Predicting Rating Curves for Global River Reaches

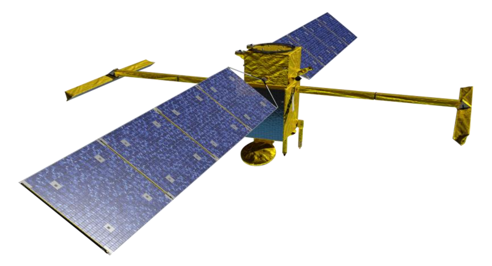
The SWOT mission provides data on an unprecedented scale globally and therefore presents the opportunity to improve Global Flood Models.

We combine WSE levels from SWOT with daily discharge data to produce global rating curves for non-extreme events.

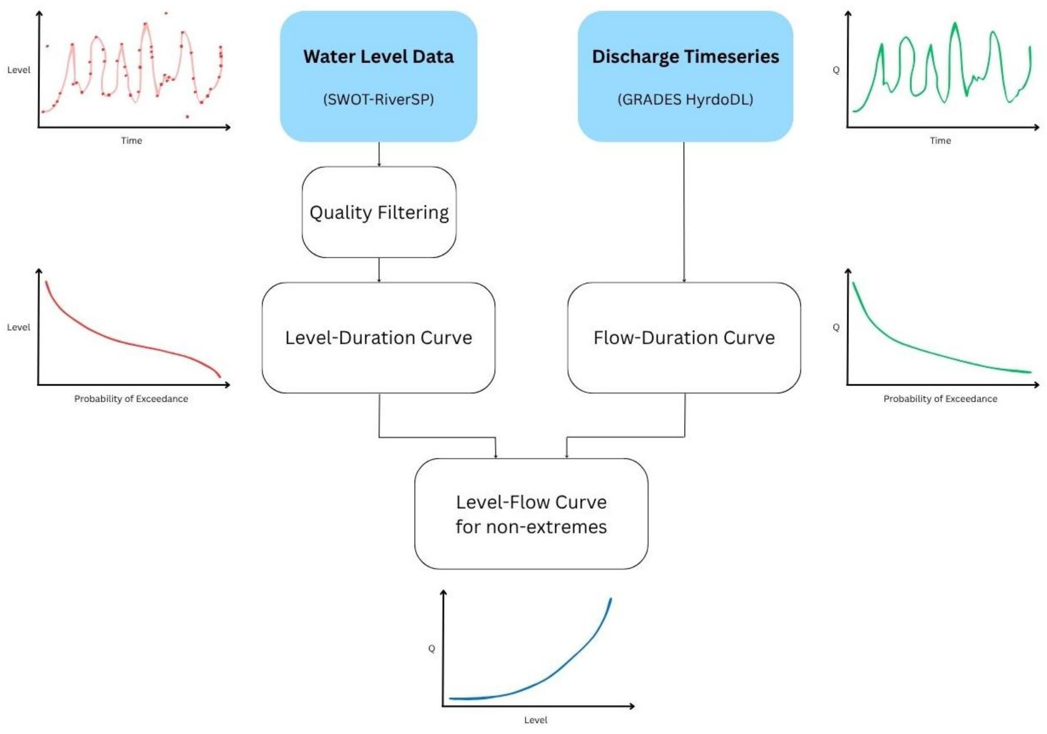
This statistical approach is a straight-forward method to estimating discharge from SWOT observation maximizing computation and time efficiency.

Aims

- To use SWOT WSE levels to **estimate discharge dynamics** at global river reaches.
- To present the minimal viable, but therefore **most efficient**, method to do this.
- To understand the suitability and effect of a **minimum exceedance probability** we can model from SWOT.
- To produce **non-extreme rating curves** that are globally consistent in both method and data inputs.



