Continental Scale Assessment of Variation in Floodplain Roughness with Vegetation and Flow Characteristics

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Key Points:

- 4,927 estimates of floodplain roughness were calculated using flow observations and compared to LiDAR vegetation data.
- Floodplain roughness increases with increasing biomass and inundation depths and decreases with increasing flow velocity.
- Our model's Manning's n estimates yield lower errors in reach-scale floodplain flow predictions than n based solely on land cover.

Abstract

Quantifying floodplain flows is critical to multiple river management objectives, yet how vegetation within floodplains dissipates flow energy lacks comprehensive characterization. Utilizing over 3.4 million discharge measurements, in conjunction with aboveground biomass and canopy height measurements from NASA's Global Ecosystem Dynamics Investigation (GEDI), this study characterizes the floodplain roughness coefficient Manning's *n* and its determinates across the continental United States. Estimated values of *n* show that flow resistance in floodplains decreases as flow velocity increases but increases with the fraction of vegetation inundated. A new function (RMSE = 0.024, r^2 = 0.74) is proposed for predicting *n* based on GEDI vegetation characteristics and flow velocity, with GEDI derived *n* values improving predictions of discharge relative to those based only on land cover. This analysis provides evidence of key hydraulic patterns of energy dissipation in floodplains, and integration of the proposed function into flood and habitat models may reduce uncertainty.

Plain Language Summary

Quantifying the capacity of floodplains to dissipate energy from flowing water is important in managing rivers, restoring habitats, and reducing flood risks. By integrating overbank flood characteristics measured at USGS gauging stations with vegetation properties of floodplains measured by NASA, this study analyzed how energy dissipation in the floodplain, via a hydraulic roughness coefficient, varies with vegetation biomass and flood depths. Results indicate that floodplain roughness increases with the density of vegetation and decreases with flow velocity. A new mathematical function is presented to estimate floodplain roughness based on remotely sensed vegetation properties for various velocities.

1 Introduction

Floods are one of the most damaging natural disasters affecting society, costing billions of dollars in damages every year (Smith, 2020). Understanding these events is important for the protection of urban and agricultural development, risk management, and ecosystem restoration actions (Bulti & Abebe, 2020). Accordingly, a wide variety of hydraulic models have been developed for prediction and forecasting of river response to flood events and restoration actions, with the vast majority of these model predictions dependent on how a floodplain roughness attenuates flow (Hunter et al., 2007). Manning's equation (Manning, 1891) is the most widely used hydraulic formula relating roughness to discharge and velocities in river channels and floodplains (Yen, 1992). Its application requires knowledge of the geometric characteristics of the channel (area, hydraulic radius, and slope) as well as a key roughness coefficient, n. This empirical coefficient is used to account for energy dissipated due to friction losses, but it is rarely measured directly in the field (R. Ferguson, 2013) due to logistics and safety concerns, and it is difficult to predict for a future land use policy or engineering design. As a result, Manning's n is typically specified from simplified lookup tables (Chow, 1959; Cowan, 1956), and studies have demonstrated that uncertainties in n can lead to large errors in depth and discharge estimates (Durand et al., 2016; Lee & Mays, 1986).

Manning's equation in irrigation canals (Manning, 1891) has traditionally attributed energy losses in open channels primarily to vegetation. Lookup tables, such as those by (Chow, 1959), include specific n values for different land cover types, indicating the influence of vegetation on Manning's n. While most studies focus on flow resistance of vegetation in the main channel, limited attention has been given to variations in floodplain vegetation resistance during inundation events (R. Ferguson, 2013; Yen, 2002). Prior models (Fathi-Maghadam & Kouwen, 1997; Kouwen & Fathi-Moghadam, 2000; Petryk, 1975) of flow resistance for emergent vegetation, highlighted vegetation density as the most important factor contributing to Manning's *n*, and suggest *n* varies with the square root of the vegetation inundation fraction and inversely with flow velocity. However, these models were developed spanning limited conditions, e.g. only four individual trees of different types tested in (Kouwen & Fathi-Moghadam, 2000), and remain difficult to parametrize in practice. Furthermore, human modifications to floodplains, including the replacement of vegetation with agricultural fields, roads, and urban development, have altered floodplain roughness. Artificial structures like levees further decrease floodplain extent and disrupt land cover, reducing energy dissipation in the remaining floodplain (Knox et al., 2022). Consequently, the original vegetation classes developed for canals may no longer adequately explain floodplain roughness in overbank areas.

