From Experts to Providers of Humanitarian Actions:
Developing Flood Forecast Models for Forecast-based Financing

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1. Background

Forecast-based financing (FbF) is a novel financial mechanism facilitating humanitarian actions prior to anticipated floods[1]. Transferable methdologies to setting up flood forecast models specifically designed for FbF is needed to extend the application beyond pilot projects. In this study, a novel model suitability matrix is developed as a flexible framework for model evaluation to i) better couple model development to model application and ii) underpin upscaling of FbF. A pilot project of FbF at Nangbeto Dam (Togo, West-Afria) is used as case study. A set of models are developed to improve the forecast skill of the existing FbF-forecasting model, FUNES[2].

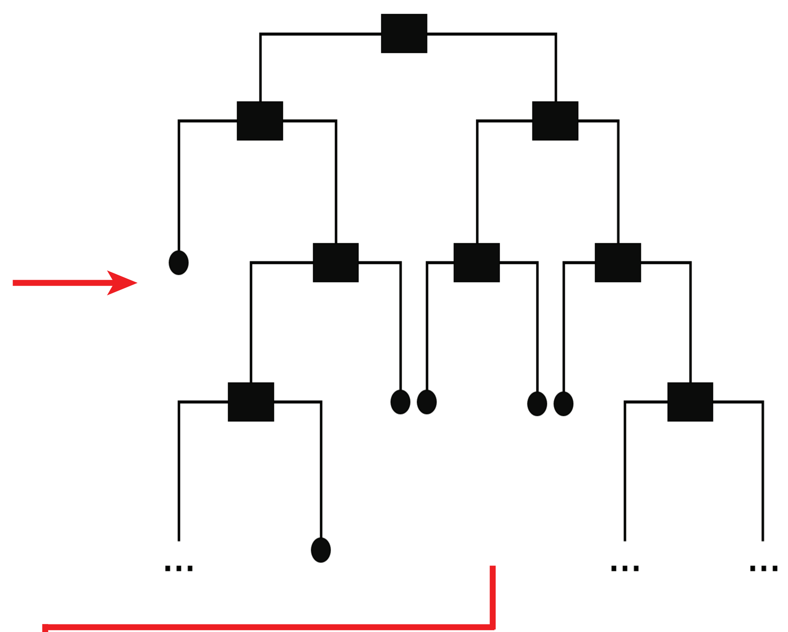
2. Model Development

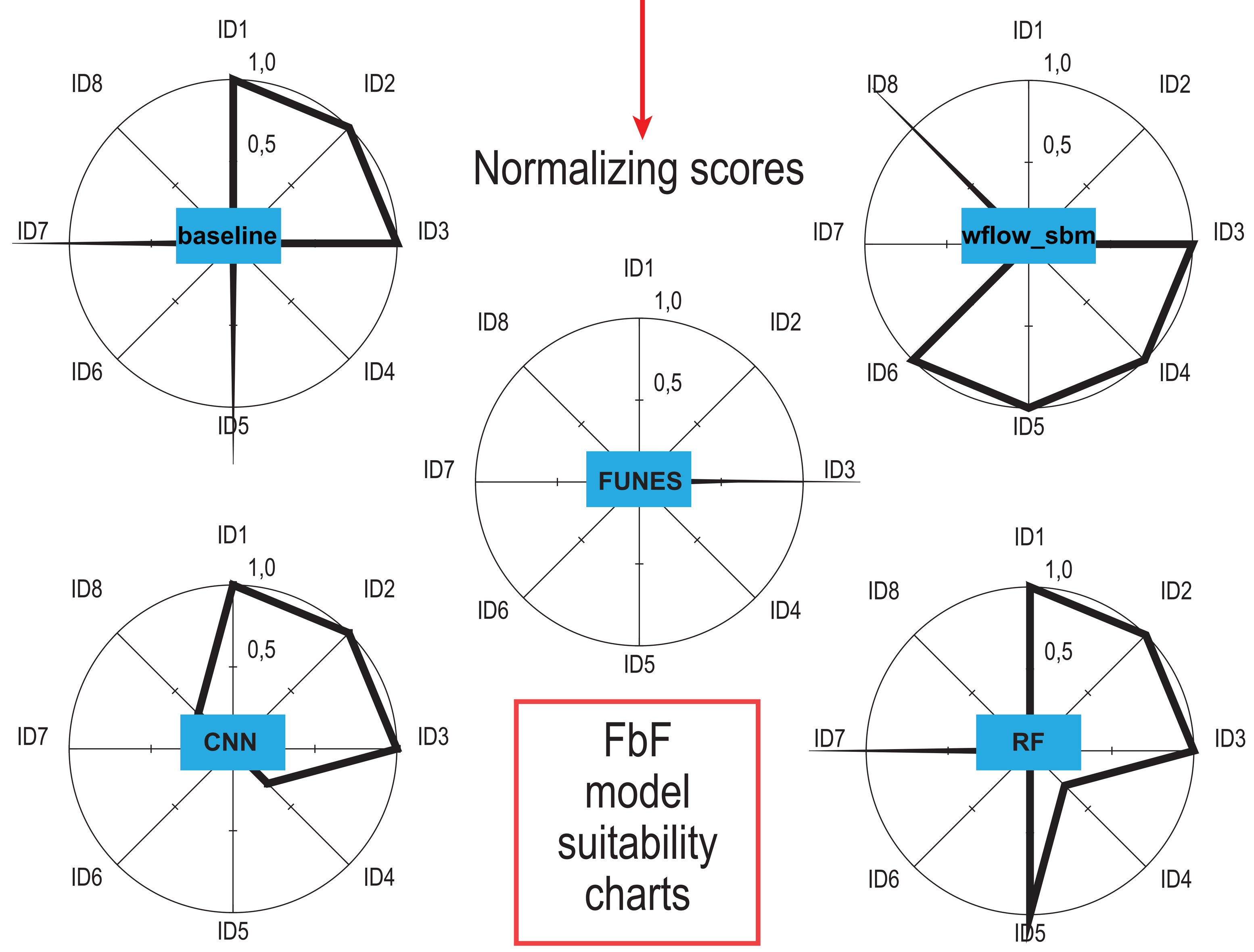
FUNES is a machine learning model (k nearest neighbour) predicting inflows to Nangbeto Dam with four days lead-time using forecasted precipitation. Inflow predictions connect to forecast thresholds currently employed for FbF downstream of the dam. In this study, the following models were developed to improve the forecast skill: A naïve model (baseline) assumes inflows to continue ten days into the future; a process-based distributed hydrological model (wflow_sbm[3]) was set up, calibrated and forced using globally available data; and autoregressive machine learning models of increasing complexity (random forest (RF) to convolutional neural network (CNN)) were trained on local in-situ measurements of daily flows at Nangbeto Dam (1987-2016). The baseline model, wflow_sbm, RF and CNN predict inflow to the dam with ten days lead-time (note distinctly different from "usable lead-time" in Section 3).

