, J. Transp. Stat., 9, 63–76, http://hdl.handle.net/1942/1500, 2006b.

Jaroszweski, D. and McNamara, T.: The influence of rainfall on road accidents in urban areas: A weather radar approach, Travel. Behav. Soc., 1, 15–21, https://doi.org/10.1016/j.tbs.2013.10.005, 2014.

Juga, I., Nurmi, P., and Hippi, M.: Statistical modelling of wintertime road surface friction, Meteorol. Appl., 20, 318–329, https://doi.org/10.1002/met.1285, 2013.

Keay, K. and Simmonds, I.: The association of rainfall and other weather variables with road traffic volume in Melbourne, Australia, Accident Anal. Prev., 37, 109–124, https://doi.org/10.1016/j.aap.2004.07.005, 2005.

Keay, K. and Simmonds, I.: Road accidents and rainfall in a large Australian city, Accident Anal. Prev., 38, 445–454, https://doi.org/10.1016/j.aap.2005.06.025, 2006.

Knapp, K. K., Smithson, L. D., and Khattak, A. J.: Mobility and safety impacts of winter storm events in a freeway environment, Tech. rep., Center for Transportation Research and Education, Iowa State University, https://rosap.ntl.bts.gov/view/dot/23579, 2000.

Malin, F., Norros, I., and Innamaa, S.: Accident risk of road and weather conditions on different road types, Accident Anal. Prev., 122, 181–188, https://doi.org/10.1016/j.aap.2018.10.014, 2019.

Martin, J.-L.: Relationship between crash rate and hourly traffic flow on interurban motorways, Accident Anal. Prev., 34, 619–629, https://doi.org/10.1016/S0001-4575(01)00061-6, 2002.

Menard, S.: Applied logistic regression analysis, vol. 106 of *Quantitative Applications in the Social Sciences*, SAGE Publications, 2002.

Mills, B., Andrey, J., Doberstein, B., Doherty, S., and Yessis, J.: Changing patterns of motor vehicle collision risk during winter storms: A new look at a pervasive problem, Accident Anal. Prev., 127, 186–197, https://doi.org/10.1016/j.aap.2019.02.027, 2019.

Pardowitz, T., Osinski, R., Kruschke, T., and Ulbrich, U.: An analysis of uncertainties and skill in forecasts of winter storm losses, Nat. Hazard. Earth Sys., 16, 2391–2402, https://doi.org/10.5194/nhess-16-2391-2016, 2016.

Peden, M., Scurfield, R., Sleet, D., Mohan, D., Hyder, A. A., Jarawan, E., Mathers, C. D., et al.: World report on road traffic injury prevention, 2004.

Peralta, C., Ben Bouallègue, Z., Theis, S., Gebhardt, C., and Buchhold, M.: Accounting for initial condition uncertainties in COSMO-DE-EPS, J. Geophys. Res.: Atmos., 117, https://doi.org/10.1029/2011JD016581, 2012.

Scott, P.: Modelling time-series of British road accident data, Accident Anal. Prev., 18, 109–117, https://doi.org/10.1016/0001-4575(86)90055-2, 1986.

Shankar, V., Mannering, F., and Barfield, W.: Effect of roadway geometrics and environmental factors on rural freeway accident frequencies, Accident Anal. Prev., 27, 371–389, https://doi.org/10.1016/0001-4575(94)00078-Z, 1995.

Shmueli, G. et al.: To explain or to predict?, Stat. Sci., 25, 289–310, https://doi.org/10.1214/10-STS330, 2010.

Stephan, K., Klink, S., and Schraff, C.: Assimilation of radar-derived rain rates into the convective-scale model COSMO-DE at DWD, Q. J. Roy. Meteor. Soc., 134, 1315–1326, https://doi.org/10.1002/qj.269, 2008.

Stipdonk, H. and Berends, E.: Distinguishing traffic modes in analysing road safety development, Accident Anal. Prev., 40, 1383–1393, https://doi.org/10.1016/j.aap.2008.03.001, 2008.

Theofilatos, A. and Yannis, G.: A review of the effect of traffic and weather characteristics on road safety, Accident Anal. Prev., 72, 244–256, https://doi.org/10.1016/j.aap.2014.06.017, 2014.

