Gas exchange in large rivers influenced by hydraulic geometry: implications for remotely sensing gas exchange via the SWOT satellite

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## Key Points

* River channel efficiency effects the relationship between gas exchange and dissipation of turbulence
* Wide, less “efficient” river channels exert greater influence on near-surface turbulence than narrower, more efficient ones
* BIKER algorithm exploits this theory, predicting gas exchange velocity and fluxes from simulated SWOT satellite data and in situ data

## Keywords

gas exchange, fluvial geomorphology, open-channel flow, remote sensing, SWOT, biogeochemistry, ungauged basin

## Abstract

*AGU Advances. So 250 words here* *AGU advances is 8000 words total, the format seems to be a long letter so I’ve tried to right this in that style.*

## Plain Language Summary

*Necessary for AGU advances (200 words)*

## 1 Introduction

Natural systems play a fundamental role in the budgeting and accounting of the global carbon cycle under climate change. Since the publication of Cole et al. (2007), the global river network is recognized to emit substantial amounts of carbon to the atmosphere, in addition to exporting it to the oceans. Current estimates of total carbon dioxide evasion () to the atmosphere from the global river network vary from 650-1800 Tg C/yr (Lauerwald et al., 2015; Raymond et al., 2013) **maybe add Shaoda here**, with 167 Tg-C/yr coming from mountain streams alone (Horgby et al., 2019). Despite its incredibly small percentage of the global land surface (0.47%- Raymond et al., 2013), this flux is on par with the total oceanic uptake rate (Gruber et al., 2019; Horgby et al., 2019) and the global forest carbon uptake rate (Pan et al., 2011). It is still relatively poorly constrained but is clearly a critical component of the global carbon cycle. Equation 1 represents this flux given the gas concentration gradient between the water and the air and the gas exchange velocity *k*. Consult Appendix A for variable nomenclature used in this study.

The structure of equation 1 necessitates that calculations of this flux are highly sensitive to one’s measurements/estimates of *k* (Hall and Ulseth, 2020). More broadly, fluvial *k* for various dissolved gases are of significant importance to aquatic ecologists modeling stream metabolism (e.g. Bernhardt et al., 2018) and water quality engineers modeling river responses to pollutant loadings (among other things- Chapra, 2008). Because of this far-reaching importance, decades of work have focused on elucidating the physical mechanisms behind *k* in oceans and lakes (Wanninkhof et al., 2009) and, to a lesser extent, fluvial gas exchange (Hall and Ulseth, 2020). Given that *k* should scale with near-surface turbulence in a turbulent flow (Hall and Ulseth, 2020), extensive field and labratory experiments have converged on the ‘small-eddy model’ as proposed by Lamont and Scott (1970), which scales *k* via the smallest-scale turbulent eddies (e.g. Lorke and Peeters, 2006; Moog and Jirka, 1999; Vachon et al., 2010; Wang et al., 2015; Zappa et al., 2007, 2003). This model is provided as equation 2, where is the dissipation rate of near-surface turbulence, is the kinematic viscosity and *Sc* is the Schmidt number. Note that we directly measuring is non-trivial and though a frequent model is to impose the log-law-of-the-wall to scale bottom shear to the surface, this necessiarly assumes that bed shear alone effects turbulence which is often not the case.

While this model works reasonably well in non-fluvial environments where turbulence production is mostly limited to bottom shear or wind shear (e.g. Lorke and Peeters, 2006; Zappa et al., 2007), there is considerable uncertainity in how it applies to fluvial systems. First, ‘bubble-mediated gas exchange’ in whitewater might lead to substantially higher *k* in small mountain streams with very large bedload (Hall et al., 2012; Ulseth et al., 2019). Additionally, ‘form-drag shear’ via river channel banks, meanders, bars, etc. further complicate scaling fluvial *k* (Moog and Jirka, 1999). Those authors proposed modeling fluvial *k* via form-drag dissipation , assuming that total reach stream power is responsible for all turbulence production and therefore dissipation. Numerous authors have since shown that this model () reasonably predicts *k* in rivers (Moog and Jirka, 1999; Raymond et al., 2012; Ulseth et al., 2019), though it should be stressed that . This is because refers to a depth-scale disispation rate and is not necessairily indicative of the near-surface dissipation rate. Consequently, the, relationship usually has a slope much steeper than the 1/4 in equation 2.

Compared to small streams, relatively little attention has been paid to gas exchange in very large rivers. Large rivers are often conceptualized as a hybrid condition of both fluvial and non-fluvial *k* dynamics. To date, the handful of existing field studies of large-river *k* suggest that *k* begins to be influenced by wind shear once the water surface is less protected, though little else is well-established (Alin et al., 2011; Beaulieu et al., 2012; Wang et al., 2021). This is also presumably limited to forested environments that provide shelter from wind.

These mechanistic uncertainties are additionally limited by a large dearth of field-measured fluvial *k*. Wang et al. (2021) attempted to address this by simulating *k* in 35 rivers using a stream metabolism model (Appling et al., 2018) and in situ dissolved oxygen (DO) datasets. They found that equation 2, coupled with modeled via the log-law-of-the-wall, is valid in their simulated rivers and that *k*~streamflow relationships break down in large rivers. However, they did not directly compare against *k* measurements made in extremely small systems (Ulseth et al., 2019) and stopped short of parsing out hydraulic explanations for their results.

Finally, these mechanistic uncertainties are then propogated through upscaling workflows when biogeochemists predict *k* across thousands of rivers (e.g Borges et al., 2015; Horgby et al., 2019; Lauerwald et al., 2015; Raymond et al., 2013) via equation 1 coupled with hydraulic geometry (HG: the scaling relationships between streamflow and river channel hydraulics- Leopold and Maddock, 1953). It is currently not well understood how sensitive global estimates of fluvial gas evasion are to the specific HG model that is employed by the worker. Further, these approaches rely on either in situ discharge records or modeled streamflow which introduces additional uncertainities. This is all exacerbated in ungauged basins that cover large areas, especially in the carbon-rich Arctic inland waters, where little in situ information is available and fieldwork is impractical (Gleason and Durand, 2020).

A potential alternative to this upscaling approach is to directly estimate a river’s hydraulic properties from remote sensing (RS) data. Remote sensing of river hydraulics is a burgeoning subfield within remote sensing of hydrology, often in service of remote sensing of river discharge (RSQ- Gleason and Durand, 2020). This is accomplished via two general approaches: ‘gauged’ methods which rely on in situ river data to calibrate one’s method to the river(s) at hand and ‘ungauged’ techniques which focus on hydraulic generalizability in the service of merely improving existing knowledge in data-poor domains (Gleason and Durand, 2020). Many, but not all, of these ungauged approaches are developed in the context of the upcoming NASA/CNES/UKSA/CSA Surface Water and Ocean Topography (SWOT) satellite mission. SWOT is expected to launch in 2022 and provide the world’s first global measurements of water surface extent and elevation at novel temporal resolutions. SWOT is a wide swath radar interferometer and will sample rivers every 1 to 7 days per 21 day repeat cycle and will measure rivers wider than 100m with a goal of expanding this to rivers at least 50m wide (Biancamaria et al., 2016). A decade of SWOT work has explored the multi-parameter problem of estimating the river hydraulic parameters of roughness and bathymetry from remote sensing to produce the SWOT discharge product (e.g. Andreadis et al., 2020; Brinkerhoff et al., 2020; Brisset et al., 2018; Durand et al., 2014; Garambois et al., 2020; Garambois and Monnier, 2015; Gleason et al., 2014; Hagemann et al., 2017; Larnier et al., 2020; Oubanas et al., 2018).

