Sensitivity Analysis of a Beaver Dam Model

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Abstract

Many watersheds are suffering from water quality issues, drought and low summer flows, wildfires, floods, or other climate-related vulnerabilities. Beaver-assisted restoration is a promising technique for restoring riparian ecosystems and increasing watershed resiliency. Beaver dam modeling is an important step in planning restoration efforts, since it enables the selection of reaches with suitable conditions for beaver dams. In this project, we explore the Beaver Restoration Assessment Tool (BRAT), a modern dam capacity model with widespread use. We apply BRAT to the Siletz Watershed on the Oregon Coast, interrogating model outputs. We perform sensitivity analysis on the Fuzzy Inference System (FIS) at the core of BRAT, using One at a Time (OAT) and Monte Carlo methods for local and global sensitivity analysis, respectively. By applying different adjustments to the FIS, we gain insight into which design decisions of BRAT have the most impact and how confident we can be in the robustness of the model. We found BRAT to be conservative and robust, with the most influential parameter being slope cutoffs. Since this is largely consistent with the beaver literature, we are pleased with BRAT's performance. Finally, we initiate community engagement by preparing a survey to collect field data that could be used for BRAT validation in future work.

1. Introduction

1.1 Objectives

This project has three primary objectives. One, to analyze and contextualize the outputs of the Beaver Restoration Assessment Tool (BRAT), a beaver dam capacity model, when applied to the Siletz River Basin in Oregon. Two, to perform local and global sensitivity analysis on the Fuzzy Inference System (FIS) of BRAT. And three, to prepare for future community data collection to enable model validation and restoration planning.

1.2 Literature Review

This review of the literature will briefly summarize beaver-assisted restoration, provide an overview of beaver dam modeling and FIS, discuss the current state of BRAT and knowledge gaps, and mention opportunities for community science.

1.2.1 Beavers for Restoration

The North American beaver (*Castor canadensis*) is well known as an ecosystem engineer and a keystone species. There is growing excitement about the ability of beavers, specifically beaver dams or dam analogs, to restore riparian ecosystems [1]. Beaver dams can slow stream flow, promote water storage, trap sediment, create streamside pools, and increase riparian vegetation diversity, among other restorative effects on incised or damaged stream ecosystems [2], [3]. These positive impacts extend to climate resiliency, particularly against drought and wildfire [4], [5]. However, beaver reintroduction should be done with special attention given to the specific region and possible tradeoffs [6].

The Siletz River Basin in coastal Oregon is, like many other water systems in the West, beginning to experience low summer flows, drought risk, and higher temperatures due to climate change. Anecdotally, nearby logging and deforestation has also increased river sediment content. These trends are concerning for water quality and the river's ability to support vegetation, fish populations, and other species. In Oregon, climate change is expected to negatively impact fish populations, particularly coho salmon [7]. It is suggested that river management should continue to focus on resiliency for both fish populations and their habitats. As stated, beaver dams are one such method to help restore drought resilience and riparian ecosystems.

In Oregon, beavers were nearly extirpated following European settler-colonialism and the fur trade. In the last century, beaver populations are known to have recovered somewhat, thanks to shifting policies. Oregon recently changed beavers' legal classification from a pest to a furbearer, essentially meaning they cannot be killed at will by landowners [8]. However, there is no proper census or mapping of beaver in the state currently. A recent landscape genetics study found that coastal beavers are dispersing within watersheds, without significant limitation by stream slope or distance to water [9]. The observed gene flow suggests that populations are doing well and that translocation within the same watershed may be most effective.

Beaver-assisted restoration (BAR) projects have greatly increased in popularity in the last 10-15 years, particularly in the American West. Beaver translocation is the most common method, in which beavers are moved into the area of focus. The use of beaver dam analogs has also increased. However, many of these BAR projects lack post-implementation monitoring, making it difficult to assess their success or failure. Translocation can be problematic in terms of beaver migration, dam destruction, or beaver-human conflict [10]. Predation can also significantly diminish translocated beaver populations, complicating restoration efforts [11]. Criticisms of current beaver restoration practices suggest that translocating beavers becomes harmful if their relationship with land and people is neglected. Unrealistic expectations of beaver can set them up for failure or result in conflicts with other management or human activity. Also emphasized is the importance of incorporating Native peoples and practices in relation to beaver and river stewardship [12]. Thus, the importance of careful modeling and planning, community-based partnerships, and post-implementation monitoring are made clear.

1.2.2 Beaver Dam Modeling

To help inform thoughtful beaver-assisted restoration, various beaver dam models have been developed. Early models were Habitat Suitability Indices (HSI), which consider both intrinsic (e.g. stream characteristics) and extrinsic (e.g. vegetation) factors to model the suitability of reaches for damming. One of the first was Allen's 1983 HSI model, which identified suitabilities based on a number of variables including stream gradient, canopy cover, and other vegetative characteristics [13]. Development and analysis of additional HSIs continued, with results generally showing regional success but limitations in applying to other regions or predicting future conditions [14].

One such HSI model was developed in 1998 by McComb and Suzuki for beaver dam sites on the Oregon Coast. Their model focused on 3 geomorphic attributes: stream width, stream gradient, and valley floor width. They also found that vegetative features of high grass, low red alder (*Alnus rubra*), and high shrub cover correlated with dam sites. The model is generally considered effective for the Oregon Coast, but later work has noted that it doesn't account for certain factors such as pool size and depth, which beavers rely on for cover and food [15].

A primary limitation of HSI models is that they focus on current dam locations rather than intrinsic, future potential for dams. A more recent modeling effort by Dittbrenner et al. took this intrinsic potential approach by focusing on geomorphic variables while ignoring vegetation. Their Beaver Intrinsic Potential (BIP) model utilizes stream width, stream gradient, and valley width, which were identified as the most common variables among dam capacity models to date [16]. The model categorizes stream segments by their intrinsic ability to support beaver dams, with the expectation that vegetation may change over time or be restored prior to the addition of beavers. The model was validated as accurate in the Washington study area.

Most recently, some models have been developed employing machine learning. Fairfax et al. created EEAGER, a neural network approach that identifies beaver dams from aerial imagery [17]. Matechuk developed a random forest model to predict beaver habitat suitability, selecting six input variables inspired by previous models such as BRAT. Notably, slope and proximity to hydrologic features were found to be the most influential of the six variables.

1.2.3 BRAT Overview

The Beaver Restoration Assessment Tool (BRAT) is a general dam capacity model first published in 2017 by Macfarlane et al. of Utah State University's Ecogeomorphology & Topographic Analysis Laboratory lab [18] and has been used in a number of studies and projects since. BRAT was designed to be computational and open-source, broadly applicable, and restoration-focused by predicting dam capacity rather than current dam sites. Thus, the model seeks to address the shortcomings of traditional HSIs. BRAT relies on several major criteria for dam building: a reliable water source, suitable vegetation streamside (30m buffer) and within riparian foraging distance (100m buffer), likelihood that channel-spanning dams could be built during low flows, likelihood that a beaver dam will withstand floods, a suitable stream gradient, and small enough stream width. This criteria was based on existing beaver literature and calibrated using Utah streams. Publicly-available datasets were used (e.g. LANDFIRE vegetation rasters, USGS Hydrography layers), though other input sources may also be used. Notably, the model is not a hydrologic model, but instead estimates parameters using regional equations.

The model first combines vegetation suitabilities for both buffers using a Fuzzy Inference System (FIS), outputting an intermediate dam capacity based solely on vegetation. This output is then run through a combined FIS, which limits capacity by baseflow, peak flow, and stream gradient with membership functions based on Utah streams. The model outputs dam density, measured in dams/km, categorized as either None, Rare, Occasional, Frequent, or Pervasive. The model was validated on four distinct Utah watersheds and performed well. While the researchers recognize that higher-resolution inputs or more computationally-intensive models may improve accuracy, they were pleased with the model's performance given its efficiency and use of public data.

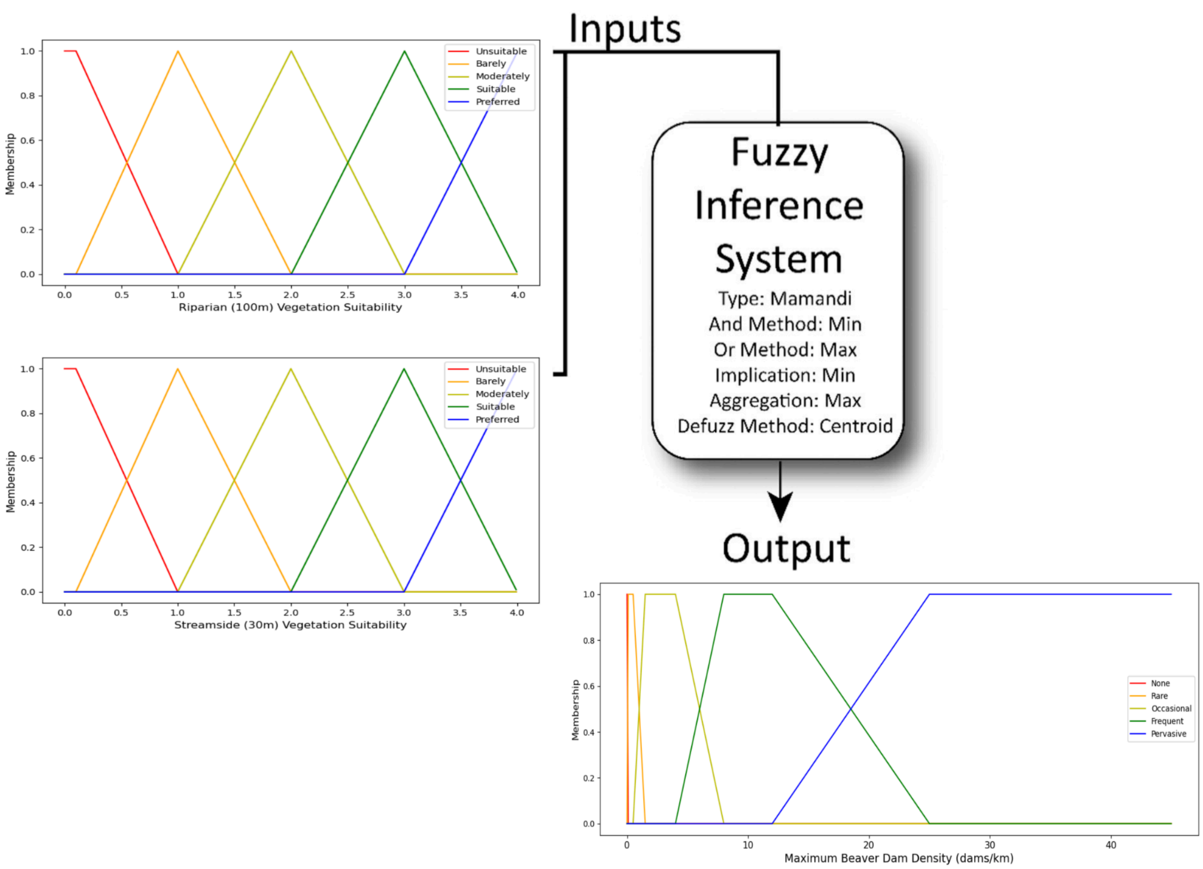


Figure 1. BRAT's Vegetation Fuzzy Inference System. Step 1/2 in the model. [18].

Table 1. BRAT's Vegetation FIS Rule Table. [18].

		100m Riparian Suitability				
		Unsuitable	Barely	Moderately	Suitable	Preferred
30m Streamside Suitability	Unsuitable	None	Rare	Rare	Occasional	Occasional
	Barely	Rare	Rare	Occasional	Occasional	***Occasional***
	Moderately	Rare	Occasional	Occasional	Frequent	***Frequent***
	Suitable	Occasional	Occasional	Frequent	Frequent	Pervasive
	Preferred	Occasional	***Frequent***	***Pervasive***	Pervasive	Pervasive

Colored cells describe the fuzzy (categorical) output of Vegetation FIS (oVC).
Bold italic cells designate asymmetric input combination pairs.

Of note is the fact that this rule table is not symmetric. It is more harshly limited by poor vegetation suitability in the 30m buffer, while being more lenient on poor vegetation suitability in the larger 100m buffer.

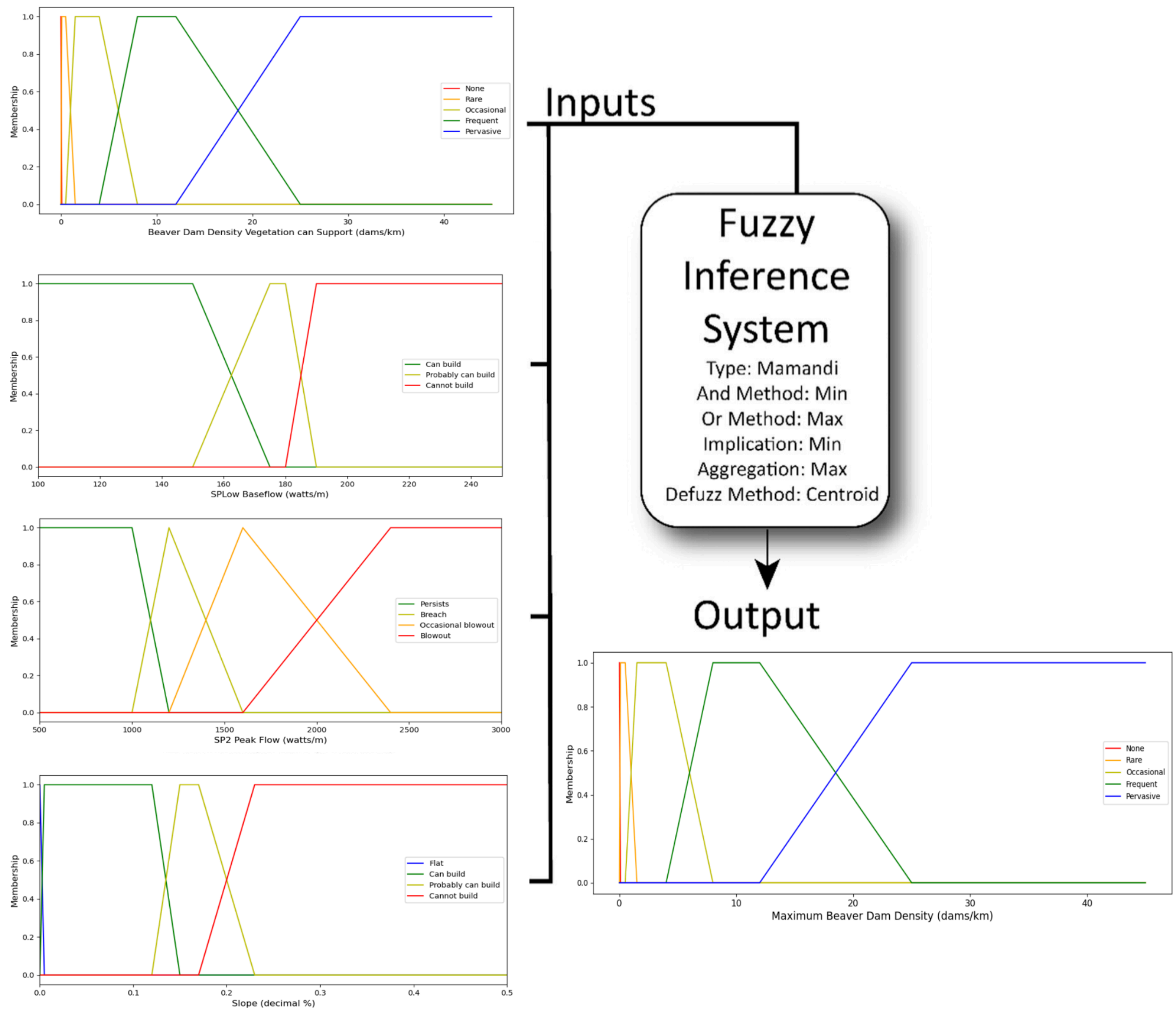


Figure 2. BRAT's Combined Fuzzy Inference System. Step 2/2 in the model. The rule table for this FIS is not shown here due to size, but can be found in the original paper [18].

<u>1.2.4 Fuzzy Inference Systems</u>

Fuzzy inference systems like the one used in BRAT are based on Zadeh's seminal work on Fuzzy Sets [19], and were later formalized by Mamdani and Zadeh [20], [21]. BRAT uses this Mamdani FIS (as opposed to a Sugeno FIS, an alternative system). They enable a crisp input (e.g. vegetation suitability score) to have varying degrees of membership in output categories (e.g. 20% suitable, 80% moderately suitable). Expert-based rule systems can then be employed to generate fuzzy outputs, which can be defuzzified back into a crisp output. FIS performs well on data with uncertainty and has been used for modeling in various fields [22], [23], [24], [25], [26]. However, sensitivity analysis can be used to further verify model robustness, particularly in the absence of validation data. One type of sensitivity analysis involves changing the parameters of the FIS itself, namely shifting, scaling, or changing the shape of the membership functions (MFs) [22]. While triangular and trapezoidal MFs are common, sigmoidal, pi, or gaussian curves can also be used [23]. In ANFIS models, which combine neural networks with FIS, bell curves have been found to be highly accurate [27], [28]. Model output distributions for the different changes can be compared to gain insight into the robustness of the system and what elements are most influential.