The main goal of this study was to characterize roughness in floodplains across the continental US and its relationship with flow and vegetation characteristics. Specially, we examined how floodplain roughness varied with flow velocity, vegetation inundation fraction, and floodplain biomass. Direct estimates of floodplain Manning's *n* were produced using field measurements collected by the United States Geological Survey (USGS) during overbank flows. Estimated *n* values were then related to remotely sensed vegetation height and biomass data to quantify their influence on energy dissipation in floodplains. Finally, an empirical function was developed to characterize interactions between floodplain roughness, velocity, and vegetation properties. Additionally, we conducted cross-validation analyses to validate our methodology and compared our results with existing approaches for estimating floodplain roughness.

2 Materials and Methods

In this study, Manning's equation is applied specifically to the floodplain, separate from the main river channel. The floodplain discharge is isolated by subtracting the discharge within the main channel from the total measured discharge (see Supporting Information Figure S1 for a schematic of the floodplain as defined in this study). Values of Manning's *n* are then derived by inverting Manning's equation and solving for the floodplain roughness (see Supporting Information) during periods of overbank flow (Reclamation, 2001). The necessary parameters for calculation of *n* are obtained from field measurements datasets provided by the USGS (USGS, 2021a). The flood stage height is determined by the National Weather Service (NWS, 2021; Slater et al., 2015), and friction slope estimates are obtained from the National Hydrography Dataset (NHD) (USGS, 2021b). Estimates of *n* were constrained to those sites meeting strict quality control metrics including consistency with current USGS rating curves and observed channel geometries (Liu, 2011; Vinutha et al., 2018).

$$Q = \frac{k}{n}\, S^{1/2} R^{2/3}\, A \qquad \text{(eq. 1)}$$

where Q is discharge [L^3 t^{-1}], S is the friction slope, defining the energy loss along a reach [L L^{-1}], R the hydraulic radius [L], A is cross-sectional area [L^2], k is a unit conversion factor, and n is Manning's roughness coefficient.

At USGS gauging stations where *n* values are estimated, vegetation characteristics, such as aboveground biomass density and vegetation canopy height, are obtained from NASA's Global Ecosystem Dynamics Investigation (GEDI) (Potapov et al., 2021). GEDI is a LiDAR system mounted on the International Space Station that provides calibrated values of vegetation height and biomass globally at a 25m base resolution and gridded final products at 1km resolution (Dubayah et al., 2021, 2022; Milenković et al., 2022) . Previous research suggests that Manning's roughness coefficient is related to vegetation inundation fraction, flow velocity, and vegetation properties (Chow, 1959; Yen, 1992; Rob Ferguson, 2013). A semi-empirical function of *n* is formulated, based on prior models, that incorporates GEDI-derived vegetation properties. The function parameters are determined by fitting a linearized equation to values of Manning's roughness coefficient, flow velocity, and aboveground biomass at USGS sites. For a detailed explanation of the methodology please refer to the Extended Methodology section S1 in the supplementary information document.

To assess the performance of our newly developed function, we conducted a cross-validation analysis, which involved the application of Manning's equation to compute floodplain flow during observed overbank events. This process utilized the same measurements acquired by the USGS, along with Manning's n values estimated through a five-fold cross-validation approach (detailed in the Supplementary Information). Importantly, the Manning's *n* values used for fitting our function were distinct from those employed to validate discharge calculations at these sites.

To comprehensively evaluate our method, we compared the results not only against the directly measured discharge but also against discharges calculated using estimated roughness coefficients from other studies. These alternative approaches include the Geospatial Stream Flow Model (GeoSFM) proposed by (Asante et al., 2008), which parameterizes Manning's n values for different land cover classes for use in a distributed hydrologic model. This model integrates geospatial and time-series data in near-real time, generating daily forcing evapotranspiration and precipitation data from various remote sensing and ground-based sources. GeoSFM employs widely available terrain, soil, and land cover datasets for initial model setup and parameter estimation, making it adaptable for data-scarce environments. The model performs geospatial preprocessing and postprocessing tasks and hydrologic modeling within an ArcView GIS environment, offering seamless integration of GIS routines and time series processing. It identifies and maps wide-area streamflow anomalies, disseminating daily results, including streamflow and soil water maps, through various channels (Internet map servers, flood hazard bulletins, and more).