Tibshirani, R.: Regression shrinkage and selection via the lasso, J. R. Stat. Soc., pp. 267–288, https://doi.org/10.1111/j.2517-6161.1996.tb02080.x, 1996.

Tiedtke, M.: A comprehensive mass flux scheme for cumulus parameterization in large-scale models, Mon. Weather Rev., 117, 1779–1800, https://doi.org/10.1175/1520-0493(1989)117<1779:ACMFSF>2.0.CO;2, 1989.

Wahl, S., Bollmeyer, C., Crewell, S., Figura, C., Friederichs, P., Hense, A., Keller, J. D., and Ohlwein, C.: A novel convective-scale regional reanalyses COSMO-REA2: Improving the representation of precipitation, Meteorol. Z., https://doi.org/10.1127/metz/2017/0824, 2017.

Weyrich, P., Scolobig, A., Bresch, D. N., and Patt, A.: Effects of impact-based warnings and behavioral recommendations for extreme weather events, Weather Clim. Soc., 10, 781–796, https://doi.org/10.1175/WCAS-D-18-0038.1, 2018.

Wood, S. N.: Generalized additive models: an introduction with R, Chapman and Hall/CRC, 2017.

Yannis, G. and Karlaftis, M. G.: Weather effects on daily traffic accidents and fatalities: a time series count data approach, in: Proceedings of the 89th Annual Meeting of the Transportation Research Board, pp. 10–14, 2010.

Ziakopoulos, A. and Yannis, G.: A review of spatial approaches in road safety, Accident Analysis & Prevention, 135, 105 323, 2020.

Table 1. Descriptions of predictor variables used in different logistic regression models for hourly probabilities of weather-related road accidents in Germany administrative districts.

Name	Description
$\overline{P}$	Temporal average of accident probability of in an administrative district
$\overline{P}' = -log(1/\overline{P}) - 1$	$\overline{P}$ transformed using the inverse logistic function.
H	A categorical variable for the hour of the day
Pr_{RAD}	Hourly precipitation in mm from RADOLAN data aggregated to district level
$Pr_{EPS,i}$	Hourly precipitation in mm from ith ensemble member of COSMO-DE-EPS aggregated to district level
$Pr_{EPS,m}$	Ensemble mean of hourly precipitation in mm calculated from COSMO-DE-EPS ensemble members aggregated to district level
T_{REA}	A binary variable indicating whether the COSMO-REA2 near surface temperature aggregated to district level is above or below 0°C
$T_{EPS,i}$	As T_{REA} but derived from the ith ensemble member of COSMO-DE-EPS
$T_{EPS,m}$	As T_{REA} but derived from the ensemble mean of COSMO-DE-EPS
P_H	Accident probability as predicted by model HOUR (see Table 2) based on $\overline{P}$ and H
$P_H{}' = -log(1/P_H) - 1$	P_H transformed by the inverse logistic function

Table 2. Description of different logistic regression models for hourly probabilities of weather-related road accidents in Germany administrative districts and their degrees of freedom (Df). Formulas are written using the statistical formula notation system as used in programming languages as R and Python, with colons indicating interaction terms. See Tab. 1 for a definition of variables.