Method



We create a level-flow relationship for each SWORD reach independently, using a 2-step quantile matching method:

Level-Duration

The probability of exceedance p of WSE is calculated empirically from observations, only for $p < p_{min}$. Sensitivity analysis led us to chose $p_{min} = 0.05$. That is, for a timeseries of quality-filtered WSE data W, each value w has quantile p such that

$$p(w) = P(W \geq w)$$

Flow-Duration

Based on the approach of Quimpo et al. [1], we obtain a frequency distribution of discharge by fitting an exponential distribution to a discharge timeseries. That is, undefined, positive parameters λ, α, and only when $p < p_{min}$, we assume that the discharge q has the form

$$q(p) = \lambda e^{-\alpha p}$$

Level-Flow

We then quantile match these two distributions to estimate the discharge for any input WSE level from SWOT such that $q(w) = q\big(p(w)\big)$.

$$w \rightarrow p \rightarrow q$$

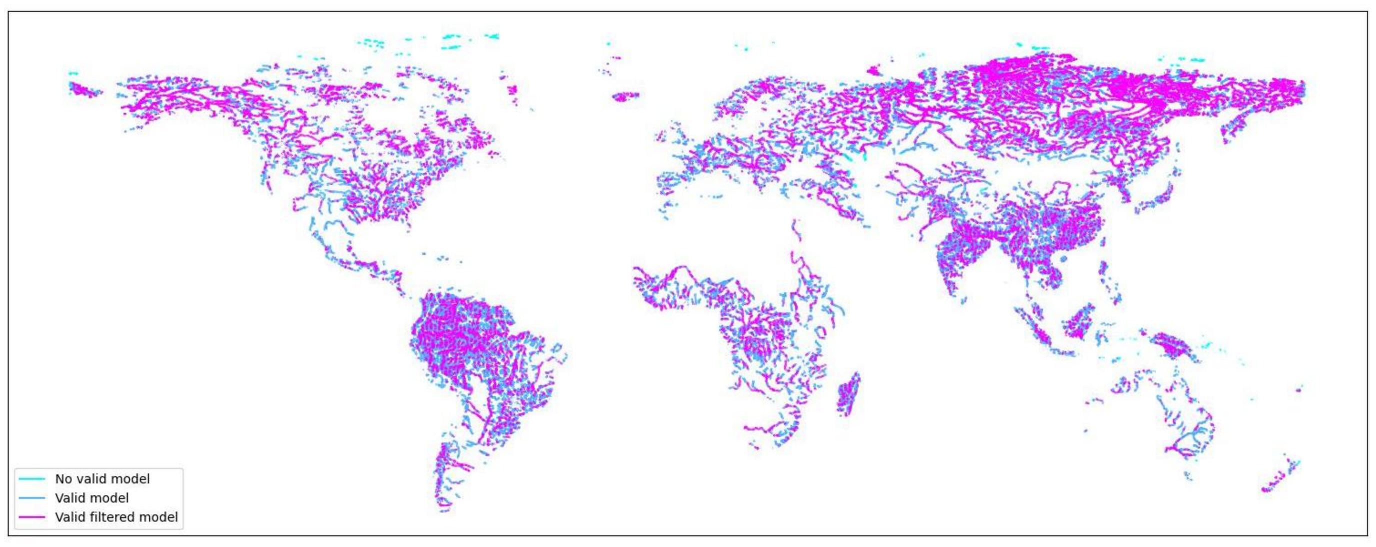
Data

We use **SWOT River-SP** [2] for WSE levels and **GRADES-HydroDL** [3] for daily discharge values. In order for our model to run, we therefore need valid data from both datasets.

- For SWOT, this is positive WSE levels labelled "good", "suspect" or "degraded", but not "bad".
- For GRADES, this is positive parameters, when an exponential distribution is fitted to the daily timeseries.
- To improve the model, we place stricter filters on the SWOT WSE data by applying the Montpellier configuration.

