LETTER

# Reply to Luo et al.: Robustness of causal effects of galactic cosmic rays on interannual variation in global temperature

Tsonis et al. (1) recently used convergent cross mapping (CCM) (2) to identify a causal relationship between cosmic rays (CRs) and interannual variation in global temperature (ΔGT). Subsequently, Luo et al. (3) questioned this finding using the Clark implementation of CCM (version 1.0 of the multispatial CCM package).* This version of the CCM code, which has since been debugged by Clark, unfortunately contains errors that are not in the original rEDM software package that Tsonis et al. used.† Thus, though well-intentioned, the Luo et al. (3) analysis is incorrect.

However, despite the erroneous analysis, Luo et al. (3) raise valid concerns over the robustness of the finding. Here, we demonstrate that the CR effect on ΔGT is robust to reasonable measures of global temperature, and clarify technical details for determining significance with CCM.

CCM uses cross-map prediction as a metric for causality: a variable $y$ has a causal effect on $x$ when the attractor manifold constructed from lags of $x$ can estimate values of $y$. Causality is established when cross-map performance increases with library size, $L$, and is significantly better than an appropriate null model at the largest $L$. Sugihara et al. (2) were the first (to our knowledge) to construct an effective test for causality using these ideas.

As Luo et al. suggest, different ways of subsampling the data to construct libraries, can yield slightly different values for ρ. Indeed, the rEDM software package provides three different sampling methods: (*i*) taking contiguous segments of length $L$ from among the available $\underline{x}$ as in ref. 2, (*ii*) taking bootstrap samples with replacement as in ref. 4, and (*iii*) taking random subsamples without replacement as in ref. 1.

There are reasons for choosing one method over another. For example, method *i* should not be used to examine a strongly autocorrelated time series and either *ii* or *iii* would be preferable as they sample libraries without consideration for time. Also note that the rEDM cross-validation procedure addresses Luo et al.'s (3) concern over having the pair ($\underline{x}_j$, $y_j$) in the library when predicting $y_j$.

The second issue raised by Luo et al. (3) is the robustness of the CR–ΔGT relationship to different temperature data records. As discussed in the Intergovernmental Panel on Climate Change AR5 report, HadCRUT4 is the most primary and credible global temperature record (5), with reasonable uncertainty estimates. Other records such as Goddard Institute for Space Studies (GISS) and National Climatic Data Center (NCDC) data have periods that fall outside the 90% confidence interval of HadCRUT4 (see figure 2.19 of ref. 5) and are not as highly regarded. This is partly due to infilling, spatial averaging, or interpolation: smoothing practices known to obscure nonlinearity (6), which would diminish residual interannual CR effects, especially if first differenced time series are used. Thus, among available records, the HadCRUT4 and HadCRUT3v time series are sensible choices for this study, whereas GISS and NCDC are not.

Fig. 1 examines the CR–ΔGT relationship using all three library-sampling methods as well as the four temperature time series examined by Luo et al. (3). As shown, this relationship is robust to both library sampling and reasonable data choices. We note that the significance of causality is determined only at the largest library size, with convergence being a further necessary condition to demonstrate causation.

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*https://github.com/adamtclark/multispatialCCM/tree/a79cc9861701d60846e7a4c66ae627897793c7e0.

†https://www.github.com/ha0ye/rEDM.

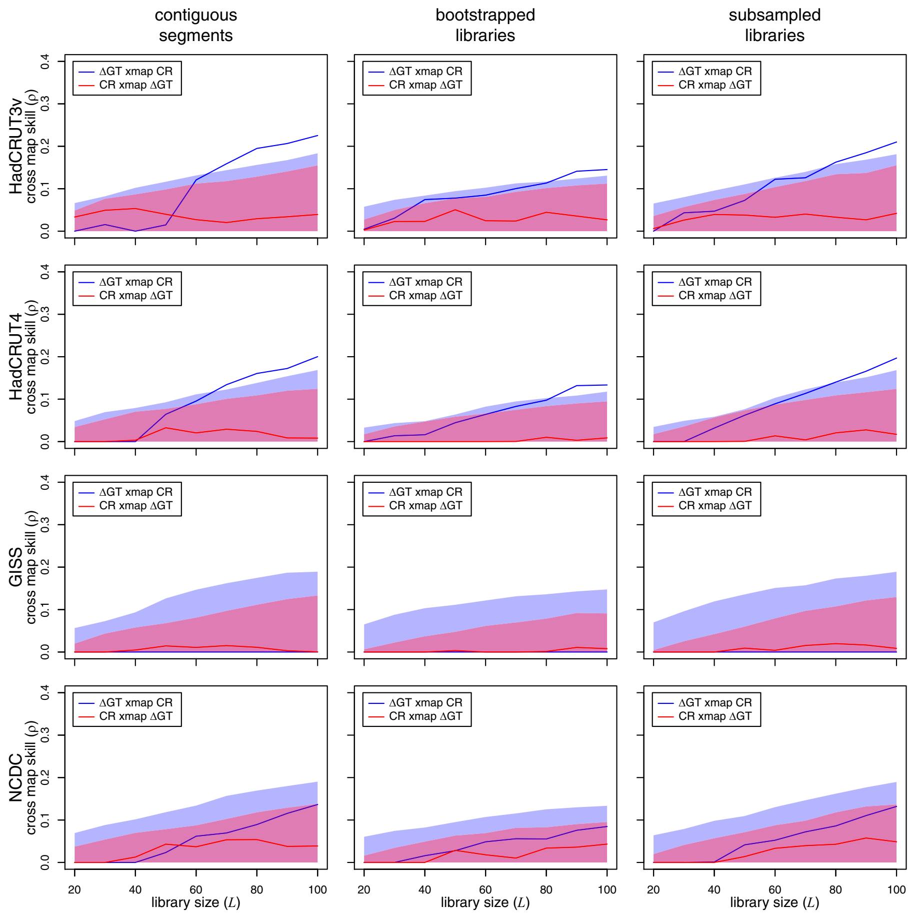


**Fig. 1.** CCM results for four different global temperature time series (HadCRUT3v as in ref. 1, HadCRUT4, GISS, NCDC) and using three different library-sampling methods (contiguous segments, bootstraps, and subsamples). For each panel, the blue line denotes the effect of CRs on interannual temperature variability ("ΔGT xmap CR"), whereas the red line denotes causality in the opposite direction ("CR xmap ΔGT"). The red and blue regions denote the lower 95% quantile for null distributions generated using phase-randomized surrogates. Other parameters were the same as in ref. 1 (selection of $E$, $\tau$, and prediction delay), but due to an indexing error in ref. 1, data from 1899–2011 were used, and the prediction delay is −1 (instead of −2) for HadCRUT3v xmap CR. Medians over different library samples were computed as a robust measure of central tendency to account for nonnormal and system-specific distributions of $\rho$. Both HadCRUT3v and HadCRUT4 show the influence of CRs, whereas the more processed GISS and NCDC time series fail to do so. Conversely, there is no evidence for an effect of temperature on CRs (as expected).