Additionally, Kalyanapu et al., (2009) determined Manning's n values by land cover class in a hydrologic modeling study focused on understanding the effects of land cover use on runoff and peak discharge. This research assesses the sensitivity of hydrologic models to Manning's *n* changes, a parameter crucial for representing surface roughness. Large watershed models often rely on land use/land cover datasets to assign Manning's n values based on land use or cover classes. While this approach is convenient, it introduces potential errors. Kalyanapu's study compared Manning's n values derived from manual inspection of aerial photos to those estimated using the National Land Cover Dataset (Homer et al., 2012). The results revealed significant differences in the magnitude and spatial distribution of Manning's n values, particularly at subcatchment levels. These differences, while not significantly altering runoff responses at the watershed outlet for large-scale models, became pronounced with increasing Manning's *n* deviation.

To ensure a fair and consistent comparison, we standardized our analysis using the International Geosphere-Biosphere Programme (IGBP) land cover classification (Loveland et al., 1999). Within this framework, we calculated the median velocity and median flow depth for each land cover class and subsequently derived the Manning's n value using our model. This approach allowed us to assess the performance of our function in relation to established methodologies and gain valuable insights into its efficacy in estimating floodplain roughness. We use medians instead of raw values to address the potential bias introduced by the inherent relationship between velocity and roughness, allowing for a fairer comparison against methodologies that do not consider velocity during the selection process.

3 Results

After data processing and quality control, a total of 4,927 estimates of floodplain Manning's *n* were calculated successfully at 804 sites, based on the analysis of 3,379,166 total measurements obtained from 31,142 unique gauge sites (Barinas et al., 2023). Included with this dataset of generated *n* values (see dataset in Supporting Information) are all the necessary variables measured by the USGS that were used when inverting Manning's equation to solve for *n*: measured discharge (Q), width (w), depth (z) obtained from USGS field measurements, and friction slope (S) from the NHD datasets. Intermediate variables are also included in this dataset: discharge, velocity, width, and depth, for both the main channel (Q_{mc}, V_{mc}, w_{mc}, z_{mc}) and the floodplain (Q_{fp}, V_{fp}, w_{fp}, z_{fp}). Complementary information included in the dataset are the USGS site ID, date of measurement, coordinates, and number of values of *n* calculated at that site.

Examining all floodplain roughness estimates over the continental United States, the national median of the estimated floodplain Manning's *n* values was 0.021, with a 5th and 95th percentile of 0.001 and 0.326, respectively. On average, a mean of 18 values of *n* were obtained per site, with an average of 155 values per state. Site-averaged *n* values revealed consistent spatial patterns across the continental United States (see Supporting Information Figure S2). These patterns are influenced by factors like vegetation biomass and velocities (Figure 1).

Vegetation biomass was shown to drive variability in floodplain roughness, with values of *n* for different vegetation classes and heights complied in Table S1 in the Supplementary Information). Areas dominated by Grasses, Shrubs, and Woodland, the most common vegetation classification in the GEDI dataset, tended to have a median Manning's n value of 0.017 for a median biomass on the analyzed sites of 18 Mg/Ha. Deciduous Broadleaf Trees, the second most common class, exhibited slightly higher roughness with a median Manning's n value of 0.025, having a median biomass of 77 Mg/Ha. Evergreen Broadleaf and Evergreen Needleleaf, despite having similar biomass densities (95 Mg/Ha and 106 Mg/Ha, respectively) contributed to different roughness values, with median Manning's n values of 0.030 and 0.010, respectively. Due to a limited number of samples, there were not enough observations to draw conclusions about the impact of Deciduous Needleleaf Trees on floodplain roughness (see Supplementary Information Table 1).

Even at a broad scale with the relatively low-resolution, remotely-sensed vegetation (GEDI) datasets used in this project, clear patterns were found between the floodplain Manning's *n* values and features (i.e. biomass, submergence) expected to predict *n* values at various velocity ranges (Figure 1). The values of *n* were inversely related to flow velocity and positively related to vegetation inundation fraction. Velocities were lowest at locations where Manning's *n* was highest. Within three velocity ranges, Manning's *n* varied with inundation fraction and vegetation biomass. Median Manning's *n* values ranged from 0.001-0.009 for the highest velocities ($V > 3$ m/s), whereas median *n* values ranged between 0.008 and 0.053 for mid-range velocity flows (1-3m/s). Under these mid to high velocities (V > 1m), Manning's *n* increased consistently with the inundation fraction and inconsistently with vegetative biomass. For low velocity flows (<1m/s), n ranged from 0.030 up to 0.388 and increases in roughness were associated inconsistently with both inundation fraction and vegetative biomass.