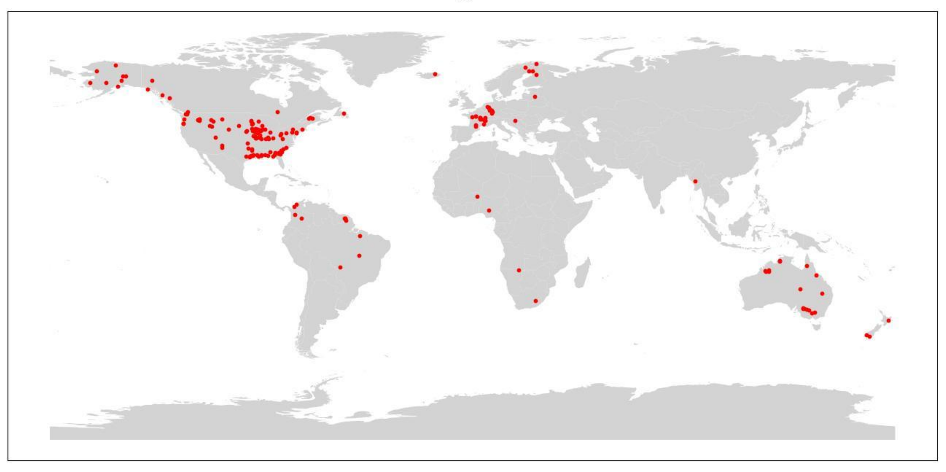
Of the 158,942 river reaches in SWORD, 102,387 have valid data for both datasets and can therefore run our discharge model, of which 52,499 also have valid filtered SWOT data, and therefore run our stricter model.

All validation is done on the stricter model.



Data availability for all SWORD river reaches

Gauges



Location of evaluation gauges

Results

- We compare to gauge data from USGS, NRFA, UKCEH, BOM, Eau France, ECCC, ANA and GRDC.
- 184 gauges after filtering by conditioning on the relationship between SWOT WSE and gauged discharge: for n the number of observations, r_s the Spearman R value, and τ_k the Kendall Tau value, we only consider gauges such that:

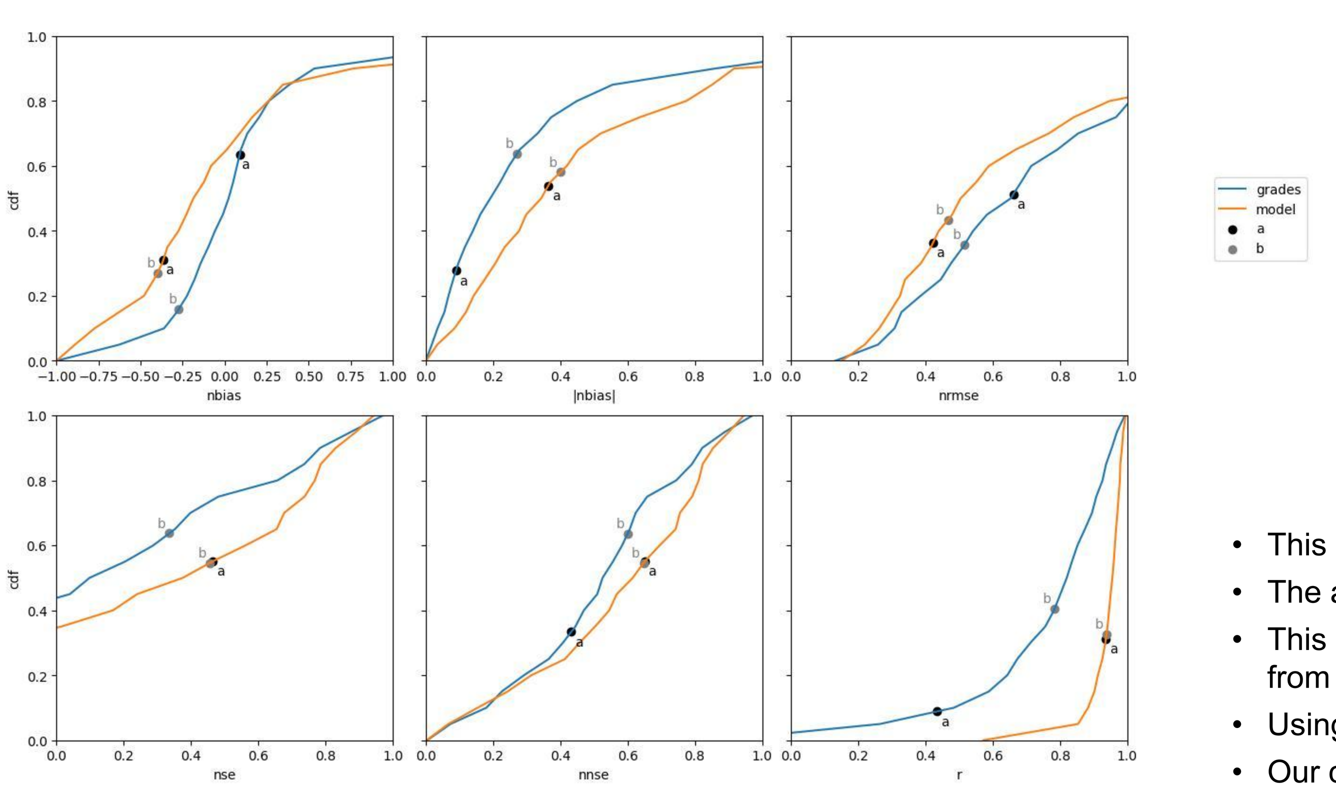
$$n > 10, \qquad r_s > 0.8, \qquad \tau_k > 0.8$$

