Nat. Hazards Earth Syst. Sci. Discuss.,
https://doi.org/10.5194/nhess-2020-352-AC2, 2021

Interactive comment on "Improving snowfall representation in climate simulations via statistical models informed by air temperature and total precipitation" *by* Flavio Maria Emanuele Pons and Davide Faranda

Flavio Maria Emanuele Pons and Davide Faranda

flavio.pons@lsce.ipsl.fr

Received and published: 14 March 2021

Pons and Faranda present and assessment of statistical models in order to better represent the snowfall using data from gridded-climate products. The assessments include Europe and comprise the winter months of December, January and February. ERA5 reanalyses between 1978 and 2018 and IPSL-WRF between 1979 and 2005were used to evaluate the statistical models. Overall, the methods presented improve the representation of the snowfall, and due to the characteristics of the methods,

an important advantage is its applicability to larger areas using gridded climate products.

Although the overall research fit in the journal, there are several points that need to be addressed. More importantly, I think that a better rationale for this works is necessary as well as some changes in the structure and/or a reduction in the length. In view of this, I suggest mayor revisions. I do really hope that this review will be useful to the authors to improve their manuscript.

A: We thank the reviewer for the feedback, we will try to address each one of the following points, and to do as much as possible of the suggested modifications.

Q: It is not clear why is important to use these statistical models. Extreme events and its impacts (e.g. February 2018) are barely mentioned in the Introduction and also the limitations in represent snowfall events of the Climate models using emission scenarios. What is the main goal of applying these methods? For the experiment presented, it seems that is to find a better representation in climate change models scenarios. But, It is applicable to weather forecast as GFS for instance? It would be useful to have a better idea of why this work is important. To extend the rationale of the work presented.

A: These models are not meant to be applied to weather forecasting, but rather to correct or complete two types of data: 1) observational dataset where temperature and precipitation are available, but snowfall is not; 2) climate projection data. Even though climate projections are obtained with deterministic models of the atmosphere like weather forecasting, the latter is not characterized by the same level of uncertainty as secular simulations; weather forecasting outputs are interpreted by meteorologists, and automatic weather forecasting already incorporates more complex statistical/machine learning algorithms to approximate local weather (for example, as in the output of weather apps). Concerning the extremes: we mention compound extremes as their study has been our first motivation to work with snowfall and to find a way to reconstruct it in a more accurate way. However, it is not necessarily the case where a compound weather extreme only involves a very extreme daily snowfall, indeed the ensemble of weather conditions determines the severity, including the persistence of several snowy days. For this reason, we looked for a method able to correct the entire probability distribution, thus including but not limited to the improvement of extremes. We observe the capability of the models to improve extremes in the better representation of the snowfall distribution tails in Fig_Alps_2 and Fig_Norway_2 (see attachments). In the text, this is mentioned at lines 707-8. This is indeed a very synthetic statement, due to the fact that the figure is quite self-explanatory in this sense.

In summary, we briefly mention compound extremes as our own motivation, while in the text we try to make it clear that this method could be used also in case of hydrological studies based on data and analysis of climate projections of snowfall, which is why we do not give a specific focus to extreme snowfall events, but to the variable as a whole.

Q: Some sections are hard to read. The Introduction seems more appropriate for a review paper, maybe avoid the details of each earlier model. Method section also seems lengthy and hard to follow, I suggest to try to go to the point. Results also contain information that is not appropriate for this section (see below). I suggest re-restructuring the manuscript, and move some sections to a Supplementary Material in order to reduce the length of the manuscript.

A: We agree about the length of the paper, we will move the lengthy Subsections 3.1.2-3.1.4 about statistical methodology to an Appendix, with the exception of the first paragraph of 3.1.2, which will be modified to:

In order to overcome the limitations of the STM of f_s, we aim at reproducing the potentially nonlinear relationship between T and f_s. As already mentioned in Section \ref{int1}, we decide not to adopt NLS to directly fit S-shaped functions to the data. Other than the sensitivity of this methodology to the optimization algorithm and to initial values, we envisage two more reasons to avoid direct S-shape fitting. First,

there is no prior indication of which among the possible S-shaped functions (logistic, hyperbolic tangent, sigmoid) is universally better; this would require to compare the fit and the predictive performance of different specifications at each grid point. Moreover, the points separating the asymptotically horizontal regimes from the centre of the S-shaped curve can be seen as corresponding to two temperature thresholds analogous to T_{low}^* and T_{high}^* in \cite{pipes1977ubc}. While the values of these threshold temperatures carry interesting information, it is not immediate to retrieve them from the specified S-shaped functions, nor it is to inform the NLS estimates with these threshold values if their estimate is available.