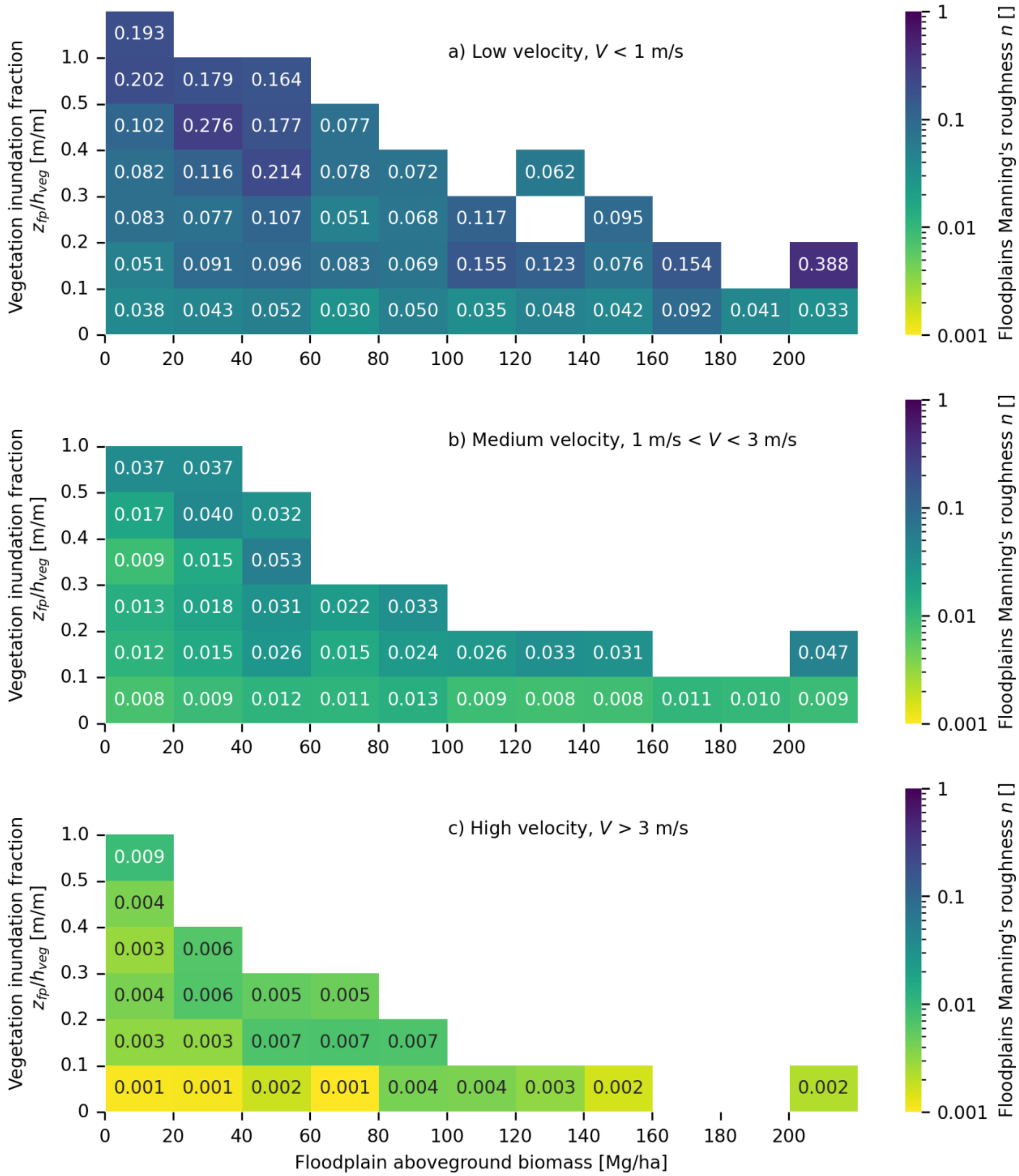

Figure 1. Median floodplain Manning's *n* values for different levels of floodplain aboveground biomass and vegetation inundation fraction. Numerical values within each box represent the median *n* value for the corresponding range of vegetation inundation fraction and aboveground biomass and results shown only when at least five values are available.

