Regional Climate Model Biases, Their Dependence on Synoptic Circulation Biases and the Potential for Bias Adjustment: A Process-Oriented Evaluation of the Austrian Regional Climate Projections

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Abstract The Austrian regional climate projections are based on an ensemble of bias adjusted regional climate model simulations. Bias adjustment (BA) improves the usability of climate projections for impact studies, but cannot mitigate fundamental model errors. This argument holds in particular for biases in the temporal dependence, which is strongly influenced by the large-scale circulation. Global climate models (GCMs), underlying regional climate projections, suffer from substantial circulation errors. We therefore, conduct a process-based evaluation of the Austrian climate projections focusing on large-scale circulation errors, their regional imprints and the potential for BA. First, we define nine synoptic weather types and assess how well the considered climate models represent their occurrence and persistence. Second, we assess biases in the overall dry and hot day probabilities, as well as conditional on synoptic weather type occurrence; and biases in the duration of dry and hot spells. Third, we investigate how these biases depend on biases in the occurrence and persistence of relevant synoptic weather types. And fourth, we study how much an overall BA improves these biases. Many GCMs misrepresent the occurrence and persistence of relevant synoptic weather types. These biases have a clear imprint on biases in dry and hot day occurrence and spell durations. BA in many cases helps to greatly reduce biases even in the presence of circulation biases, but may in some cases amplify conditional biases. Persistence biases are especially relevant for the representation of meteorological drought. Biases in the duration of dry spells cannot fully be mitigated by BA.

1. Introduction

To enhance transparency and the comparability of climate impact studies, many national and international initiatives have produced standardized regional climate projections (e.g., Cayan et al., 2013; Chimani et al., 2016; Fischer & Strassmann, 2018; Hagemann et al., 2011; Hempel et al., 2013; Murphy et al., 2009). Often, these projections are based on an ensemble of regional climate models, run according to a set of climate change scenarios (Giorgi et al., 2009). Bias adjustment (BA) is becoming more and more a routine application in the construction of such projections (Cayan et al., 2013; Chimani et al., 2016; Fischer & Strassmann, 2018; Hagemann et al., 2011; Hempel et al., 2013). It is, in particular, desired for the calculation of threshold sensitive climate indicators such as rainfall occurrence and drought, or hot days, and heatwaves (Dosio & Paruolo, 2011; Workshop Report, 2015).

Within the VALUE initiative (Maraun et al., 2015), it has been shown that BA can substantially improve the representation of regional climate when applied to a well-performing model (Gutiérrez et al., 2019; Hertig et al., 2019; Maraun, Huth, et al., 2019; Maraun, Widmann, & Gutiérrez, 2019; Widmann et al., 2019; Soares et al., 2019). There is, however, growing evidence that BA cannot mitigate all climate model errors (Ehret et al., 2012; Maraun, 2016), especially, if they are linked to fundamentally misrepresented processes (Haerter et al., 2011; Maraun et al., 2017). This argument holds in particular for biases in the temporal structure, which is to a large extent controlled by the synoptic-scale atmospheric circulation (Addor et al., 2016; Maraun et al., 2017). Standard global climate models (GCMs), which are the basis of most regional climate projections, still show substantial errors in the representation of, for example, the midlatitude atmospheric circulation (Davini et al., 2016; Dawson et al., 2012; Dunn-Sigouin & Son, 2013; Schiemann et al., 2020). Also, the persistence of circulation patterns is often under-represented (Dawson et al., 2012; Dunn-Sigouin & Son, 2013; Schiemann et al., 2020), potentially affecting the representation of droughts and heatwaves.
Addor et al. (2016) and Maraun et al. (2017) have demonstrated the impact of biases in the large-scale circulation on the BA of regional climate. In the presence of large-scale circulation errors, an unconditional BA (e.g., for the whole year, or season- or even month-dependent) of precipitation can only adjust the overall annual (seasonal, monthly) precipitation, but would inevitably keep residual precipitation biases for specific weather types (Addor et al., 2016). An adjustment of wet-day frequencies may improve the overall spell length distribution, but may also result in a misrepresentation of both short and long dry spells (Maraun et al., 2017). Thus, any BA should be complemented by a thorough process-based evaluation to understand the plausibility of the adjustment and to identify potential artifacts (Addor et al., 2016; Maraun et al., 2017).

