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# Applying neural network for identification of land surface model parameters

**Ruslan Chernyshev**[1,2], Mikhail Krinitskiy[1,3], and Viktor Stepanenko[1,2,4]
[1]Research Computing Center, Lomonosov MSU, Moscow, Russia
[2]Faculty of Geography, Lomonosov MSU, Moscow, Russia
[3]Shirshov Institute of Oceanology, Russian Academy of Sciences, Moscow, Russia
[4]Moscow Center for Fundamental and Applied Mathematics, Moscow, Russia

This work is devoted to development of neural networks for identification of partial differential equations (PDE) solved in the land surface scheme of INM RAS Earth System model (ESM). Atmospheric and climate models are in the top of the most demanding for supercomputing resources among research applications. Spatial resolution and a multitude of physical parameterizations used in ESMs continuously increase. Most of parameters are still poorly constrained, many of them cannot be measured directly. To optimize model calibration time, using neural networks looks a promising approach. Neural networks are already in wide use in satellite imaginary (Su Jeong Lee, et al, 2015; Krinitskiy M. et al, 2018) and for calibrating parameters of land surface models (Yohei Sawada el al, 2019). Neural networks have demonstrated high efficiency in solving conventional problems of mathematical physics (Lucie P. Aarts el al, 2001; Raissi M. et al, 2020).

We develop a neural networks for optimizing parameters of nonlinear soil heat and moisture transport equation set. For developing we used Python3 based programming tools implemented on GPUs and Ascend platform, provided by Huawei. Because of using hybrid approach combining neural network and classical thermodynamic equations, the major purpose was finding the way to correctly calculate backpropagation gradient of error function, because model trains and is being validated on the same temperature data, while model output is heat equation parameter, which is typically not known. Neural network model has been runtime trained using reference thermodynamic model calculation with prescribed parameters, every next thermodynamic model step has been used for fitting the neural network until it reaches the loss function tolerance.

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