We propose a way to extend the method by \cite{pipes1977ubc} using a two-step approach: \begin{enumerate} \item[I] determine the optimal number m of thresholds temperatures for each grid point and their value, using a breakpoint search algorithm; \item[II] in each of the $m + 1$ regimes corresponding to the estimated m thresholds, we describe the relationship between T and f_s using a regression model. \end{enumerate}

In Appendix \ref{appx}, we describe the search algorithm used to determine the threshold temperatures at each grid point, and we show three different ways to perform MTR: segmented regression on logit-transformed data, beta regression with logit link function, and spline regression on logit-transformed data.

Q: Maybe a Discussion section will do the manuscript more clearer moving some Results and Conclusion paragraphs to this section, allowing concentrate (and reducing) the Conclusions to the main findings.

A: Thank you for the suggestion, we will rename the Conclusions section to Discussion (and we will add a Limitation paragraph as suggested by another reviewer) and we will add a brief Conclusions section:

We have presented two statistical methods equally effective in estimating the snowfall fraction of total precipitation, provided that a reliable measure of near-surface temperature is available. This is a relevant problem in both hydrology and climatology, since an accurate estimation of snowfall is a troubled objective in case of both observed or simulated precipitation.

Both model are an extension of traditional precipitation phase partitioning methods based on estimating the snowfall fraction of total precipitation on the base of one or multiple threshold temperatures. We estimate such thresholds by means of a break-point search algorithm.

The two model perform better than their more traditional competitors in terms of prediction error and correlation between real and reconstructed values in a train-test sets validation framework based on the ERA5 reanalysis dataset, showing robustness to climate change. When applied to reconstruct the snowfall in a regional circulation climate model, both techniques produce results with a markedly reduced bias respect to ERA5, when compared to raw climate model simulations.

We conclude that statistical models based on segmented linear or spline regression and informed by bias corrected temperature and precipitation are capable of providing a reliable reconstruction of snowfall that can replace more complex or non-feasible bias correction technique, with better performances than similar models based on parametric assumptions or binary separation.

Q: Additionally, please note that some literature refers to the "separation of snowfall" as "precipitationâ ÌĘAËĞRphase partitioning methods (PPMs)" (e.g. Harder and Pomeroy,2014). Consider in to use this terminology.

A: We will mention this terminology in the same paragraph interested by your comment about lines 58-59 (see below) so that readers familiar with the term can find the article, if interested. We also use the term in the new brief Conclusions section.

Q: Other comments (line number indicated):

16: This was already mentioned in Line 12.25-30: Add a more specific statement

about why statistical models are better than physics parameterization or simplifications in climate models. Is this just a thought? Or Do you have more evidence of this? some references?

A: We are not sure we correctly understand the line number citation in this question, but concerning the statements at lines 25-30, which seems to be the problem:

We do not mean to state that statistical models are better than climate models due to physical parameterizations; we point out how a statistical step is usually required to perform a bias correction on variables simulated in climate models. Usually this step is a BC as described later in the section, but for snowfall this cannot be conducted effectively without massive complications. So our strategy is to use a well established framework, i.e. the reconstruction of snowfall from T and precipitation, to replace the BC step of snowfall, which is a derived quantity affected by more problems than total precipitation.

To avoid the confusion, we will reformulate the paragraph to:

"In this manuscript we explore the possibility of reconstructing snowfall from bias corrected temperature and precipitation via adequate statistical models, to obtain an improved estimate compared to raw snowfall simulation from the climate model.

Climate Models are the primary tool to simulate multi-decadal climate dynamics and to generate and understand global climate change projections under different future emission scenarios. Both regional and global climate models have coarse resolution and contain several physical and mathematical simplifications that make the simulation of the climate system computationally feasible, but also introduce a certain level of approximation. This results in statistical biases that can be easily observed when comparing the simulated climate to observations or reanalysis datasets."

Q: 50: "Hemispheric".

A: Thank you, we will correct this typo

Q: 58-59: Worth to mention that solid precipitation also depends on relative humidity and could be useful to estimate the mixed-phase or sleet (e.g. Ding et al., 2014).

A: We will add this consideration modifying the text as follows:

Besides the discontinuity of snowfall fields - a feature in common with total precipitation - snowfall is the result of complex processes which involve not only the formation of precipitation, but also the existence and persistence of thermal and hygrometric conditions that allow for the precipitation reaching the ground in the solid state. As a result, snow is often observed in mixed phase with rain, especially when considering daily data. This phase transition poses additional challenges to the bias correction of snowfall, namely the need of separating the snow fraction, using the available meteorological information. Ideally, methods to perform such separation, also known as precipitation phase partitioning methods, should be based on wet-bulb temperature, to which the snow fraction is particularly sensitive in the case of mix precipitation/sleet (Ding et al., 2014). However, due to the difficulty to estimate this parameter in the case of climate models, the task is usually performed relying on temperature data.

