state that the relationship between discharges and reported events does not always hold, and we can identify two reasons behind this. First, there are some months in which simulated total peak discharges (at the aggregated national scale) were relatively low, although flood losses were reported. If we examine the damage database used in our study[5], it becomes clear that these specific flood events are very small. For both the May 1991 and July 1994 events in Austria, the total reported losses do not exceed US$100,000. Second, there are months with high simulated river discharge (at the aggregated national scale) but without reported flood losses. This effect is likely to occur because the high discharges do not always happen in populated areas where they cause losses. Following the terminology of the Intergovernmental Panel on Climate Change[6], the peak discharge deviation may have coincided with a flood hazard, but the lack of exposure results in no flood risk. In those cases, our model would therefore simulate floods, but with low or zero economic losses. Modelled discharge peaks versus observed gauge discharge at 554 stations across Europe have been fully validated[7]. We emphasize that the analysis of discharge correlations is conducted at the level of 1,007 individual sub-basins and that the economic risk modelling is performed at the grid-cell level (100 m × 100 m) rather than the national scale.

Raschke's final argument relates to the overestimation of relatively frequent losses, specifically for the 1-in-10-year return period. We acknowledge that our model outcomes do not perfectly represent reported losses, as can be expected. There are a substantial number of uncertain elements in our modelling chain, some of which can be validated while others cannot. These model elements include the grid-cell-based damage modelling, the assessment of discharge correlations, the dependency modelling and the protection standard estimation. In addition to uncertainties surrounding tail dependency in different basins, we acknowledge that uncertainties surrounding the newly developed protection standard database can lead to overestimation of high-frequency losses, as Raschke points out. Whereas validation of the modelled protection levels was performed with the data available, the number of empirical data points is very limited (Supplementary Table 2 in ref. 2). For the same reason, we necessarily assumed homogeneous protection levels within each basin, while this is often not the case in reality. Hence, for a basin with a protection level of 100 years, we assume that no inundation (and therefore no damages) would occur below this frequency anywhere in the basin, whereas some regions (for example, peripheral urban or semi-urban areas) may not have the same level of protection as more densely populated areas.

The only way to reduce this specific uncertainty in future large-scale risk modelling studies would be to develop a detailed geo-referenced dataset of actual flood protection levels and observed losses. We emphasize that the method still represents the most sophisticated approach at the continental scale to date, as most large-scale models simply assume that no protection measures are in place, leading to large overestimations of risk[8].

While uncertainties persist and may propagate, especially in the lower ranges of modelled risk estimates, we reject Raschke's claim that this would falsify the risk model[1]. We do emphasize that we present a first approach to a continental-scale disaster risk assessment that includes basin dependencies, and that the results should therefore not be considered as a final answer. Although a full sensitivity analysis focusing on each individual part of the risk modelling was not possible in this study, the quantification of uncertainties and further validation of model elements on lower spatial levels should be a research priority. ❐

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CORRESPONDENCE:

Spatiotemporal patterns of warming

To the Editor — Ji *et al.*[1] present a methodology to analyse global (excluding Antarctica) spatiotemporal patterns of temperature change, using mean monthly temperatures obtained from the updated Climate Research Unit (CRU) high-resolution gridded climate database[2,3]. Their analysis fails to take into account several key characteristics of the CRU database, seriously compromising the conclusions regarding the spatiotemporal patterns of global warming during the twentieth century.

Climatic data comes from thousands of stations scattered non-randomly across Earth, with much higher densities at mid-latitudes than in the tropics or the Arctic, creating spatial bias. A distance-weighted interpolation from available meteorological stations was implemented to fill spatial gaps in the CRU database[2–4]. Land pixels outside a search radius of 1,200 km from the closest meteorological station were given the corresponding CRU 0.5° 1961–1990 mean monthly climatology[4,5] (Supplementary Fig. 1; other search radii apply to other variables in the CRU database).

In terms of temporal bias, the CRU dataset logically contains many fewer observations in the early part of its record. This is particularly prevalent in remote tropical and Arctic regions, where temperature records abound with long-term climatological averages. Consequently, the temporal autocorrelation of such time series is artificially high, and the climatic variability they portray for the early decades of the record is meaningless (Fig. 1).

Ji *et al.*[1] fail to address these spatial and temporal biases. Supplementary Fig. 2 strongly suggests that the absence of a trend