Name	**Formula**	**Df**
models using radar and reanalysis data (2007-2012)		
NULL	$y \sim 1 + \overline{P}'$	2
HOUR	$y \sim 1 + \overline{P}' + H$	25
RAD	$y \sim 1 + \overline{P}' + H + T_{REA} + (Pr_{RAD})^{0.2}$	27
RAD_INT	~~$y \sim 1 + \overline{P}' + H + T_{REA} + (Pr_{RAD})^{0.2} + P : H + P : T_{REA} + P : (Pr_{RAD})^{0.2} + H : T_{REA} + H : (Pr_{RAD})^{0.2} +$~~ $y \sim 1 + \overline{P}' + H + T_{REA} + (Pr_{RAD})^{0.2} + \overline{P}' : H + \overline{P}' : T_{REA} + \overline{P}' : (Pr_{RAD})^{0.2} + H : T_{REA} + H : (Pr_{RAD})^{0.2}$	99
RAD_IND	As RAD but without $\overline{P}'$, fitted to all 401 districts individually	401×29
RAD_INT_IND	As RAD_INT but without $\overline{P}'$, fitted to all 401 districts individually	401×73
models using radar, reanalysis and weather forecast data (2011-2012)		
EPS_HOUR	$y \sim 1 + P'_H$	2
EPS_RAD_INT	$y \sim 1 + P'_H + T_{REA} + (Pr_{RAD})^{0.2} + P'_H : T_{REA} + P'_H : (Pr_{RAD})^{0.2} + T_{REA} : (Pr_{RAD})^{0.2}$	6
EPS_MEM$_i$_INT	$y \sim 1 + P'_H + T_{EPS,i} + (Pr_{EPS,i})^{0.2} + P'_H : T_{EPS,i} + P'_H : (Pr_{EPS,i})^{0.2} + T_{EPS,i} : (Pr_{EPS,i})^{0.2}$	6
EPS_MEAN_INT	$y \sim 1 + P'_H + T_{EPS,m} + (Pr_{EPS,m})^{0.2} + P'_H : T_{EPS,m} + P'_H : (Pr_{EPS,m})^{0.2} + T_{EPS,m} : (Pr_{EPS,m})^{0.2}$	6
EPS_PMEAN_INT	As EPS_MEM$_i$_CON_INT, but using ensemble mean probabilities for verification	20×6

Table 3. Verification measures for models using radar and reanalysis data; Akaike information criterion (~~2007–2012~~AIC), area under receiver operating characteristic curve (AUC), true positive rate (TPR), logarithmic score (LR) and Brier score (BS). Scores computed in a yearly cross-validation approach for each administrative district are shown as ~~averages~~ an average of all districts. Skill scores of AUC, LS and BS are computed with the model HOUR as reference (see Tab. 2). The best value of each score is underlined.

Model	**NULL**	**HOUR**	**RAD**	**RAD_INT**	**RAD_IND**	**RAD_INT_IND**
AIC	1885238	1856974	1629688	1624719	-	-
AUC	0.5000	0.6157	0.8056	0.8097	0.7977	0.7740
TPR	-	0.3252	0.6715	0.6707	0.6644	0.6366
LS	0.0324	0.0319	0.0280	0.0279	0.0282	0.0302
BS	0.0079	0.0079	0.0077	0.0077	0.0077	0.0077
AUCSS	-0.3053	0.0000	0.4923	0.5033	0.4714	0.4095
LSS	-0.0147	0.0000	0.1194	0.1211	0.0969	-0.0144
BSS	-0.0012	0.0000	0.0205	0.0208	0.0203	0.0124

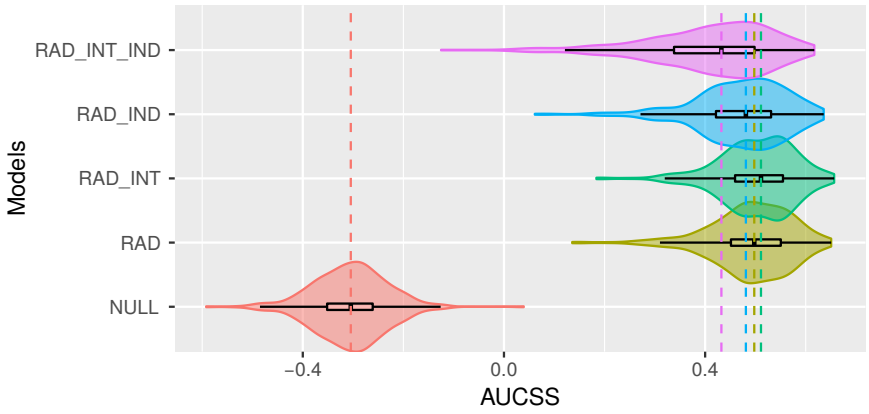

Figure 1. Distribution of the cross-validated area under receiver operating characteristic curve skill score (AUCSS~~values~~) of 401 administrative districts is shown for different logistic regression models for weather-related accident probabilities. The probability density is smoothed by a kernel density estimator (shading). The median is indicated by vertical dashed lines.