1.2.5 BRAT Usage

A number of papers have investigated BRAT and used it in different ways. One such theme is using BRAT as a temporal or predictive model. Scamardo et al. compared BRAT's existing and historic capacity outputs to draw conclusions about how beaver dam capacity has declined over time in Colorado [29]. Similarly, Stoll examined the existing vs. historic capacity in Canada [30]. Stoll also scaled the hydrologic parameters (Q2) to investigate dam capacity under simulated flooding.

Using inputs other than the original datasets has also been explored. Kornse and Wohl explored higher-resolution vegetation inputs, specifically using the 2017 National Agriculture Imagery Program (NAIP) [31]. They tested NAIP data processed with both pixel-based and image-based supervised classification. The study found that pixel-based NAIP was more accurate than LANDFIRE, though object-based NAIP best matched field observations. BRAT capacity outputs were found to be highly sensitive to the vegetation input. Scamardo and Wohl highlighted how LANDFIRE's low resolution can lead to certain inaccuracies, suggesting that

BRAT be used in tandem with expert site scoring [32]. Freeman's 2024 analysis of BRAT in British Columbia agreed that BRAT relies heavily on vegetation, but found that BRAT performed decently well on vegetation suitability prediction, at least compared to hydrologic characteristics [33]. Interestingly, Stoll concluded that a finer vegetation raster had minimal impact on BRAT outputs [30]. Clearly, more interrogation is needed about the sensitivity of BRAT to vegetation inputs and suitability ratings.

Field validation is common after applying BRAT to a new area. This is usually done by comparing field observations of sites to their modeled capacity. However, satellite imagery has also been used to record dams. While most validation results are promising [18], [33], it is also common that observed beaver capacity is much lower than modeled capacity [15], [16]— a common trend possibly explained by factors ignored in the model (such as predation, preference for pools, or low population due to continued human extirpation). This is somewhat expected since BRAT only predicts future capacity, but nonetheless reinforces the importance of regional validation and investigation of other factors.

BRAT can be fine-tuned to the area of study. Although BRAT is meant to perform as a general model, it is clear that fine-tuning and validating can be highly beneficial. For example, Suplick applied BRAT to a California watershed, fine-tuning the vegetation suitability and slope gradient cutoffs, and combined model outputs with extensive interviews and field validation to make recommendations for beaver-assisted restoration [34]. The BRAT model architecture was also replicated in Great Britain and showed strong success in predicting dam capacity after being calibrated to regional data [35]. BRAT has also been used to inform the placement of beaver dam analogs, since they have similar requirements to real dams [36].

Currently, the original “pyBRAT” model (which relies on legacy ArcGIS 10.x) has been superseded by “sqlBRAT,” which is open-source but contains the same core model. sqlBRAT is integrated with the Riverscapes Consortium’s suite of tools and has been automated to run in the cloud [37]. sqlBRAT has already been run on a majority of the continental US, including the Siletz River Basin [38]. While this wealth of publicly available BRAT outputs should prove valuable to restoration projects and river managers, it is still important to interrogate, fine-tune, and validate model outputs before making restoration recommendations. While the original model was carefully designed, calibrated, and validated, this was done in Utah. Additional sensitivity analysis of the model’s parameters and FIS assumptions is needed. While Stoll found that BRAT was sensitive to Q2 but not Qlow in their area of study [30], more complete sensitivity analysis of parameters as well as different criteria (e.g. importance of vegetation vs hydrology) should be explored. Furthermore, to our knowledge, tweaking the fuzzy logic at the core of the model has not been explored either.

1.2.6 Community Data for Validation

Gathering field data to validate BRAT outputs in the Siletz watershed would greatly increase confidence in the model’s outputs for this region. While model validation is usually done using field data gathered by the researchers, this is an excellent opportunity to engage the community and incorporate local and Native knowledge of the region into our evaluation of model outputs.

The use of community-based data collection for ecology has been on the rise, noted for its large scale and mutual benefits [39]. It has even been employed for beaver tracking. In Hungary, the BeaverMap survey app has already provided valuable data for mapping the distribution of Hungarian beaver, creating beaver-maintained wetlands, and solving human-beaver conflicts [39]. In Finland, community field data collection has been used for years to track the long-term distribution of two different species of beaver [40]. It is clear that community-based field data can be an effective strategy for tracking beaver and beaver dams.

To our knowledge, community field validation has not been used in the BRAT context, nor in the Siletz river basin. This gap in the literature presents an exciting opportunity to involve the community, particularly Native Siletz members, in planning beaver-assisted restoration projects to improve watershed resiliency.

1.2.7 Summary

There is a growing literature on modeling for beaver-assisted restoration. The potential of this technique to improve riparian ecosystem health is well established. Nonetheless, restoration projects — particularly translocation — must be done with careful planning, community involvement, and post-implementation monitoring. Beaver dam capacity models such as BRAT prove a useful tool to screen watersheds for optimal damming sites. In order to increase confidence in model outputs, additional sensitivity analysis and output interrogation is needed. Model validation is also an essential step, and community-based data collection offers a novel and exciting method to gather validation data. Evaluating the practicality and robustness of dam capacity models like BRAT is needed and will help build the foundation for eventual restoration.

1.3 Area of Study

Our area of focus was the Siletz River Basin. The boundary contains four different 10-digit Hydrologic Unit Codes (HUCs): Lower Siletz River, Middle Siletz River, Upper Siletz River, and Rock Creek (1710020407, 1710020405, 1710020404, and 1710020406, respectively) (Figure 3). All four regions combined were used for data analysis. The Lower Siletz Region was used for the one at a time (OAT) FIS Sensitivity Analysis. Part of the Lower Siletz River HUC extends outside of the Siletz watershed boundary; this region was clipped out for mapping purposes but retained for all analysis.

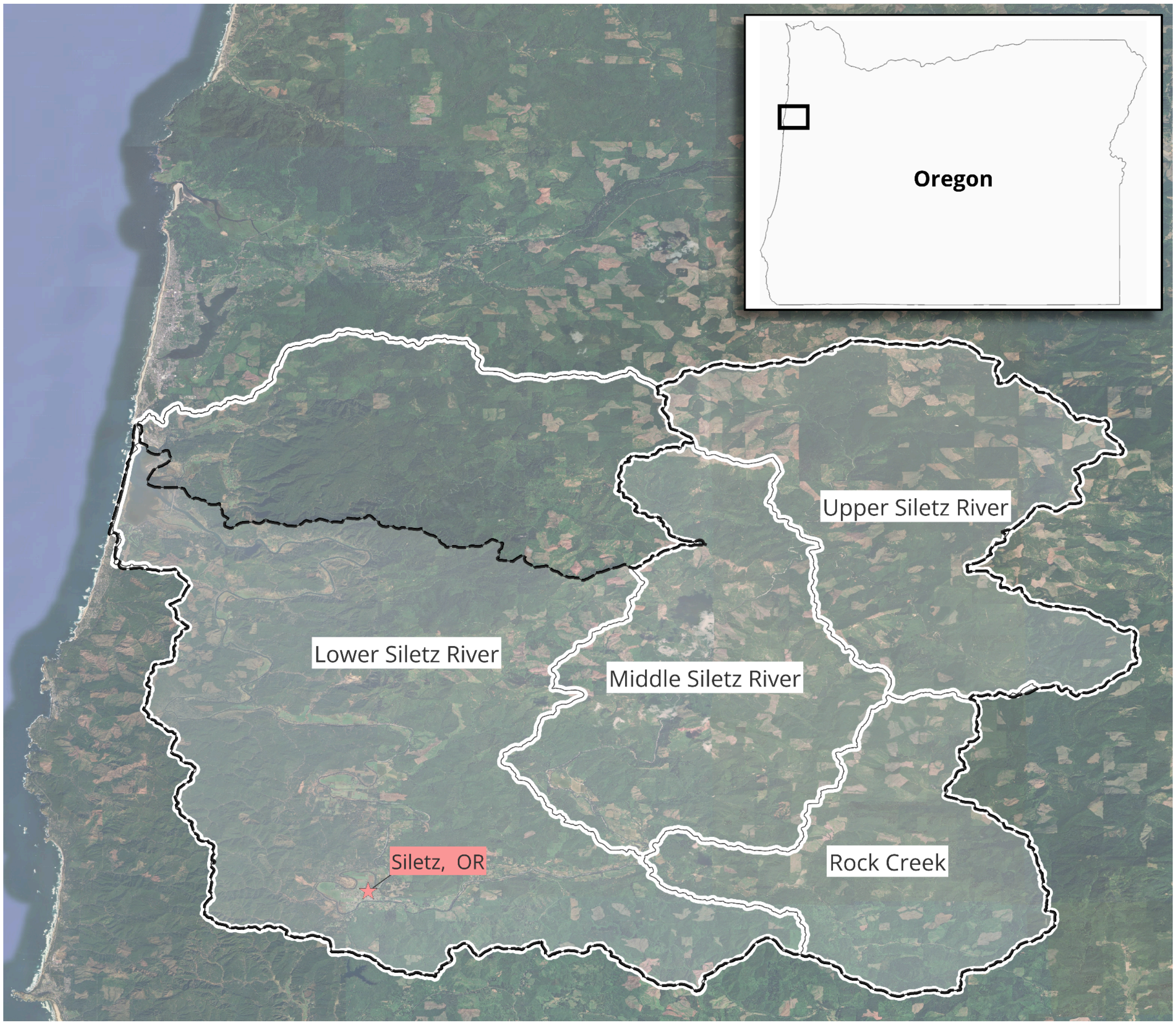


Figure 3. The Siletz Watershed and its Four HUCs. Black dashed line designates the Siletz watershed boundary. White lines designate each 10-digit HUC.

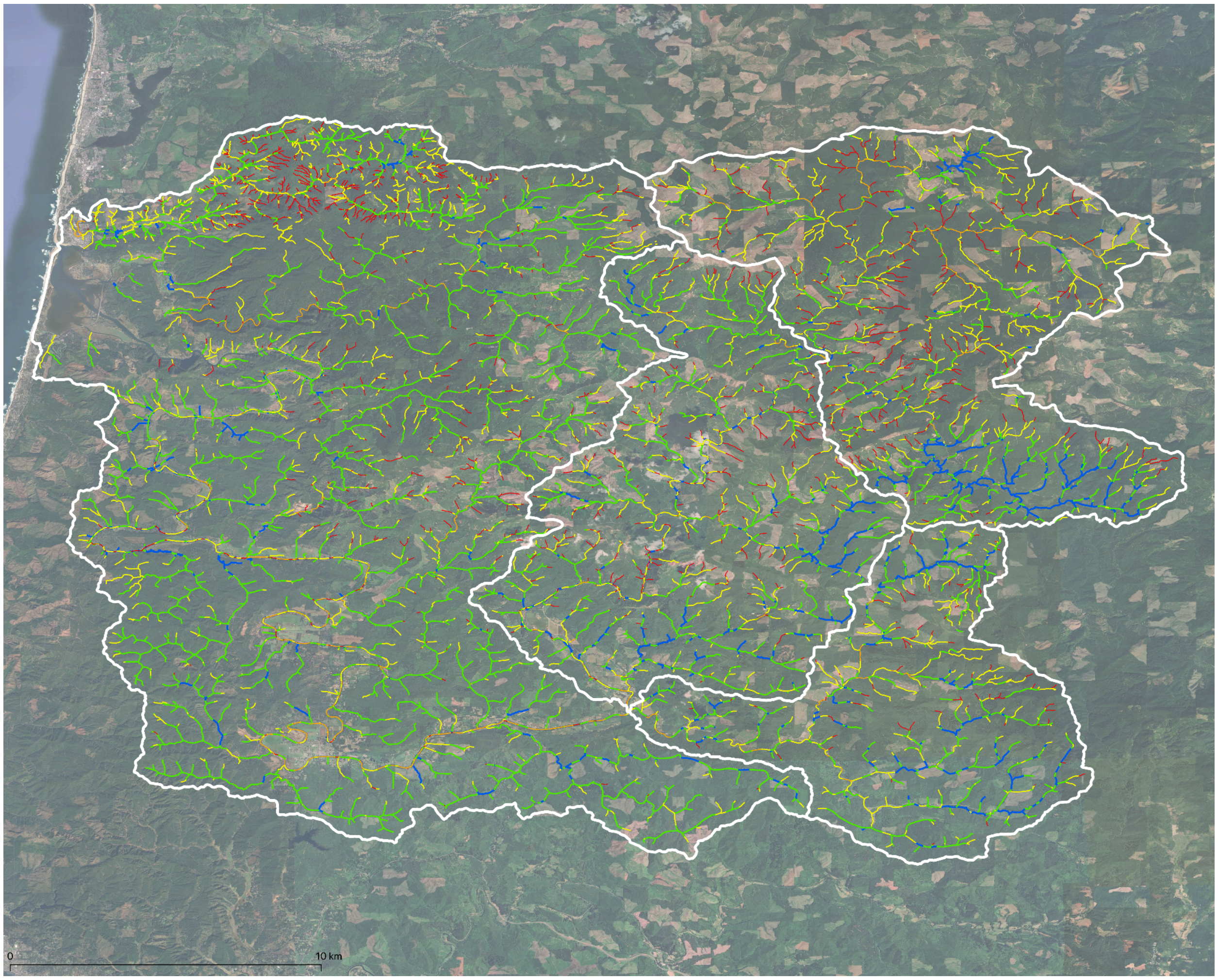


Figure 4. BRAT Outputs for the four HUC10s in the Siletz Watershed.

The latest BRAT outputs can be obtained from the Riverscapes Data Exchange [41], where the BRAT model is automatically run on HUCs across the continental United States.

1.4 Terminology

Many variable names and other shorthands are used for convenience through the rest of this report. A few are summarized below for reference.

Table 1. Explanation of Commonly Used BRAT Terms and Variable Names.

Term	Meaning
iVeg100EX	Existing vegetation suitability in the stream segment's 100m riparian buffer.
iVeg_30EX	Existing vegetation suitability in the stream segment's 30m streamside buffer.
iHyd_SPLow	Baseflow stream power (watts/m) of the segment
iHyd_SP2	Peak flow stream power (watts/m) of the segment. Derived from 2-year flood Q2.
iGeo_Slope	Slope of the stream segment. Generally in decimal % form.
oVC_EX	Existing maximum dam capacity (dams/km) based solely on vegetation. Output of the Vegetation FIS.
oCC_EX	Existing maximum dam capacity (dams/km) based on all factors (vegetation and hydrology). Output of the Combined FIS and the primary model output.

2. Methodology

2.1 BRAT Setup & Installation

The open-source code for Riverscapes Tools was forked on GitHub. sqlBRAT version 5.1.5 was installed and set up locally on both an M2 MacBook Air and a Dell PC laptop. A few minor tweaks were made to the code to fix bugs encountered when running the tools locally. Complete installation documentation can be found in the Appendix.

Riverscapes Tools follow a “waterfall” model, where the outputs of lower-level tools are used as inputs into higher-level tools. sqlBRAT uses outputs from RSContext, Hydrologic Context, Anthro, and Valley Bottom tools. The most recent runs of these tools were downloaded from the Riverscapes Data Exchange and used as inputs when running BRAT locally. The BRAT run for Lower Siletz River, using the same inputs as the public run, was reproduced locally to verify proper setup.

Note that sqlBRAT received changes and the public data was updated during the timeline of this project. The capacity in the Siletz regions did worsen on average in the newest data. The latest runs from July 2025 were used in Standard Output Analysis. However, version 5.1.5 of the model was still used in the OAT FIS Sensitivity Analysis.

2.2 Standard Output Analysis

For the standard outputs, publicly available BRAT data for the four HUCs of interest was downloaded from the Riverscapes Consortium Data Exchange portal. Each BRAT project stores data in an SQLite database (brat.gpkg) but also produces a report summarizing the outputs (brat.html). The results of the four BRAT projects of interest were also manually aggregated into a single database. The combined data was visualized using custom python scripts.

2.3 FIS Sensitivity Analysis

Sensitivity Analysis (SA) was performed on BRAT's Fuzzy Inference System (FIS) by tweaking antecedent (input) membership functions. Three types of adjustments were used: shifting the MFs left or right, scaling (stretching or compressing) the MFs, and changing the MF shape. The consequent (output) membership functions were not adjusted.

One at a Time (OAT) method was used for local sensitivity analysis, providing exploratory results. Monte Carlo method was used for global sensitivity analysis.

2.3.1 One at a Time

The Lower Siletz watershed was used for FIS runs since it has the most number of reaches. A number of "one at a time" adjustments were planned using both manually selected values and according to the following formulas. Table 1 shows a reference to the scipy membership functions and Table 2 explains the adjustment formulas used.

Table 2. Relevant Scikit-Fuzzy Membership Functions.