- We performed sensitivity analysis on p_{min}, to choose the optimal value and to show the necessity for such a value to exist in our method.
- We then evaluate both our model and GRADES flow values against gauge data on dates where there are all three.

Model evaluation

- The bias in our method is larger than that of GRADES: our flow distribution is trained on GRADES, and we therefore expect this to be our upper bound for skill.
- We see **increased skill** as defined by other metrics that more closely rely on **dynamics**, shapes and patterns due to the accuracy of SWOT WSE levels.
- The nRMSE, NSE and correlation (such as Spearman's R) statistics all show improvements, when considering all reaches.

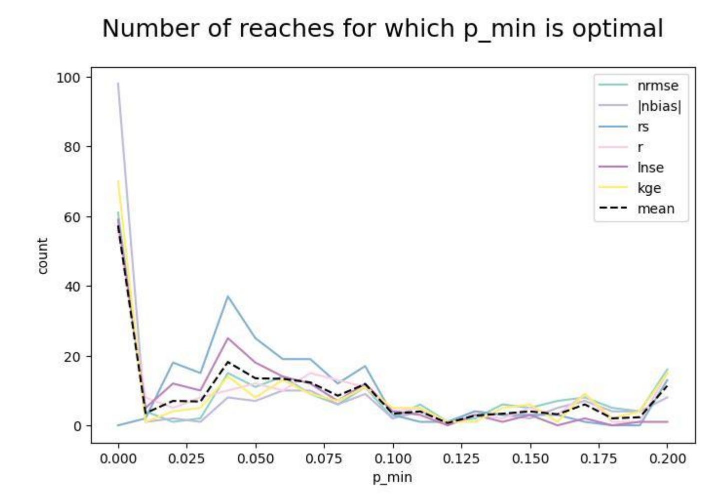
Validation Metrics



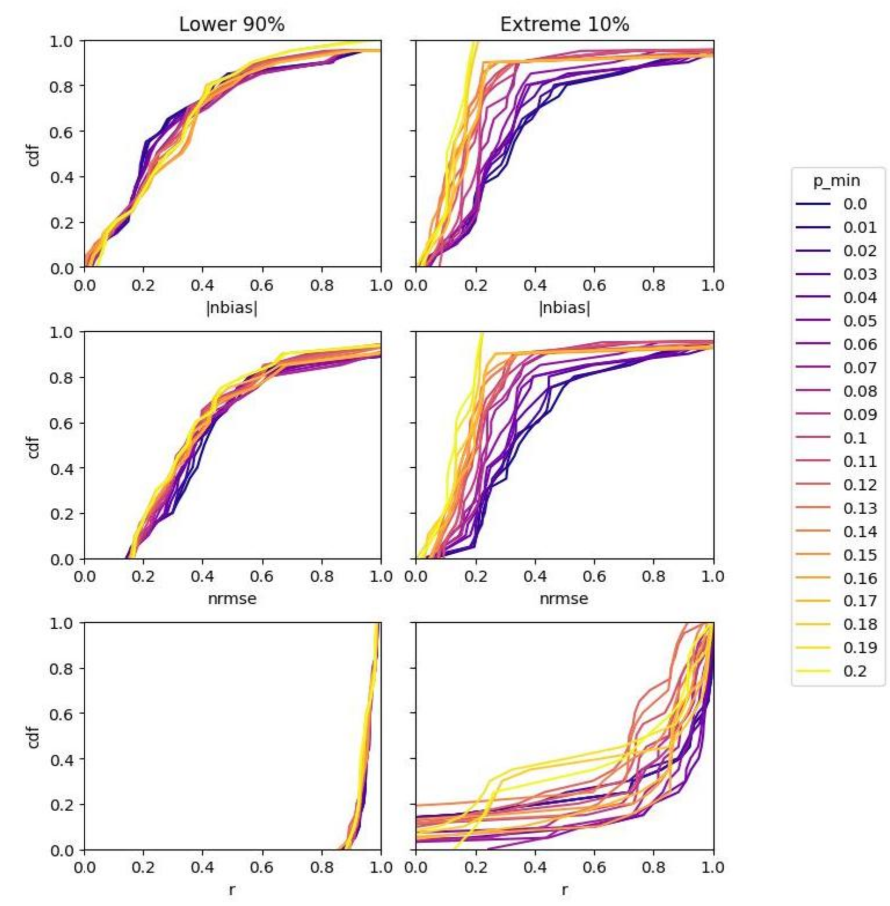
The cumulative distribution functions of 6 metrics. The metrics obtained from comparing gauged data to GRADES (only at SWOT observation dates) are shown in blue, and to our modelled data in orange. The location of each example reach below are marked on each graph.

