Short Communication

On the spatial representativeness of temporal dynamics at European weather stations

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ABSTRACT: The prospects of validating areal data from climate models by site observations depend critically on the spatial representativeness of the sites. This paper introduces a simple parameter-free approach to quantify the spatial representativeness of single stations with an application to time series of daily near surface air temperature and precipitation at European weather stations. Complementing classical methods such as spatial auto-correlation and variogram, our approach provides a well defined area around each station for which the station is representative, based on a similarity threshold but otherwise without any limiting assumptions about distribution or spatial stationarity of the data. This area is interpreted as the station’s ‘inverse footprint’ and its areal extent provides a measure of representativeness. We find a generally higher representativeness for temperature compared to precipitation, but also a strong seasonal dependence. For instance, temperature representativeness in boreal winter is related to the influence of circulation with large ‘inverse footprints’ over Central and Eastern Europe and Scandinavia. Representativeness in summer exhibits similar patterns but is lower. Precipitation representativeness displays related patterns of representativeness and circulation control in winter, but vanishes in summer, probably due to the small-scale characteristics of convective precipitation. Precipitation representativeness is strikingly high around the Mediterranean, which is a consequence of the large numbers of synchronous dry days in this region. The physical plausibility of the results underlines the applicability of our approach. Although not investigated here, the ‘inverse footprint’ also provides information on the directional dependence of representativeness at the station level.

KEY WORDS spatial representativeness; inverse footprint; synchronous dynamics; gridded versus station data

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1. Introduction

Spatial representativeness of observational sites has been a subject of interest for many years and continues to be investigated through different approaches (Jacobs, 1989; Fraedrich et al., 1995; Vinnikov et al., 1996; Milewska and Hogg, 2001; Hargrove and Hoffman, 2003; Carvalhais et al., 2010; Mittelbach and Seneviratne, 2012; Pfahl and Wernli, 2012). These concepts are especially relevant for the validation of climate models, which produce areal data on grid cells. Given the fundamentally different nature of measurements from observational sites, the comparison of these two types of data is not necessarily straightforward. For example, grid cell sizes of current Global Climate Models (GCMs) are of the order of 100 × 100 km². The areal average of precipitation of such a grid cell is potentially very different from the precipitation observed at a weather station located in that grid cell, in particular if the spatial representativeness of that station is low (like in alpine regions). This can be particularly critical when investigating processes related to heavy precipitation events (Seneviratne et al., 2012).

Another application of the concept of spatial representativeness is the design or the extension of observational networks, where regions with high spatial variability and hence low representativeness need higher station densities (Plummer et al., 2003). Spatial representativeness also provides guidance for determining suitable grid cell sizes when interpolating station data.

There is no unique definition of spatial representativeness, but its general notion can be understood as the ‘decay of similarity with distance’. This concept was for instance formerly applied in the assessment of spatial characteristics of soil moisture measurements (Vinnikov et al., 1996; Robock et al., 1998). Similarly, (Milewska and Hogg, 2001) analyse pairwise correlations between Canadian precipitation stations and find that their decay with distance is exponential. This feature can be used to determine an 1/e-radius of similarity which quantifies the average representativeness of this station network.

Probably the most widely used characterization of spatial representativeness is the variogram (Wackernagel, 2003), which is, for example, employed for advanced
spatial interpolation techniques. Applications in climate science include analyses of remote sensing datasets (Roman et al., 2009) and spatial representativeness analysis of eddy-covariance sites relating to remote sensing data (Chen et al., 2012). The variogram sums the squared differences between a variable at pairs of stations as a function of distances between the stations. Typically exponential dependencies are assumed, from which different characteristics of the spatial correlation structure can be inferred, such as sill (the value of the variogram as distance approaches infinity), range (the minimum distance where the variogram value becomes acceptably close to the sill) and nugget (the variogram value at 0 distance). Range and nugget measure spatial representativeness and noise of the investigated field, respectively. The variogram can be generalized to take into account a directional dependence of the range. Note that the variogram requires second order stationarity of the underlying spatial process, which means that the temporal means at the stations and the co-variances between station pairs must not depend on the actual locations of the stations but on their relative distance only.

