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Temporal properties of spatially aggregated meteorological time series

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ABSTRACT

Large-scale crop simulations with process-based models rely on meteorological input data of coarse spatial resolution. We assess how spatial aggregation of meteorological data to coarser resolutions affects the data's temporal properties. This is largely unknown as is the impact which this aggregation effect (AE) has on simulations which use such aggregated data as input. In simulations of crop yield AE may exceed 10% in single years. We hypothesize that AE should be analysed with regard to both temporal and spatial input data properties. For this purpose, we analysed changes in temporal multifractal properties of meteorological variables due to spatial averaging from 1 to 100 km resolution. Results show that temporal properties of the time series were affected depending on the meteorological variable. We argue that the magnitude of this effect depends on local orography and climate. Similar impact of spatial aggregation on temporal properties can therefore be expected in regions of comparable orography and climate. These changes in multifractal properties potentially affect results of continuous dynamic simulations.

1. Introduction

Meteorological time series are essential for a wide range of research areas. At the same time, research related to the environment often involves modelling. In order to extend our knowledge to situations for which measurements are scarce, not efficient or not available (e.g. large scales, future), process-based models are increasingly applied. For instance, process-based crop models are useful tools to assess crop production from the field (e.g. Nendel et al., 2013) to the global (e.g. Rosenzweig et al., 2014) scale. Such simulation requires input data at the target resolution, which is often not available. Resolutions may then be sampled or model input data may be derived by spatial (dis-)aggregation from other resolutions (Fig. 1), (Ewert et al., 2011, 2015). For instance, weather input is not measured at the regional or global scale, but rather aggregated from higher resolution.

Large-scale simulations often require input data of low resolution and only few data types can be measured or derived directly at these scales, e.g. via remote sensing. Therefore meteorological time series for large-scale simulations are usually either simulated with the help of climate models or are spatially aggregated from measured time series at high resolution. The use of climate models is common in weather forecasting, climate projections and studying aspects of climate change (e.g. Tao et al., 2016) along a range of aggregation and scaling (Fischer et al., 2013; Gong et al., 2003; Ning et al., 2015) as well as bias correction approaches (Piani et al., 2010; Hoffmann and Rath, 2012). However, spatial meteorological data aggregation in environmental simulation studies is often achieved directly via spatial averaging (Janssen et al., 2009; Zhao et al., 2013). Still, most models using meteorological time series as input are developed and calibrated at the scale at which model driving variables are obtained. Crop models for instance are usually developed and calibrated at the field scale (Van Ittersum et al., 2003; Hansen et al., 2006).

Complex dynamical process-based models are typically composed of non-linear functions. Using such models of non-linear functions with linearly averaged input data at larger scales may therefore lead to biased simulations (Fig. 2). This is the so-called nonlinear aggregation error (Cale et al., 1983) or aggregation effect AE (Hoffmann et al., 2015, 2016b; Zhao et al., 2015a). The AE of meteorological time series has been investigated by several publications, e.g. with regard to crop (Angulo et al., 2013; De Wit et al., 2005; Easterling et al., 1998; Folberth et al., 2012; Hoffmann et al., 2015, 2016b; Van Bussel et al., 2011a,b; Zhao et al., 2015a,b) or environmental models (Ershadi et al., 2013; Pierce and Running, 1995). For instance the AE of 30-year regional yield due to the

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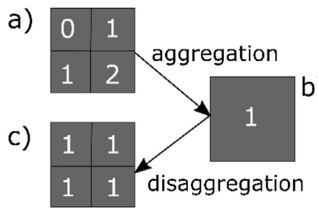

Fig. 1. Illustration of spatial (dis-)aggregation via averaging. Gridded values at high resolution (a) are averaged to a coarser resolution (b). Disaggregation allocates values of a coarser resolution (b) to a higher resolution (c).

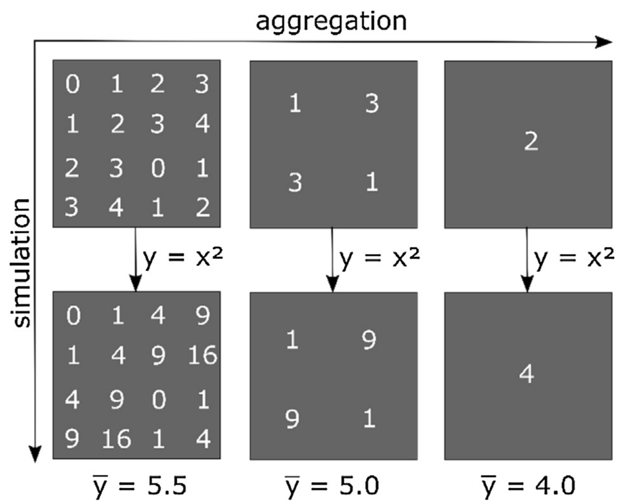

Fig. 2. Illustration of aggregation effect in dynamic simulations due to spatial averaging of input data. In the example blocks of four cells are averaged. As a result the spatial mean of the simulation output, exemplified by the function $y = x^2$, decreases from 5.5 to 4.