Q: 116: Change "Section ??" to "Section 4".

A: Thank you, we will correct this typo

Q: 125-128: This paragraph sounds like a better justification of the work and fits with the overall aim of the journal. Consider to move to the Introduction section and explain a bit more the justification of this study.

A: Thank you, we will move this paragraph to the Introduction section.

Q: 134-135: The election of these months is a bit contradictory if the aim is to analyse extreme events causing disruption. Of course, extreme events largely occur in winter, but over other seasons (end of Autumn, the beginning of Spring) extreme snowfall events could occur. For instance, the so-called "Beast from the East" in 2018 was between the end of February and beginning of March. If analysis months is not extended

maybe change the title to "Improving winter snowfall representation..."

A: We agree that adding more months would be more complete. However, since we will apply this method to an ensemble of climate projections including off-winter months, which will indirectly give also a further validation, we think it is more practical to simply change the title as suggested.

Q: 147: Delete extra "( )".

A: Thank you, we will correct this typo

Q: 241: Numbering missing.

A: Thank you, we will correct the numbering of this section, which will also be moved to an Appendix.

Q: 246: Delete extra "( )".

A: Thank you, we will correct this typo

Q: 509: Fig. 2 is mentioned here before Fig. 1. Also change to "Fig. 2" to be consistent with the rest of the manuscript.

A: Thank you, we will correct this typo and the order of the figures.

Q: 526: You refer here to Fig. 2 I guess not Fig. 1.

A: Thank you, we will correct this typo

Q: 551: Most of section 4.2 seems more appropriate to the Methods section (or Supplementary Material). For instance, lines 575-585 is an explanation of the Kruskal-WallisH test, lines 593-601 is an explanation of the U-test. Here, you must show the results after applying these tests.

A: Thank you, we will move these explanations to the technical appendix

Q: 536: Numbering missing.

A: Thank you, we will correct this typo

Q: 737-755: These paragraphs are a repetition of previous statements already presented in the Introduction and related to limitations of previous methods, observational data and the physics of the climate models. I think is not necessary to repeat in the Conclusions.

A: These sentences will no longer be in the Conclusions section, which is now much shorter as explained above. If the referee agrees, we would leave them in the now Discussion section, where we think it could be useful to summarize these concepts, given that the paper is quite long.

Q: Figure 7d): Legend is not visible. Figures: please add units and names to the axis where these are missing.

A: Thank you, we will correct these issues with the figures.

Interactive comment on Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2020-352, 2020.

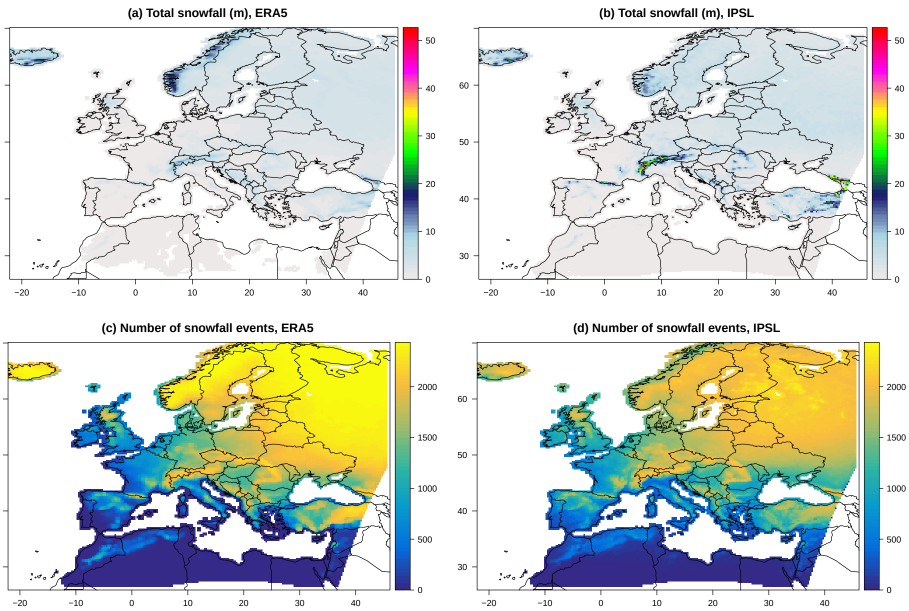

Fig. 1.

