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DOWNSCALING CLIMATE MODELS: COMPARING DYNAMICAL VERSUS DATA DRIVEN PROCEDURES

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Abstract:

Regional Climate Models (RCM) implemented to dynamically downscale coarse resolution General Circulation Models (GCMs), considerably increase the spatial resolution, reliability and consistency of climate data and thereby enhancing the overall relevance for societal decision-making in the context of climate change. However, more importantly, the infrequent but high impact climate extremes events are not yet being adequately sampled. Presently, the high computational costs of running RCM simulations are a major bottleneck for generating the required large number of simulations at very high spatial and temporal resolution.

Here we investigate whether the computationally intensive dynamically downscaled at 30km, bias corrected and further refined (5km) archived climate model simulations can be partially replaced or extended by convolutional neural networks (CNN). Note, our approach of using CNNs skips the use of dynamical downscaling entirely. While CNNs have demonstrated some success in downscaling GCMs, it is still unclear whether CNNs can learn physical relationships that hold across past, present and future climates. Our study aims to further build trust in artificial intelligence (AI) models such as CNNs in climate-related applications, through comprehensively understanding the physical relationships learnt by AI-based methods. We primarily focus here on using CNNs to generate high resolution (5km) temperature and precipitation from the large archive of CMIP3 to CMIP5 simulations. We then compare the downscaled CMIPx climate projections with an existing methodology which dynamically downscales, and bias corrects GCMs to 5km resolution. Our focus is to determine whether the relationships learnt by CNNs are physically consistent with dynamical methods. The procedure involves the following steps:

(1) use high-resolution gridded observed data (e.g. daily rainfall and temperature);
(2) use reanalysis (ERA5/ERA40) low-resolution driving data (wind, geopotential height, moisture, …);
(3) train CNN to map from (2) to (1) and validate the CNN-based downscaling for generating fine-scale features as present in the high-resolution observed data;
(4) apply the trained CNN model to archived (CMIP3/5/6) low resolution climate model simulations instead of reanalysis input data (2), to generate CNN-based high-resolution climate data; and finally
(5) compare the results from the two independent approaches using standard (root mean square, …) and purpose-designed metrics.

After successful implementation, we will acquire the potential to increase the ensemble size of the downscaled high resolution climate simulations for New Zealand by several orders of magnitude, providing a valuable resource for climate adaptation studies particularly with regards to climate extremes.