For Austria, the ÖKS15 climate projections (Chimani et al., 2016) have been constructed by bias adjusting a set of regional climate model simulations from the EURO-CORDEX experiment (Jacob et al., 2014). Here, we present a process-based evaluation of these projections and investigate the following research questions: (1) How well are occurrence and persistence of synoptic weather types represented by EURO-CORDEX models? (2) How strong are biases in the overall dry and hot day probabilities, as well as conditional on synoptic weather type occurrence? How strong are biases in the duration of dry and hot spells? How do these biases depend on biases in the occurrence and persistence of relevant synoptic weather types? (3) How much does an overall BA improve the representation of dry day and hot day probabilities, conditional on these weather types? How much does an overall BA improve the representation of dry and hot spell duration?

In Section 2, we give a brief overview of the ÖKS15 climate projections and the underlying climate models, and introduce the methods used for the process-based evaluation. In Section 3, we present the evaluation results, followed by a discussion and conclusions.

### 2. Data and Methods

The ÖKS15 projections are based on a selection of RCM projections from the EURO-CORDEX initiative (Jacob et al., 2014), following RCP4.5 and RCP8.5. The selection of models (see Table 1) was not based on model performance, but rather on the availability at the start of the ÖKS15 project. All models have been bias adjusted with the scaled distribution mapping method (Switanek et al., 2017), which is a trend-preserving quantile-mapping approach. The mapping was based on a parametric model, assuming a Gaussian distribution for temperature and a gamma distribution for precipitation. To define wet days, a threshold of 1 mm was chosen. If a model produced too few wet days, no wet day adjustment was conducted. The adjustment

### Table 1

| GCM          | Realization | RCM            | References                                                                 |
|--------------|-------------|----------------|-----------------------------------------------------------------------------|
| CNRM-CM5     | r1i1p1      | CCLM4-8-17     | (Böhm et al., 2006; Rockel et al., 2008; Voldoire et al., 2013)              |
|              | r1i1p1      | SMHI-RCA4      | (Samuelsson et al., 2011; Voldoire et al., 2013)                            |
| EC-EARTH     | r12i1p1     | CCLM4-8-17     | (Böhm et al., 2006; Hazeleger et al., 2010; Rockel et al., 2008)            |
|              | r12i1p1     | SMHI-RCA4      | (Hazeleger et al., 2010; Samuelsson et al., 2011)                           |
|              | r1i1p1      | KNMI-RACMO22E  | (Hazeleger et al., 2010; van Meijgaard et al., 2008; van Meijgaard, 2012)   |
|              | r13i1p1     | DMI-HIRHAM5    | (Christensen et al., 1998; Hazeleger et al., 2010)                          |
| IPSL-CM5A-MR | r1i1p1      | WRF331F        | (Dufresne et al., 2013; Skamarock et al., 2005)                             |
|              | r1i1p1      | SMHI-RCA4      | (Dufresne et al., 2013; Samuelsson et al., 2011)                            |
| HadGEM2-ES   | r1i1p1      | CCLM4-8-17     | (Böhm et al., 2006; Collins et al., 2011; C. Jones et al., 2011;            |
|              |             |                | Rockel et al., 2008)                                                        |
|              | r1i1p1      | SMHI-RCA4      | (Collins et al., 2011; C. Jones et al., 2011; Samuelsson et al., 2011)     |
| MPI-ESM-LR   | r1i1p1      | CCLM4-8-17     | (Böhm et al., 2006; Rockel et al., 2008; Samuelsson et al., 2013)           |
|              | r1i1p1      | SMHI-RCA4      | (Samuelsson et al., 2011; Stevens et al., 2013)                            |
was calibrated over the period 1971–2000, separately for each calendar day of the year over a 31-day moving window. The GPARD data set (presentation at DACH 2013, 2013) served as observational reference for daily precipitation, the SPARTACUS data set (Hiebl & Frei, 2016) for daily maximum temperature. Both data sets are based on interpolated station data and have a nominal resolution of 1 × 1 km.

