# Stochastic Emulation of Regional Climate Models with Diffusion Models: Assessing the Added Value

Mikel Legasa*[1], Achille Gellens[2], Redouane Lguensat[3], and Mathieu Vrac[4]

[1]Laboratoire des Sciences du Climat et de l'Environnement (LSCE-IPSL), CEA/CNRS/UVSQ, Université Paris Saclay, Centre d'Etudes de Saclay, Orme des Merisiers, 91191 Gif-sur-Yvette, France – CEA-CNRS-Université Paris Saclay, Institut Pierre Simon Laplace, Paris, France – France

[2]Laboratoire des Sciences du Climat et de l'Environnement (LSCE-IPSL), CEA/CNRS/UVSQ, Université Paris Saclay, Centre d'Etudes de Saclay, Orme des Merisiers, 91191 Gif-sur-Yvette, France – Institut Pierre Simon Laplace, Paris, France, CEA CNRS UVSQ - Université Paris-Saclay – France

[3]Institut Pierre-Simon Laplace, IRD, Paris, France – Institut Pierre-Simon Laplace, IRD, Paris, France – France

[4]Laboratoire des Sciences du Climat et de l'Environnement (LSCE-IPSL), CEA/CNRS/UVSQ, Université Paris Saclay, Centre d'Etudes de Saclay, Orme des Merisiers, 91191 Gif-sur-Yvette, France – CEA-CNRS-Université Paris Saclay, Institut Pierre Simon Laplace, Paris, France – France

**Abstract**

Machine learning emulators aim to provide a cost-effective alternative to regional climate models (RCMs) by replicating their downscaling function. They do so by statistically linking a set of large-scale predictors, well simulated by global climate models (GCMs), to RCM-simulated fields of the high-resolution variable of interest, such as precipitation. Diffusion models are generative deep learning models that can be conditioned on large-scale predictors to act as RCM-emulators, thereby functioning as conditional stochastic weather generators (stochastic statistical downscaling/emulation).
Diffusion models are appealing for stochastic weather generation: they produce highly spatially-detailed samples that represent probability distributions rather than single deterministic fields, thus enabling large ensembles of downscaled realizations at a fraction of RCM costs. However, they are more computationally demanding than state-of-the-art deterministic machine learning approaches, and the extent of their added value when downscaling for climate applications still remains an open question.

Thus, in this context, investigating the potential added value of diffusion models is both relevant and timely. Indeed, recent studies using deterministic ML methods (such as Wang et al. 2023; Doury et al. 2024) indicated that emulating high-resolution fields does require generative/stochastic approaches, particularly when it comes to representing extreme weather events and especially for complex variables like precipitation (Watson, 2022, 2023). Nevertheless, while generative methods, such as diffusion models, may offer an advantage for simulating extremes (Aich et al. 2024, Addison et al. 2025, Tomasi et al. 2025), they also potentially exhibit more instability (for instance, diffusion models are known to produce hallucinations, see e.g., Aithal et al. 2024), potentially introducing additional biases into the modelling chain.

*Speaker

In this work, we will examine both the benefits and potential downsides that diffusion models can bring to the field of stochastic emulation, keeping a focus on specific questions of interest to climate scientists, such as their skill in simulating precipitation extremes (a clear case where deterministic models fall short, and of great interest in terms of climate impacts). We will do so by emulating high-resolution precipitation fields, a key variable for many hydro-meteorological applications notably difficult to predict, within the EURO-CORDEX domain. Our goal is to provide a clear, evidence-based view of where diffusion models help, and to assess their relevance in downscaling applications. We will also discuss practical guidelines (such as conditioning variables and evaluation metrics) and outline priorities within the stochastic downscaling community.

**Keywords:** rcm emulator, diffusion model, deep learning, stochastic emulator, statistical downscaling, hybrid statistical downscaling