While the assumption of second order stationarity is sensible for station networks over climatologically homogeneous regions, areas with a pronounced topography and different climate regimes require more refined approaches. Station-centred variograms (Janis and Robeson, 2004) alleviate the stationarity constraints, but are necessarily based on fewer station pairs compared to all pairs of the investigated region, which potentially makes the estimation of the (e.g. exponential) dependency between difference and distance unreliable. Furthermore, the generalization of the variogram to include directional dependence (Kitanidis, 1997) is unfeasible for station-centred variograms unless the station density is very high (Janis and Robeson, 2004). Similar constraints apply to other measures of spatial auto-correlation (Fischer and Getis, 2010).

In this paper, we propose a robust alternative to assess the representativeness of individual stations (as opposed to the above-mentioned representativeness within an entire network). The approach defines the area (termed ‘inverse footprint’) for which a station is representative, that is, any station within the ‘inverse footprint’ shares a minimum similarity with the representative station. In other words, within this ‘inverse footprint’, any user can rely on the information from that station, to the extent that the chosen minimum similarity allows for.

The aim of our study is primarily to provide a climatological perspective on the evaluation of these ‘inverse footprints’, based on observations. However, there would be a number of possible applications, including climate model validation, determining suitable grid sizes for interpolation and network improvement.

The remainder of this paper is organized as follows. Section 2 briefly introduces the data of our study and describes our approach. Results are presented and discussed in Section 3. Section 4 concludes with an outlook.

2. Data and methods

This section introduces the employed data (Section 2.1) and our approach to spatial representativeness (Section 2.2).

2.1. Data

We use daily station data from the European Climate Assessment & Dataset (ECA&D) project (Klein Tank et al., 2002) for near surface air temperature and precipitation. We selected stations spanning the 1971–2000 period, which maximizes the number of available stations. Note that analyses of different 1971 to 2000 sub-periods and longer periods with slightly fewer stations produce robust results.

We furthermore use two indicators of large-scale circulation for the interpretation of our results. First, we correlate the daily North Atlantic Oscillation (NAO) index with our time series (see, e.g. Wanner et al., 2001, data downloaded in April 2013 from http://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/nao.shtml #publication). Second, we analyse the variance in our time series which is explained by the ‘Grosswetterlagen’ (GWL) circulation pattern classification (Hess and Brezowsky, 1977, maintained by the German Weather Service DWD). This subjective classification system assigns each day since 1881 one of 29 different circulation patterns (or a 30th for undefined situations) based on sea level pressure maps and 500hPa geopotential heights over Europe and the North Atlantic. The GWL time series is available from http://cost733.geo.uni-augsburg.de/cost733wiki/Cost733Cat2.0 (accessed in April 2013).

There are many classification schemes for large-scale circulation patterns over Europe, which are all targeted at different purposes (see Beck and Philipp, 2010 for an overview and evaluation). Although our choice is therefore arbitrary to some extent, it relates our analyses to the many studies based on the GWL classification (e.g. Pinto et al., 2007; Besselaar et al., 2010, on the influence of circulation on extreme snow fall or temperature). Furthermore, since the results from the NAO and the circulation pattern analyses agree reasonably (see hereafter), we can infer that the chosen classification scheme is sufficiently indicative of the large-scale atmospheric control on the investigated station time series.

Further details of the GWL classification and its nomenclature are provided in the Appendix S1, Supporting Information.

2.2. Spatial representativeness

We propose the concept of a station’s ‘inverse footprint’ to define the spatial representativeness of the station. The here defined ‘inverse footprint’ corresponds to the area surrounding a station in which other stations exhibit similarity above a chosen cutoff. For temperature, the similarity of a station pair is measured as the rank-based correlation between their anomaly time series. For precipitation, we address similarity regarding concurrent

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wet day/dry day occurrences and rank-based correlations of wet day precipitation anomalies separately. See below for details of the computations.