Weather and climate of Austria are strongly controlled by the midlatitude atmospheric circulation, regionally modified by the influence of the Alps and rather continental toward the East. We represent the circulation by a small set of dominant synoptic weather types, based on the classification by Lamb (1972). We first calculated 27 types for the region (5°W–25°E, 35°N–55°N) using the objective classification by Jenkinson and Collins, (1977) and P. Jones et al. (1993) based on ERA-Interim data for the period 1979–2005. We, then, combined these 27 types into nine weather types based on the pattern correlations and root mean squared differences of the associated precipitation patterns over Austria (Table 2). These weather types represent major features of the atmospheric circulation such as blocking highs and Genua lows, which are relevant for drought, heatwaves, or extreme precipitation over Central Europe (Awan & Formeyer, 2017; Hofstätter et al., 2018). For each model simulation, the large-scale atmospheric circulation on a given day was assigned to one of these weather types. As reference period for all analyses presented in the following, the period 1979–2005 has been chosen, which is the overlap between the periods covered by ERA-Interim, GPARD, and SPARTACUS. Given the focus on meteorological drought and heatwaves, we consider the summer half year (April–September) only.

### 3. Results

To provide context for the following analyses, Figure 1 shows the annual mean dry day (a) and hot day probabilities (b) for Austria. Both panels illustrate the influence of continentality and topography with a strong gradient toward drier and hotter conditions in the east of Austria and higher temperatures in the valleys. The rectangles mark three regions, the Northern Alps (1), Eastern Austria (2), and the Southern Alps (3), which serve to illustrate selected results in further detail below.

### 3.1. Representation of Weather Types

First, we evaluate the representation of synoptic weather types by the chosen models. Figure 2 shows the seasonal cycle of the occurrence probability of the nine defined weather types on a given day, separately for each calendar month; panel (a) depicts the results for the ERA-Interim reanalysis, panels (b) to (d) for selected climate models (see supporting information for all models). It is evident that the performance differs strongly from model to model, and that no model represents all features of the seasonality in weather type occurrence.

| Weather type | Lamb weather types | Flow over Austria | Precipitation over Austria |
|--------------|--------------------|-------------------|---------------------------|
| 1            | N, NE, AN          | northerly         | wet in northwest, drier in southeast |
| 2            | E, SE, AE, ASE     | easterly (North Sea high) | dry, in particular northeast |
| 3            | S, SW, CS, CSW     | southerly (Celtic Sea low) | wet in west, dry in east |
| 4            | W, NW, CN, CNW     | westerly (central European low) | everywhere, mostly west |
| 5            | C, CW              | weak southerly (Alpine low) | wet in southwest, drier in northeast |
| 6            | A, ANE             | weak southerly (Alpine high) | dry, in particular southeast |
| 7            | CNE, CE, CSE       | easterly (Genua low) | wet in southwest, dry in northeast |
| 8            | AS, ASW            | south westerly (Atlantic low) | dry, in particular east |
| 9            | AW, ANW            | westerly (Scandinavian low) | wet in northwest, drier in southeast |

See supporting information for figures. Flow types defined by Lamb (1972): N, E, S, W: northerly, easterly, southerly, westerly; A, anticyclonic; C, cyclonic; and corresponding hybrid types.
Figure 1. Observed dry (a) and hot (b) day probability (April–September). The black rectangles mark three considered regions: Northern Alps (1), eastern Austria (2), and Southern Alps (3).

Figure 3 summarizes the performance in representing weather types for all chosen models at an annual resolution. Panel (a) presents the occurrence frequency, panel (b) additionally the persistence. The occurrence frequency of WT1 (northerly) and WT2 (easterly) are under-represented by most models, compensated by an overrepresentation of other weather types. The persistence of almost all weather types is overestimated.

Figure 2. Seasonal cycle of weather type occurrence. (a) ERA-Interim, (b) EC-EARTH/CCLM, (c) CM5A/WRF, and (d) MPI-ESM/CCLM.
by most models. In particular, IPSL-CM5A/WRF has deficits in representing occurrence and persistence of many weather types.

### 3.2. Observed and Simulated Conditional Indices

Surface weather, and thus dry and hot day probabilities depend on the occurrence of weather types. Figure 4 illustrates this point for two example weather types. Dry day probabilities are high in an easterly flow
Biases in the overall unconditional dry and hot day probabilities can thus in principle result from both biases in the occurrence probability of different weather types, and the biases in dry and hot day probabilities conditional on these weather types. An overall unconditional BA (as all state-of-the-art methods), even if it would reduce unconditional biases, could therefore increase conditional biases in case of biases in the occurrence on the underlying weather types (Addor et al., 2016). We, thus, assess biases in dry day and hot day probabilities conditional on weather types prior and after BA. The relationship between biases in dry and hot day probabilities on the one hand, and biases in the occurrence probability of weather types on the other hand will be investigated in Section 3.4.