Membership Function	Equation	Scikit-Fuzzy Command
Trapezoidal	Vertices left-to-right: a,b,c,d	`trapmf(x, [a, b, c, d])`
Triangular	Vertices left-to-right: a,b,c	`trimf(x, [a, b, c])`
Generalized Bell Curve	$f(x) = 1 / (1 + \|(x\text{-}c) / a\|^{2b})$ a = width b = slope c = center	`gbellmf(x, a, b, c)`
Gaussian	$f(x) = e^{((x - mu)2) / (sigma)2}$	`gaussmf(x, mu, sigma)`
Pi (spline-based)	Vertices left-to-right: a,b,c,d $f(x;a,b,c,d) = \begin{cases} 0, & x \le a \\ 2\left(\frac{x-a}{b-a}\right)^2, & a \le x \le \frac{a+b}{2} \\ 1-2\left(\frac{x-b}{b-a}\right)^2, & \frac{a+b}{2} \le x \le b \\ 1, & b \le x \le c \\ 1-2\left(\frac{x-c}{d-c}\right)^2, & c \le x \le \frac{c+d}{2} \\ 2\left(\frac{x-d}{d-c}\right)^2, & \frac{c+d}{2} \le x \le d \\ 0, & x \ge d \end{cases}$	`pimf(x, a, b, c, d)`

Source: [42]

Table 3. MF Adjustment Formulas Used in OAT Adjustments

Adjustment	Formula
Shift	Shift = 10% of first MF crossover*
Scale	Static scale factors (x0.75 and x1.5), since scaling is inherently dynamic.
Shape — "Best Fit" (Gaussian)	Mean = triangle peak = b Standard Deviation = ¼ base width
Shape — "Best Fit" (Pi)	a = triangle left foot (a) b = triangle peak (b) c = triangle peak (b) d = triangle right foot (c)

* "Flat" category MF is exempted from shift due to near-zero values. "Can" and "Probably" cross is used instead.

Shape adjustments require the most intervention. Two types of adjustments were designed. "Best fit" utilized pi functions to closely match trapezoids and asymmetric triangles. "Loose fit" was created by hand and visual inspection, using more unwieldy bell functions. See Figure 7 for visualization and Table 5 for full specifications.

Each individual adjustment run is described in Table 4. Additionally, there were some adjustments manually selected not according to a formulaic approach. BRAT was run on Lower Siletz for each adjustment independently. Following the runs, a script was written to aggregate the results of each adjustment into a single database and calculate relevant statistics.

Table 4. OAT Adjustments Applied to BRAT's Fuzzy Inference System.

Type of Adjustment	Input MFs Adjusted	Adjustment	Label	#
None	None	None	Standard	0
Shift (except min & max bounds)	Combined FIS: Baseflow (SPlow)	–16.25 watts	SPL-16.25	1
		–10 watts*	SPL-10	2
		+10 watts*	SPL+10	3
		+16.25 watts	SPL+16.25	4
	Combined FIS: Peak flow (SP2)	–110 watts	SP2-110	5
		–50 watts*	SP2-50	6
		+50 watts*	SP2+50	7
		+110 watts	SP2+110	8
	Combined FIS: Slope**	–0.0135 (–1.35% slope)	SLO-1.35	9
		–0.01 (–1% slope)	SLO-1	10
		+0.01 (+1% slope)	SLO+1	11
		+0.0135 (+1.35% slope)	SLO+1.35	12
Scale	Vegetation FIS: Both inputs	Scale factor = 0.75 (y≅0.33 MF intersect)	VEGx0.75	13
		Scale factor = 1.5 (y≅0.67 MF intersect)	VEGx1.5	14
	Combined FIS: SPlow, SP2, & Slope	Scale factor = 0.75 (y≅0.33 MF intersect)	HYDx0.75	15
		Scale factor = 1.5 (y≅0.67 MF intersect)	HYDx1.5	16
	Both FIS (Vegetation & Combined)	Scale factor = 0.75 (y≅0.33 MF intersect)	BOTHx0.75	17
		Scale factor = 1.5 (y≅0.67 MF intersect)	BOTHx1.5	18

Shape	Vegetation FIS	Pi & Gaussian (best fit)	VEGcv1	19
		Bell & Gaussian (loose fit)*	VEGcv2	20
	Combined FIS: SPlow, SP2, & Slope	Pi & Gaussian (best fit)	HYDcv1	21
		Bell & Gaussian (loose fit)*	HYDcv2	22
	Vegetation and Combined FIS	Pi & Gaussian (best fit)	BOTHcv1	23
		Bell & Gaussian (loose fit)*	BOTHcv2	24

* Non-formulaic adjustment (manually chosen)
** “Flat” category MF & left edge of “Can” MF are not shifted due to their near-zero values.

Visualization of membership functions under certain adjustments are shown below (Figures 5-7).

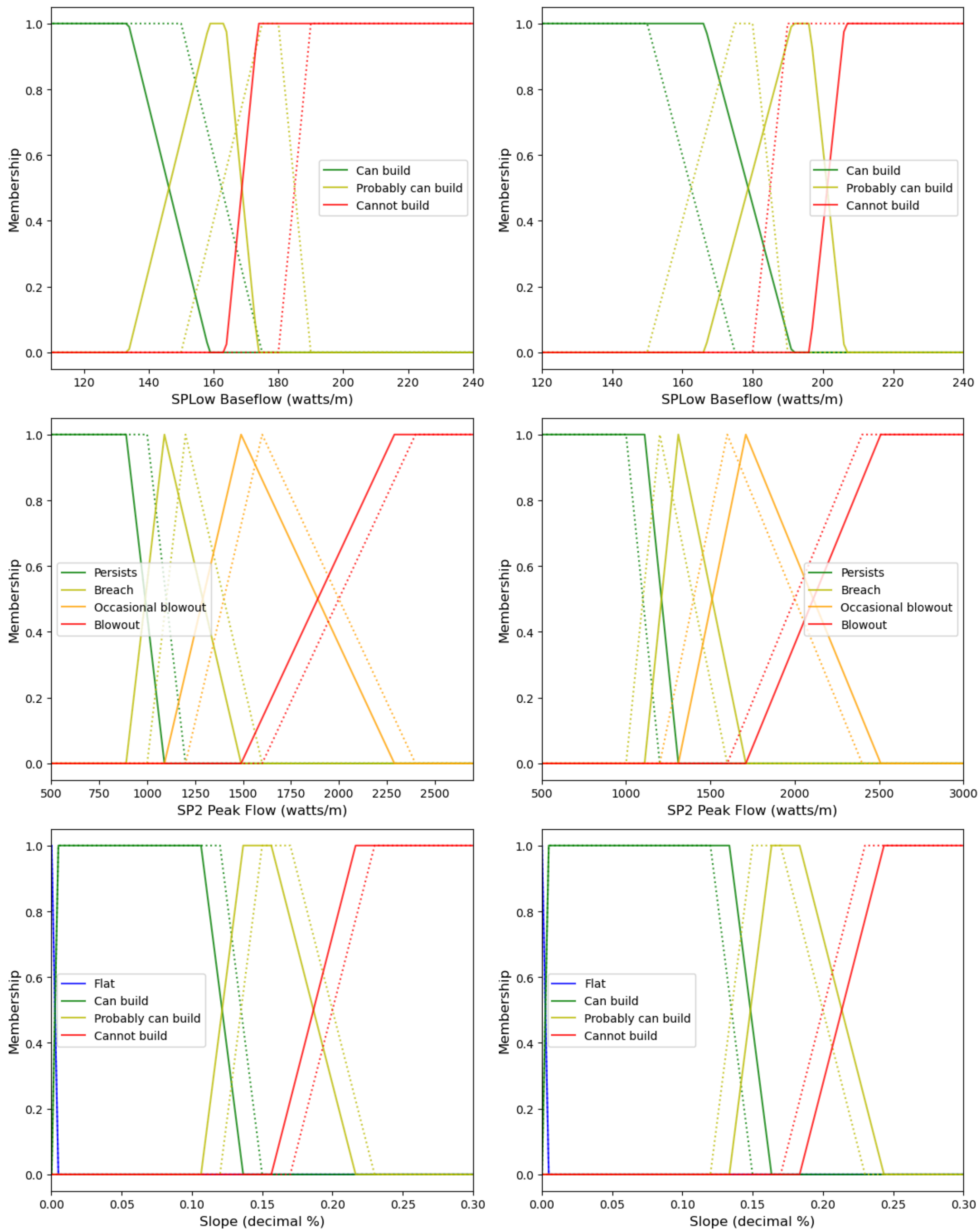


Figure 5. Shift Adjustments. Dotted lines are standard MFs. Solid lines are MFs under the larger, formulaic shifts: adjustments 1, 4, 5, 8, 9, and 12.

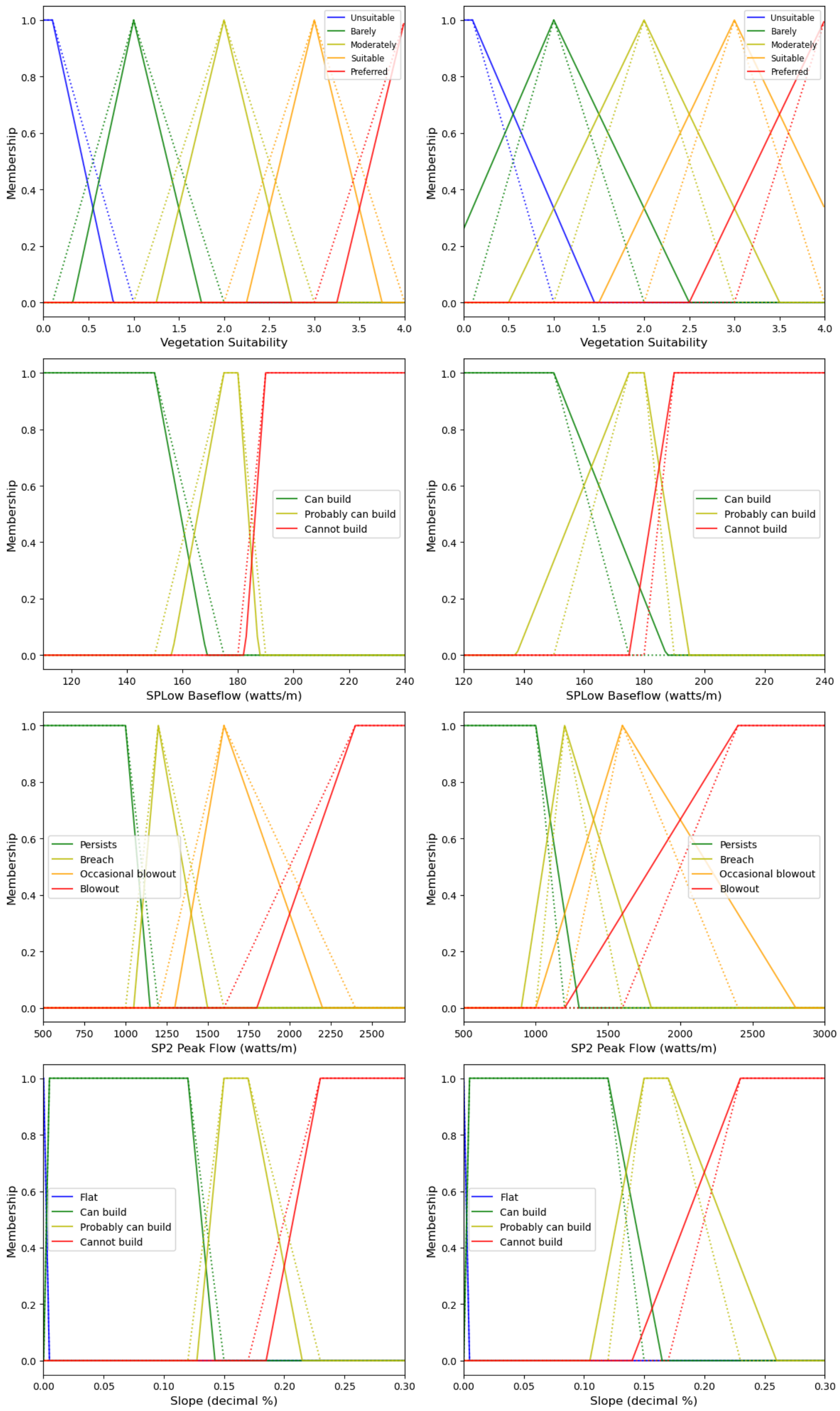


Figure 6. Scale Adjustments. Dotted lines are standard MFs. Solid lines are MFs under compression (x0.75; left side) and stretching (x1.5; right side).

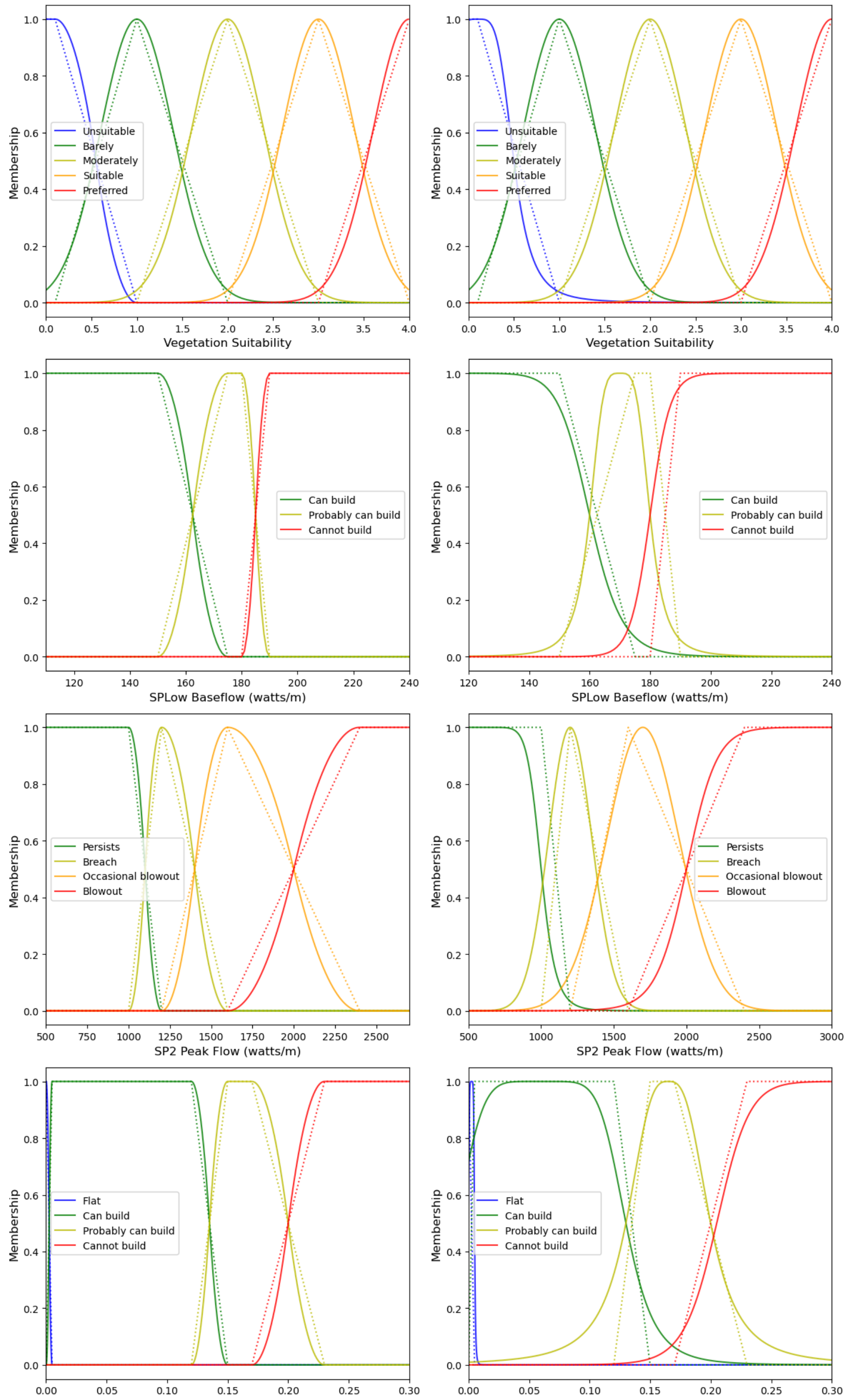


Figure 7. Shape Adjustments. Dotted lines are standard MFs. Solid lines are MFs using the "best fit" curves (left side) and "loose fit" curves (right side).

Table 5. Membership Function Specifications for Shape Adjustments.

Input*	Category	Standard MF	"Best Fit" Curved MF	"Loose Fit" Curved MF
Riparian & Streamside (same)	Unsuitable	trapmf: 0, 0, 0.1, 1	pimf: -0.01, 0, 0.1, 1	gbellmf: 0.4, 2, 0.1
	Barely	trimf: 0.1, 1, 2	gaussmf: 1, 0.4	gaussmf: 1, 0.4
	Moderately	trimf: 1, 2, 3	gaussmf: 2, 0.4	gaussmf: 2, 0.4
	Suitable	trimf: 2, 3, 4	gaussmf: 3, 0.4	gaussmf: 3, 0.4
	Preferred	trimf: 3, 4, 4	gaussmf: 4, 0.4	gaussmf: 4, 0.4
SPlow	Can	trapmf: 0, 0, 150, 175	pimf: -0.01, 0, 150, 175	gbellmf: 85, 8, 75
	Probably	trapmf: 150, 175, 180, 190	pimf: 150, 175, 180, 190	gbellmf: 10, 2, 170
	Cannot	trapmf: 180, 190, 10000, 10000	pimf: 180, 190, 10000, 10000.1	gbellmf: 4910, 750, 5090
SP2	Persists	trapmf: 0, 0, 1000, 1200	pimf: -0.01, 0, 1000, 1200	gbellmf: 500, 5, 500
	Breach	trimf: 1000, 1200, 1600	pimf: 1000, 1200, 1200, 1600	gaussmf: 1200, 150
	OccBlowout	trimf: 1200, 1600, 2400	pimf: 1200, 1600, 1600, 2400	gaussmf: 1700, 250
	Blowout	trapmf: 1600, 2400, 10000,10000	pimf: 1600, 2400, 10000, 10000.1	gbellmf: 4200, 20, 6200
Slope	Flat	trapmf: 0, 0, .0002, .005	pimf: -0.01, 0, .0002, .005	gbellmf: 0.0025, 3, 0.0025
	Can	trapmf: .0002, .005, .12, .15	pimf: .0002, .005, .12, .15	gbellmf: 0.07, 3, 0.06
	Probably	trapmf: .12, .15, .17, .23	pimf: .12, .15, .17, .23	gbellmf: 0.035, 1.5, 0.165
	Cannot	trapmf: .17, .23, 1, 1	pimf: .17, .23, 1, 1.01	gbellmf: 0.38, 14, 0.585

* Dam density MFs (Veg density output; Comb density input and output) were not adjusted.