In this context, here we revist the fundamental mechanisms behind gas exchange and turbulence in large rivers to answer the following question: does *k*’s relationship with form-drag fundamentally change along the stream-to-river continumn and how does this relate to one of the classical models of gas evasion in aquatic systems (equation 2)? We exploit the findings from this simple analysis to develop a novel methodology that predicts (*k* normalized to a Schmidt number of 600) and its explicit uncertainity solely using SWOT observations. The method requires no in situ inputs of any kind (although in situ data can be ingested and will improve results). We name the RS of algorithm BIKER, or the ‘Bayesian Inference/Inversion of the Evasion Rate’ and validate it for 47 SWOT-observable rivers from around the world using hydraulic models to produce SWOT-like data (as SWOT has not yet launched). We also quantify BIKER’s sensitivity to the expected SWOT measurement errors on 17 of those rivers: while SWOT data represent a sea change in inland water monitoring, it is expected to have an approximately 10cm error in water surface elevation (Biancamaria et al., 2016) as well as river width errors (Frasson et al., 2021). Finally, we use previously published dissolved data to represent a hypothetical in situ sensor and compare the bulk carbon efflux from the 47 rivers as calculated using BIKER and previously published in situ techniques for predicting .

## 2 Data

Numerous datasets were used in this study. Please see Figure 1 for a map of the approximate locations for the data used in this study. We also provide a flowchart detailing the entire study as Figure S1.

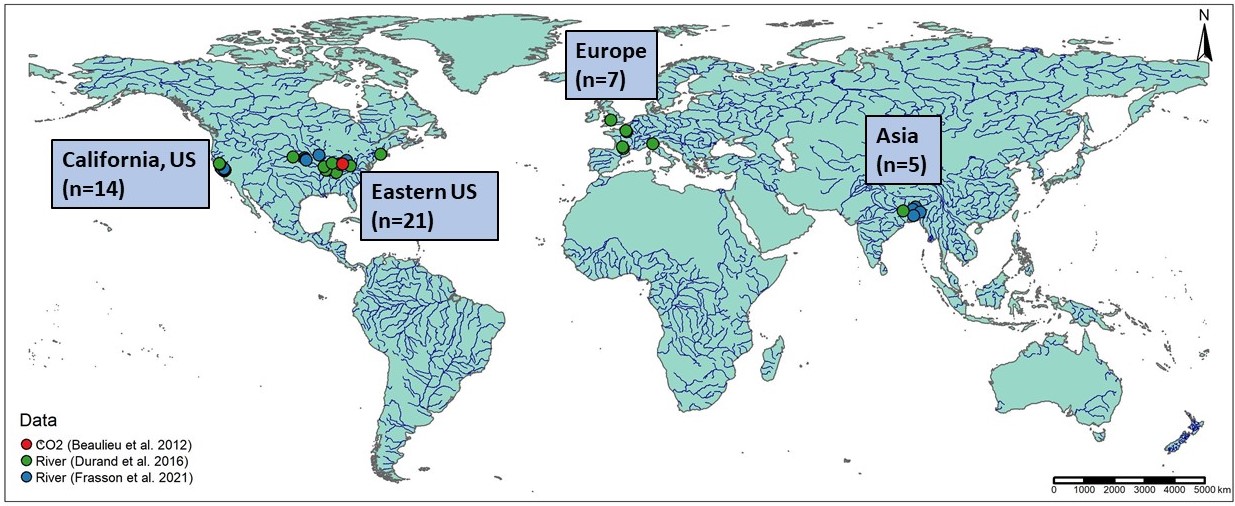


Figure 1: Map of the 47 hydraulic models and 1 timeseries of CO2 samples used in this study. Note that hydraulic model locations are approximate as some of the models are not geo-referenced. Not mapped here are over 170,000 discrete measurements of river channel hydraulics from across the continetal United States (Brinkerhoff et al. 2019) and over 700 gas exchange velocity measurements (Ulseth et al. 2019).

Gas exchange theory (section 3) is explored using the dataset from Ulseth et al. (2019) who measured and/or collected from the literature over 700 measurements of stream hydraulics and and is, to our knowledge, the largest collection of field-measured river and stream . To assess general hydraulic conditions in rivers across geographic contexts, we additionally use a previously published compilation of field hydraulics measurements (Brinkerhoff et al., 2019). These were originally made to calibrate United States Geological Survey (USGS) streamgauge rating curves. That dataset contains over 530,000 unique measurements of river channel velocity, width, and discharge from across the continental United States. This is to our knowledge the largest collection of field measurements of river channel hydraulics. Ultimately, this dataset was filtered down to 171,553 discrete measurements for this study (see Text S1 for our filtering protocol).

BIKER validation (section 4) was performed on 47 SWOT-simulated rivers. Because SWOT has yet to launch, it is standard practice to benchmark SWOT-related algorithms on “SWOT-like” data. These simulated rivers are simply river-reach-averaged hydraulic model outputs where the water surface heights and widths are labelled as RS observations and are used as the sole inputs to BIKER. Here, we use 47/51 rivers collected by Frasson et al. (2021) and Durand et al. (2016). These are the two benchmarking studies that have explored RSQ algorithm performance for the SWOT mission. The approximate locations of these rivers are plotted in Figure 1, and please consult both of those papers for all of the hydraulic model specifications. Ultimately, the 47 rivers are spread across the United States, France, Italy, the United Kingdom, and Bangladesh. We omit three models from Durand et al. (2016) because they lack enough hydraulic information to calculate the shear velocity , which is necessary for algorithm validation and is explained in section 4. These are two models for the Saint Lawrence River and one for the Tanana River.

To assess the influence of measurement error on BIKER’s performance (section 4), we use the error model developed by Durand et al. (2020) and implemented on 17/47 of the rivers by Frasson et al. (2021). Error in SWOT measurements will come from both the error tolerances intrinsic in the satellite data product as well as radar layover error. Layover error is the phenomenon when radar returns from different places arrive at the sensor at the same time, leading to taller landscape features appearing closer to the sensor than shorter landscape features that are the same horizontal distance from the sensor (Durand et al., 2020). Width errors due to poor water classification are ignored as they were in Frasson et al. (2021).

For the evasion and carbon efflux calculations (section 5), we use 26 bi-weekly dissolved samples made by Beaulieu et al. (2012) at one location in the Ohio River for one calender year from 2008-2009 (Figure S2). Note that this data is for the Ohio River only but was applied to all 47 rivers (which includes multiple sections of the Ohio River). Because we are exclusively interested in the relative differences between estimates and not the raw fluxes themselves, any data representative of SWOT-observable rivers was deemed acceptable for this validation exercise.

## 3 Form-drag in large rivers and implications for scaling fluvial gas exchange velocity

Turbulence is fundamental to fluvial geomorphology and open-channel flows and has been the subject of extensive research across scientific and engineering disciplines for over a century. As noted in the introduction, turbulence in river flows is usually generated by shear forces at the riverbed, but also across the entire flow depth via ‘form-drag’ from riverbanks, meanders, bars, suspended sediment, etc (Moog and Jirka, 1999). This concept is synonymous with the geomorphic idea of available stream power, or the total energy dissipated from a river reach via the liquid’s potential energy along its slope (Bagnold, 1966, originally derived from first-principles by 1960). Both Raymond et al. (2012) and Moog and Jirka (1999) confirmed that (simply the available stream power normalized by the water mass) is far greater than in open-channel flows, therefore generating the majority of fluvial TKE dissipation.

While form-drag dissipation is effectively an alternative representation of reach-scale stream power, little attention has been paid to the resulting scale-dependecy of . Available stream power, and thus ‘form-drag’ shear, exists at the depth-scale and is scale-dependent: while small roughness elements near the bed produce form-drag, if they are small relative to the total flow depth they will exert little influence on near-surface dissipation (Moog and Jirka, 1999). This means that, if all other properties of a river flow are held constant but the channel is progressively made wider and shallower, its depth will decrease and its wetted perimeter (and therefore total frictional resistance) will increase. This concept is illustrated graphically in Figure 2 and relates the geomorphic concept of ‘river channel efficiency’ to turbulence: all else being constant, a less efficient channel (wide/shallow) will have greater frictional resistance and therefore form-drag (Chow, 1959). As shown via the orange arrows in Figure 2, the inefficient channel should 1) produce more turbulence, and 2) turbulence generated via form-drag should more readily reach the surface (the red arrows in Figure 2). Note that to compare wetted perimeters across many rivers with different channel areas, we use the hydraulic radius (channel area divided by the wetted perimeter) as compared to the mean flow depth (channel area divided by the width). An efficient channel will have a low ratio while an inefficient channel will have a high ratio that approaches 1.