Figure 5 illustrates this discussion for the biases in dry day probabilities conditional on WT2 occurrence, before (left) and after (right) bias adjustment (April–September).

Figure 5. Biases in dry day probability conditional on WT2 occurrence, before (left) and after (right) bias adjustment (April–September).
Figure 7 shows the corresponding example models for hot day probability, conditional on WT3 (southerly flow). All shown models underrepresent hot day probabilities in low-lying areas. Biases in high elevation regions are small, because – trivially – observations and models show a low hot day probability only, independent of the weather type (compare also Figure 4). Biases in low-lying areas are substantially decreased by BA, but the low biases in high elevation regions are slightly amplified, and the negative biases of MPI-CLIM in Eastern Austria are turned into substantial positive biases.

Figure 8 shows that, overall, BA reduces biases in many cases, but in some situations relatively low biases are substantially amplified (e.g., WT2 and CM5A-WRF).

3.3. Observed and Simulated Temporal Indices

Meteorological drought and heatwaves are key climatic phenomena, their atmospheric drivers being persistent patterns of the large-scale circulation resulting in dry spells and high temperatures. Thus, the representation of meteorological drought and heatwaves should depend strongly on the representation of the persistence of large-scale weather types. Moreover, standard BA only indirectly adjusts persistence by adjusting the marginal distributions. Therefore, the adjustment should – in the presence of biases in the persistence of weather types – not be able to fully mitigate biases in the duration of dry spells and heatwaves. Here, we therefore investigate biases in the summer (April–September) mean maximum consecutive dry days (representing meteorological drought) and hot days (representing heatwaves) before and after BA.
The relationship between these biases and biases in the persistence of weather types will be investigated in Section 3.4.

As a reference, Figure 9 shows the observed mean summer maximum consecutive dry (left) and hot (right) days. Dry spells are longest in the east and south of Austria, in particular, in the inner Alpine valleys of Carinthia (central southern Austria). Heatwaves are longest in the eastern lowlands of the Pannonian Basin.

Figure 10 illustrates typical model biases in dry spell duration. Before BA (left), models strongly underestimate the dry spell duration. The adjustment of the dry day probability (right) helps to strongly reduce the dry spell duration bias, but a residual bias remains. In some regions, the adjustment even reverses the biases such that the dry spell duration is over-represented.

Biases in heatwave duration (Figure 11) are, prior to BA (left), typically much lower than those in dry spell duration (partly because heatwaves are shorter than dry spells). BA helps to remove the effect of overall too warm or too cold model simulations, but does not account for the effect of persistence biases in the relevant weather types. Thus, after BA (right), biases are again substantially reduced, but do not vanish and may as well change sign.
Figure 12 summarizes the results across all models for dry spells (left) and heatwaves (right). In both cases, biases are substantially reduced, but for some models substantial biases remain, or biases are even amplified (as for dry spells in the HadGEM2-ES/CLM model). The bias reduction is much stronger for heatwaves than for dry spells. The maximum number of consecutive dry days is much higher than the maximum number of consecutive hot days (Figure 9), suggesting that dry spells are much more controlled by persistence.

Figure 8. Biases in hot day probability conditional on different weather types (April–September). Red: raw simulations; blue: bias adjusted simulations. The whiskers show the interquartile range, the horizontal line the median.

Figure 9. Observed temporal indices. Mean summer (April–September) maximum consecutive (a) dry days and (b) maximum hot days.
than heatwaves, which are more dominated by the marginal temperature distribution and thus, stronger improved by BA.

3.4. Influence of Weather Type Biases on Regional Biases

Here, we explicitly investigate the influence of biases in the occurrence and persistence of weather types on the occurrence and persistence of dry and hot days.

Figure 13 shows how biases in dry and hot day probability are linked to biases in the occurrence probability of weather types (red circles), measured by the correlation between these biases across all considered models. Especially, an underrepresentation of WT2 (easterly) occurrence results in too few dry and hot days in all considered regions, whereas, too many days with WT4 (westerly flow) result in too few dry and hot days. Biases in the occurrence of other weather types may have region-specific though weaker influences on dry and hot day occurrence.