2.3.2 Monte Carlo Simulation

A Monte Carlo simulation was performed to get a better idea of how BRAT model outputs continuously change under adjustments. Specifically, shifting and scaling were selected for the simulation since they are continuous variables, while changing the shape was not simulated since it is discrete. Similar to the OAT runs, vegetation suitability was not shifted, and the oVC and oCC categories were not adjusted.

Rather than running BRAT on an entire HUC, a smaller synthetic input space was designed for computational efficiency reasons. Specifically, each of the 5 input variables (30m suitability, 100m suitability, baseflow, peak flow, and slope) were generated from statistical distributions and fed into the FIS in every simulation.

Two primary simulations were performed: one in which the inputs were generated from uniform distributions, and the other where they were generated from distributions representative of the actual reaches in the Siletz watershed.

Simulation 1 used uniform distributions. They were designed to cover the full breadth of an input's FIS membership functions. Right bounds were determined by the value at which an input gains full membership in the final category (Table 7). Although these distributions are not representative of the Siletz watershed, they provide a more even representation of all of the MF categories.

Table 6. Uniform Input Distributions for Generating a Synthetic Input Space.

Variable	Description	Distribution	Parameters (Bounds)
iVeg_30EX	Mean vegetation suitability in stream segment 30m buffer	Uniform	[0, 4]
iVeg100EX	Mean vegetation suitability in stream segment 100m buffer		[0, 4]
iHyd_SPlow	Baseflow (watts/m) of the stream segment		[0, 200]
iHyd_SP2	2-year peak flow (watts/m) of the stream segment		[0, 2400]
iGeo_Slope	Slope of the stream segment		[0, 0.23]

Simulation 2 used distributions sampled from Siletz watershed data. For each input variable, a histogram was generated from the data of all Siletz reaches. Data was preprocessed by filtering outliers using specified quantiles for SPlow, SP2, and Slope to improve histograms and distribution fitting (Table 6). Common distributions were fitted to the data with scipy's "fit" function, which uses maximum likelihood estimates for each distribution parameter. Only the three best distributions are shown, but more were tested and eliminated. The best distribution for each variable was manually selected based on visual inspection. Perfect fits are not the goal since many of the variables contain extremes.

Table 7. Sampled Input Distributions for Generating a Synthetic Input Space.

Variable	Description	Quantile	Distribution	Distribution Parameters
iVeg_30EX	Mean vegetation suitability in stream segment 30m buffer	1.00	Normal	Mu = 2.234 Sigma = 0.5708
iVeg100EX	Mean vegetation suitability in stream segment 100m buffer	1.00	Normal	Mu = 2.110 Sigma = 0.3793
iHyd_SPlow	Baseflow (watts/m) of the stream segment	0.995	Exponential	Location = 0.0 Lambda = 3.311
iHyd_SP2	2-year peak flow (watts/m) of the stream segment	0.95	Exponential	Location = 244.0 Lambda = 302.9
iGeo_Slope	Slope of the stream segment	0.995	Pareto	b (shape) = 2.375 Location = -0.3477 Scale = 0.3477

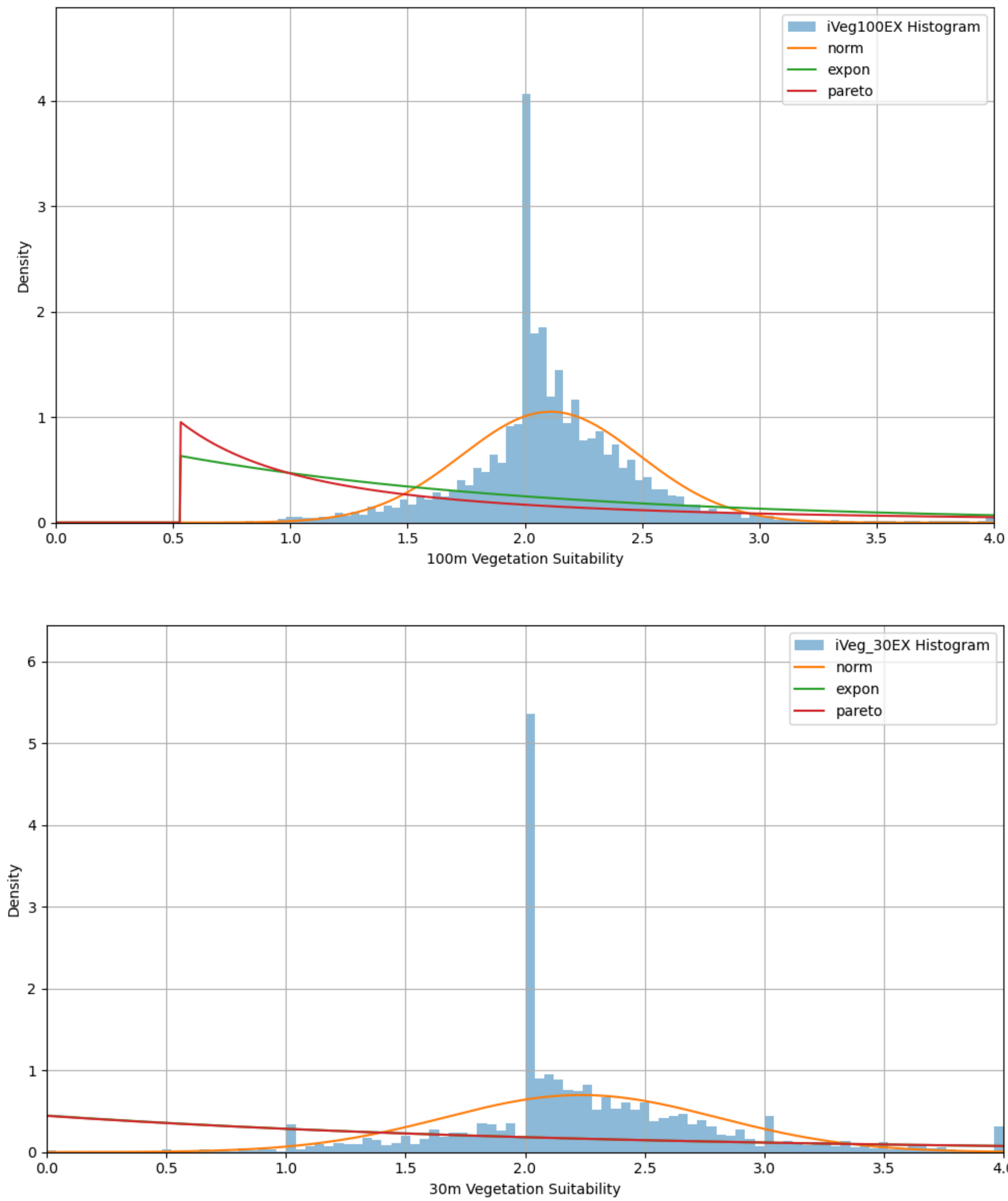


Figure 8. Fitted Siletz Input Distributions for Vegetation FIS Inputs. Generated using scipy's fit function on Siletz Watershed input data, with outliers filtered by quantile.

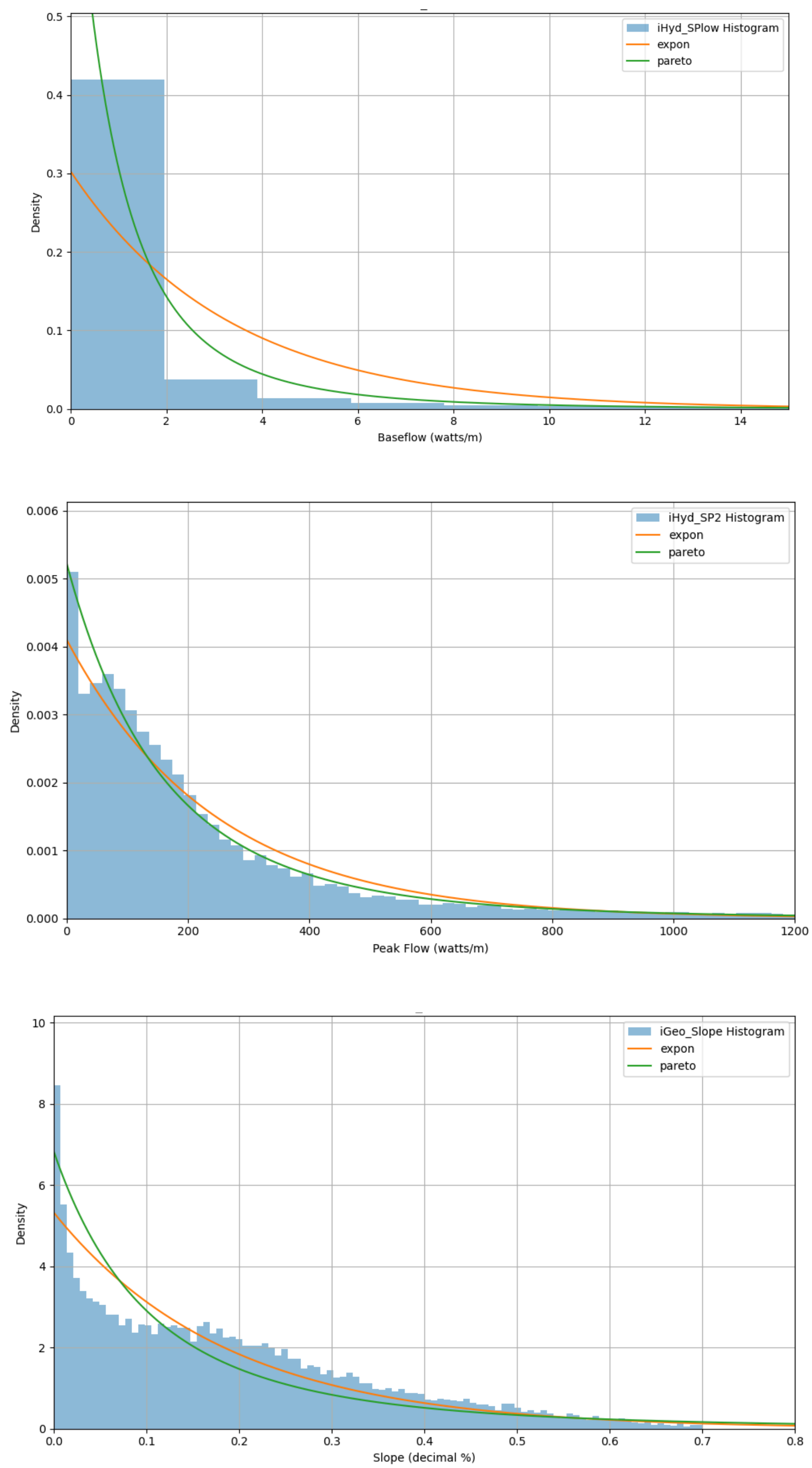


Figure 9. Fitted Siletz Input Distributions for Combined FIS Inputs (hydrology). Generated using scipy's fit function on Siletz Watershed input data, with outliers filtered by quantile.

After an input space was generated, BRAT's FIS was run on these inputs *n* times, each with a different set of FIS adjustments applied (Figure 11). Truncated normal distributions were used to generate adjustments in both simulations. The mean was set as the no-adjustment value (0.0 for shift, 1.0 for scale). For shifting, standard deviations were calculated as 10% of the final Membership Function crossover (after which an input has majority membership in the final category). For scaling, since scale factors are inherently dynamic, the standard deviation was chosen as 0.15 for all variables (Table 8, Figure 10).

Truncation was necessary to prevent extreme values (rare, but possible without truncation) that rendered the FIS non-functional. Bounds for shifts were selected such that MFs could not be shifted left past 0. Bounds for scale were chosen by visual inspection ensuring membership functions didn't become nonsensical.

Table 8. FIS Variables Adjusted in Each Monte Carlo Simulation.

Adjustment	Variable	Distribution	Mean	Standard Dev.	Distribution Bounds
Shift	SPLow (baseflow)	Truncated Normal	0	18.5	[-135, 135]
	SP2 (peak flow)		0	200	[-900, 900]
	Slope		0	0.02	[-0.10, 0.10]
Scale	100m suitability	Truncated Normal	1	0.15	[0.5, 1.5]
	30m suitability				
	SPLow (baseflow)				
	SP2 (peak flow)				
	Slope				

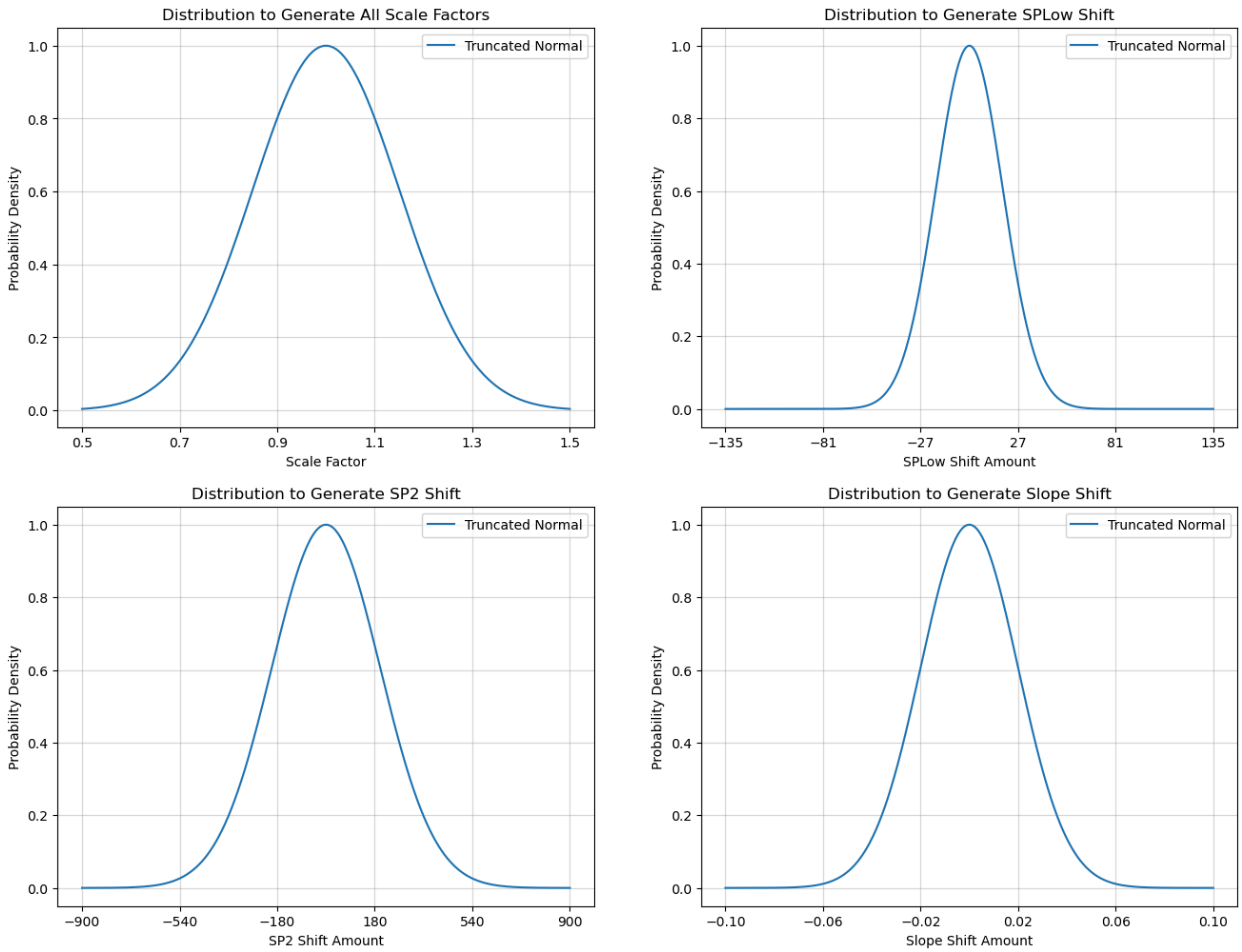


Figure 10. Distributions to Generate Adjustment Values for Each Simulation.

Two simulations were performed. Simulation 1 used n=250 *uniformly*-distributed inputs and was run n=1000 times. This covers "worst case" and "best case" values more evenly, though not explicitly. Simulation 2 used n=500 *Siletz*-distributed (normal, exponential, pareto) inputs and was also run n=1000 times. This simulation is relevant to the Siletz watershed, but less informative on hydrologic limiting factors, since it emphasizes "base case" input values that are likely in the Siletz watershed [43]. The results were recorded and statistics for both simulations calculated in an SQLite database. A diagram of Simulation 2 is shown below (Figure 11).