Based on calculated n values, observed flow velocities (V) and depths within the floodplain (z_{fp}), as well as GEDI estimated vegetation height (h_{veg}) and biomass (B), an empirical function relating Manning's n (See Extended Methodology S1) provided a reasonable fit to observed data (r^2 = 0.74):

$$n = 0.0321 \frac{B^{0.20}}{V^{0.99}} \left(\frac{z_{fp}}{h_{veg}}\right)^{0.5} \quad \text{(eq. 2)}$$

This function, visualized across observed conditions in Figure 2, predicted *n* with a root mean squared error (RMSE) of 0.024 (see scripts in Supporting Information). It further illustrated how Manning's *n* varies with flow and vegetation properties, with an inverse proportionality between Manning's *n* and flow velocity. A difference in roughness of nearly one order of magnitude was found between low velocities (<1m/s) and very high velocities (up to 5m/s) (Figure 2). Within specific velocity ranges, the values of *n* are notably influenced by vegetation inundation fraction, with greater roughness associated with higher levels of inundated vegetation. Furthermore, the data and function demonstrated that biomass tended to increase roughness more at low biomass levels (visually inspecting tangent lines revealed the inflection point to be approximately 30 Mg/Ha), whereas its influence decreased at higher biomass levels. This could explain why the function had less predictive power with biomass at higher levels of vegetation inundation fractions; High inundation fractions were not frequently observed at high biomass levels.

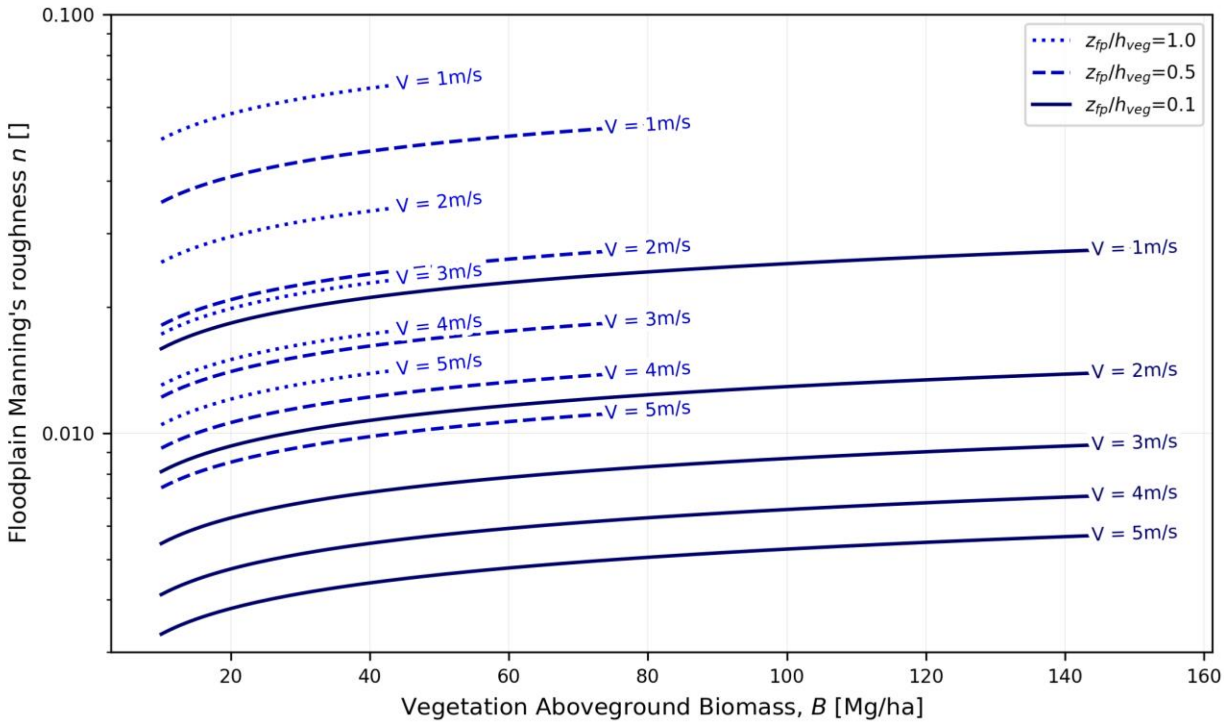

Figure 2 – Manning's *n* modelled as a function of aboveground biomass, *B*, and flow velocity, *V*, modeled for different levels of vegetation inundation fraction (z_{fp}/h_{veg}). Lines extend up to biomass levels of 50, 80 and 150 Mg/ha for fractions of inundation of 1.0, 0.5 and 0.1, respectively based on the total number of values within each range as depicted in Figure 1.