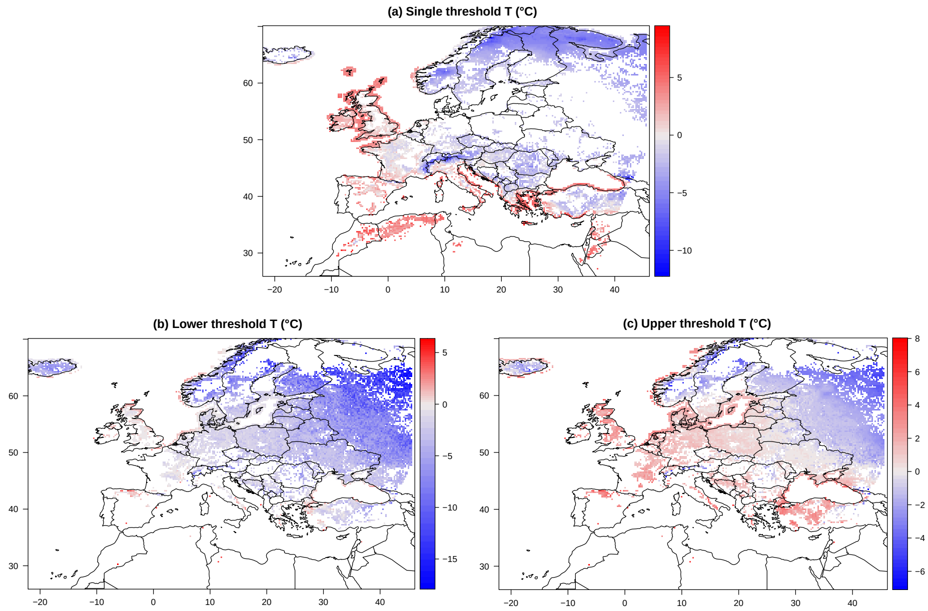
(a) Single threshold T (°C)
(b) Lower threshold T (°C)
(c) Upper threshold T (°C)

Fig. 2.

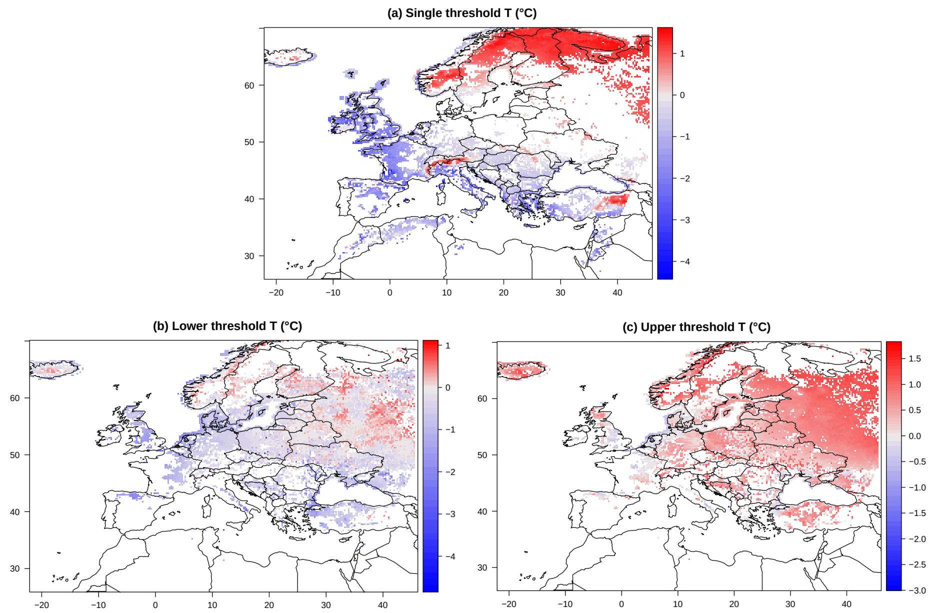
(a) Single threshold T (°C)
(b) Lower threshold T (°C)
(c) Upper threshold T (°C)

Fig. 3.