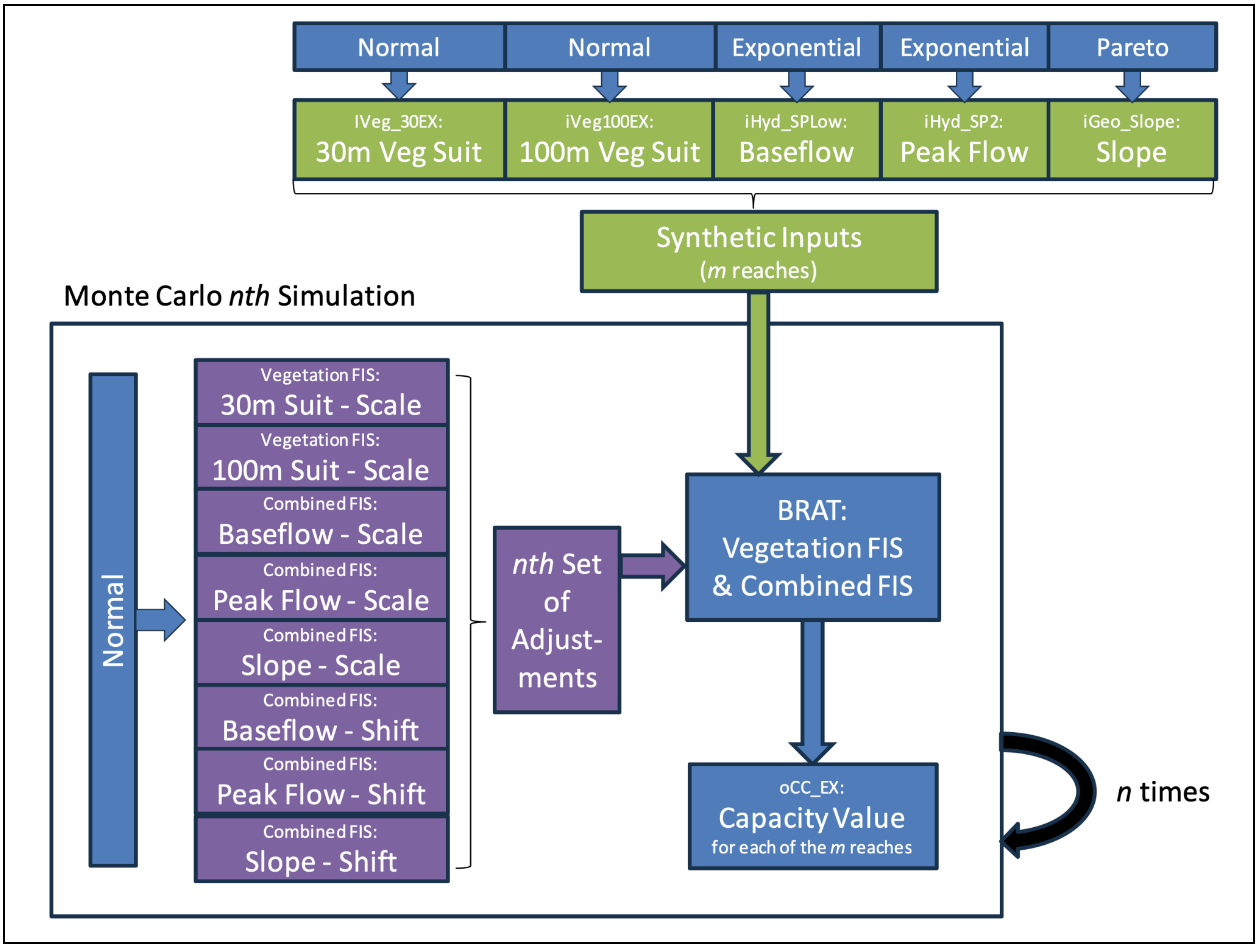


Figure 11. Design of BRAT Monte Carlo Simulation 2 (Siletz Inputs). Simulation 1 follows the same design, except uniform distributions were used to generate the synthetic inputs.

Table 9. Summary of Monte Carlo Simulation Methods

	Input Distributions	# Inputs	Adjustment Distributions	# Adjustments / Simulations
Simulation 1	Uniform	250	Truncated Normals	1000
Simulation 2	Siletz (normal, exponential, pareto)	500		

3. Results & Discussion

3.1 Standard Output Analysis

sqlBRAT generates an informative report for all its runs, accessible on the Riverscapes Data Exchange [41]. However, each run is at the HUC10 level. As discussed, we are interested in the whole Siletz Watershed, which includes four HUC10s. So, public BRAT results for all four HUCs were aggregated in a custom SQLite database and analyzed. Do note that the Lower Siletz region that falls outside the Siletz boundary was not clipped; all reaches of all four HUCs were included in this analysis.

3.1.1 Aggregated Input Histograms

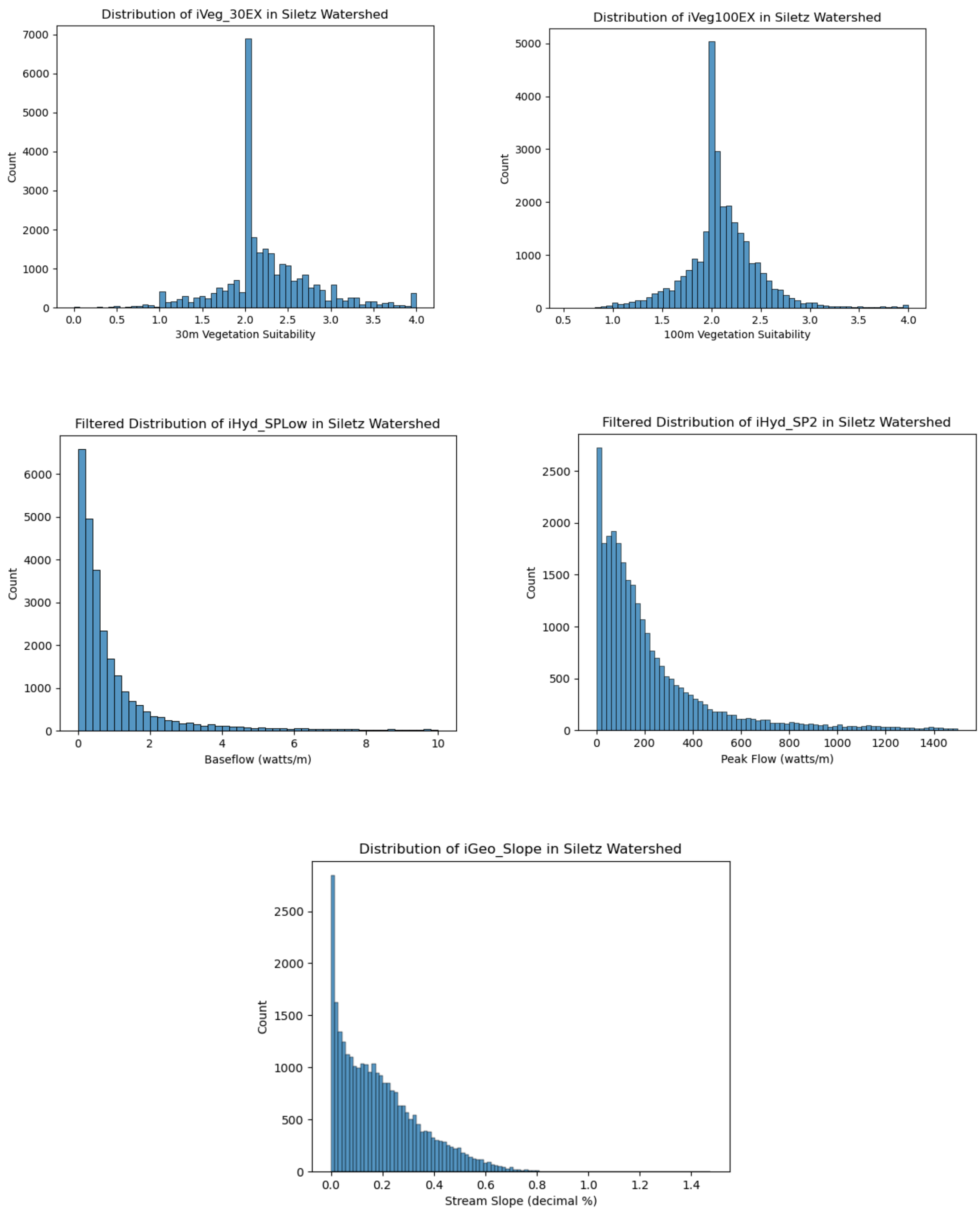


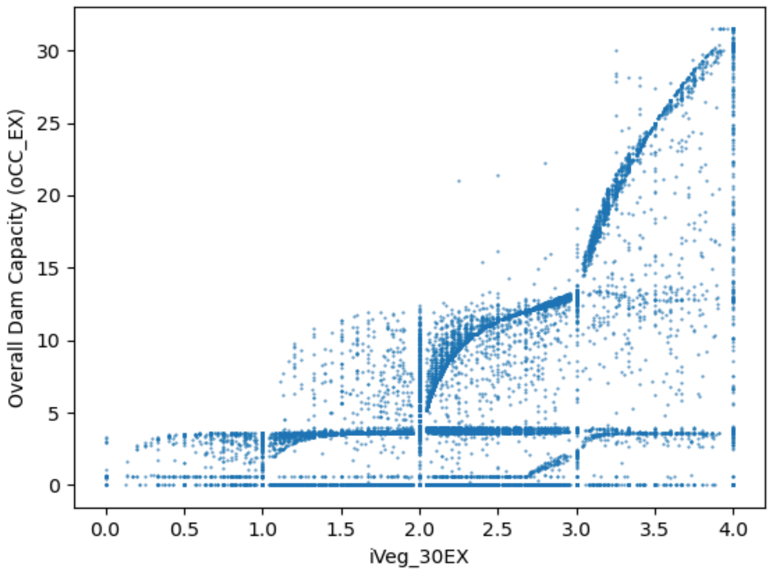
Figure 12. Input Distributions for all four HUCs combined. Plots titled “Filtered” had outliers past the max x-axis value removed from the data for better visualization.

The input histograms provide insight into the features of the Siletz watershed. The majority of vegetation is categorized with moderate suitability (~2.0), though the larger 100m riparian buffer shows more variability. This suggests that dam capacity could be increased with vegetation restoration efforts to increase suitable building materials.

For hydrology, streams have very low baseflow values (the inputs were filtered <10 watts/m to yield a visible histogram). BRAT only begins characterizing baseflows in limiting categories > 150 watts/m. Peak flows are more distributed, but still low, with most reaches avoiding limiting categories that begin >1000 watts/m. Stream slope shows the most variance across the input space: limiting slope categories begin > 0.12 slope. This suggests that slope is the primary limiting hydrologic factor in BRAT outputs for the Siletz watershed.

3.1.2 Aggregated Scatter Plots

Scatter plots correlating output capacity to different input variables were generated. These give insight into the sensitivity of BRAT to different inputs. In some cases, the patterns of the FIS membership functions and rule tables can be visually seen in the plot.



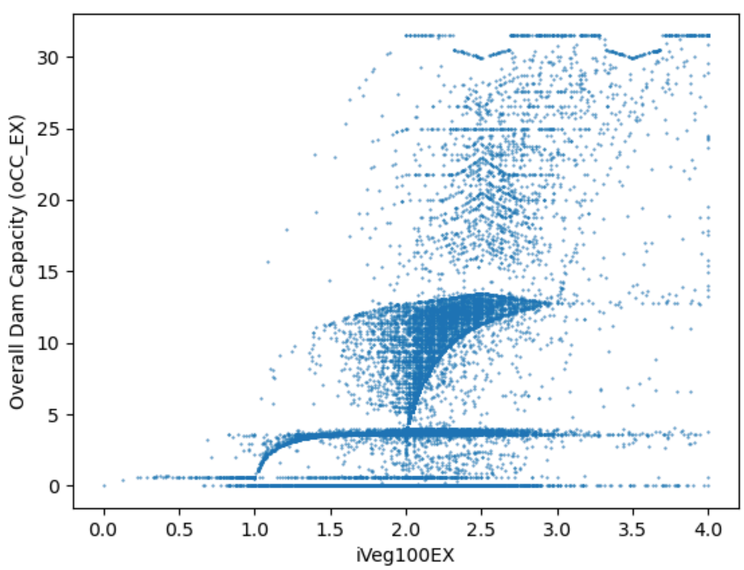


Figure 13. Influence of Vegetation Suitabilities on Output Capacity.

The vegetation scatter plots show a few interesting patterns. Firstly, the high number of reaches with average suitability around 2.0 is clear. The general positive trend is also apparent: more suitable vegetation yields higher dam capacity. The transitions between membership categories are also visible between integer values (e.g. Figure 13, x=2.0 to 3.0, where membership transitions to “Suitable” and peaks at 2.5). Between the two, the riparian suitability appears to show more variation and higher-on-average capacities. This can be explained by the Vegetation FIS rule table asymmetry, where the 100m buffer is more lenient, thus yielding higher capacity more quickly as 100m suitability increases. Of course, these plots are exploratory, and do not truly isolate the variables since different reaches may have different limiting hydrologies.

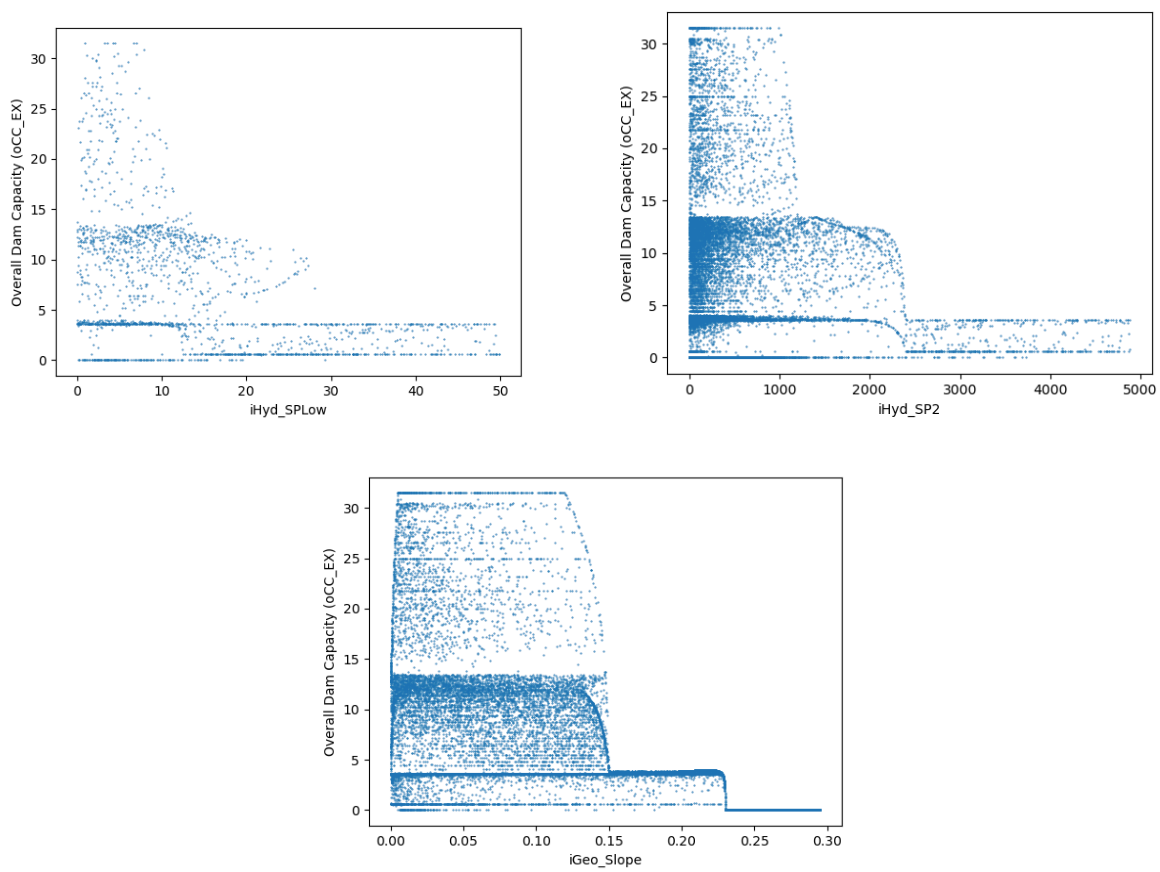


Figure 14. Influence of Hydrologic Inputs on Output Capacity. From left-right: baseflow, peak flow, and slope.

The hydrology plots confirm the histogram distributions and illustrate the FIS rules. These plots are filtered to include a subset of data points within a maximum x value such that the trends are visible. Baseflow is less meaningful since it is rarely a limiting factor in the Siletz watershed. Peak flow and slope are much clearer: you can see capacity trend sharply downwards as peak flow enters the “Breach” category from 1000-1200 watts/m, and later the “Blowout” category from 1600-2400 watts/m. The “Occasional Blowout” category is less defined. Similarly for slope, capacity is sharply limited in the “Probably” category from 0.12-0.15 and then set to 0 dams/km after the 0.23 cutoff where reaches have full membership in the “Cannot” category.

