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A Process-Informed Determination of Credibility Across Different Downscaling Methods

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Despite the ongoing advancements in Earth system simulation, the results from Global Climate Models (GCMs) are still not refined enough to be directly applied to numerous climate impact issues. There are many techniques available to downscale GCM outputs to finer resolutions, from basic statistical adjustments to more complex methods like dynamical downscaling and machine learning. However, these methods often yield different results, making it difficult to assess their relative reliability, particularly when comparing statistical versus dynamical downscaling methods.

We consider downscaled results to be credible when the phenomena and processes producing it are consistent; for instance, if it's raining, the necessary conditions for rain (such as lift and atmospheric moisture) should be present. To assess various downscaling techniques, and demonstrate this technique, we examine the occurrence of rainfall at a location the Southern Great Plains, specifically near the DOE ARRM site in Oklahoma during May, the rainiest month. In this scenario, we are looking for an atmospheric setup that produces uplift at this location and corresponds with the northward movement of moisture from the Gulf of Mexico.

By comparing the composite synoptic-scale meteorological conditions on days with and without rain from the GCM being downscaled or from the downscaling method, as appropriate, we can verify if the outcomes of downscaling GCM precipitation align with the processes that drive them. This method offers a process-based added-value analysis strategy for all kinds of downscaling techniques, which extends beyond basic measures of statistical resemblance.

We've used two regional climate models (RegCM4 & WRF), a machine learning technique (U-Net CNN), and four statistical methods of different complexities to downscale precipitation from three distinct GCMs. By using this method to compare them with each other and the raw GCM results, we've discovered that all downscaling methods can yield plausible outcomes when the GCM performs well, as they inherit its credibility. However, when the GCM's performance is subpar, only dynamical methods can rectify regional circulation errors, unlike the other methods. Interestingly, we also found that simpler statistical methods outperform more complex non-dynamical methods when dealing with poor GCM inputs.