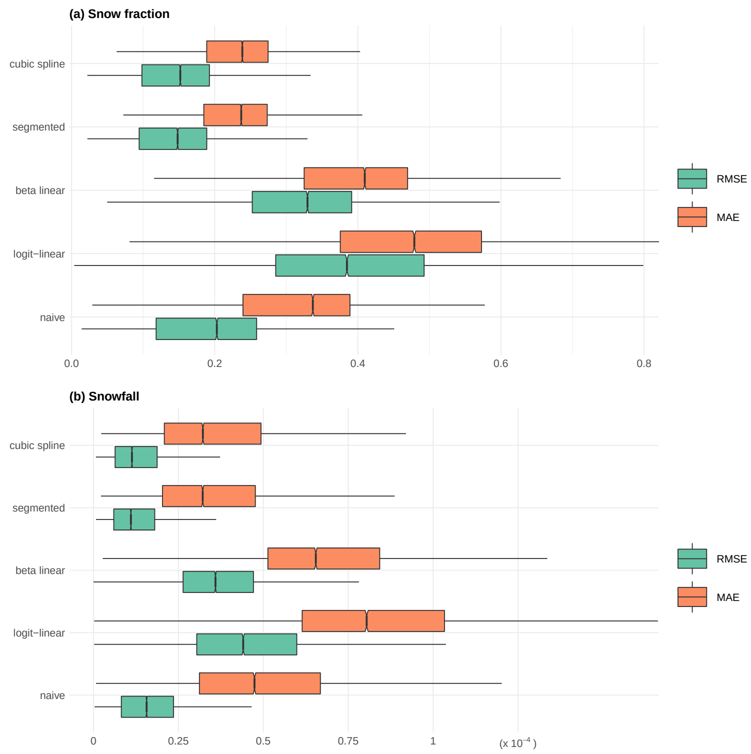
(a) Snow fraction
cubic spline
segmented
beta linear
logit−linear
naive
0.0
0.2
0.4
0.6
0.8
RMSE
MAE
(b) Snowfall
cubic spline
segmented
beta linear
logit−linear
naive
0
0.25
0.5
0.75
1
(x 10^{-4})
RMSE
MAE

Fig. 4.

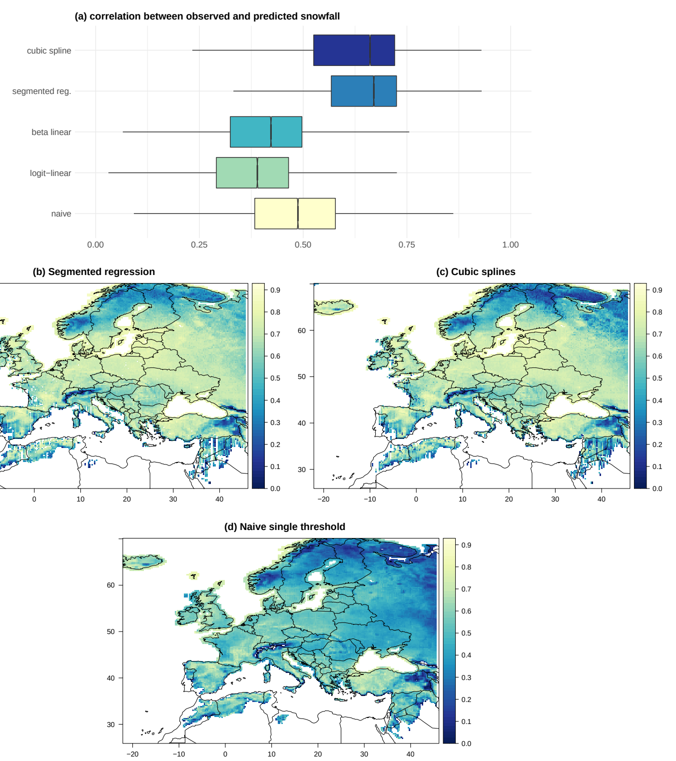
(a) correlation between observed and predicted snowfall
cubic spline
segmented reg.
beta linear
logit−linear
naive
0.00
0.25
0.50
0.75
1.00
(b) Segmented regression
(c) Cubic splines
(d) Naive single threshold

Fig. 5.