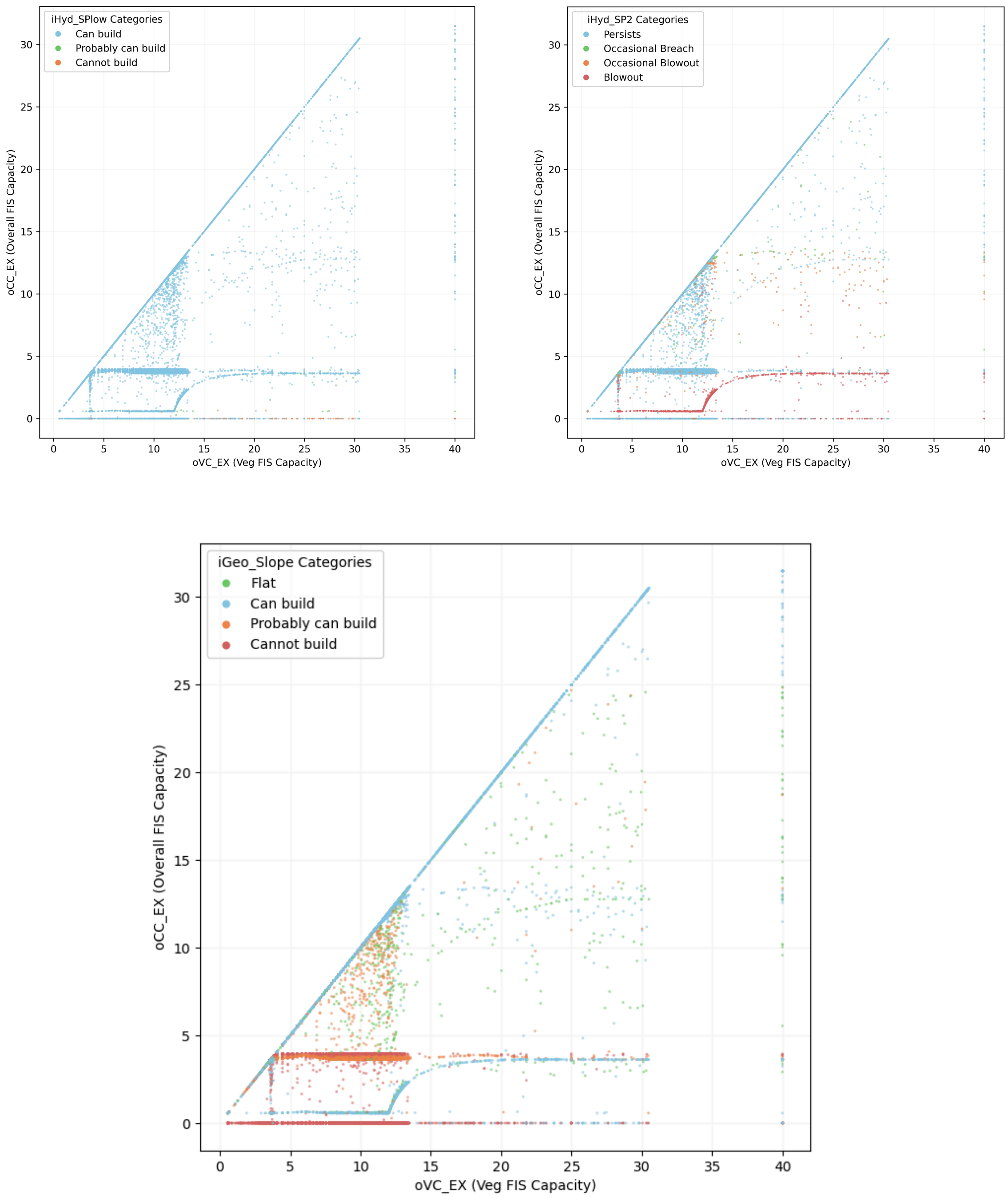


Figure 15. Hydrologic Limitation. Dam capacity based solely on vegetation (oVC) is then decreased in the Combined FIS due to each hydrologic variable before being output (oCC).

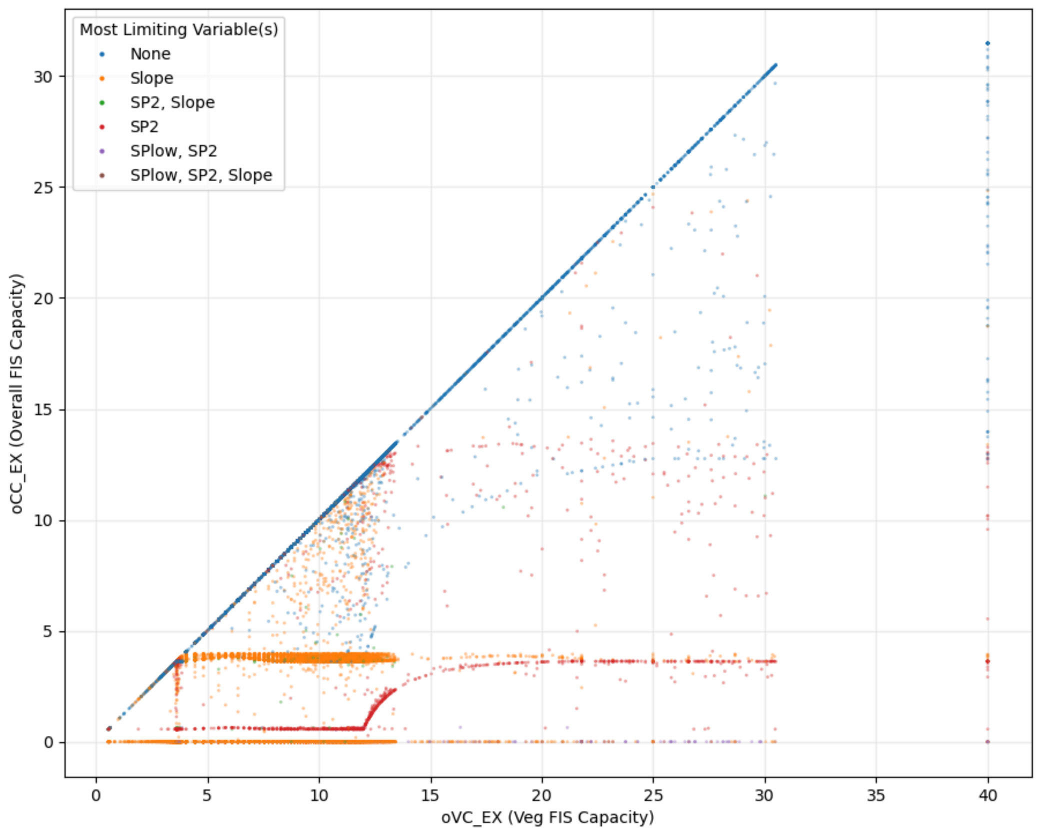


Figure 16. Dominant Hydrologic Limitation Across All Three Variables. Each point represents a reach, and the most limiting variable is the one with the most extreme category.

The scatter plots demonstrate that slope is the most limiting hydrologic factor in the Siletz watershed, as evidenced by the large orange cluster from 4-13 oVC and the prevalence of orange along the oCC=0 line (presumably, reaches with slope > 0.23). Peak flow is also limiting, as seen by the red trail from 4-30 oVC. Baseflow is not problematic, as previously observed. In most cases, either slope or peak flow alone take over as the dominant limiting factor.

3.1.3 Aggregated Outputs

Table 10. Summary of Capacity Categories in Each HUC. See Figures 18-20 for visuals.

Distance (km)						
	None	**Rare**	**Occasional**	**Frequent**	**Pervasive**	**TOTAL**
Lower Siletz	570.17	49.23	653.05	684.18	47.71	2,004.34
Middle Siletz	320.25	8.86	216.98	161.48	36.58	744.15
Upper Siletz	413.34	24.39	293.77	134.39	48.56	914.45
Rock Creek	136.61	8.83	154.84	101.86	29.80	431.94
ALL HUCs	1,440.37	91.31	1,318.64	1,081.91	162.65	4,094.88
Percent (%)						
	None	**Rare**	**Occasional**	**Frequent**	**Pervasive**	**TOTAL**
Lower Siletz	28.5%	2.46%	32.6%	34.1%	2.38%	100%
Middle Siletz	43.0%	1.19%	29.2%	21.7%	4.92%	100%
Upper Siletz	45.2%	2.67%	32.1%	14.7%	5.31%	100%
Rock Creek	31.6%	2.04%	35.9%	23.6%	6.90%	100%
ALL HUCs	35.2%	2.23%	32.2%	26.4%	3.97%	100%

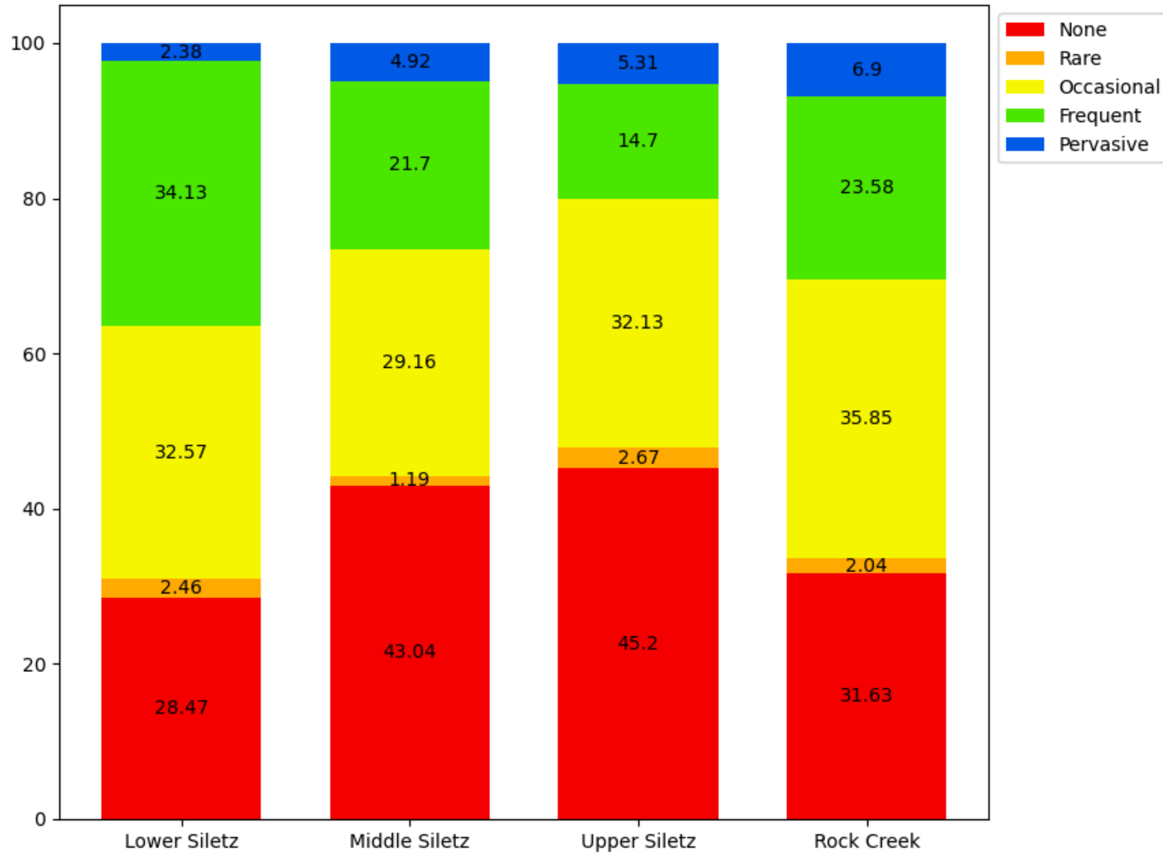


Figure 17. Capacity Category Percents in Each HUC. Reaches are categorized as None (0 dams/km), Rare (0-1 dams/km), Occasional (1-5 dams/km), Frequent (5-15 dams/km), and Pervasive (16-40 dams/km) matching BRAT standards. Percent for a given category is calculated as length of watershed in that category divided by total length of all reaches in that watershed.

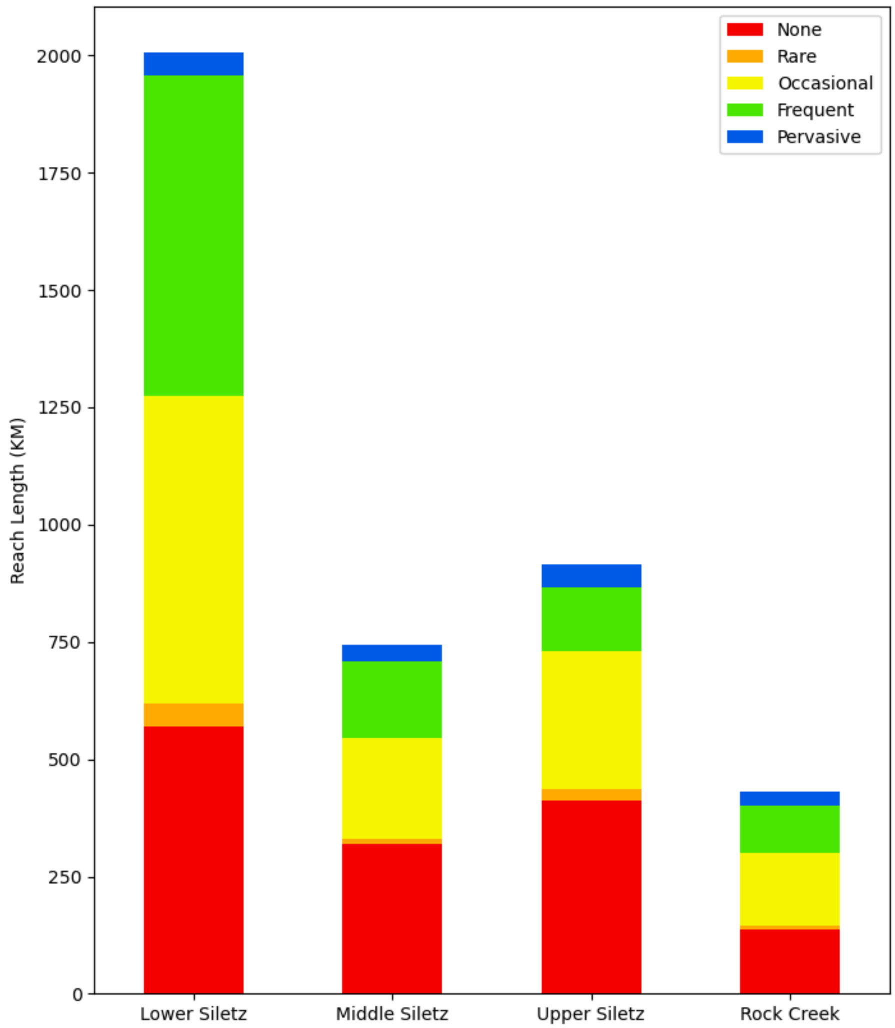


Figure 18. Capacity Category Kilometers in Each HUC. Reaches are categorized as None (0 dams/km), Rare (0-1 dams/km), Occasional (1-5 dams/km), Frequent (5-15 dams/km), and Pervasive (16-40 dams/km) matching BRAT standards.

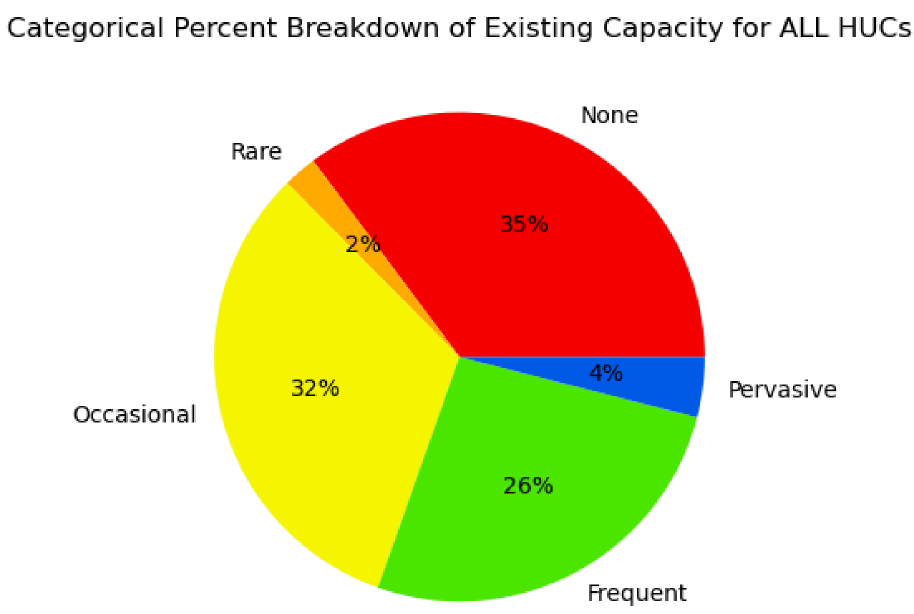


Figure 19. Percent of Watershed (all four HUCs) that falls into each Capacity Category. Reaches are categorized as None (0 dams/km), Rare (0-1 dams/km), Occasional (1-5 dams/km), Frequent (5-15 dams/km), and Pervasive (16-40 dams/km) matching BRAT standards.