The cross-validation analysis conducted in this study reveals the performance of the proposed function in estimating USGS measured flows (Figure 3). Our findings indicate that this function offers higher accuracy and less dispersion, as evidenced by a Kling-Gupta efficiency (KGE) of 0.38 and a percent bias (PBIAS) of -16%. In comparison, alternative methods for determining roughness coefficients yielded less accurate results, with KGE values of 0.33 and 0.10, and PBIAS values of -43% and -85% for GeoSFM and Kalyanapu et al. (2009), respectively.

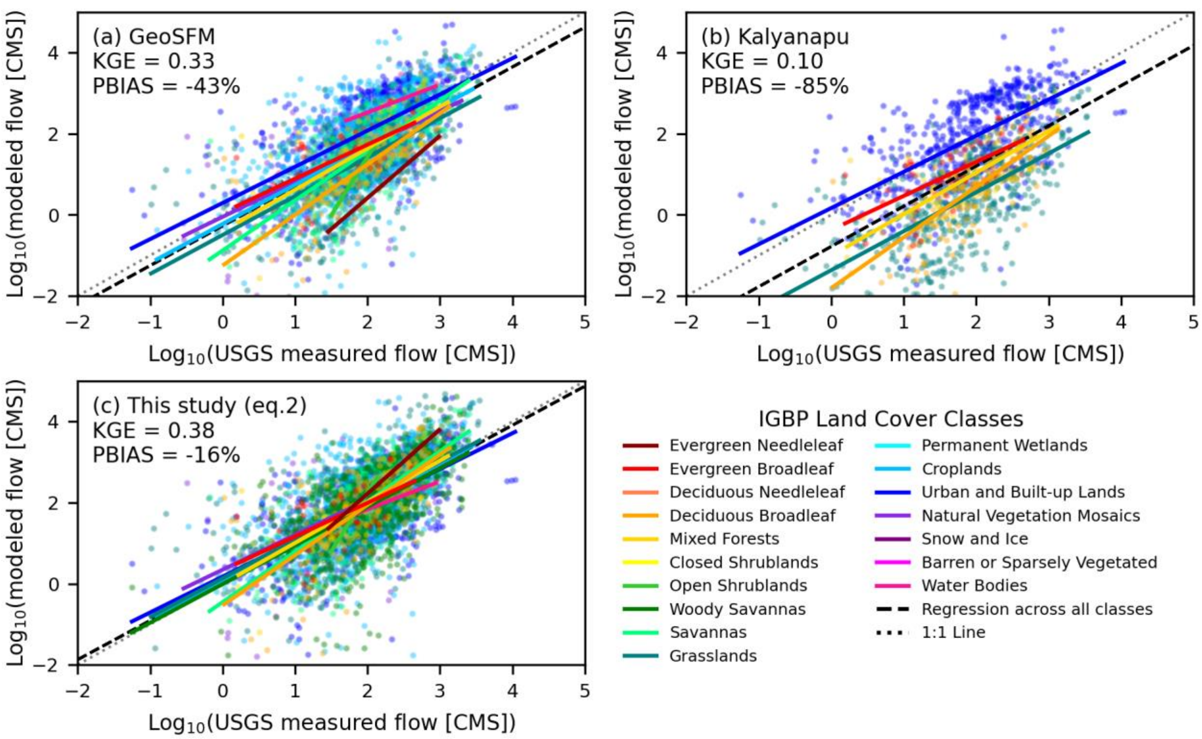

Figure 3 - Measured vs. estimated discharge based on three approaches to estimating floodplain roughness: (a) the Geospatial Stream Flow Model (GeoSFM), (b) Kalyanapu et al's study (2009) on land-use effects on model outputs, and (c) from the function developed in this study (eq. 2). These were calculated with median velocities and median flow depths per land cover class. Kling-Gupta efficiency (KGE) and percent bias (PBIAS) are reported across all vegetation classes.

