

Long-term trends in rainfall erosivity derived from a deep learning reconstruction framework [Abstract]

Hadi Shokati, Kay D. Seufferheld, Peter Fiener, Thomas Scholten

Angaben zur Veröffentlichung / Publication details:

Shokati, Hadi, Kay D. Seufferheld, Peter Fiener, and Thomas Scholten. 2026. "Long-term trends in rainfall erosivity derived from a deep learning reconstruction framework [Abstract]." In *EGU General Assembly 2026, Vienna, Austria, 3–8 May 2026*, EGU26–1408. Göttingen: Copernicus.
<https://doi.org/10.5194/egusphere-egu26-1408>.

Nutzungsbedingungen / Terms of use:

CC BY 4.0



EGU26-1408, updated on 25 Jun 2026

<https://doi.org/10.5194/egusphere-egu26-1408>

EGU General Assembly 2026

© Author(s) 2026. This work is distributed under the Creative Commons Attribution 4.0 License.



Long-Term Trends in Rainfall Erosivity Derived from a Deep Learning Reconstruction Framework

Hadi Shokati¹, Kay D. Seufferheld², Peter Fiener², and Thomas Scholten^{1,3}

¹University of Tübingen, Soil Science and Geomorphology, Tübingen, Germany (hadi.shokati@uni-tuebingen.de)

²Institute of Geography, Augsburg University, Augsburg, Germany

³University of Tübingen, Cluster of Excellence Machine Learning: New Perspectives for Science, Germany

Quantifying long-term soil erosion dynamics, for example, to better assess the effects of climate change on soil erosion, requires temporally continuous records of rainfall erosivity, a key input for explicit soil loss modeling. However, high-temporal-resolution precipitation data are rarely available historically at large scales. We present a data-driven framework to overcome this constraint and to reconstruct annual gridded rainfall erosivity (R-factor) for Germany from 1930 to 2000. First, high-temporal-resolution gridded precipitation from the RADOLAN product (2001–2025) was used to compute spatial maps of rainfall erosivity for the modern period based on standard intensity-based erosivity formulations. These modern R-factor maps served as target fields to train a convolutional neural network (CNN) that learns the relationship between erosivity and commonly available predictors, including monthly and annual precipitation statistics, temperature indices, and large-scale climatic indicators. The CNN model was trained and evaluated using spatial-temporal cross-validation and independent station holdouts to quantify predictive skill and uncertainty. After validation, the model was applied retrospectively to coarse-resolution historical climate records to generate annual 1-km gridded R-factor estimates for 1930–2000. The reconstructed time series reveal spatially coherent patterns and multi-decadal trends in rainfall erosivity that are not captured by coarse aggregated proxies, and they provide a physically informed dataset for retrospective soil erosion modeling and climate-impact assessments.