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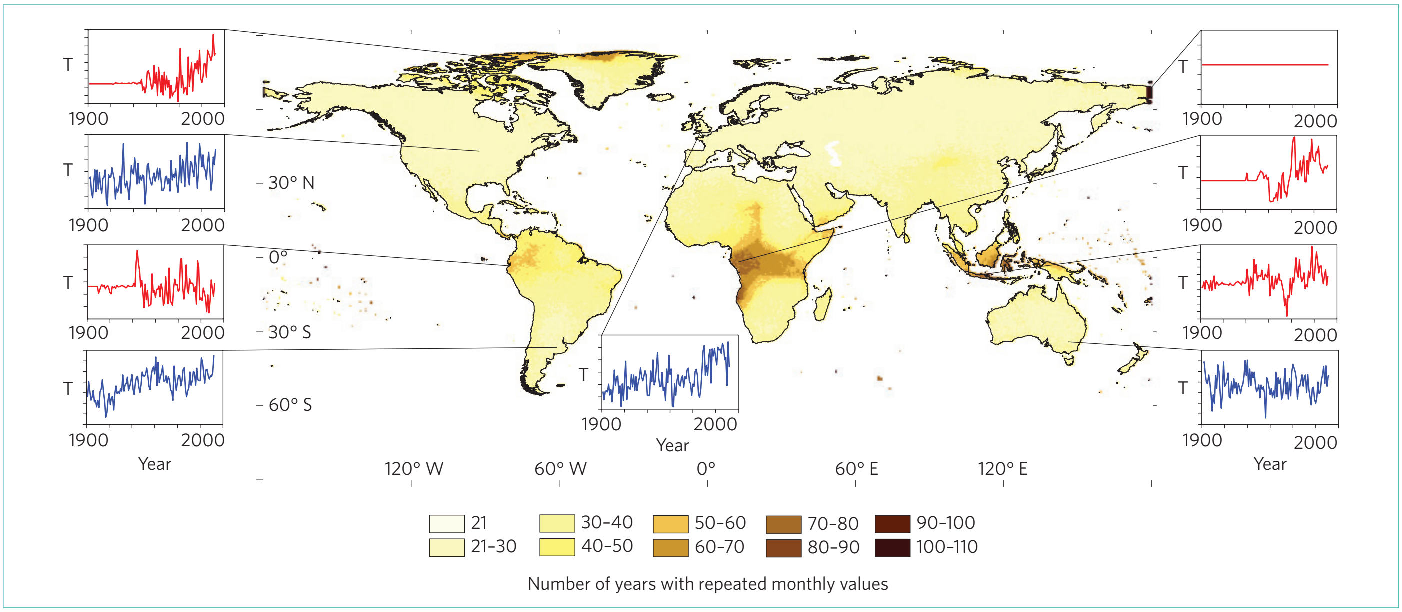

Figure 1 | Number of years with repeated monthly temperature values per 0.5° land grid cell (for example, repeated March temperature values over different years; period 1901–2012). Note the large area in which many repeated values are found, strongly suggesting the substitution of missing values with the corresponding Climatic Research Unit 0.5° 1961–1990 mean monthly climatology[4,5], especially in the initial decades of the twentieth century. Inset: the temperature time series show the consequences of this on climatic variability for grid cells with good coverage (in blue) versus grid cells with poor coverage (in red; T, normalized temperature). The indiscriminate use of all time series invalidates the frequency approach used in Ji *et al.*[1].

over the first half of the twentieth century in many tropical and Arctic regions can be attributed to the lack of climatic information and the corresponding flattened time series representing a succession of climatological means. Likewise, station availability corresponds with early-warming signals in the mid-southern and mid-northern latitudes. Consequently, early-warming hotspots (between 1900 and 1950) — and their delayed-warming counterparts — share the spatial patterns of meteorological station availability: that is, early-warming regions largely coincide with the availability of climatic data. It is of concern that many of the regions with the highest observed lag-1 autocorrelation in Ji *et al.*[1] (Supplementary Fig. 6 of Ji *et al.*[1]) occur in tropical regions with many repeated values (Fig. 1). The frequency decomposition method shown in Supplementary Fig. 4 of Ji *et al.*[1] for three grid cells in North America would reveal the above-mentioned limitations if applied to many tropical regions.

We suggest it is very likely that the spatiotemporal temperature patterns described in Ji *et al.*[1] are strongly contaminated by the spatial and temporal heterogeneities of the CRU database. Independently of the high spatiotemporal locality of the statistical procedures used in Ji *et al.*[1], this problem affects the whole analysis, as this consists of a global comparison between all regions (that is, comparisons between regions with adequate data and regions with poor data are biased) and time periods (that is, artificially flattened trends in the early twentieth century will reflect slower warming trends than observed trends in late twentieth century).

Reliable results using this approach may be obtained by restricting the analysis to periods and areas over which it can be carried out: this can be transparently achieved by removing all points falling outside the search radius for each month (available from the CRU). If the aim is global coverage, the optimal period should not start before the 1950s (see, for example, Burrows *et al.*[6]), although this would compromise the authors' aim to capture long-term trends[1]. ❐

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Additional information

Supplementary information is available in the online version of the paper.

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Reply to 'Spatiotemporal patterns of warming'

Wu *et al.* reply – Macias-Fauria *et al.*[1] highlight deficiencies in the high-resolution gridded climate database[2,3] prepared by the Climate Research Unit (CRU). In our analysis[4], yearly averaged land surface air temperature (SAT) at each grid from this database was decomposed using the multidimensional ensemble empirical mode decomposition[5–8] (MEEMD) and these nonlinear secular trends from all grids were then pieced together into the spatiotemporal evolution of land SAT trends. Land SAT was independently decomposed grid by grid. The spatial and temporal biases of land SAT in the

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