For each station, its surrounding stations are selected for which the similarity measure is above the pre-defined cutoff. The choice of the cutoff value for identifying stations within the ‘inverse footprint’ determines the level of spatial detail of the representativeness analysis, a higher cutoff value resulting in more spatial detail and vice versa. An upper limit of this cutoff results from the station density. The convex hull of these selected stations defines the ‘inverse footprint’. Figure 1 illustrates the derivation of the convex hull. Its area gives, depending on the time frame (annual or seasonal), the spatial representativeness of that station. Note that, although we restrict our analysis to the area of the convex hulls, other characteristics may be of interest as well, such as their orientation in space, which is related to the anisotropy of the spatial correlation structure.

We use all days for the annual time scale and the days from two meteorological seasons (December–January–February, DJF, and June–July–August, JJA) for the seasonal time scale to calculate correlations and agreements on wet and dry days.

Prior to the analysis, station locations are projected onto a Lambert equal area projection (Annoni et al., 2004) to allow for a meaningful computation of the convex hull areas. While the projection introduces some slight topological inconsistencies (eg. the edges of the convex hulls are no longer great circle arcs), the obtained ‘inverse footprints’ are sufficiently small to make the effect of such inconsistencies negligible. Although projecting each hull separately with a hull-centered projection would be more accurate, again our study area is sufficiently limited to justify our use of the one universal projection (which is also recommended in Annoni et al., 2004).

2.2.1. Temperature similarities

We apply piece-wise linear interpolation to the medians of daily temperatures from each of the January, February, March, April, May, June, July, August, September, October, November, and December months over the entire period to obtain a daily climatological seasonal cycle. Subtracting the seasonal cycle from the daily temperatures yields anomaly time series. Correlations between anomaly time series from pairs of stations are estimated by Spearman’s rank-based correlation coefficient, which is robust against outliers.

2.2.2. Precipitation similarities

All precipitation time series are disaggregated into daily wet/dry time series (defining a wet day if precipitation ≥1 mm) and time series of wet day anomalies. The climatological seasonal cycle of wet day precipitation is determined from the medians of the daily wet day precipitation amounts of each month, to which we apply the same piece-wise linear interpolation as for temperatures. Subtracting the wet day seasonal cycle from the wet day precipitation amounts yields wet day precipitation anomalies. We define the wet/dry agreement between pairs of stations as the percentage of days where both stations are concurrently wet or dry. For the wet day precipitation similarity, we compute Spearman’s rank-based correlation coefficient of the wet day anomaly time series over the subset of days at which both stations are wet.

2.2.3. Hull derivation

For each station, we identify the stations with similarities above the chosen cutoff and determine the convex hull of these stations (Figure 1). If by chance far-away stations have similarities above the cutoff, the hull may contain a large fraction of stations which do not exhibit the required similarity. Since the hull is supposed to contain an area where stations are similar to the considered station, we iteratively remove the station which is the furthest from the considered station, until at least 90% of the stations within the hull are similar with respect to the chosen cutoff.

3. Results

This section discusses the derived patterns of representativeness for temperature (Section 3.1) and precipitation (Section 3.2). Weather dynamics are naturally linked to large-scale circulation, and the respective sections provide additional maps on the relation between the station time series and large-scale circulation to guide the interpretation of the representativeness patterns.

Besides rank-based correlations and wet/day agreement described in Section 2.2, we have experimented with different ways of quantifying between-station similarity, including averaged differences of anomalies which are stratified to an ordinal scale, with different specific setups. The obtained results are very robust, independent on the details on the similarity quantification (not shown). Here, due to their frequent use and straightforward interpretability, we show results from the correlation and wet/day agreement computations.
3.1. Spatial representativeness of temperature

The top row of Figure 2 displays the results of the representativeness analysis with respect to the correlations of daily temperature anomalies for the annual time frame (all days) and the winter (days of December-January-February, DJF) and summer (days of June-July-August, JJA) seasons. The similarity cutoff is set to 0.7 (for cutoffs between 0.4 and 0.8, see Figure S1 in Appendix S1). The stations in Central, North-Eastern Europe and Southern Scandinavia display large areas of representativeness, often reaching or even exceeding 800,000 km$^2$ (which would, e.g. correspond to a circle with a radius of approximately 500 km). Although the general patterns largely resemble one another, some seasonal variations in spatial representativeness are apparent, with highest representativeness in winter, in particular over Central Europe. The annual pattern is close to the average of the DJF and JJA patterns.