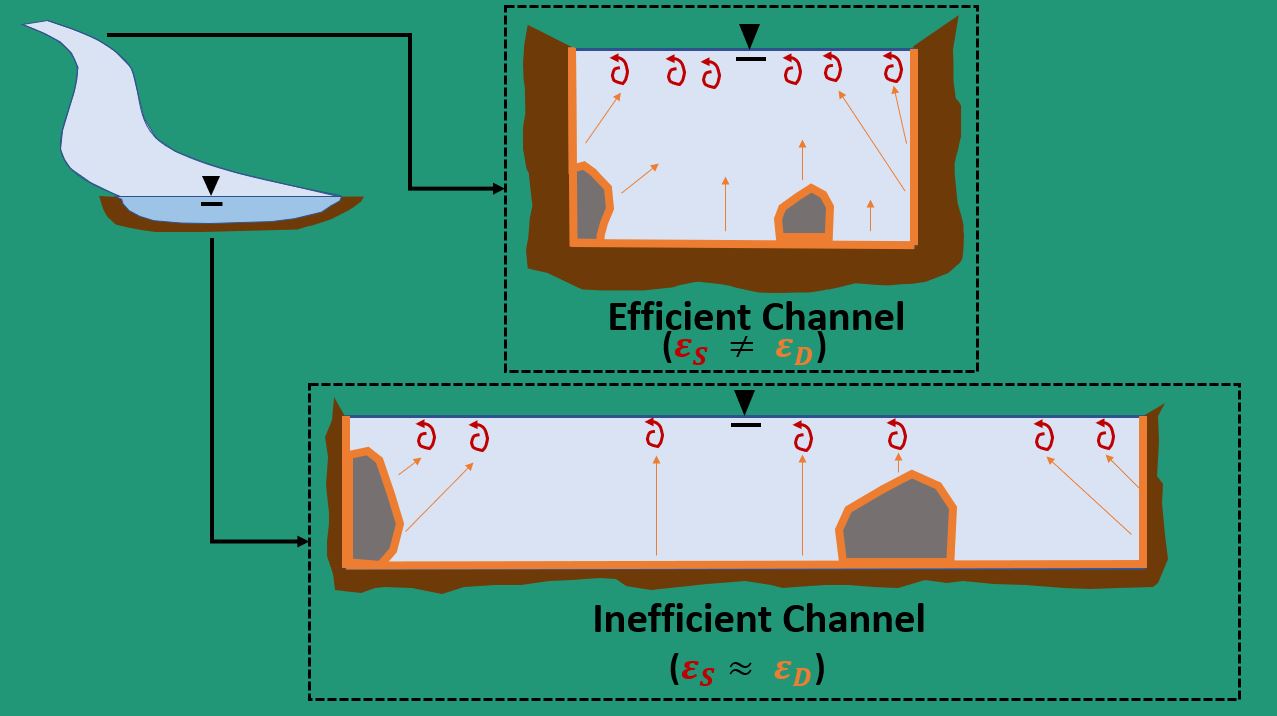


Figure 2: Conceptual model relating river channel efficiency to the turbulent dissipation rate. All else being constant, a less efficient channel shape (wide/shallow) should 1) have more form-drag and thus turbulence and 2) turbulence generated via form-drag should more readily reach the surface. This is illustrated by the orange arrows, where the inefficient channel arrows more frequently reach the surface (and influence surface turbulence- red arrows).

This all suggests that, for incredibly inefficient river channels, . The channel produces so much turbulence from form-drag, and the flow is so shallow relative to its width, that depth-scale dissipation should be nearly synonymous with near-surface dissipation and equation 2 could be equivalently written as . To explore when (if at all) this occurs in rivers, we fit models using 701 river measurements from Ulseth et al. (2019). First, we defined ‘channel inefficiency’ using minimum thresholds ranging from 0.75 to 0.995 and then we fit the two models outlined in equations 3 and 4 (because all of the data are normalized to Schmidt numbers of 600, we convienantly fold the viscosity and Schmidt numbers into the model coefficients). The goal of this analysis is to find at what threshold does 1) equation 3’s b parameter approximate 1/4 and thus mirror equation 2 and 2) equation 4’s goodness-of-fit (via the coefficient of determination ) reach a suitably high value that it is deemed physically valid.

The results of this analysis are plotted in Figure 3a, along with channel geometry schematics to highlight the progressive shift from efficient to inefficient river channels. Equation 3’s b parameter only begins to approximate 1/4 when is within 1% of the mean flow depth. At this point, the model’s goodness-of-fit also reaches a reasonable value of round(models\_eD4[models\_eD4$name == 'Rh=H',]$r2,2). This indicates that a river is sufficiently inefficient when its hyradulic radius approximates the mean flow depth, and at that point . Figures 3b and 3c plot the model fits for this final scenario where As Figure 3c confirms, the small-eddy model is viable when a channel is so inefficient that dissipation via form-drag approximates the near-surface dissipation rate in equation 2. Figure 3b further confirms this, where the slope of the generalized model (equation 3) equals 0.28 which is nearly equivalent to 1/4.