Overall for the Siletz Watershed, dam capacity isn't extremely high but does show promise, namely in the Frequent (5-15 dams/km) category. The watershed does show variation between HUCs. Lower Siletz is obviously the largest region, offering the most reaches marked as Frequent or Pervasive. That said, Rock Creek still wins on absolute km and percentage of reaches categorized as Pervasive. Rock Creek also displays the highest average capacity. Middle and Upper Siletz likely suffer from steeper slopes and/or poorer vegetation, thus limiting capacity.

More work is needed, but BRAT's preliminary results suggest targeting Rock Creek's high-capacity reaches as well as considering Lower Siletz for its high volume of potentially suitable reaches.

3.2 FIS Sensitivity Analysis

3.2.1 One at a Time

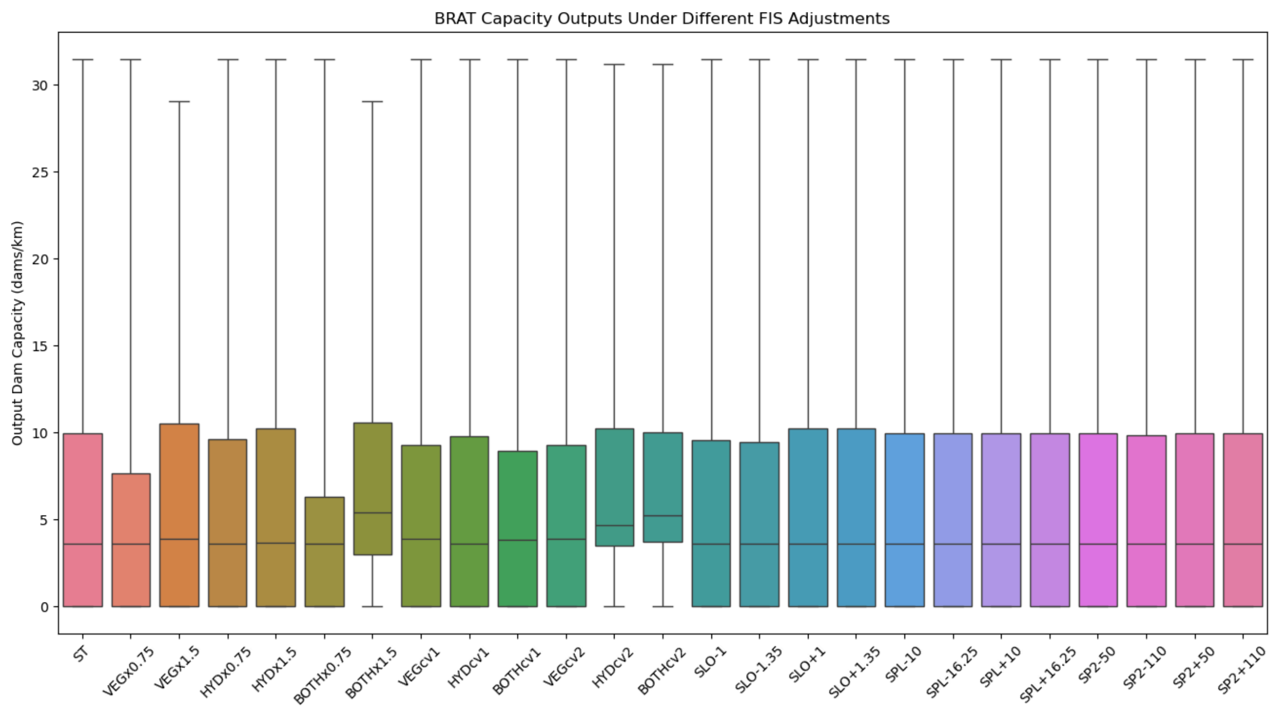


Figure 20. BRAT Capacity Outputs Under Different FIS Adjustments. Line represents mean output capacity, upper and lower regions represent quartiles, and whiskers represent min and max of the data. From left-right: Scale (Vegetation FIS, Combined FIS, Both), Shape ("best fit" curves, "loose fit" curves), and Shift (Slope, SPlow Baseflow, SP2 Peak Flow) adjustments.

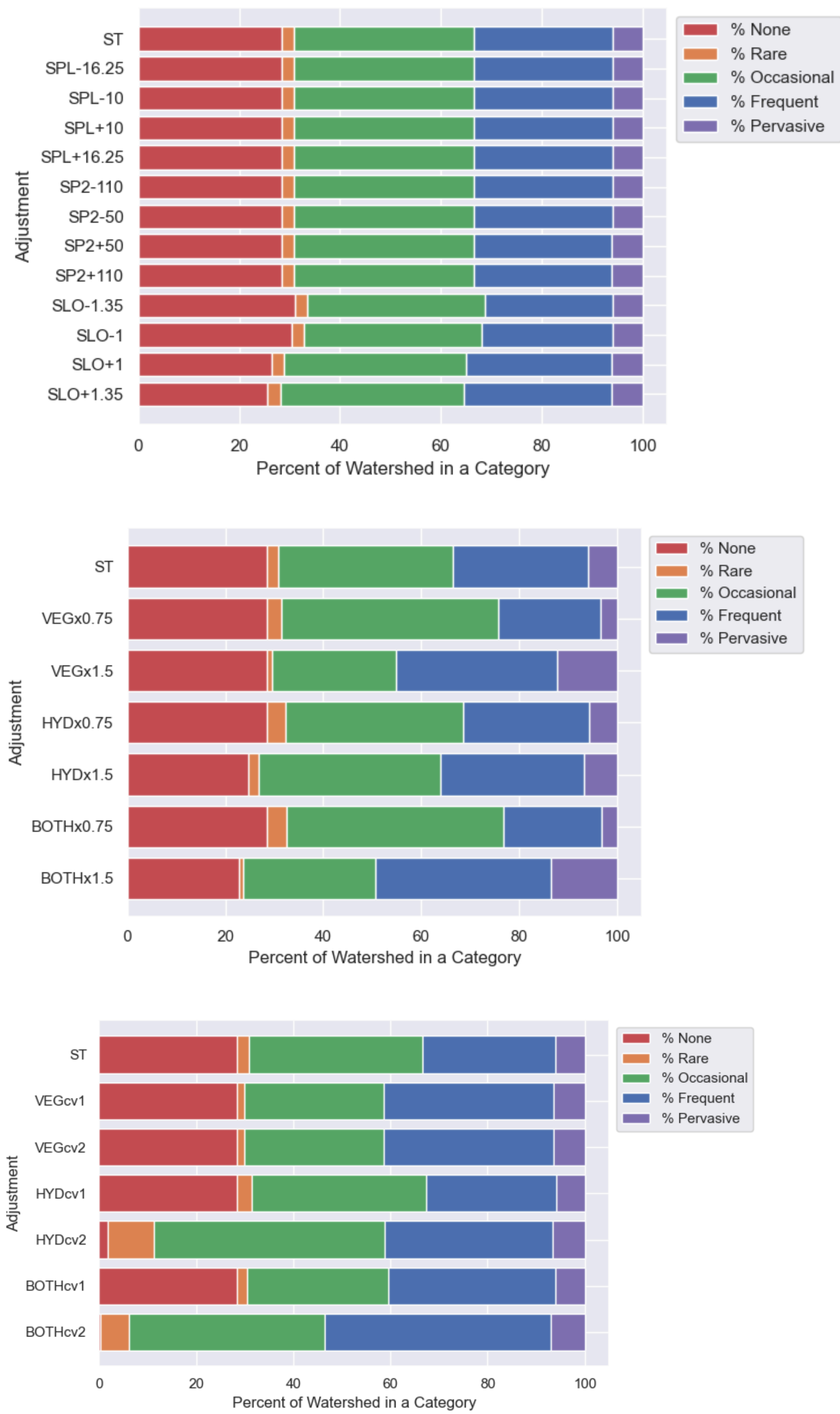


Figure 21. Capacity Categories Under Different FIS Adjustments. ST = no adjustments.

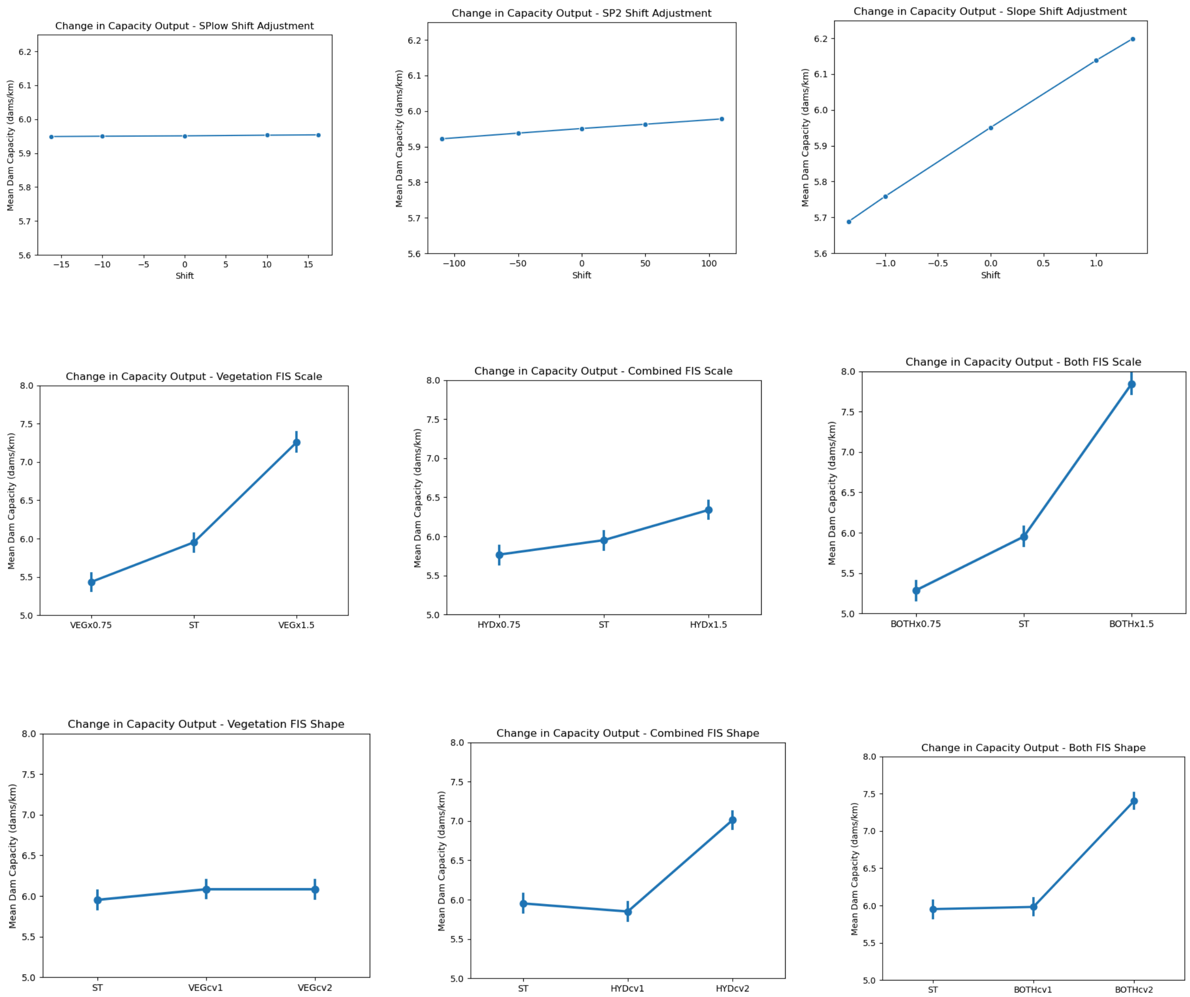


Figure 22. Change in Mean Capacity Under Each Local Adjustment. From left to right, top to bottom: Shifts (SPLow, SP2, Slope); Scales (Veg, Combined, Both); Shape (Veg, Combined, Both). Error bars represent standard deviation for each run.

The OAT Sensitivity Analysis revealed that the model is most sensitive to shape adjustments, especially under "loose fit" conditions since these shapes did not approximate the original MFs well. The "best fit" shapes did not have a significant effect, indicating that the model is not intrinsically sensitive to linear versus curved membership functions so long as they are well approximated.

Scaling the MFs of both FIS (Vegetation and Combined) also yielded a large change, perhaps indicating a compounding effect. When only scaling one of the FIS but not the other, vegetation had a larger effect, likely because it determines the initial vegetative capacity that is then limited by the Combined FIS. Clearly, the model is sensitive to stretching and compressing membership functions, with stretching increasing capacity outputs. This is likely because stretching allows more reaches to take membership in more categories, "diluting" the influence of limiting categories during the fuzzification. The standard BRAT FIS has all MFs intersect at μ=0.5 membership. This is not a requirement in fuzzy logic, but feels like a natural default to use. Thus, we can say the BRAT FIS is reasonably designed in terms of MF scale.

The model was surprisingly resilient to shifts in the MFs, but this is likely due to the Siletz input data being relatively non-limiting for SPLow and SP2. In line with this hypothesis, shifting the Slope had the biggest impact of the shifts.

The global sensitivity analysis achieved by Monte Carlo simulation offers a more standardized view on these changes.

3.2.2 Monte Carlo

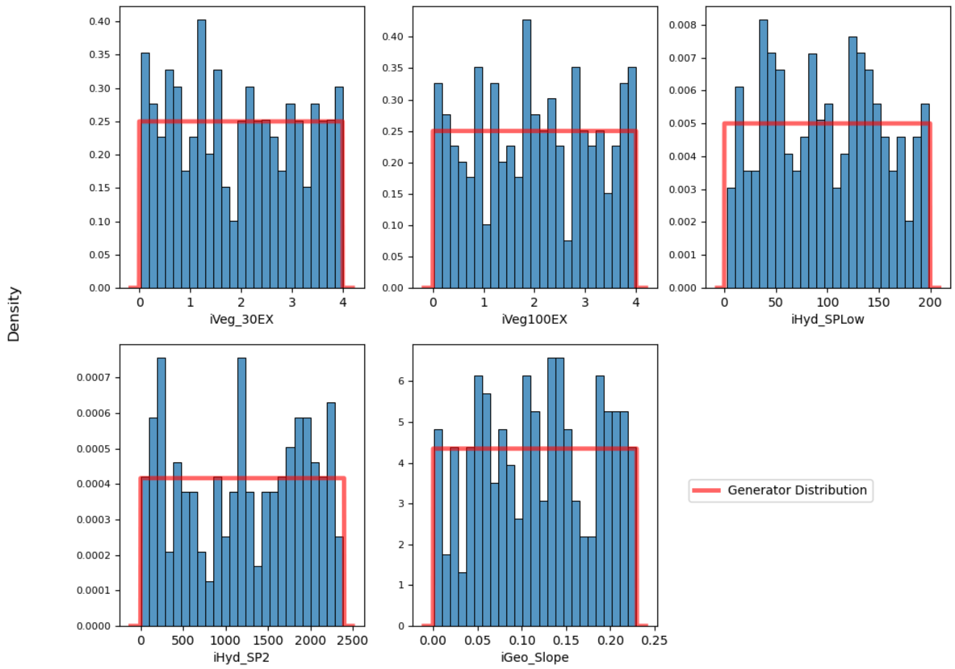


Figure 23. Simulation 1 (Uniform) n=250 Synthetic Inputs Compared to Distributions.

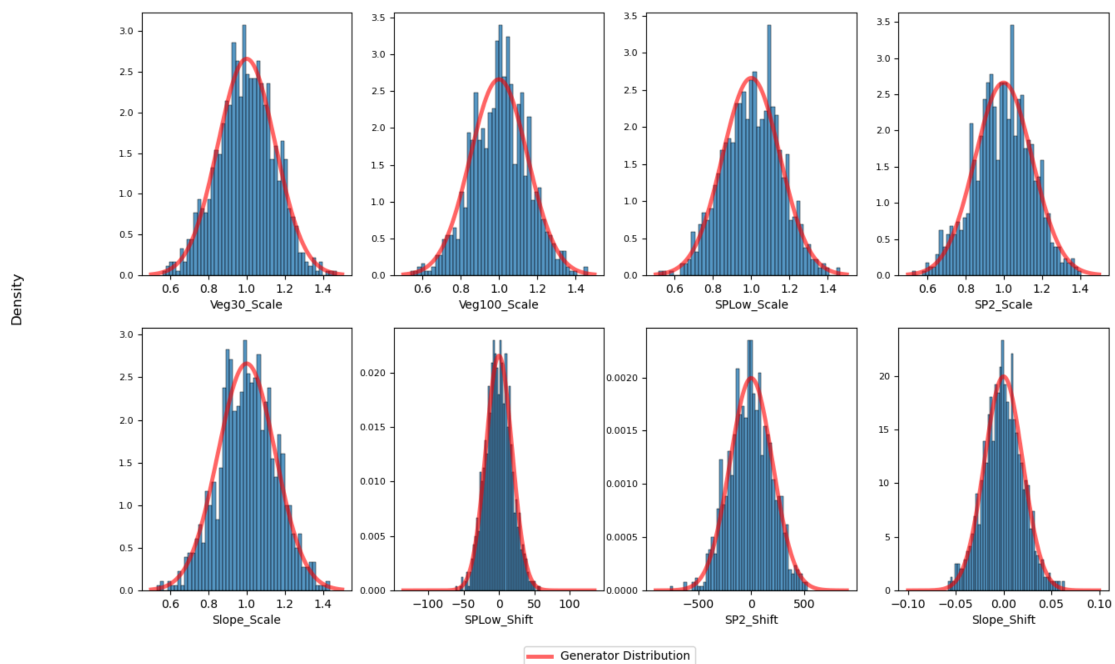


Figure 24. Simulation 1 (Uniform) n=1000 Adjustments Compared to Distributions.