Adjusting unconditional biases in dry and hot day occurrence indirectly affects the influence of weather type occurrence biases, as models with a stronger dry or hot day occurrence bias will be adjusted more strongly than models with a weaker bias. If the adjustment fully removes unconditional dry and hot day...
occurrence biases (which is not the case as the BA method uses a parametric transfer function and the method is calibrated over a period different to the period considered here), the influence should trivially fully vanish. In fact, Figure 13 shows that the influence of weather type occurrence biases is consistently reduced for dry day probability biases and even stronger so for hot day probabilities (blue triangles).

We further illustrate this finding using selected weather types in the Northern Alps region as examples (Figure 14). Climate models with a strong negative bias in WT2 occurrence have a strong negative bias in dry day probability (top left panel). BA strongly reduces the overall dry day probability biases, but a relatively strong influence remains (see also Figure 13 top left panel, WT2). A corresponding behavior, but with different sign of the dependence, is evident for the WT4 influence (top right panel).

A similar influence of WT2 and WT4 occurrence biases and hot day probability biases exists prior to BA (bottom panels). BA removes the scatter across models and drastically reduces the strength of the bias correlations (see also Figure 13 bottom left panel, WT2 and WT4). A residual bias of roughly 1% remains, probably because the chosen BA method uses a parametric transfer function.

Also for biases in the persistence of dry spells and heatwaves, a strong influence of biases in the persistence of especially WT2 and WT4 can be found (Figure 15). BA only marginally reduces this influence on biases in the maximum number of consecutive dry days (top panels), confirming the relevance of weather type

Figure 11. Biases in mean summer (April–September) maximum consecutive hot days. Left: unadjusted models, right: adjusted models.
persistence biases for dry spell persistence biases as discussed above. The reduction of the influence on heatwave persistence by BA is much stronger, corroborating that heatwave persistence biases are mostly controlled by biases in the marginal temperature distribution.

Figure 16 illustrates these results. Prior to BA, a strong influence of weather type persistence biases on biases in dry spell (top panels) and heatwave (bottom panels) persistence are evident. BA basically removes this influence for heatwaves, but only marginally affects the influence for dry spells.

4. Discussion and Conclusions

We conducted a process-based evaluation of the ÖKS15 regional climate projections for Austria with a focus on large-scale circulation errors, their regional imprints, and the potential for BA. Our main results are as follows:

(1) The downscaled global climate models (GCMs) used in ÖKS15 have substantial biases in the occurrence probability and persistence of synoptic-scale weather types. In the summer half year (April–September), the occurrence of WT1 (northerly) and WT2 (easterly) is under-represented by most models, WT6 (Alpine high, corresponding to a westerly flow over Central Europe) is slightly over-represented by many models. Weather type persistence is over-represented for many WTs, in particular for WT2 (North Sea high), WT5 (Alpine low) and WT6 (Alpine high), but also for WT4 (Central European low). IPSL-CM5A/WRF331F sticks out as the model having particular difficulties in representing weather type occurrence and persistence. These findings are in line with our understanding that current generation GCMs simulate too zonal a North Atlantic storm track, too few occurrences of ridges or negative phases of the North Atlantic Oscillation, and too weak persistence in the atmospheric circulation (Davini et al., 2016; Dawson et al., 2012; Zappa et al., 2013).

(2) Dry day probabilities are too low in all considered models and for all weather types. This underrepresentation partly stems from the drizzle effect (Gutowski et al., 2003). But additionally, dry day probability biases depend strongly on biases in the occurrence probability of relevant weather types. In particular, too few WT2 (easterly flow) occurrences and too many WT4 (westerly flow) occurrences result in too few dry days. Hot day probabilities are too low for most considered models and weather types, although the HadGEM-driven RCMs tend to simulate too many hot days. Again, biases depend on biases in the occurrence probability of weather types, again especially WT2 and WT4. Dry and hot spell duration are under-represented by most considered models. Biases in the marginal distributions can partly explain this bias, that is, the drizzle effect and temperature biases. Only the HadGEM-driven
RCMs simulate too long a duration of both phenomena. But also biases in dry and hot spell duration are strongly influenced by biases in weather type persistence, again in particular WT2 and WT4.