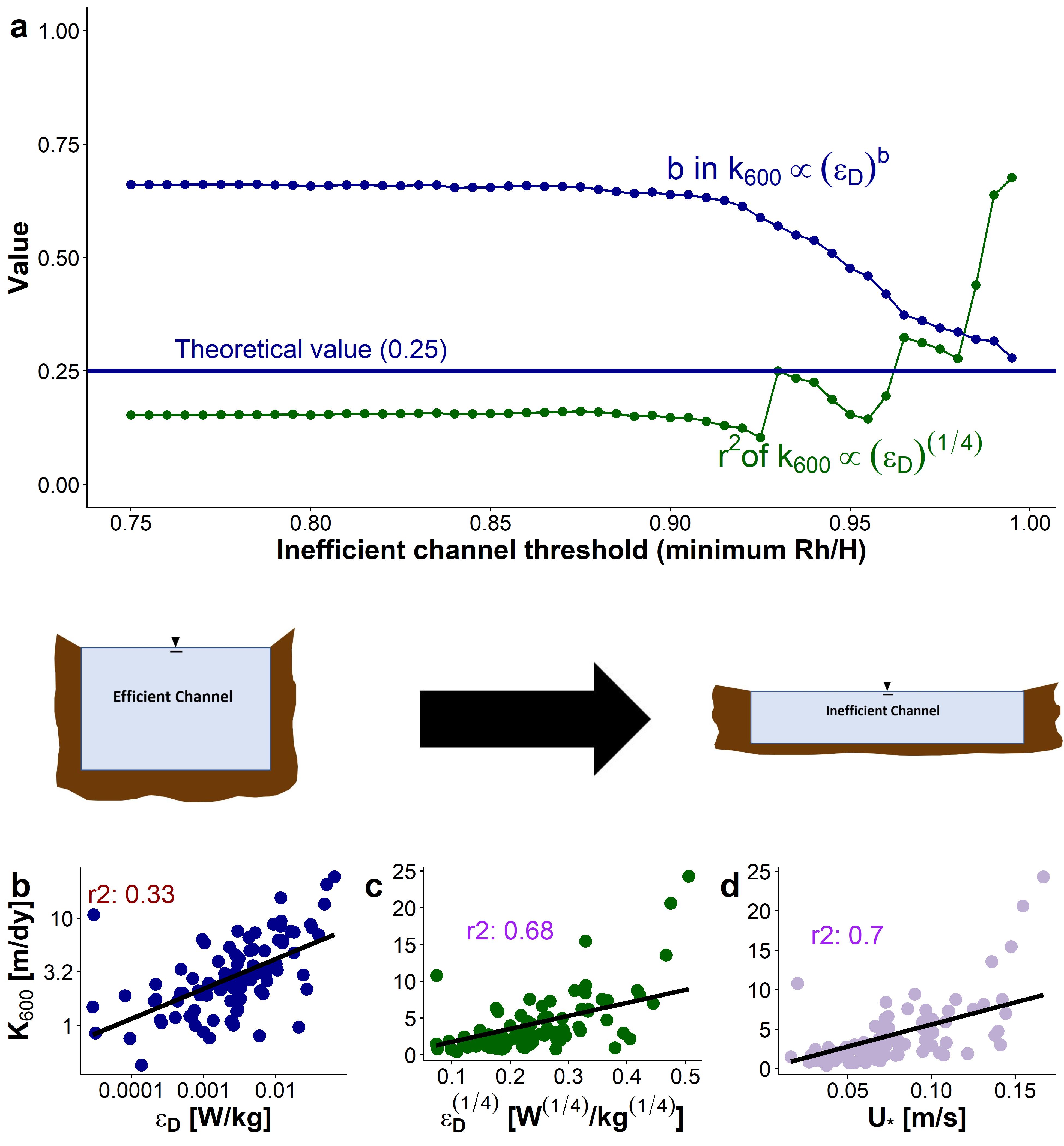


Figure 3: Model development for predicitng k from form-drag dissipation in rivers. (a) Rh/H thresholds versus fitted model results. Dark blue is the fitted b parameter in equation 3 and dark green is the goodness-of-fit of equation 4 as defined by the coefficient of determination. Once a channel is maximally inefficient, i.e. Rh=H, equation 4 is a viable model for k and equation 3 empirically recovers the theoretical value of 1/4 as outlined in equation 2. (b-d) Fitted model results for inefficient channels (defined as Rh/H >= 0.995) predicting k via the shear velocity U\*, equation 4, and equation 3 (respectively). Note that colors align to the same models for subpanels a, c, and d. Further note that the coefficient of determination in subpanel (d) refers to log-transformed residuals and hence is not directly comparable to those in subpanels (b) and (c).

Finally, becuase refers to a depth-scale quantity, we tested whether a more parsimonious model is possible by removing the ‘middle-man’, i.e. the Kolmogorov velocity scale that the small-eddy model is based on (Lamont and Scott, 1970), and directly predicting *k* from depth-scale turbulence. Figure 3d plots the fitted model. For this data, explains 70% of variation in and, as expected, the fitted model is nearly identical to Figure 3c in scaling dynamics and variance explained. This all indicates that depth-scale turbulent production/dissipation dominates the surface dissipation signal in extremely inefficient river channels. These findings build off of Ulseth et al. (2019)’s intial result that channel slope exerts a drammatic influence on *k* scaling dynamics, further suggesting that fluvial *k* is as much a function of hydraulic geometry as the turbulence properties of the flow.

With all of that said, how often is a river channel so inefficient that ? To answer this question, we join the 701 measurements from Ulseth et al. (2019) to 171,553 discrete river hydraulics measurements from across the continental United States (Brinkerhoff et al., 2019). We find that 76% of hydraulic radii are within 5% of their mean flow depth. Because these measurements were made exclusively at streamgauges where rivers are somewhat channelized and width variability is decreased, we opted for a slightly more liberal ratio of 5%. Further, because larg rivers are more likely to have inefficient channels, we identify the measurements that are SWOT-observable, i.e. width > 100m. We find that while 72% of non-SWOT observable rivers are inefficient, 94% of SWOT-observable rivers are inefficient. This significant difference, and near universality of SWOT-observable rivers being inefficient, suggests that our theoretical findings in Figure 3 should reasonably hold in nearly all rivers that SWOT will observe. This opens the door for exploiting our ‘inefficient river k model’ for remote sensing *k* via the SWOT satellite.

## 4 Exploiting the ‘inefficient river model’ to remotely sense gas exchange velocity via the BIKER algorithm

We have shown that scaling via the shear velocity () explains 70% of the variation in in inefficient rivers and that nearly all SWOT-observable rivers are inefficient. This is incredibly convenient for remote sensing because the structure of (Appendix A) reduces the model to two non-remotely-sensible terms: and an estimate of the channel area. This is explained below. By scaling *k* this way, we significantly reduce equifinality issues, where equifinality refers to an under-constrained mathematical system that has essentially infinite parameter combinations that can produce the same result: there are more unknowns than equations (Garambois and Monnier, 2015). This problem is experienced by both SWOT RSQ algorithms and in situ tools that concurrently solve for *k* and stream metabolism (Appling et al., 2018; Grace et al., 2015; Holtgrieve et al., 2010). In both of these domains, the other unknown parameters are often difficult to estimate (bed roughness and stream metabolism, respectively) while for BIKER, median channel area is relatively easy to approximate from the SWOT-observable river width (Brinkerhoff et al., 2020).

Taking all of this together, we develop the BIKER algorithm. BIKER is informed by the Hagemann et al. (2017) algorithm for ungauged RSQ and further explored in more recent work by Brinkerhoff et al. (2020). These papers conceptualize discharge as a Bayesian remote sensing problem, which we largely follow here to conceptualize as a Bayesian remote sensing problem that can be solved using SWOT data. BIKER, and Bayesian inference in general, starts from Bayes rule (equation 5), where is some set of non-remotely-sensible parameters we want to solve for (including ), *x* is the observed data, is the sampling model where data are conditional on the parameters, and is the joint prior distribution of the parameters. Therefore, we are interested in solving for , or the ‘posterior’ distribution. For BIKER, *x* is the SWOT-observables: river width *W* and water surface elevation *H* (which is used to calculate the water surface slope ). Note that is usually computationally intractable to integrate, so Bayesian inference tools require only the proportionality to be specified: . Sampling algorithms are then used to approximate the posterior distribution, as is done in BIKER.

The heart of BIKER is its reformulation of the model as a Bayesian sampling model that is conditional only on the data that SWOT will provide. To do this, is first written as a function of SWOT-observables *W* and . This algebra is carried out using the model parameter from Figure 3d (56.0294) and yields equation 6, assuming the channel is inefficient (). Here, *A* is wetted channel area. *A* is further split into the SWOT-observable portion *dA* and the unobservable portion following Durand et al. (2014). *dA* is estimated assuming a rectangular river channel so that . Thus, there are no reliances on bed roughness, flow velocity, or any other terms that are difficult to infer from river width (if we implemented the nearly identical model in Figure 3b, we would need to simultaneously estimate roughness and/or velocity which becomes a much more difficult problem).

Next, equation 6 is written as a Bayesian sampling model, in which all of the SWOT observations are sampled from the unknown model parameters ( and ). This is equation 7 after log-transforming all of the variables to describe them as normal distributions. refers to the uncertainty inherent in equation 6’s estimates. Equation 7 also necessitate that we specify prior distributions for the parameters and . Prior distributions, defined by their hyperparameters, formalize the a priori estimates (and uncertainties) for the non-remotely-sensed terms. More intuitively, BIKER priors represent our ‘prior river knowledge’ of what and probably are for some river since they cannot be remotely sensed. Hyperparameter specifications are detailed in Text S2, however the goal was to rely on absolutely no in situ information such that we could run this method on any river on Earth solely using SWOT observations. Priors could in theory be improved if there is available a priori information about the river.

With the sampling model (equation 7) and hyperparameters described (Text S2), a joint posterior distribution conditional on the SWOT observations is specified. To approximate this distribution, we use a Markov Chain Monte Carlo (MCMC) algorithm implemented using the Stan probabilistic programming language. Specifically, Stan uses a Hamiltonian Monte Carlo sampler which reduces computation time relative to other sampling algorithms (Hagemann et al., 2017).

We validate BIKER on 47 SWOT-simulated rivers using daily observed hydraulics and the metrics described in Table S1. We also re-validate BIKER on the 17 rivers with the SWOT error model that corrupts the river width and slope. Regardless of the validation setup, we do not have observed data for these rivers, and to our knowledge no field dataset of exists in the type of temporal and spatial frequency that SWOT (and therefore the BIKER algorithm) provides. Therefore, we take the model outlined in Figure 3b and use that to calculate the observed that BIKER is validated against. With this setup, we are directly exploring BIKER’s ability to infer observed and from *W* and *H* alone, as the *k* scaling model has already been sucessfully validated (Figure 3). This is elaborated on in Text S3.