Defining criteria and thresholds

ID	CRITERIA
1	Forecast skill
2	Usable lead-time
3	Computational efficiency
4	Flexibility
5	Robustness
6	Uncertainty
7	Requirements of technical expertise
8	Potential methodological transferability

Assigning scores w/ decision tree





3. Model Evaluation

Using a decision tree, the models were given quantitative scores on eight criteria. The thresholds here reflect expert judgement by the authors. Points were assigned and summed over forecast lead-times prior to linear normalization between 0 and 1.

ID1: Forecast skill (Kling-Gupta Efficiency > 0.7)
ID2: Usable lead time (Nash-Sutcliffe Efficiency > 0.0)
ID3: Computational efficiency (model run < 10% of minimum forecast lead-time)
ID4: Flexibility (ability to adapt to catchment changes or model coupling)
ID5: Robustness (reproducibility)
ID6: Uncertainty (degree to which uncertainty is communicated in model output)
ID7: Requirements of technical expertise (training time for local staff < 1 week)
ID8: Potential methodological transferability (use of global data in the model)

4. Implication

The model suitability matrix is adaptable on a case-by-case basis, in which thresholds collectively defined by model developer(s) and providers of humanitarian actions embed needs at end-user level; this targets the application of FbF during model development, thereby increasing practical value and underpinning upscaling of FbF.

References

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