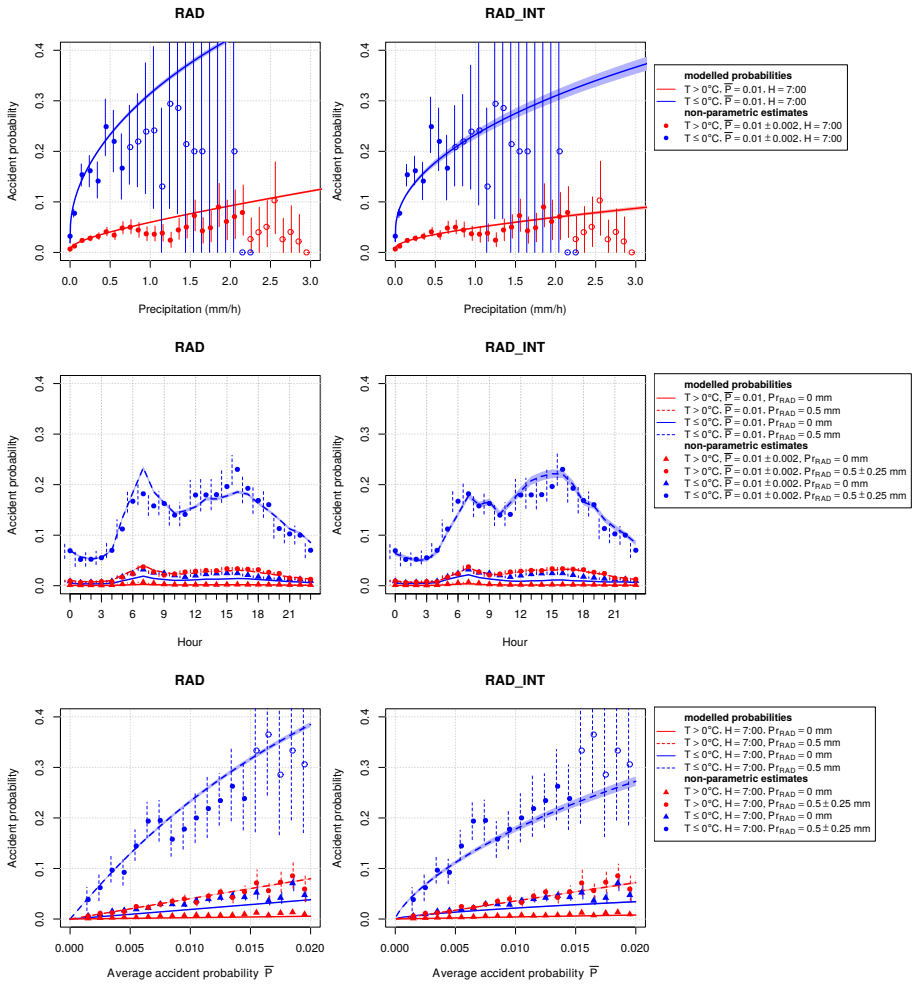

Figure 2. Comparison of modeled probabilities of weather-related road accidents with non-parametric probability estimates. Probabilities (lines) and 95% confidence intervals based on standard errors (shading) of model RAD (left) and RAD_INT (right) are displayed as a function of hourly precipitation (top), hour of the day (middle) and the temporal average accident probability of the administrative district (bottom) for different parameter settings (see legends for details). Non-parametric estimates of probabilities (markers) and 95% confident intervals based on bootstrapping (vertical lines) are shown for corresponding parameter ranges.

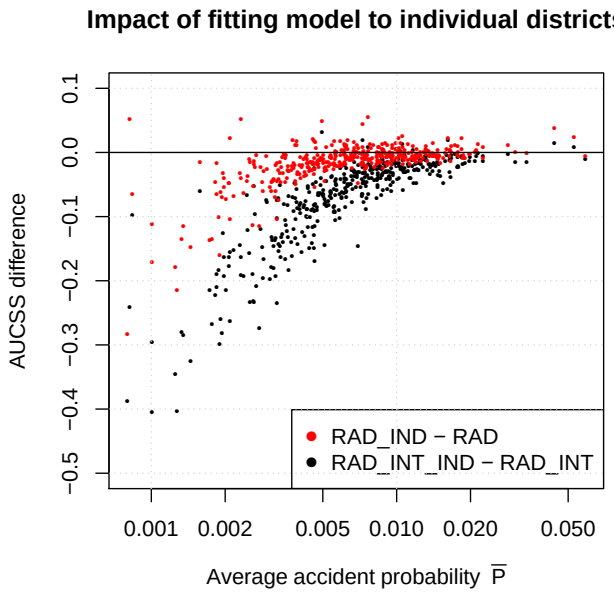

Figure 3. Differences of area under receiver operating characteristic curve skill score (AUCSS) values between the models RAD_IND and RAD (red) and RAD_INT_IND and RAD_INT (black). AUCSS differences are shown for each of the 401 administrative districts vs. the average accident probability $\overline{P}$ of the respective districts (dots).