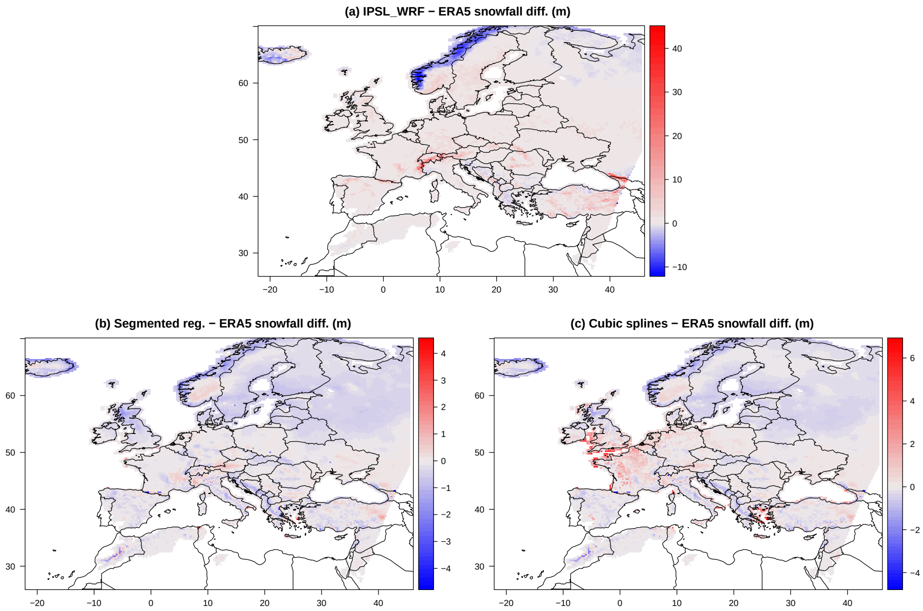
(a) IPSL_WRF − ERA5 snowfall diff. (m)
(b) Segmented reg. − ERA5 snowfall diff. (m)
(c) Cubic splines − ERA5 snowfall diff. (m)

Fig. 6.

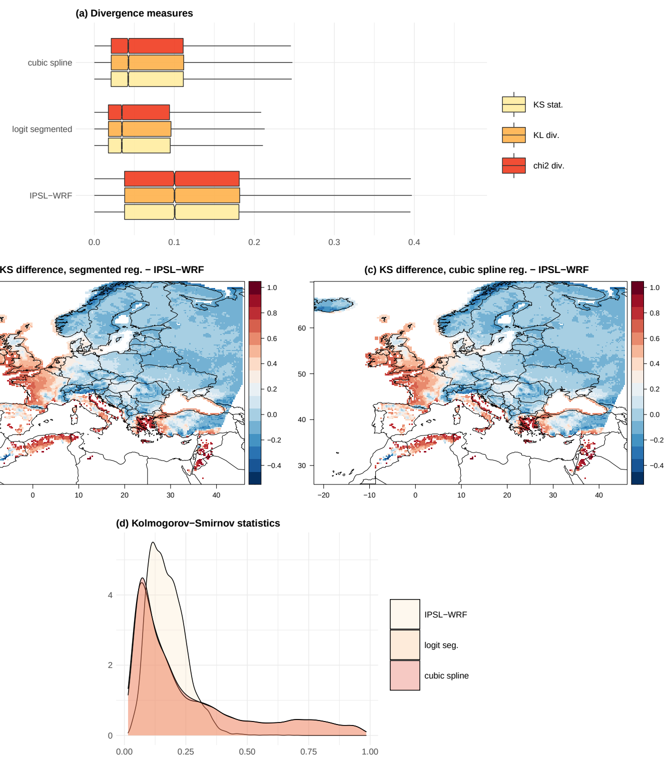
(a) Divergence measures
cubic spline
logit segmented
IPSL−WRF
KS stat.
KL div.
chi2 div.
(b) KS difference, segmented reg. − IPSL−WRF
(c) KS difference, cubic spline reg. − IPSL−WRF
(d) Kolmogorov−Smirnov statistics
IPSL−WRF
logit seg.
cubic spline

Fig. 7.

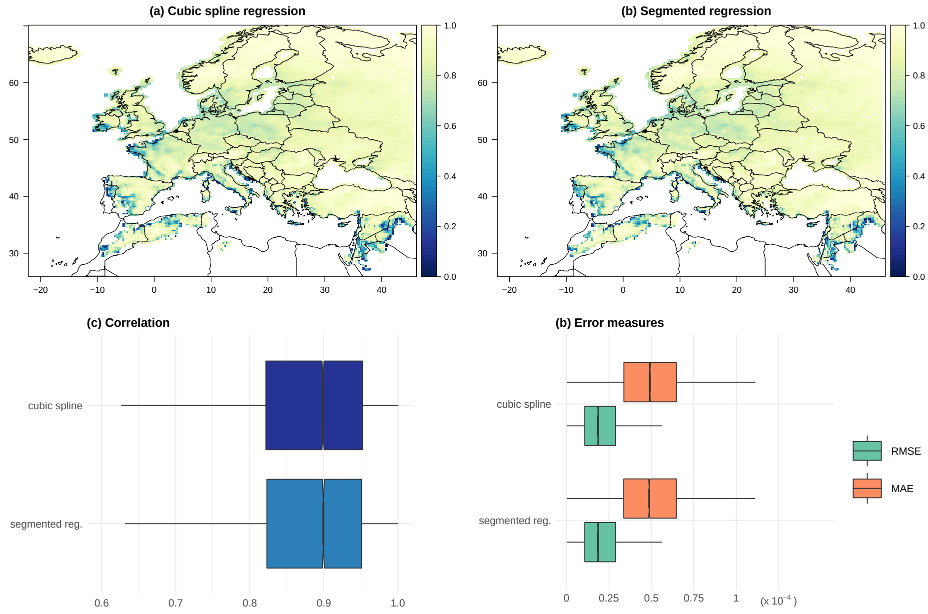
(a) Cubic spline regression
(b) Segmented regression
(c) Correlation
(b) Error measures
cubic spline
segmented reg.
RMSE
MAE
(x 10^-4)

Fig. 8.