Choice of p_{min}

- The majority of the error comes from the rarest events.
- We limit this by introducing a **minimum value** p_{min} we choose to model above: we don't apply our model to WSE values where $p < p_{min}$.
- However, this reduces the datapoints where we can run our model.
- Our sensitivity analysis looks at both raw skill and its skill in comparison to GRADES and looks to optimize the opposing points above.
- We decide to model above $p = 0.05$.



Count of reaches where p_{min} is the optimal value, defined by 6 different metrics. This is the smallest value for nRMSE and |nBias|, and the largest value for Spearman R (rs), Pearson R (r), LNSE and KGE.

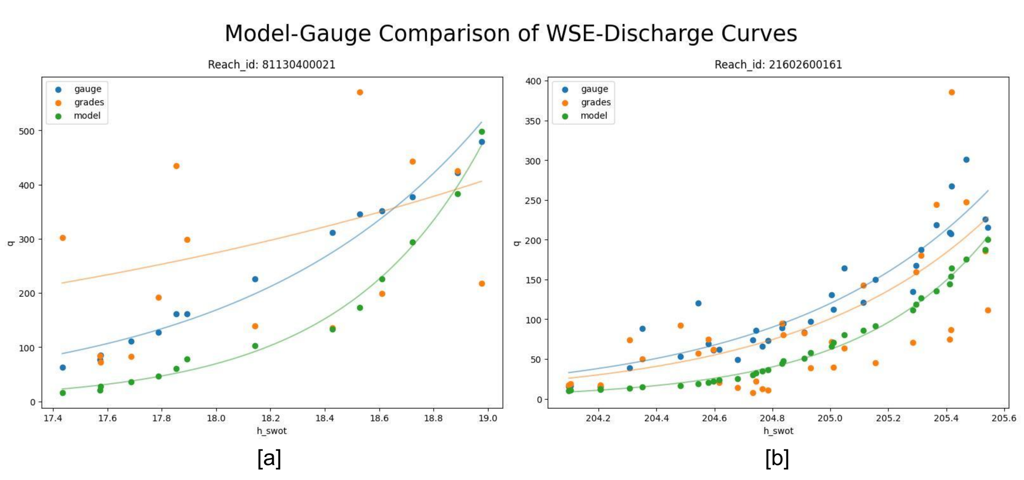


The cumulative distribution functions of |nBias|, nRMSE and r. The metrics are obtained from comparing the discharge timeseries from gauges to that from our model, using different p_{min} values, to the lower 90% and upper 10% of WSE observations.