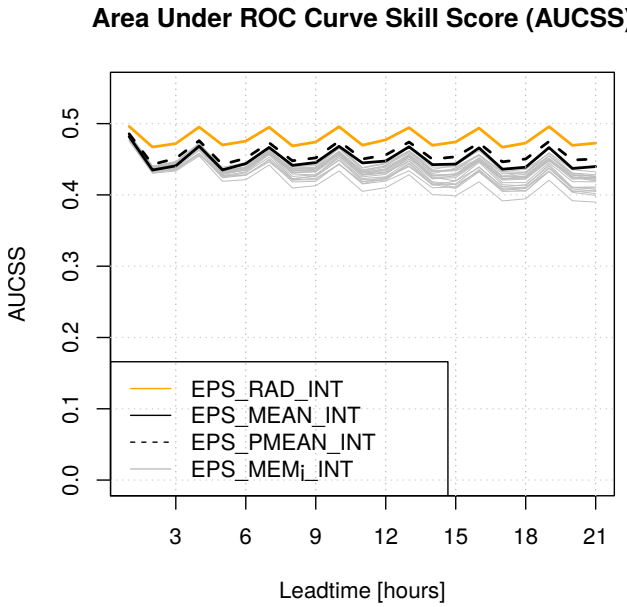

Figure 4. Area under receiver operating characteristic curve skill score (AUCSS) values of different models for hourly probabilities of weather-related road accidents using radar, reanalysis and weather forecast data from 2011-2012 as a function of ~~leadtime~~lead time.