(3) An overall bias adjustment (BA) trivially improves the overall representation of dry and hot day probabilities. But also occurrence biases conditional on weather types are indirectly reduced by adjusting the marginal distributions. In some cases, however, the overall bias adjustment may amplify biases for specific weather types. BA also indirectly improves the representation of dry spell and heatwave duration. This improvement is much stronger for hot spells than for dry spells, indicating that heatwaves are much more dominated by the marginal temperature distribution, whereas dry spells are longer and more influenced by persistent weather types. BA, in general, reduces the correlation between biases in weather type occurrence and persistence on the one hand, and biases in dry and hot day occurrence as well as dry and hot spell duration on the other hand. This reduction is much stronger for hot days.
than for dry days. The reduction for dry spell duration is negligible, indicating again the importance of weather type persistence for meteorological drought.

To summarize, standard BA (including the chosen SDM as well as other variants of quantile mapping) in many cases helps to greatly reduce biases even in the presence of circulation biases, and is indispensable for many impact applications. In some cases, however, occurrence biases conditional on selected weather types may be amplified by BA, corroborating similar findings by Addor et al. (2016). Persistence biases are especially relevant for the representation of meteorological drought. Biases in the duration of dry spells cannot fully be mitigated by standard BA.

To improve the representation of temporal structure, such as the duration of drought and heatwaves, an explicit adjustment of temporal biases has been proposed (Cannon, 2016, 2017; Plani & Haerter, 2012; Vrac & Friederichs, 2015). It has, however, been argued that such an adjustment inevitably destroys the relationship between the atmospheric circulation as simulated by the driving model and the adjusted surface weather (Marau et al., 2017). The effect of such adjustments on the credibility of future drought and heatwave projections has not been assessed yet. Hence, any such adjustments should be conducted very carefully, and it should be kept in mind that simulated changes in drought and heatwave length are only as credible as the simulated changes in the underlying atmospheric circulation (Marau et al., 2017).

In any case, our study demonstrates that a careful selection of GCMs is required for projecting climate across a chosen region, in particular, when interested in drought and heatwaves (Note that RCMs may...
to some extent modify the representation of weather types within their domain, Prein et al., 2019). For GCMs very badly representing the occurrence of persistence of important weather types, BA may even deteriorate raw model simulations. These results, thus, highlight the relevance of process-based evaluation, and provide further evidence that BA should not be considered a black box that may be applied without understanding of the relevant climatic processes and how they are represented in climate models. These findings directly illustrate the emerging discussion on adequacy for purpose (Baumberger et al., 2017; Maraun & Widmann, 2018; Parker, 2009): for any given purpose – such as regional drought projections – it has to be assessed whether the available models are adequate for the desired purpose. Further research could attempt to constrain future projections based on the representation of weather types in present climate (Hall et al., 2019).

Figure 15. Correlation across climate models between biases in the persistence of a specific weather type and biases in mean summer (April–September) consecutive dry (top) and hot (bottom) days for three regions (marked in Figure 1). Red circle: raw simulations; blue triangle: bias adjusted simulations.
Our findings – and potential corresponding studies for other regions and phenomena – should be considered in the design of future regional climate ensembles such as the planned downscaling of CMIP6 GCMs within the CORDEX activities. As the design of current model ensembles has, in general, not been informed by process-based model evaluation, our findings are highly relevant for stakeholders. Users of regional climate information on drought and heatwaves may employ our results to subsample the ÖKS15 projections for their specific purpose. But such a subsampling might even be relevant for future ensembles, designed based on a process-based performance evaluation. Regional climate model ensembles have to be quite generic as they span still a large region and have to represent a broad range of phenomena. Thus, for different purposes different subensembles may be adequate.

**Data Availability Statement**

The EURO-CORDEX simulations are available from the Earth System Grid Federation (ESGF, e.g., [https://esgf-data.dkrz.de/](https://esgf-data.dkrz.de/)), the ÖKS15 simulations from the Climate Change Center Austria ([https://data.ccca.ac.at/group/oks15](https://data.ccca.ac.at/group/oks15)). The observational data sets GPARD1 and SPARTACUS have been provided by the Austrian Zentralanstalt für Meteorologie und Geodynamik (ZAMG).
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