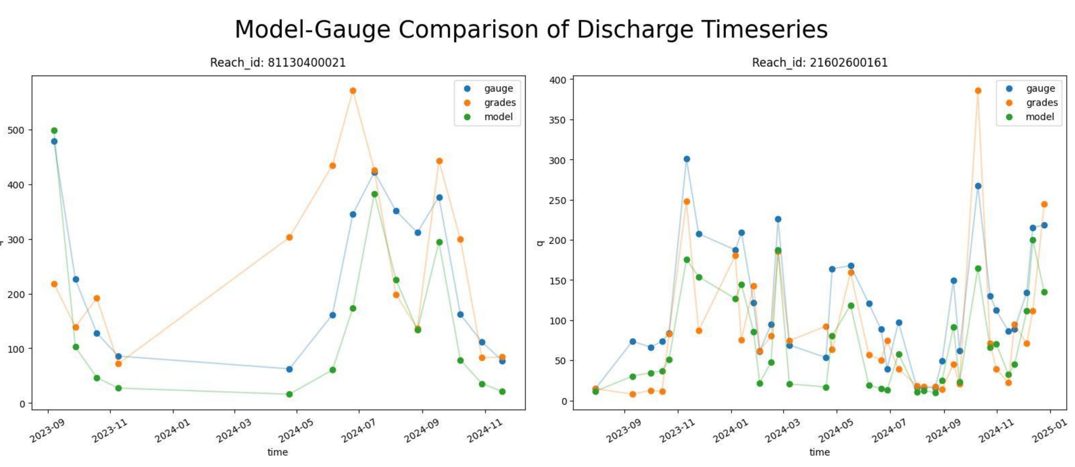
Conclusions

- This method improves the predictive skill of the input discharge to **discharge dynamics**.
- The absolute bias is increased but not significantly.
- This model can be run for **future SWOT observations without further computation** from the flow-duration step from the predefined parameters.
- Using $p_{min} > 0$ will improve accuracy, particularly in the larger events.
- Our choice of $p_{min} = 0.05$ means we can still estimate discharge at 95% of all filtered SWOT observations.
- We can then apply a physical model to estimate the extremes, where statistics of historical data are less informative.

Example reaches: GRADES flow values are in the correct range, but do not follow the same dynamics as the gauged data, where our model does by design, due to the skill of SWOT WSE levels (b) and GRADES does much better but is still less consistent than our model (a). The position of these reaches in the cumulative distribution for each metric is labelled on the cdf plots above.



WSE-Discharge curves at 2 reaches. The gauged data is shown in blue, GRADES timestamped data in orange, and the results of our model in green. Data values are shown by points, while a fitted exponential curve is plotted for each method to show the overall trend.



Discharge timeseries for gauged (blue), GRADES (orange) and modelled (green) datasets. These are only plotted on dates for which there was a valid SWOT WSE observation.

References

[1] Quimpo, R. G., Alejandrino, A. A. & McNally, T. A. Regionalized Flow Duration for Philippines. *Journal of Water Resources Planning and Management* 109, 320–330 (1983).

[2] JPL D-56413. SWOT Product Description Document: Level 2 KaRIn High Rate River Single Pass Vector (L2_HR_RiverSP) Data Product, Revision C. (2025).

[3] Yang, Y. *et al.* Global Daily Discharge Estimation Based on Grid-Scale Long Short-Term Memory (LSTM) Model and River Routing.

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