Figure 4a plots the validation results for (with no SWOT measurement error) across all rivers and all timesteps. The points are the posterior means while the black lines are the 95% confidence intervals (CIs) for the predictions. is strongly correlated with the BIKER-predicted ( of 0.87). Using absolutely no in situ information, BIKER captures the magnitude of the predictions and most points fall on or near the 1:1 line. The regression of the estimates (solid grey line) nearly recovers the 1:1 line (dashed black), but there is an over/underestimation bias in the largest/smallest values. The RMSE for the BIKER predictions is 2.57 m/day) across all observations.

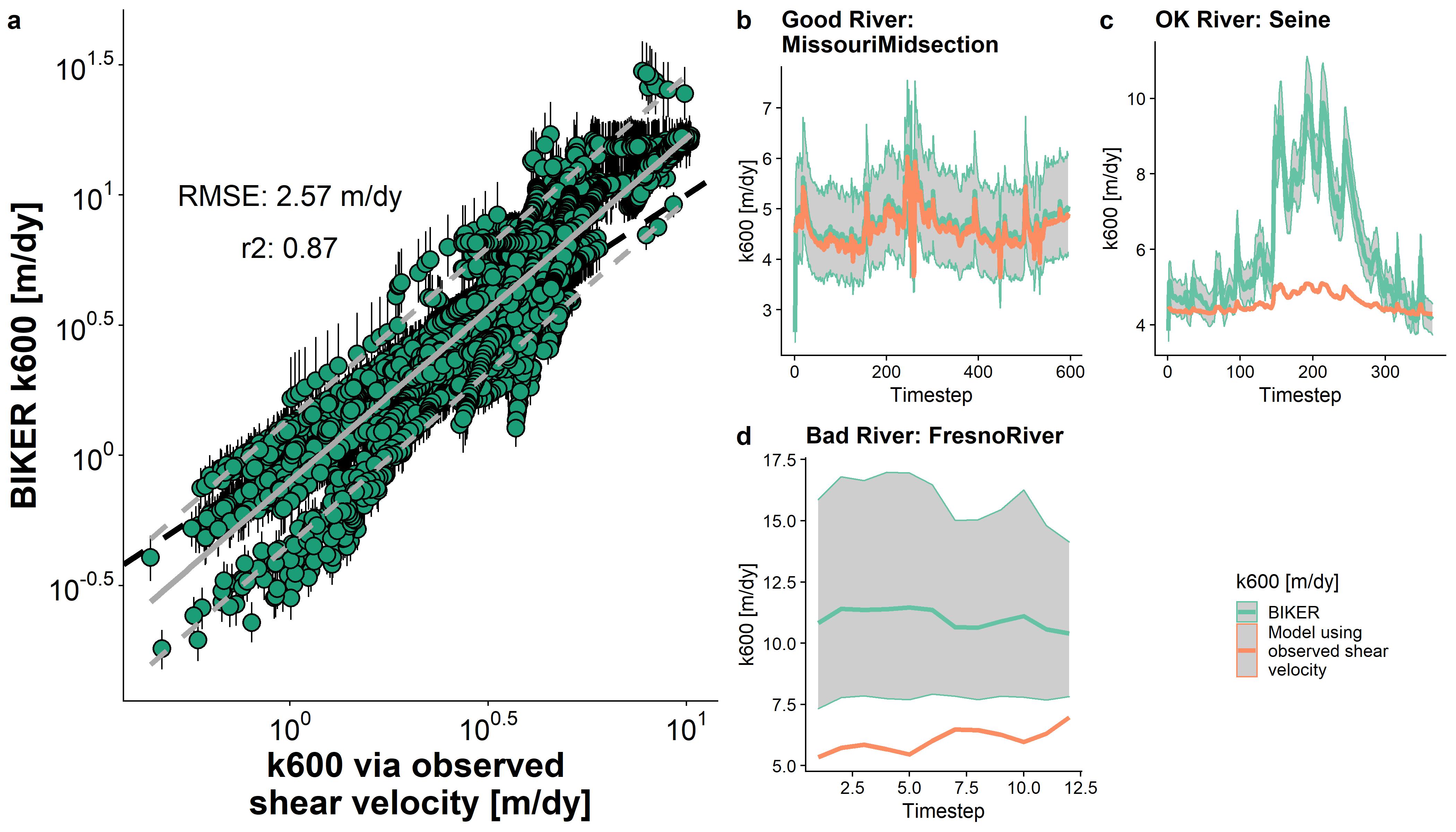


Figure 4. a: Validation of BIKER for 47 SWOT rivers. Black bars are 95% CIs for the modeled values. Grey line is linear regression (and 95% prediction intervals are dashed) and dashed black line is 1:1 line. b-d: validation timeseries for three rivers representative of good, reasonable, and poor BIKER performance. b) was randomly selected from the upper tertile of NRMSE scores, c) was randomly selected from the middle tertile, and d) from the worst tertile. See Figure S3 for all other rivers. Model results include the posterior means and 95%.

Figure 4b-d are representative timeseries plots of predicted and observed for three rivers chosen randomly from those with ‘good’ NRMSE scores (b), ‘okay’ NRMSE scores (c), and ‘bad’ NRMSE scores (d). See Table S1 for the definition of NRMSE, the Figure 4 caption for how this was determined, and Figure S3 for the other river timeseries plots. For the Missouri Midsection River, the entire timeseries of is nearly perfectly predicted, while in the Seine River the dynamics (peaks and valleys) are reasonably captured but they are magnified to be far larger than the observed dynamics. Generally, though, mean is reasonably recovered for the Seine, as confirmed visually. In the Fresno River, there is significant positive bias in the estimates but also massive uncertainty (per the 95% CIs) in those estimates, indicating that BIKER is highly uncertain about its output (and rightfully so). Correct temporal dynamics are also largely missing from BIKER’s Fresno River predicitions.

Figure 5a plots validation metrics calculated for each river with and without SWOT measurement error (green and purple, respectively). The points making up these boxplots (47 and 17, respectively) are overlain atop the boxplots. See Table S1 for metric definitions. SWOT measurement errors neglibly influence BIKER’s performance across all four error metrics (Figure 5a), though caution should be used in over-interepting boxplots with a sample size of only 17. Given Figure 5a, we deem that SWOT measurement error does not exert a significant influence on BIKER and so the results presented for the rest of the manuscript assume no measurement error in order to use all 47 rivers.

