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## Emulation techniques for rapid flow-like geohazards: a case studybased performance analysis

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Several powerful physics-based computational landslide run-out models have been developed and validated throughout the last years. The geohazards community applies these forward models in simulation tools to predict potential landslide run-out outcomes including their uncertainties, and uses inverse approaches to conduct reanalyses and to infer on model parameters for calibration purposes. Yet it remains challenging to turn these computational frameworks into robust, transparent and transferrable simulation-based decision support tools for geohazard mitigation. In particular, the landscape of uncertainties – such as those resulting from the idealised model description itself, input data (e.g., material parameters or topographic data), and numerical scheme related hyperparameters – is still not systematically managed when conducting landslide simulations. Probabilistic hazard maps that take these uncertainties into account imply a large number of model evaluations, which constitutes a computational bottle neck. This issue can be overcome by using High Performance Computing (HPC) resources along with the existing software and resources. Alternatively, physics-informed machine learning strategies use simulation results of the original process model, i.e., the simulator, to train a statistically valid representation, the socalled emulator. Once being trained, the emulator significantly reduces computational costs, while at the same time it grants access to an estimation of the introduced error. A software framework has recently been set up to integrate Gaussian process emulation and the landslide run-out model r.avaflow, an open-source mass flow simulation tool. Emulation-based sensitivity analysis was of comparable quality to conventional studies, and the computational costs were cut significantly. The emulator allowed for the first time to conduct a global sensitivity analyses at every location simultaneously for a complete landslide impact area. A joint effort across different institutes in Europe has been made in this contribution to test the potential and limitation of the emulation techniques by revisiting a number of published case studies. Selection of test cases has been made according to data availability, failure type and computational demand. Preliminary findings suggest that the emulator is capable of reducing the computational effort of modelling various flow-like landslides substantially. Future work will focus on curating a well-defined database of test scenarios across multiple institutes with cases ranging from small to medium-sized debris flows to

large rock avalanches.