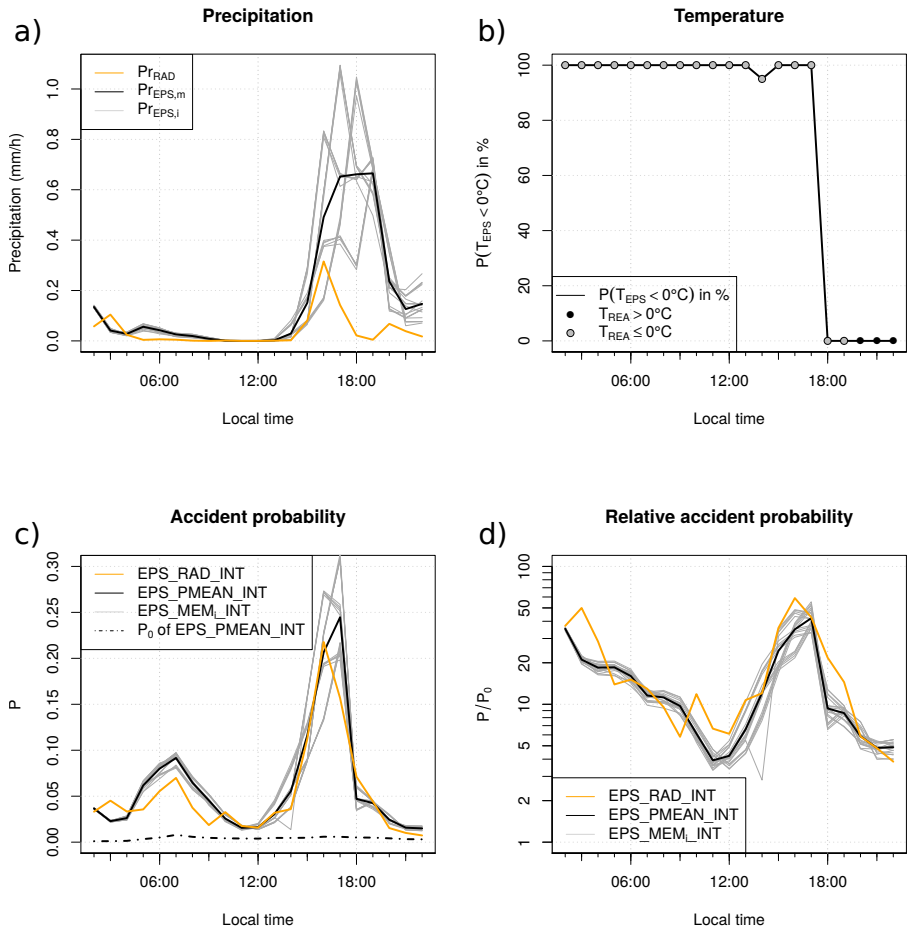

Figure 5. Application of the models EPS_RAD_INT and EPS_PMEAN_INT to a adverse winter weather event on 3rd Dec. 2012. Time series are shown for the district of Stuttgart using the COSMO-DE-EPS forecast initialized at 00 UTC. a) Hourly precipitation aggregated to district level, b) percentage of ensemble members with temperatures below 0°C, c) probability of weather-related road accidents and d) relative accident probability.

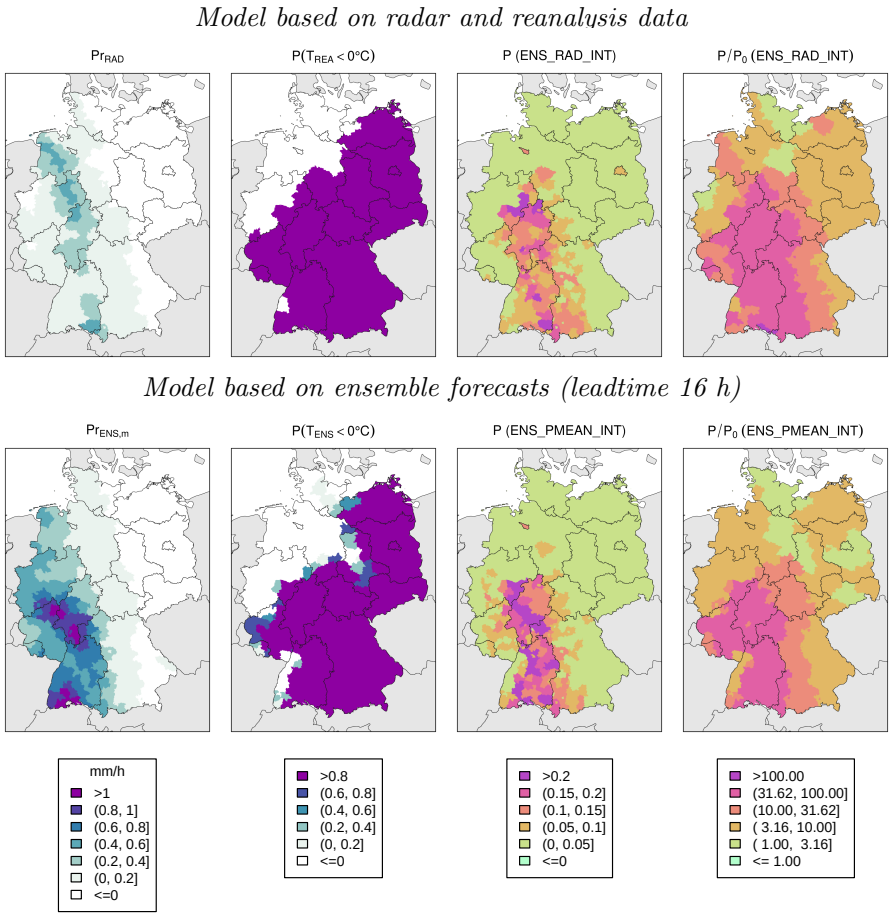

Figure 6. Model results for adverse winter weather conditions on 3rd Dec. 2012 at 17:00 local time based on models EPS_RAD_INT (top) and EPS_PMEAN_INT using the COSMO-DE-EPS forecast with a ~~leadtime~~ lead time of 16 h initialized at 00 UTC (bottom). From left to right: hourly precipitation at district level, fraction of ensemble members with temperatures below 0°C, probability of weather-related road accidents, and relative accident probability.