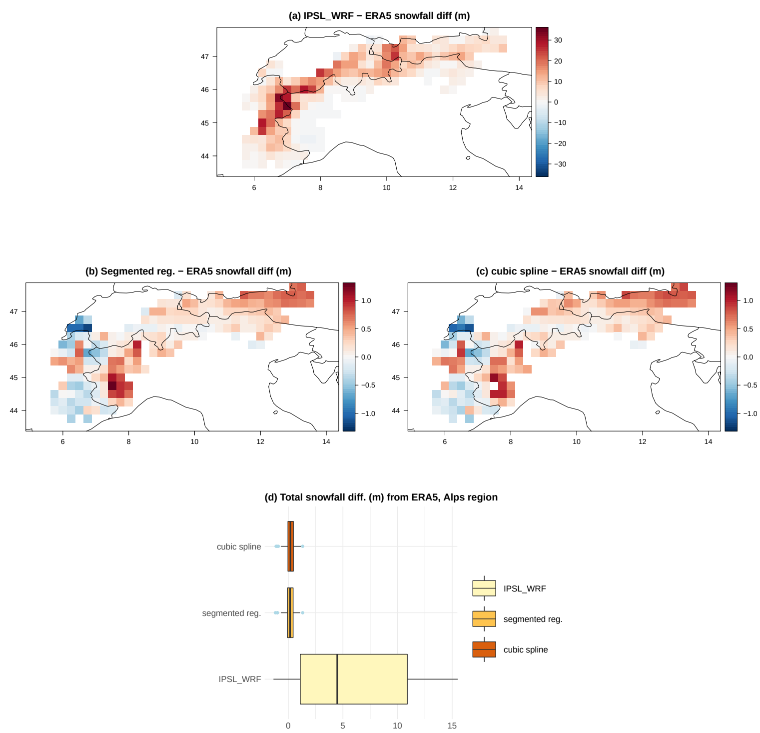
(a) IPSL_WRF − ERA5 snowfall diff (m)
(b) Segmented reg. − ERA5 snowfall diff (m)
(c) cubic spline − ERA5 snowfall diff (m)
(d) Total snowfall diff. (m) from ERA5, Alps region
cubic spline
segmented reg.
IPSL_WRF

Fig. 9.

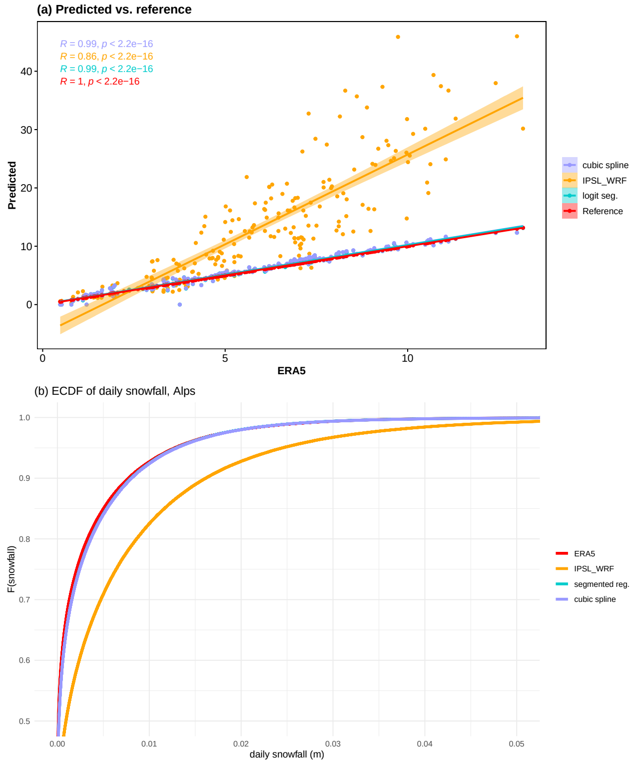
(a) Predicted vs. reference
R = 0.99, p < 2.2e−16
R = 0.86, p < 2.2e−16
R = 0.99, p < 2.2e−16
R = 1, p < 2.2e−16
Predicted
ERA5
cubic spline
IPSL_WRF
logit seg.
Reference
(b) ECDF of daily snowfall, Alps
F(snowfall)
daily snowfall (m)
ERA5
IPSL_WRF
segmented reg.
cubic spline

Fig. 10.