The large representativeness over Central and partly Eastern Europe and Southern Scandinavia in winter corresponds to the areas of relatively high correlation between the temperature anomalies and the NAO index (Section 2.1), see middle row in Figure 2. The control of large-scale circulation on temperature anomalies in these areas is further supported by the fraction of explained variance by the commonly used classification of circulation patterns (the ‘Grosswetterlagen’, GWL, see Section 2.1), which reaches values of 50% over Central Europe (bottom panel, Figure 2). While the NAO displays hardly any correlation in summer, the GWL circulation patterns still explain a considerable fraction of the variance over Central Europe.

Although some areas of high representativeness (e.g. the East-most part of our investigated region) are not found in these maps of circulation control, the strong agreement for other parts of Europe suggests the intuitive interpretation that representativeness is high in regions where station observations are controlled by large-scale circulation, which leads to a more or less synchronized day-to-day variability at the stations and correspondingly high correlations.

Patterns for different cutoffs are qualitatively similar, but the representativeness areas scale inversely with the cutoff (see Figure S1 in the Appendix S1). The cutoff thus determines the level of detail of the analysis and

![Figure 2. Areas of representativeness of ECA&D stations for daily temperature (top row) for correlations >0.7. Panels show results for annual and boreal winter and summer time frames (columns). Colours indicate areas of representativeness, black crosses mark stations where no area could be defined. Rows below: Correlations between temperature anomalies and the NAO index; variance of the temperature anomalies explained by the ‘Grosswetterlagen’ from Hess and Brezowsky (1977).](image)
needs to be adjusted according to the goal of the analysis, where an upper limit is imposed by the station density.

3.2. Spatial representativeness of precipitation

Figure 3 displays the corresponding analysis for precipitation, differentiating representativeness in terms of agreement on wet/dry days and in terms of wet day precipitation correlation. As can be expected from the generally higher spatial variability of precipitation, representativeness areas are overall smaller compared to those for temperature (compare the regions north of the Mediterranean in Figures 2 and 3, respectively), although one has to keep in mind the different similarity measures for temperature and precipitation, respectively (see Section 2.2). For the wet/dry agreement (top row in Figure 3), strikingly large representativeness areas are found in Southern Europe around the Mediterranean, hardly depending on the season. For winter, the rest of Europe, that is, the area north of the Mediterranean, displays a similar pattern as temperature, with relatively high representativeness over Central and Eastern Europe and parts of Scandinavia. This is also the only region which exhibits some representativeness at all in the wet day precipitation correlations (bottom row in Figure 3). However, summer shows much weaker representativeness for the wet/day agreement, in particular over Eastern Europe, and hardly any representativeness for the wet day precipitation correlations. The annual patterns, like for temperature, are close to the average of the DJF and JJA patterns.

While the winter pattern corresponds again to the areas where circulation controls to some degree the variability of precipitation (compare with the top two rows in Figure 4), the reduced representativeness in summer may be due to the dominance of convective precipitation, which is highly local and asynchronous between different sites. The very large representativeness values from wet/dry agreement in the South are consequent to the simple fact that most of the days (more than 70%) are without precipitation in this area, leading to a high proportion of concurrent dry days and a corresponding large area of representativeness (see bottom panels in Figure 3). See also Figure S4 in the Appendix S1, which shows that the high proportion of dry days by itself essentially establishes the high wet/dry synchronicity between the stations, although circulation (in particular stationary sub tropical high pressure systems in summer) can further add to the concurrence of dry days in this region (Ulbrich et al., 2012). Overall the representativeness from precipitation occurrence is larger than the representativeness from actual precipitation anomalies, which depend strongly on the specific local conditions.