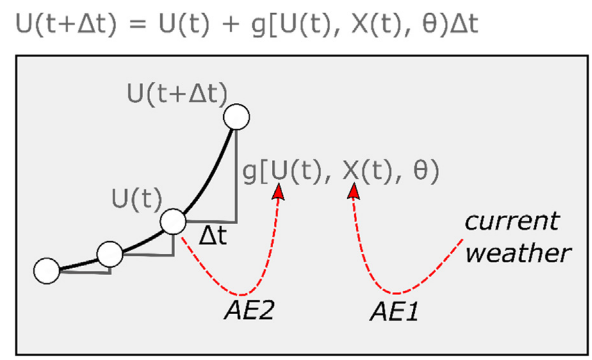

Fig. 3. Illustration of accumulated aggregation errors for one given process in a dynamic simulation. U: state of variable; t: time; Δt: time step; X: time series of meteorological variable; θ: vector of system component properties (e.g. parameters); g: mathematical function describing the relation between state variables, parameters and meteorological variables. AE1: instantaneous aggregation error made at given time step with meteorological data X(t); AE2: cumulative aggregation error resulting from aggregation errors at previous time steps. Modified from Wallach et al. (2014).

spatial aggregation of meteorological time series was reported by Hoffmann et al. (2015) and Zhao et al. (2015a). AE of crop yields up to 100 km resolution as compared to yields at 1 km resolution were in the range of ≤3.5% (bias) and ≤4.5% (root mean square deviation). These values are averages and may differ considerably for single grid cells, years or models. Due to the complex interaction of climate with different input data types and model structure, aggregation effects have been merely described in the past. Zhao et al. (2015b) made a first step in using terrain elevation as proxies for an ex ante assessment of average aggregation effects for one model. However, a general approach for estimating spatial AE across models, data types and regions has not been validated so far.

In contrast to spatial AE, temporal AE are also known to affect results of dynamic simulations (Van Bussel et al., 2011a; Weihermüller et al., 2011). While temporal aggregation is not the subject of this study, temporal and spatial aggregation must not be confused. While spatial aggregation can be conducted at any temporal resolution (e.g. spatially averaging daily time series at each day), temporal aggregation can be conducted at any spatial resolution (e.g. averaging daily values to monthly means for each grid cell). Hence, this process of averaging is similar for both spatial and temporal aggregation. Amplitudes may smooth and extreme values decrease with aggregation as they are averaged out (Hoffmann et al., 2015). For a given situation, it is therefore possible to define impact response surfaces of iso-lines of AE, showing the trade-off between temporal and spatial aggregation.

From the above, spatial aggregation is expected to impact on the temporal properties of meteorological time series. The spatiotemporal connection in the properties of meteorological time series has been considered e.g. in downscaling precipitation (Lovejoy et al., 2012; Pathirana and Herath, 2002). However, it is unknown to which extent spatial aggregation of meteorological time series affect the temporal properties with regard to multifractal properties. The latter are in turn expected to have an impact on the simulation results of dynamic, process-based models, as described in Section 2. The aim of the present work is therefore to show in a first step, how spatial aggregation of meteorological time series modifies the temporal properties with regard to multifractal properties.

Spatial data aggregation errors partially depend on the orography and climate of the region (Hoffmann et al., 2015). Therefore we test the effect of spatial aggregation of meteorological time series on their temporal properties in a select region. While this does not allow quantifiable estimate of the effect for other regions, it can be assumed that effects are comparable in regions of similar climate and orography and lower/stronger in regions of less/more pronounced orography and temporal variation. Specifically, this approach allows i) to verify whether and how spatial aggregation affects multifractal properties in general and ii) to put results into the context of the given region.

2. Conceptual basis for estimating the aggregation error

Dynamical process-based models solve differential equations at different time steps. The spatial AE described above does therefore occur at each time step for a given model variable, e.g. biomass. For that given time step, the AE in a calculated model rate might be comparable to the AE from temporal aggregation. However, the daily AE in a given model rate continuously contributes to the AE in final model output. Final model outputs (e.g. crop yields) are therefore prone to the accumulated aggregation error in the input data (Fig. 3). Neglecting specific feedbacks, e.g. of AE early in the season on the simulation later in the season, a simplified concept can be drafted. The AE at any time can therefore be viewed as the sum of an instantaneous aggregation *AE1* error at a given time step t and the cumulative aggregation error *AE2* as the sum of aggregation errors of previous time steps (Fig. 3). Moreover, the rate *g* of change of the value of a state variable *U(t)* to next time step *U(t+1)* may depend on both *AE1* and *AE2*. This relation also describes the impact of aggregation errors from single events and from persisting influences. For instance, a large AE occurring only at one time step (*AE1 > 0; AE2 > 0*), e.g. from a large local meteorological event, will in the following persist only through *AE2* (*AE1 = 0; AE2 > 0*). In contrast a persisting AE, e.g. from soil aggregation, will continuously add to *AE2* (*AE1 > 0; AE2 > 0*).