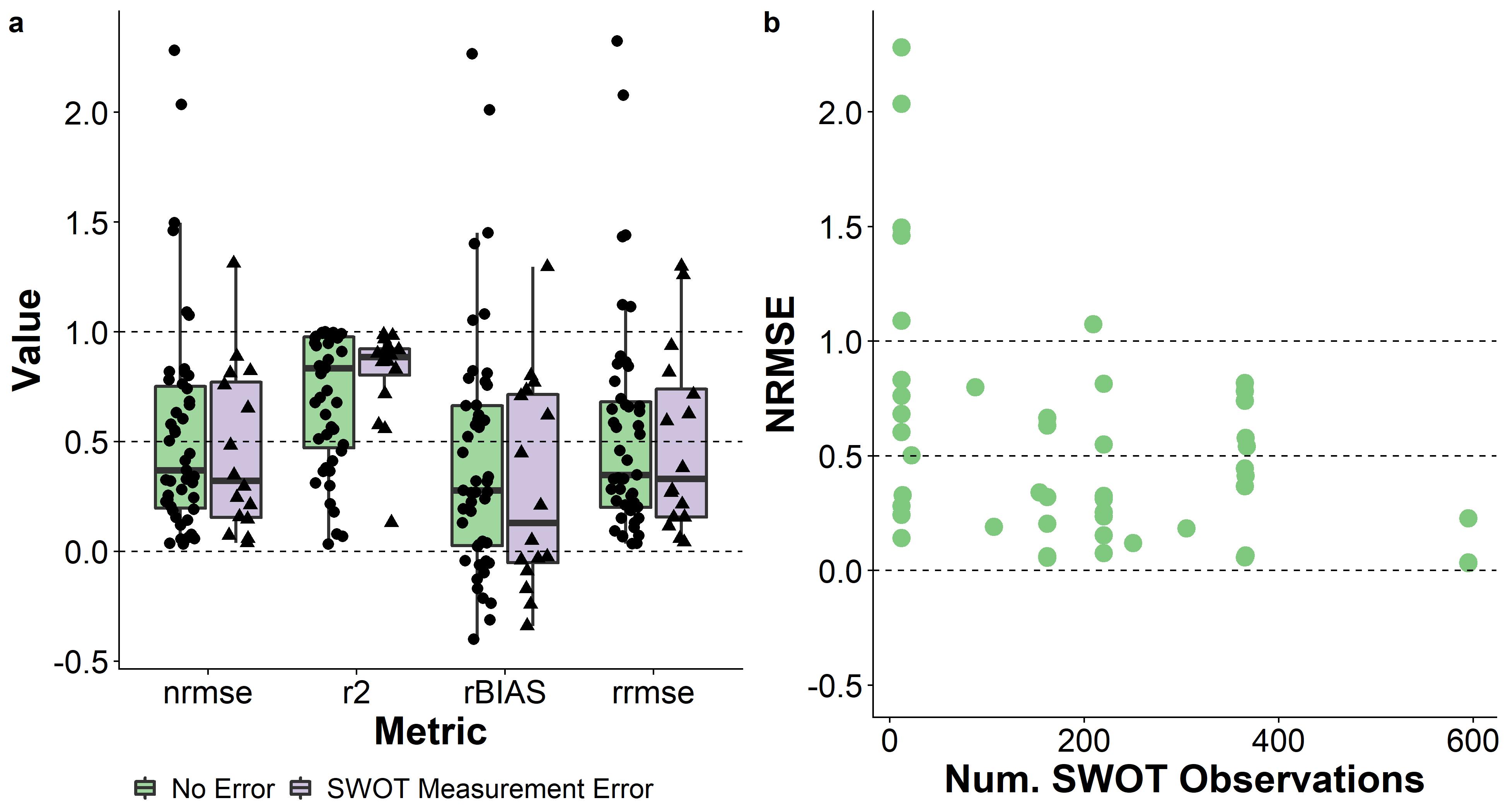


Figure 5. a: Performance metrics by river. See Table S1 for metric definitions. b: NRMSE scores (per river) versus the number of SWOT observations used in the Bayesian inversion. As expected, performance improves substantially with large amounts of data and degrades significantly with small amounts of data. Dashed lines denote scores of 0, 0.50, and 1. CIs.

Median river-specific is 0.83, which is excellent given that absolutely no in situ information is being used to predict . NRMSE and RRMSE have median scores of 0.37 and 0.35, respectively, which are again good for a completely ungauged method. These are comparable to the best NRMSE scores achieved by the SWOT RSQ algorithms (Frasson et al., 2021). Median rBIAS is 0.28, highlighting a positive bias in most rivers’ predictions. This further supports the visual evidence in Figure 4 that sometimes BIKER is overestimating the magnitude of and that this might be river-specific. While median and rBIAS scores were strong, the ranges of these scores were somewhat large (standard deviation for of 0.3 and for rBIAS of 0.56).

Figure 5b highlights one benefit of using Bayesian inference to estimate : because the posterior is conditional on the SWOT observations, performance should improve with more data. Figure 5b plots by-river NRMSE scores versus the number of SWOT observations. While performance varies considerably when observations are up to ~400, the three rivers with nearly 600 observations universally show excellent BIKER performance, and the worst BIKER performance is universally in rivers with only 12 observations.

## 5 Remotely sensing carbon emissions from rivers

It is one thing to accurately predict *k*, but researchers are often most interested in the actual gas fluxes from rivers and ultimately the carbon emitted from river to atmosphere. Therefore, we also explore 1) BIKER’s ability to reproduce (equation 1) from these 47 rivers, and 2) a comparison of the representative carbon efflux from BIKER with established in situ methods. The details of this workflow are in Text S4, but broadly we pair the 26 biweekly and water temperature samples (section 2, figure S2) from Beaulieu et al. (2012) with a subset of SWOT observations (as the data are not daily). We then calculate using equation 1 and assuming atmospheric is 390 uatm. Finally, we estimate a median bulk carbon efflux using BIKER’s posterior means and three other in situ models for average channel depth (used to calculate ) used for upscaling: one trained on the Brinkerhoff et al. (2019) dataset, and two previously published models (Raymond et al., 2013, 2012). See Table S2 for their definitions. This allows us to assess whether BIKER’s estimates (wholly ungauged) are comparable to gauged methods (all four HG models).

In Figure 6a, there is a very strong fit to the observed data, with an RMSE of 1.16 . The performance is notably better than for alone (Figure 4a) and there is no systematic bias in the predictions across all 47 rivers. This is presumably due to the structure of the equation, which reduces the relative importance of errors in *k* given that the data is measured in situ. prediction intervals are slightly narrower than those presented in Figure 4a as well.