Choosing different cutoffs (Figures S2 and S3 in the Appendix S1) displays the same effects as for temperature, namely an inverse scaling of representativeness areas with the similarity cutoff.

4. Conclusions

This study introduces a robust approach to assess the station-specific spatial representativeness, with an application to European weather stations. Since Europe is characterized by different climatological regimes and a diverse landscape including coastal areas and elevated topography, methods designed for climatologically homogeneous regions to quantify the dependence of similarity on distance (Milewska and Hogg, 2001, Wackernagel, 2003) are difficult to apply. We instead propose a simple derivation for the ‘inverse footprint’ of a station, that is, the surrounding area for which the station is representative in terms of daily anomaly correlations (temperature and wet day precipitation) or agreement on wet/dry days for precipitation.
Applying this derivation to daily temperature and precipitation data from the ECA&D dataset with a focus on representativeness with respect to day-to-day variability, we find higher spatial representativeness for temperature compared to precipitation. For temperature, spatial representativeness is highest over Central and Eastern Europe as well as the Southern parts of Scandinavia, especially in the winter season. This pattern corresponds largely to the control of large-scale atmospheric circulation on temperature anomalies (expressed by correlations with the NAO index and the fraction of variance explained by the ‘Grosswetterlagen’ circulation patterns from Hess and Brezowsky, 1977).

For precipitation, north of the Mediterranean the patterns of representativeness are similar to the temperature patterns, although generally weaker. In summer, representativeness is low due to the fragmented spatial distribution of the dominating convective precipitation. Representativeness from wet/dry agreement is generally higher compared to the representativeness according to precipitation amounts, due to the stronger dependence of the latter on local conditions. The wet/dry representativeness is strikingly high in the Mediterranean region, which is a direct consequence of the large fraction of dry days in this region (above 70% in all time frames).

The plausible physical interpretation of our results underlines the applicability of our approach. It can thus serve to identify regions where spatial representativeness is high enough to compare stations to gridded data, e.g. from climate model simulations or to determine suitable grid sizes for interpolation. Another field of application is the design and maintenance of observational networks, where regions of low spatial representativeness require denser station installations. While we restricted our analysis to the area of the obtained ‘inverse footprints’, in principle any other aspect of the ‘inverse footprint’ can be used, e.g. the direction-dependence of its spatial extent. This will enable a straightforward extension of the analysis into the anisotropy of the spatial correlation structure at each station. Future work will investigate this anisotropy and its relation to atmospheric circulation characteristics such as dominant flow directions.

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Supporting Information

The following supporting information is available as part of the online article:

Appendix S1. Additional figures and discussion

Table S1. Circulation patterns over Europe and the North Atlantic according to the classification in Hess and Brezowsky (1977). The descriptions refer to the dominant winds over Central Europe. Note that the identifiers are derived from the German descriptions.

Figure S1. Areas of representativeness of ECA&D stations for further similarity cutoffs for daily temperature anomalies. Panels show results for annual and boreal winter and summer time frames (columns). Colours indicate areas of representativeness, black crosses mark stations where no area could be defined. From top to bottom the cutoff for the rank-based correlation increases from 0.4 to 0.8.

Figure S2. Like Figure S1, but for the agreement on wet/dry days. From top to bottom the cutoffs for the percentage of days with agreement on wet/dry days increase from 40% to 80%.

Figure S3. Like Figure S1, but for correlations of wet day precipitation anomalies. From top to bottom the cutoff for the rank-based correlation increases from 0.4 to 0.8.

Figure S4. Synchronicity of dry days in the Mediterranean. (a) Stations with at least 80% of the days with precipitation <1mm (dry days). ((b)–(d)) Histograms of the daily numbers of stations identified in (a) which are concurrently dry. Black: Original time series. Gray: Numbers of concurrent dry stations after bootstrapping the original time series of each station individually (100 bootstraps of each station). Vertical lines indicate the respective averages. Panels display the annual time frame (b) and the seasons December-January-February (DJF), (c) and June-July-August (JJA), (d).

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