4 Discussion

Floodplains serve critical functions for society through dissipation of flood energy, among other functions, but understanding of floodplain hydraulics contains large uncertainties due in part to limited field observations of floodplain roughness. This study produced new estimates of floodplain roughness coefficients that span the range of the continental United States. The average estimates of floodplain Manning's *n* calculated in this study were similar to *n* values modeled from field measurements of vegetation features (Kouwen & Fathi-Moghadam, 2000) and the values in Chow's look-up table (Chow, 1959). Chow identified the range of average *n* values for floodplains as being from 0.040 (in cleared land with stumps) up to 0.150 (for dense willows). In comparison, the average *n* estimates in this dataset were 0.060 for low canopy height and low levels of biomass, and 0.090 for high canopy height and biomass. Kouwen and Fathi-Moghadam's (2000) study also presented mean values of *n* for four tree types that range between 0.100 for high velocity flows (2 m/s) and 0.200 for very low velocity flows (0.1 m/s) for submerged conditions (z_{pf}/h_{veg}=1), dropping down to a range of 0.030 to 0.070 for low inundation (z_{pf}/h_{veg}=0.1). A similar pattern was observed in mean values of floodplain *n* in this study (Figure 2), ranging from 0.030 for low inundation and comparable velocity (V = 1-3 m/s), up to an average of 0.250 for low velocity (V < 1 m/s) and high inundation fraction. The approach presented here has the advantage of applying global, remotely sensed biomass datasets, compared with Kouwen and Fathi-Moghadam's vegetation index, which requires local measurements of frequency, mass, and height of the trees.

Field observations revealed that Manning's *n* in floodplains was generally lower at higher velocities than at lower velocities. Even though in practice Manning's *n* is often assumed to be a constant value solely determined based on the characteristics of the surface, in reality it has been demonstrated that *n* varies with discharge (Box et al., 2021; Chow, 1959; R. Ferguson, 2013). In most river channels, Manning's *n* decreases as discharge and stage increase due to lower roughness along the banks and the submergence of bed forms with increasing flow depths (USGS, 2012). This phenomenon is also consistent with the long history of roughness in pipe flow studies (Rouse, 1943). Like river channels, where previous research has shown that flow and velocity tend to have an inverse relationship with flow resistance, our calculations demonstrate a similar pattern in floodplains. This alignment with existing research suggests that flow and velocity in both river channels and floodplains exhibit an inverse relationship with flow resistance (Chow, 1959; R. Ferguson, 2013). Mechanistically, the inverse relationship could be a result of higher roughness reducing velocities, or the bending of flexible vegetation that reduces roughness at higher velocities. Datasets presented herein are inadequate for determining the source of the relationship.

This work demonstrated that GEDI's vegetation characteristics can be used to estimate floodplain roughness. Vegetation inundation fraction was an important predictor of Manning's *n*, as demonstrated in other settings (Nepf, 2012). In addition, this national Manning's *n* database reflects how floodplain roughness increases with aboveground biomass, though relative inundation demonstrated a stronger influence on roughness than biomass. This makes sense given that a key factor influencing Manning's *n* is the total vegetation cross section obstructing flow, not just the height of the canopy (Chow, 1959). Furthermore, previous studies have found that the density of vegetation in channels was a dominant parameter for Mannings's *n* in emergent conditions (Fathi-Maghadam & Kouwen, 1997) and the analysis here demonstrated that this finding translated to the floodplain as well. Since GEDI measures these vegetation properties globally, estimations of floodplain roughness can be extended worldwide with this method, with some caveats discussed below.

As previously outlined in the methodology section, our assessment involved a cross-validation analysis of the function defined in Equation 2. This process included the application of Manning's equation (eq. 1) to calculate floodplain flow during observed overbank events, using measurements from the US Geological Survey (USGS) and Manning's n coefficients estimated by our function. We also compared our findings with discharge estimates obtained from previous studies by Asante et al. (2008) and Kalyanapu et al. (2009), offering valuable insights into the robustness of our approach.