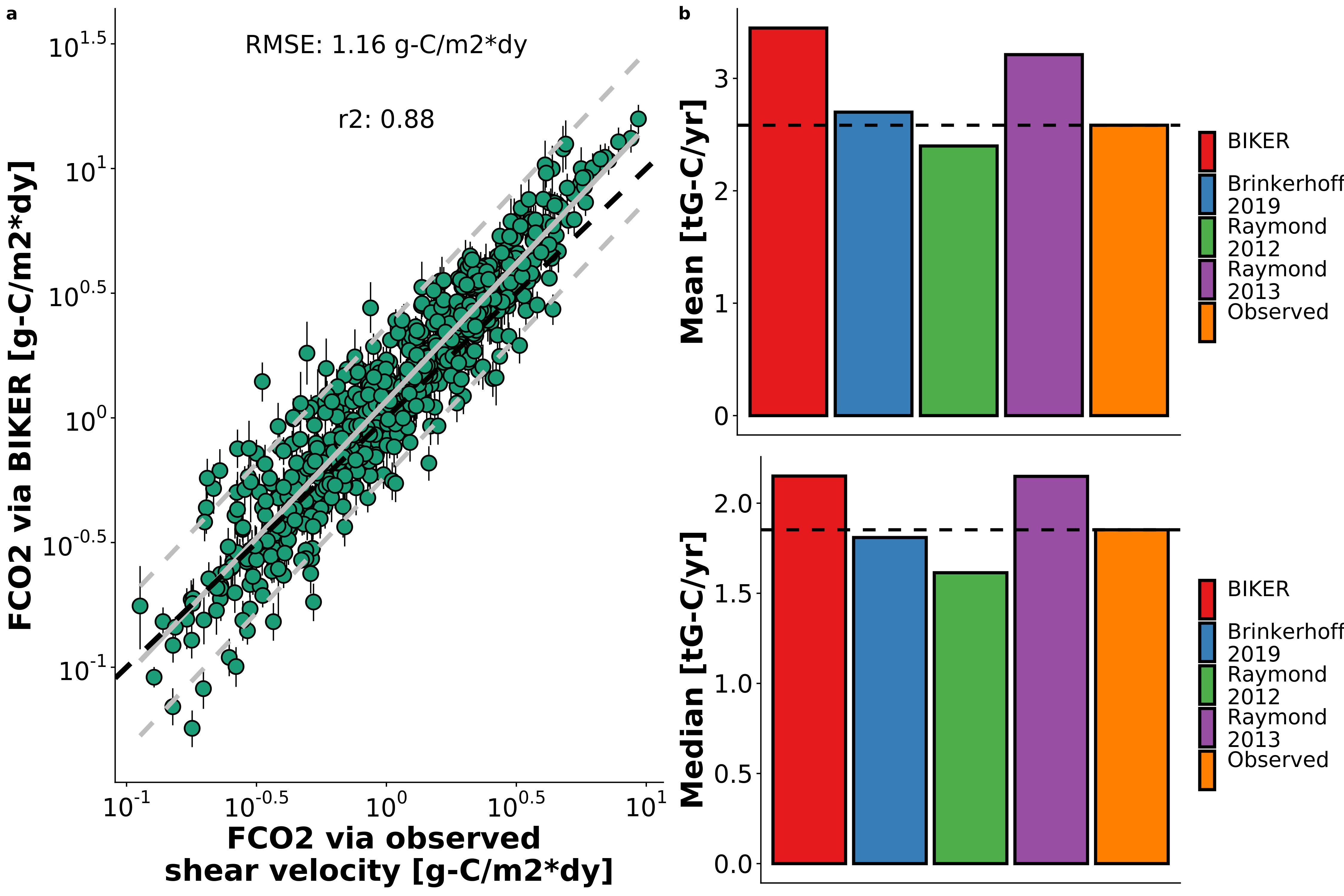


Figure 6: a: FCO2 via BIKER versus via equations 2 and 3 for every 11th timestep for the 49 rivers (grey lines are linear regression and 95% prediction intervals, while black dashed line is the 1:1 line). b-d: timeseries plots for the three example rivers from Figure 3b, 3c, and 3d.

Figure 6b compares the bulk carbon efflux (via ) from the 47 rivers using BIKER posterior means and four streamgauge-based HG models. The results are largely equivalent for both the mean and median carbon efflux. Both the BIKER estimate (2.01 gG-C/yr) and the ‘Raymond 2013’ estimate (2.15) are somewhat overestimated relative to the observed flux (1.85). The ‘Brinkerhoff 2019’ model nearly perfectly recovers the observed value (1.81). Finally, the ‘Raymond 2012’ model slightly underestimates this bulk efflux (1.61). Thus, despite BIKER using absolutely no streamgauge or other in situ data like the other 3 methods do, it provides a reasonable estimate of the carbon efflux (Figure 6b).

## 6 Discussion

### 6.1 Gas exchange along the stream-to-ocean continumn

Field studies of gas exchange in wide rivers have suggested that their *k* properties behave differently than in steeper and smaller rivers (Alin et al., 2011; Beaulieu et al., 2012; Ulseth et al., 2019; Wang et al., 2021). While it has been shown that the small-eddy model is reasonably valid across most rivers (Wang et al., 2021), it has yet to be seen why and when form-drag dissipation is similar to near-surface dissipation in the context of *k*. In section 3 we show that the geomorphic concept of channel efficiency can explain when this is the case or not (Figure 3a). In extremely inefficient channels, the ‘small-eddy’ model is physically valid in flowing water environments as confirmed in Figures 3b and 3c. This has significant implications for how we understand shear and turbulence in rivers and their influence on *k*, as compared to environments where bottom-shear dominates (like lakes or oceans).

Wang et al. (2021) proposed a conceptual model for fluvial *k* where *k* is dominated by bottom shear in small streams while in large rivers *k* is also affected by wind, biota, etc. This builds on the (Ulseth et al., 2019) finding that steep, ‘high-energy’ streams have a fundamentally different relationship than less steep rivers and this may be due to the presence of bubble-mediated gas exchange and massive roughness elements in small mountain streams. Taking both of these models, along with our results, in aggregate, we suggest a combined conceptual model that follows the geomorphic concept of the ‘river longitudinal profile’ and is outlined in Figure 7. Small streams are steep, rough, and highly efficient channels that evacuate all but the largest sediment leaving a very rough riverbed. These small streams likely have strong *k*~hydraulics relationships and surface turbulence is dominated by their huge bed roughness. However, as one moves down the stream-to-ocean continumn, river channels get wider, flatter, relatively more frictional, and far less efficient at evacuating sediment. This means there is a concurrent fining of the riverbed and an increase in form-drag. In these largest rivers, form-drag starts dominating the *k*~hydraulics relationship rather than bed roughness. While wind certainly also plays a role in *k* in these large rivers (particuarly at higher winds- Beaulieu et al., 2012), we show here that for maximally inefficient river channels form-drag alone can reasonably predict . The relationship between form-drag dissipation and wind is left to future work.

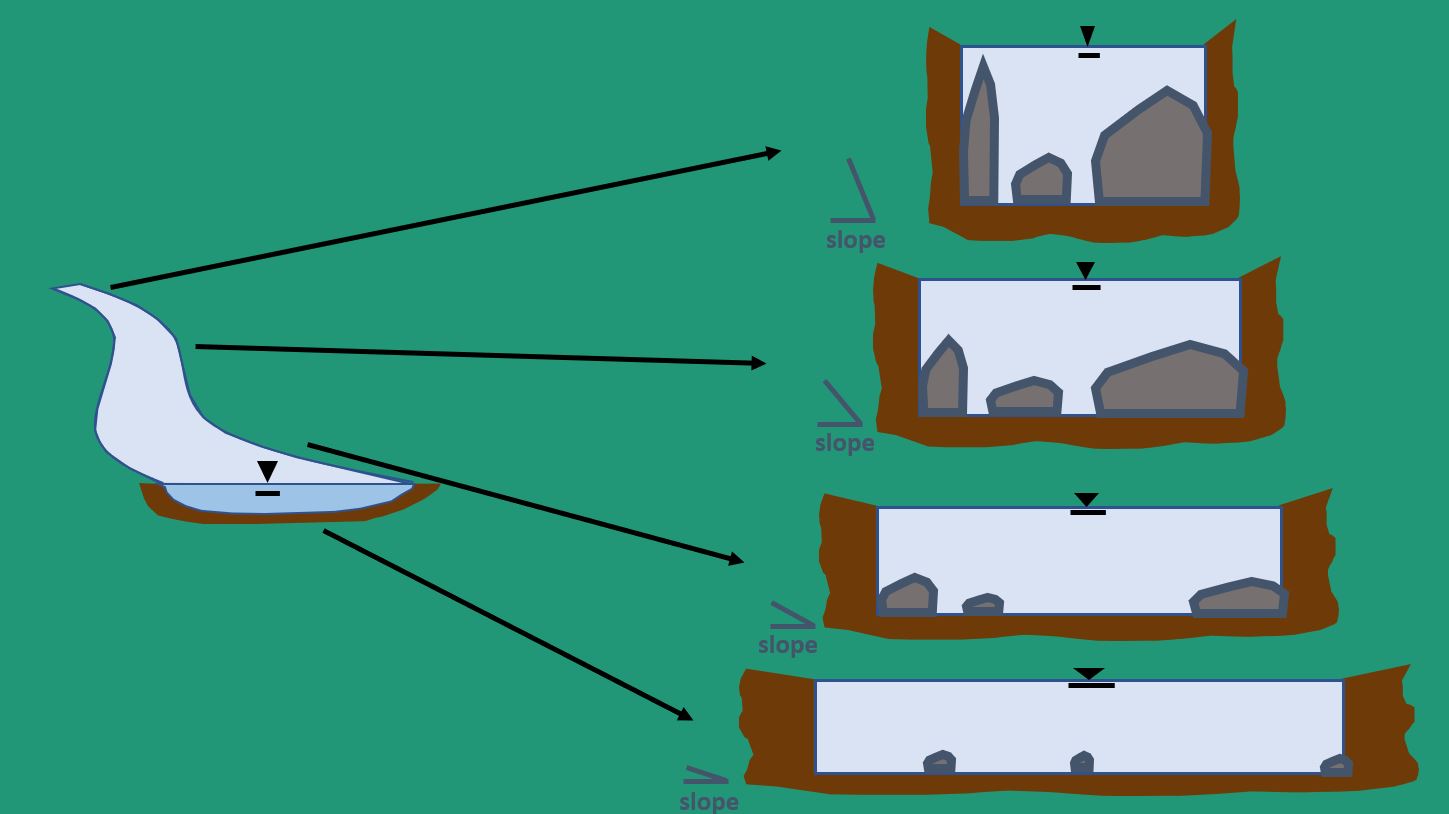


Figure 7: Conceptual model of the river longitudinal profile as it pertains to gas exchange velocity. As rivers grow in size and one moves downstream, their channels become wider, flatter, less efficient at transporting sediment, and have greater relative frictional resistance. This suggests a shift in k~hydraulics relationships from one dominated by bed roughness in small, steep, and efficient systems versus one dominated by form-drag in large, flat, and inefficient systems.