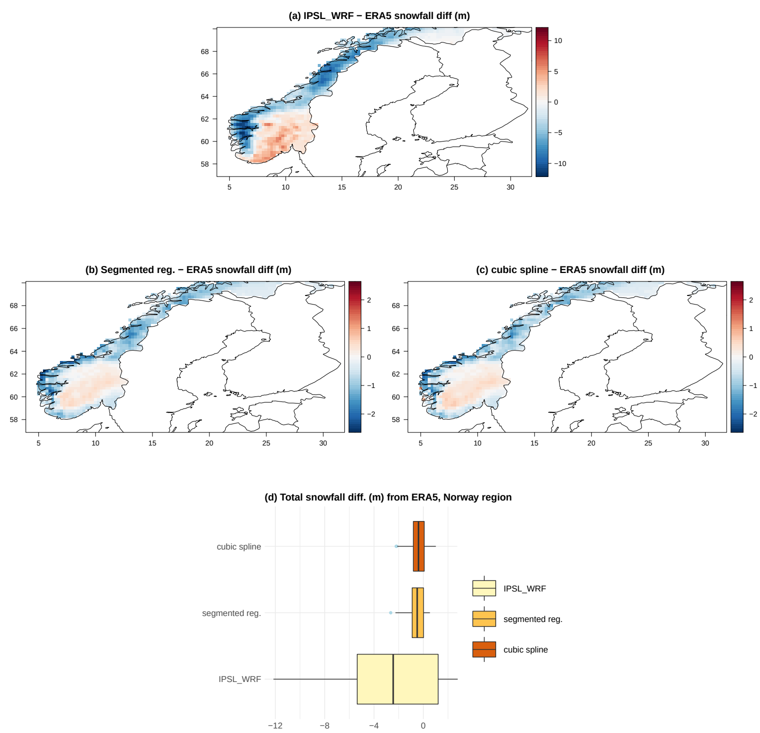
(a) IPSL_WRF − ERA5 snowfall diff (m)
(b) Segmented reg. − ERA5 snowfall diff (m)
(c) cubic spline − ERA5 snowfall diff (m)
(d) Total snowfall diff. (m) from ERA5, Norway region
cubic spline
segmented reg.
IPSL_WRF

Fig. 11.

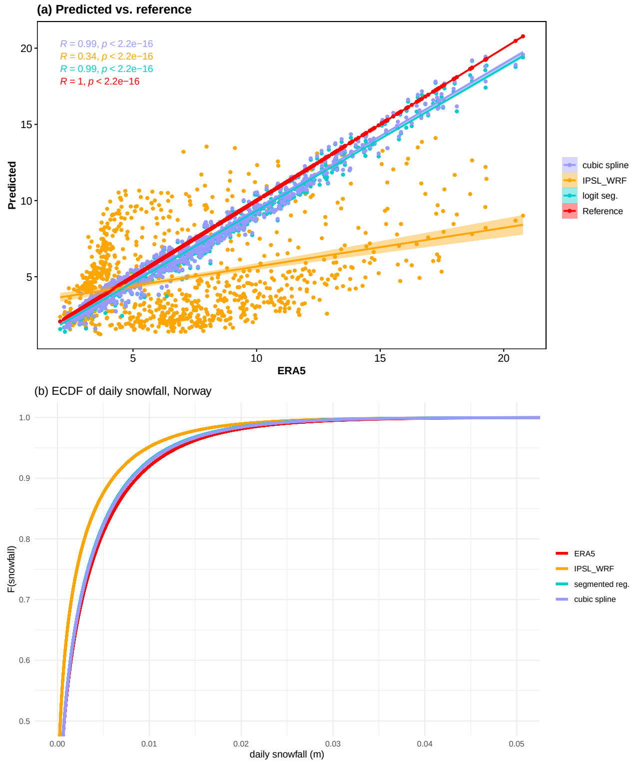
(a) Predicted vs. reference
R = 0.99, p < 2.2e−16
R = 0.34, p < 2.2e−16
R = 0.99, p < 2.2e−16
R = 1, p < 2.2e−16
Predicted
ERA5
cubic spline
IPSL_WRF
logit seg.
Reference
(b) ECDF of daily snowfall, Norway
F(snowfall)
daily snowfall (m)
ERA5
IPSL_WRF
segmented reg.
cubic spline

Fig. 12.