Our cross-validation analysis reveals notable advantages of the proposed function, which is rooted in US Geological Survey (USGS) gage data. This function demonstrated superior performance with a Kling-Gupta efficiency (KGE) of 0.38 and a percent bias (PBIAS) of -16% in estimating USGS measured flows. In comparison, alternative methods for determining roughness coefficients, such as GeoSFM (KGE = 0.33, PBIAS = -43%) and Kalyanapu's approach (KGE = 0.10, PBIAS = -85%), yielded less accurate results. Importantly, the other methods consistently underestimated flow rates across various land cover types when relying on constant roughness coefficients. This artifact is due to land cover –roughness coefficient classifications being defined based on steady and uniform flow conditions in channels (Chow, 1959) and not accounting for variation of resistance with changing flow, especially during flood events with higher flow rates. This is evident in the fact that the hydrologic models analyzed in these works utilized hydrographs, which involve unsteady flow characterized by changing flow over time. As a consequence, the roughness coefficient becomes variable in reality but not in the models. By incorporating a vegetation- and submergence-dependent Manning's *n* coefficient, the proposed function captured varying hydraulic conditions, leading to improved flow estimates when compared to methods that rely on a roughness coefficient that is independent of hydraulic conditions. Supporting this interpretation, both the GeoSFM and Kalyanapu et al. (2009) methods demonstrated relatively accurate estimates for short vegetation classes such as urban areas, built-up lands, and croplands, although they still lacked the precision displayed by our function in this study.

The Manning's *n* dataset and the function proposed in Eq. 2 have the potential to improve the performance of large-scale models such as the National Water Model (NWM). Many attempts are currently being made to reduce uncertainty in nationwide models (Johnson et al., 2019; Rojas et al., 2020), but have been focused on improving its performance by updating the geometry and roughness parameters of the main channel, without extending improvements to the floodplain (Heldmyer et al., 2022). Integrating the results from this work on floodplain roughness at USGS gauge locations into the NWM could be a logical next step.

Our study introduces a novel approach to enhance the NWM, especially during flood events, by incorporating dynamic floodplain roughness values. These values account for variations in flow velocity and vegetation properties, essential factors that are traditionally treated as constants in large-scale models. This integration offers the potential for more accurate flood predictions, improved flood risk assessments, and enhanced river management strategies. It's important to acknowledge the possibility of adjustments to other key parameters, such as channel roughness. While our study doesn't prescribe a specific approach for these adjustments, it opens an intriguing avenue for future research and collaboration.

The study datasets were subject to some limitations, including those inherent to the USGS monitoring network (Kiang et al., 2013; Tu et al., 2023), as discussed in the SI. Gaging limitations may narrow the generalizability of the results to LULCs (Land Use Land Cover) and geographic regions included in this gaging network. Further, assumptions about the geometry of a river's cross-section were made that could be inconsistent in some channels, such as where the local slope is too high or width too narrow to maintain that a hydraulic radius that is approximately equal to the hydraulic depth. Furthermore, the vegetation phenology is a snapshot in time, though it has been established that considerable differences exist in vegetation characteristics between seasons that can impact flow (Bond et al., 2020). To provide high-quality biomass and height estimates, the GEDI averages measurements. The resulting derived products do not represent a specific time of year, in contrast with USGS field measurements that were made on a specific date. Finally, vegetation data were sampled from GEDI's 1 km^2 gridded product for the area around each USGS gauge site, which leads to questions regarding what area influences Manning's roughness. Energy dissipation occurs via multiple processes during a flood (R. Ferguson, 2013), but the area of influence that has a direct effect on flow is poorly understood and is worthy of further study. The assumption made for these calculations is that the 1 km^2 average for the vegetation characteristics taken from GEDI measurements is representative of the actual area influencing energy dissipation during a flood. This assumption may not be valid at sites where there is a large variation in land cover within a 1 km^2 grid.

5 Conclusions

Floodplain roughness is a critical aspect of managing floodplains, and its societal relevance will rise with rising floodwaters under climate change, expanding floodplain development, aging flood infrastructure, and rising emphasis on floodplain reconnection for nature-based flood infrastructure and ecological restoration. While Manning's *n* is typically assumed to be a constant value in floodplain analysis and engineering applications, this study demonstrated that accurate estimation of current and modified floodplain roughness should rely on vegetation submergence and velocities, with biomass playing a smaller role.

The dataset of floodplain Manning's *n* generated in this work, and its correlation with flow and vegetation characteristics, further supported prior findings that flow resistance during a flood increases with submergence depth and biomass, and that resistance is inversely related to flow velocity. This work utilized a unique coupling of existing datasets, considering tall vegetation biomes, and demonstrated how flow and vegetation properties influence roughness across a wide range of regions and climates in the continental United States, rather than limited to a specific site or sites. Results should be generalizable across scales and landscapes that align with the input datasets and should support the management and restoration community in establishing sustainable floodplains.

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Open Research

The scripts to reproduce the dataset, figures and tables in this study are openly available at Barinas et al. (2023) under a Creative Commons Attribution License format (free registration required).

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