### 6.2 Towards remote sensing of global spatiotemporal dynamics of *k* in large rivers

To date, most field-scale studies of riverine gas exchange have focused on 1) its relationship with wind speed (e.g Beaulieu et al., 2012; Borges et al., 2004; Zappa et al., 2007), 2) average flow velocity (e.g. Alin et al., 2011; Beaulieu et al., 2012; Schelker et al., 2016), or 3) discharge (Roberts et al., 2007; Uehlinger and Naegeli, 1998; e.g. Wang et al., 2021). However, the spatiotemporal dynamics of riverine gas exchange are still weakly constrained. A few studies have investigated these dynamics, but they have been limited to individual rivers and/or limited field seasons (Hall et al., 2012; Sand-Jensen and Staehr, 2012). Wallin et al. (2011) performed a preliminary analysis in northern Sweden relating cross-section specific temporal variability in gas exchange with channel slope, but they were limited to an average of only 8 measurements per river in a single watershed. This limited knowledge of large-scale *k* spatiotemporal dynamics is due both to a lack of process-level understanding (Hall and Ulseth, 2020) but also a lack of measurements.

Therefore, estimating *k* from SWOT data is an attractive option for exploring its spatiotemporal dynamics at fine temporal resolution and at the global-scale. SWOT will provide daily hydraulic measurements for a 3 month fast sampling period for calibration and validation and sampling thereafter between 1 and 7 days per 21 day repeat cycle (Biancamaria et al., 2016). BIKER’s success in 1) infering using simulated SWOT data over a wide range of rivers (Figures 4 and 5) and 2) being robust to measurement errors internal to the SWOT data (Figure 5) bode well for BIKER’s eventual implementation on real SWOT observations. Further, BIKER’s improved performance with longer datasets (Figure 5b) bodes well for future SWOT implementation, as the three-year campaign will provide well north of 600 observations for many rivers, suggesting even better BIKER inversions than those presented here. All of this suggests that daily estimation of riverine gas exchange globally could be possible once SWOT launches.

### 6.3 Towards remotely sensing riverine carbon emissions using SWOT

Figure 6 confirms that BIKER is quite successful, without any in situ information aside from a logger, at predicting both (Figure 6a) and 2) the bulk carbon efflux (Figure 6b). This encouraging result has two main implications for future work coupling remote sensing via SWOT with in situ data. First, it confirms that we can couple BIKER and SWOT with in situ gas concentration loggers to produce estimates at novel temporal resolutions in SWOT-observable rivers. This is particualry useful given recent advances in in situ gas concentration loggers (Aho et al., 2021) but no such similar advances in modeling *k* at equivalent temporal resolutions. BIKER can likely also be ran at the field scale using arrays of pressure transducers to estimate water surface slope (rather than using satellite-based altimeters like SWOT) following recent work doing the same using the Hagemann et al. (2017) RSQ algorithm (Harlan et al., 2021).

Secondly, it is important to stress that unlike BIKER, the HG models in Figure 6b rely on an in situ streamgauge. This means that Figure 6b represents the best performance that those models could ever have; if ran using modeled discharge their accuracy would necessarily decrease. Thus, these results suggest that BIKER will be useful in two settings: 1) upscaling in ungauged rivers as hypothesized, but also in 2) potentially improving our carbon efflux understandings at gauged sites. Future work should systematically quantify prediction error from coupling global-scope HG models with modeled discharge, as is the default workflow used in fluvial upscaling studies [e.g. Lauerwald et al. (2015); Horgby et al. (2019); Raymond et al. (2013); **Liu et al in reivew**].

Figure 6b also confirms that the training data used for HG models exerts a significant influence on upscaled carbon emissions from rivers. In Figure 6b there is a nearly 0.5 Tg-C range between estimates, which is significant and nearly entirely a function of the data used to fit these depth HG models. In this context, the ‘Brinkerhoff 2019’ model likely outperforms both ‘Raymond models’ because the training data is orders of magnitude larger and more geomorphically varied than those used in the ‘Raymond’ models (530,945 measurements versus 1,026 and 10837 measurements). Meanwhile, BIKER has no similar reliance on hydraulic parameters trained on different datasets and only assumes that *dA* can be calculated by assuming a rectangular river channel. Upon SWOT’s launch, the BIKER approach to estimating *k* could be coupled with ethier existing upscaling workflows or even explicit transport models [Brinkerhoff et al. (2021); **Saccardi & Winnick in review**] to improve riverine gas flux predictions where gauges are unavailable but SWOT measurements are. This coupling could potentially be done using data assimilation techniques, which have proven very useful for similar objectives in recent RSQ work (Ishitsuka et al., 2020).

## 7 Conclusions

Gas exchange from aquatic systems has been studied for nearly a century, with a robust model (equation 2) that has been repeatedly verified across many non-fluvial environments. Despite renewed interest in fluvial gas exchange in the last decade or so, there are considerable uncertainties in how we model the gas exchange velocity in river environments and particularly in large rivers where wind increasingly influences *k*. Here, we show algebraically that TKE budgets in big rivers exist in a local equilbrium at the free surface and that we can equivalently scale *k* using any characteristic turbulence scale. We validate this using over 530,000 measurements of river channel hydraulics and over 700 discrete measurements of the normalized gas exchange velocity . We then exploit this finding to remotely sense using simulated data that will be provided by the forthcoming SWOT satellite, showing good performance and relying on absoutely no on-the-ground information. Finally, we pair this algorithm (named ‘BIKER’) with an in situ logger and show strong performance in reproducing evasion fluxes and carbon efflux from the rivers’ surfaces.

These strong results functionally open the door for global-scale, near daily estimates of fluvial gas exchange velocity once SWOT launches in 2022. This unprecedented amount of data should allow for significant insights into both the mechanistic and temporal dynamics of fluvial gas exchange in large rivers around the world. This, in turn, should allow us to better parameterize upscaling workflows such that the global fluvial carbon flux is better constrained.

## 8 Acknowledgements

C.B. Brinkerhoff was funded on **FINESST babyyyy**. BIKER is available at <https://github.com/craigbrinkerhoff/BIKER>. All code to build and generate results, figures, and the manuscript is available at <https://github.com/craigbrinkerhoff/RSK600>. We thank Renato Frasson, Michael Durand, Amber Ulseth, and Jake Beaulieu for generously making their data available for this study. We also thank the entire SWOT discharge working group for their decade-plus body of work which inspired this study.

## 9 Apendix A

*Table A1: Variable description and notation for this study.*

| **Notation** | **Description** | **Calculation (if applicable)** | **Units** |
| --- | --- | --- | --- |
| *A* | Channel cross-sectional area | NA |  |
| *Bulk carbon efflux* | carbon mass transport rate from river to atmosphere | NA |  |
|  | Water-side concentration | NA |  |
|  | Atmospheric-side concentration | NA |  |
|  | Molecular diffusion coefficient | NA |  |
|  | Dissipation rate of near-surface turbulence | log-law-of-the-wall model: |  |
|  | Form-drag turbulent dissipation rate |  |  |
|  | evasion flux from river to atmosphere | NA |  |
|  | gravitational acceleration | 9.8 |  |
|  | TKE production rate |  |  |
|  | Mean flow depth |  |  |
|  | gas exchange velocity | NA |  |
|  | gas exchange velocity normalized to |  |  |
|  | Hydraulic radius |  |  |
|  | River slope | NA |  |
|  | Schmidt number |  |  |
|  | TKE turbulent diffusion rate | NA |  |
|  | Reach-averaged flow velocity | NA |  |
|  | Shear velocity |  |  |
|  | kinematic viscosity | NA |  |
|  | Flow width | NA |  |

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