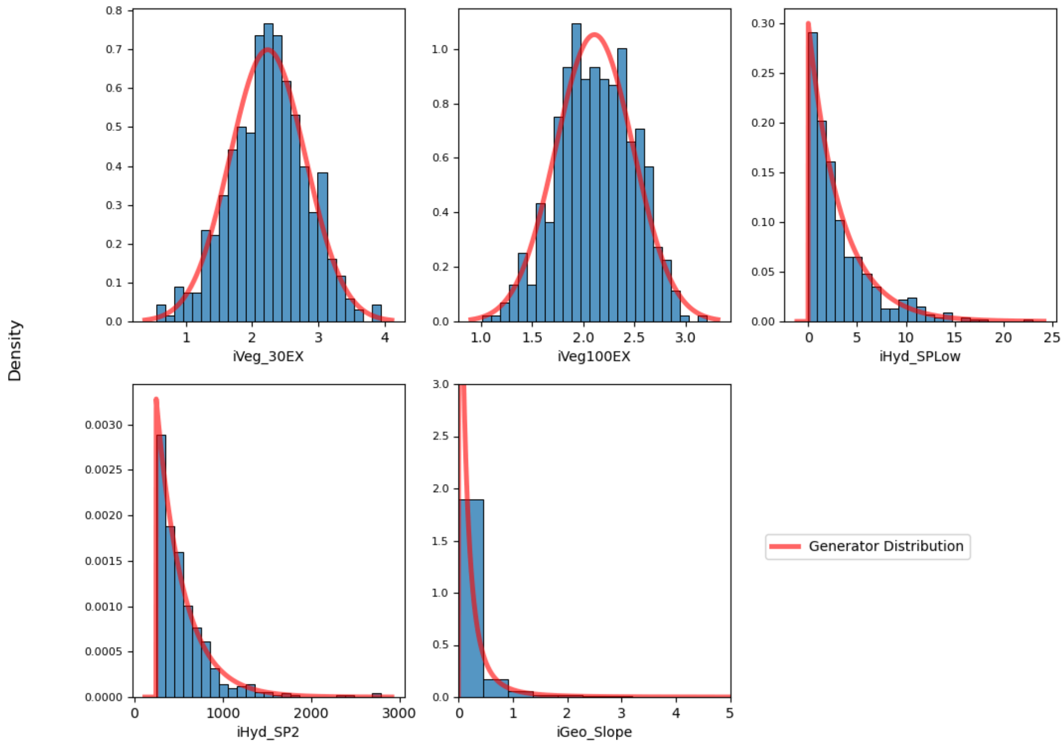


Figure 25. Simulation 2 (Siletz) n=500 Synthetic Inputs Compared to Distributions.

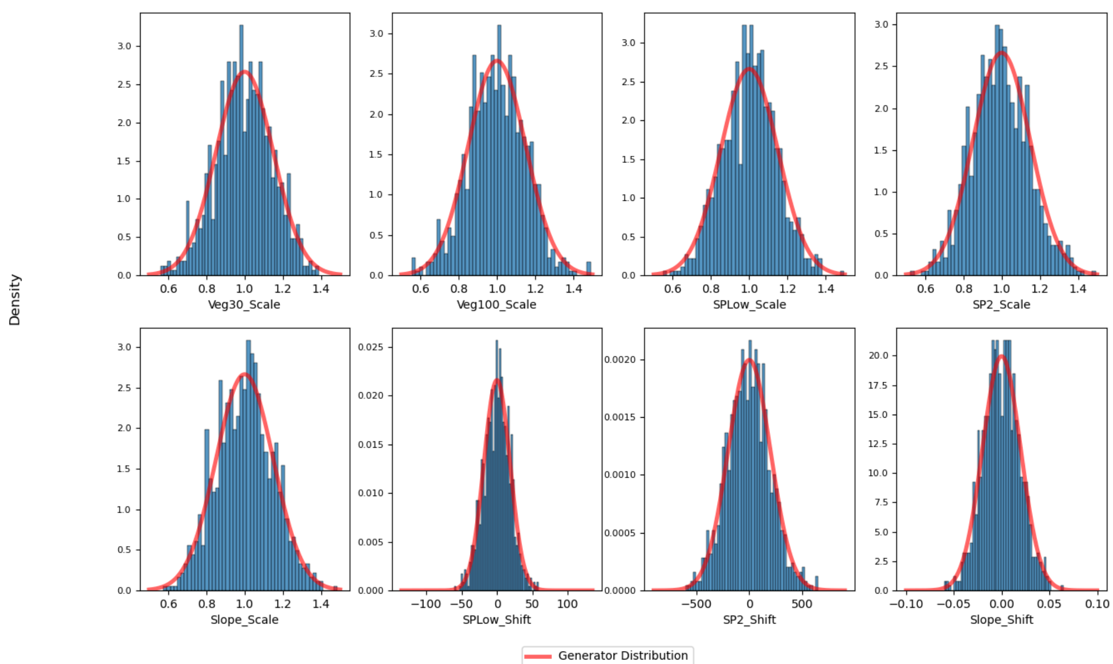


Figure 26. Simulation 2 (Siletz) n=1000 Adjustments Compared to Distributions.

The inputs and adjustments of both Monte Carlo Simulations look as expected compared to their generator distributions. This confirms the chosen sample sizes for both simulations were sufficient.

To analyze the results of the simulations, Pearson correlation coefficients were used to determine which adjustment parameter the model was most sensitive to (Figure 27). Morris Elementary Effects were also used to confirm these results (Table 11; Figure 28).

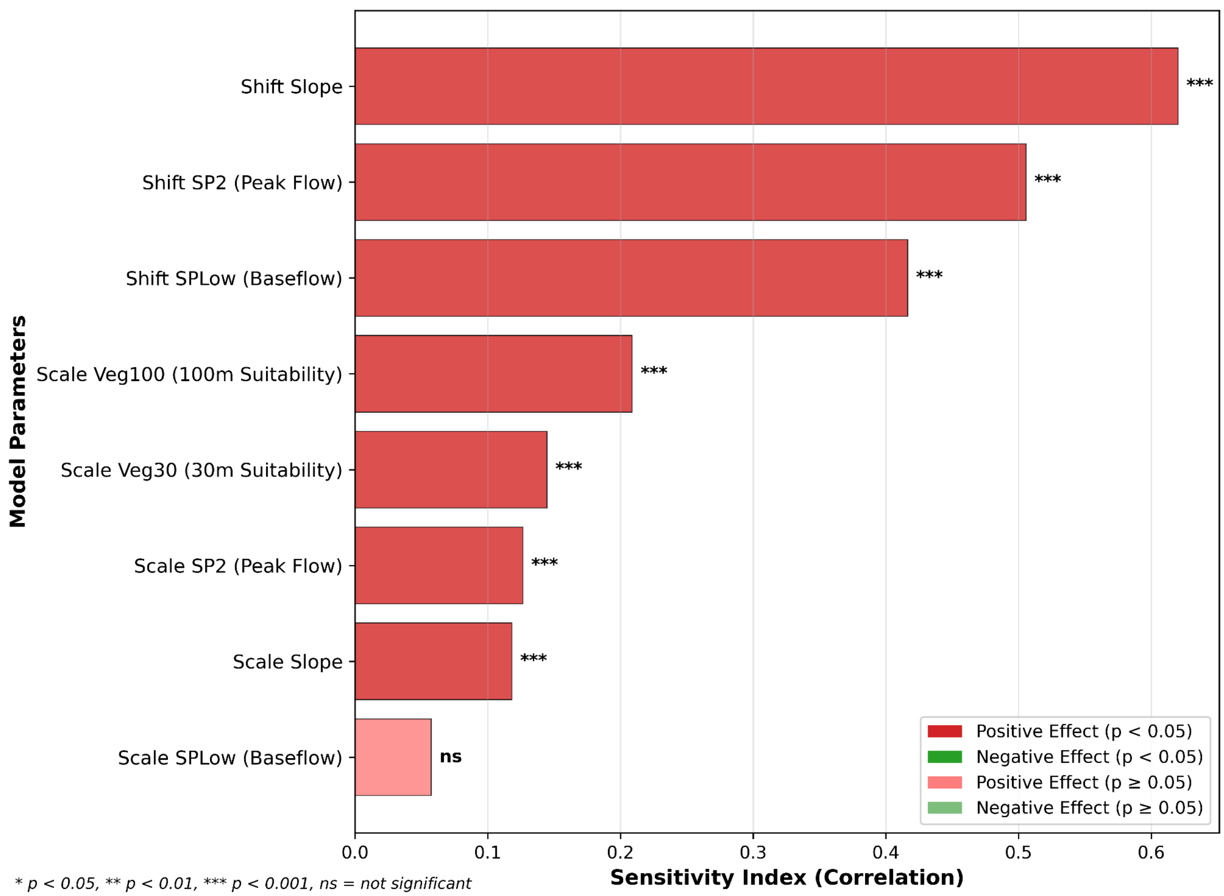


Figure 27. Simulation 1 (Uniform) Output Sensitivity to Adjustments. Measured by Pearson Correlation Coefficients. ns = not significant, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 11. Simulation 1 (Uniform) Morris Elementary Effects for Adjustments.

Adjustment	Absolute Mean* of Elementary Effects	Standard Deviation† of Elementary Effects
Shift Slope	5768.1	7789.4
Scale Peak Flow	778.0	1046.6
Scale Baseflow	770.4	1015.8
Scale Slope	761.1	1002.7
Scale 100m Veg Suitability	746.4	997.1
Scale 30m Veg Suitability	745.6	974.3
Shift Baseflow	26.4	47.6
Shift Peak Flow	4.1	11.6

*Absolute Mean indicates dominance (overall influence) of the adjustment on outputs
†Standard Deviation indicates influence (non-linear and interaction effects) on outputs

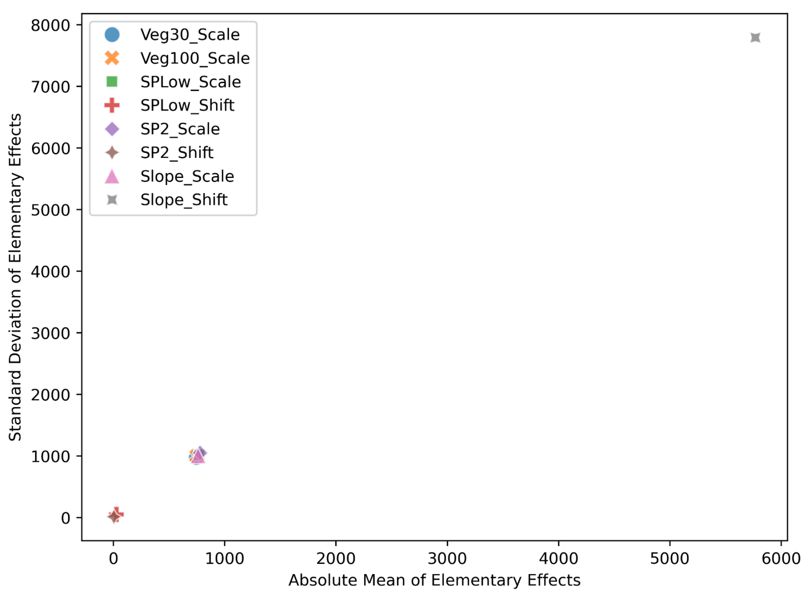


Figure 28. Simulation 1 (Uniform) Morris Elementary Effects for Adjustments. Visual representation of Table 11.

The Pearson correlation coefficients and Elementary Effects generally agree on the most sensitive parameters. With uniform inputs spanning the range of the membership functions, BRAT is most sensitive to Shifting the Slope MFs. In other words, increasing the slope cutoffs increases capacity, since more reaches will fall into acceptable categories; decreasing the slope cutoffs decreases capacity, since more reaches will fall into limiting categories. Not far behind are shifting the cutoffs for the other hydrology parameters, Peak Flow and Baseflow. This result is intuitive, since slope is harshly limiting early in the distribution.

Scaling 100m and 30m vegetation suitabilities are next most sensitive, respectively. Notably, BRAT is slightly more sensitive to adjusting the riparian 100m suitability. This is due to the rule table asymmetry (Table 1), where the model is more lenient on 100m suitability. So, stretching the riparian MFs will include more reaches in the more suitable categories compared to stretching the streamside MFs. It should not be assumed that, because BRAT is more sensitive to adjusting 100m suitability, this buffer is more important. The opposite is in fact true: BRAT is more lenient towards the 100m buffer, instead prioritizing the 30m buffer as more essential.

The same analysis was performed for Simulation 2 (Siletz-sampled inputs).

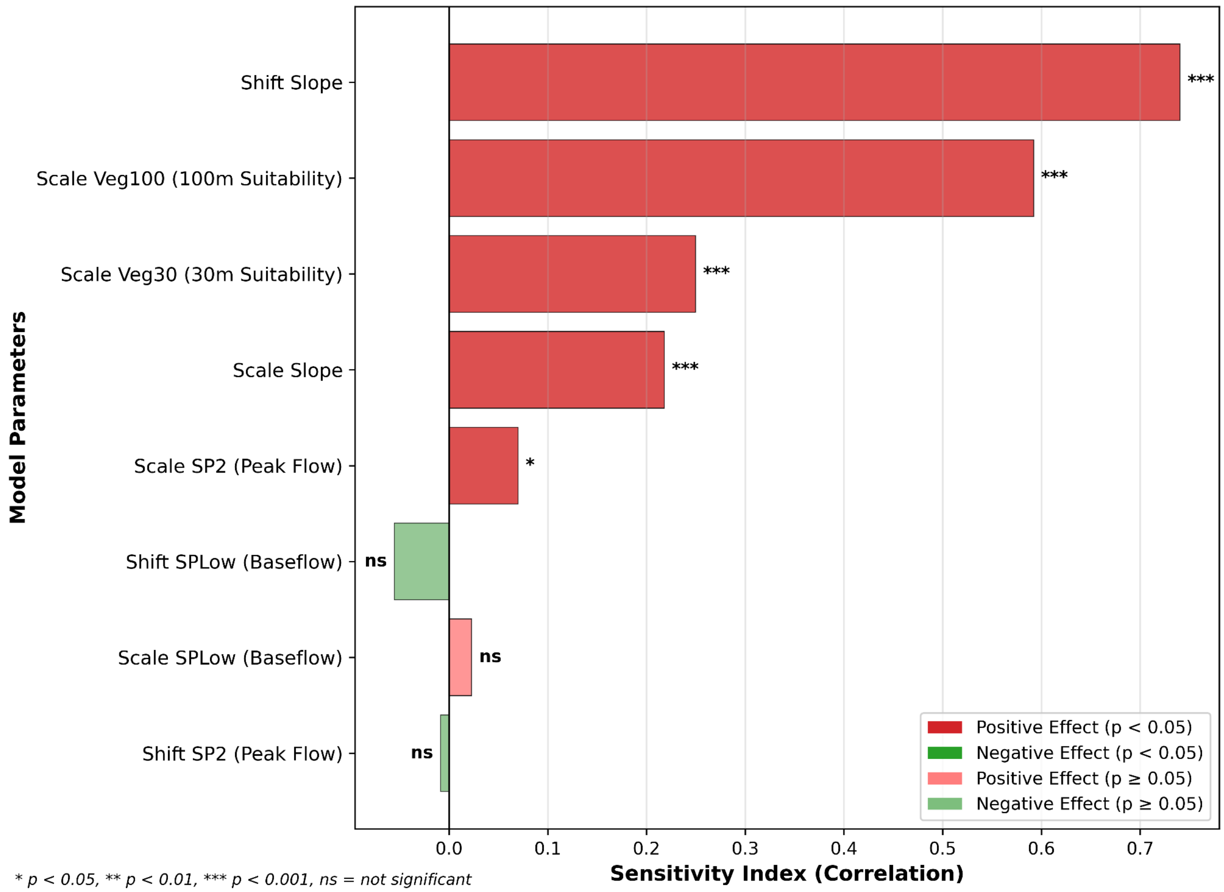


Figure 29. Simulation 2 (Siletz) Output Sensitivity to Adjustments. Measured by Pearson Correlation Coefficients. ns = not significant, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 12. Simulation 2 (Siletz) Morris Elementary Effects for Adjustments.

Adjustment	Absolute Mean* of Elementary Effects	Standard Deviation† of Elementary Effects
Shift Slope	2988.6	3919.1
Scale Slope	451.8	586.7
Scale Peak Flow	443.2	571.5
Scale Baseflow	439.9	584.3
Scale 30m Veg Suitability	427.4	571.2
Scale 100m Veg Suitability	356.7	488.9
Shift Baseflow	17.9	31.4
Shift Peak Flow	4.0	14.1

*Absolute Mean indicates dominance (overall influence) of the adjustment on outputs
†Standard Deviation indicates influence (non-linear and interaction effects) on outputs

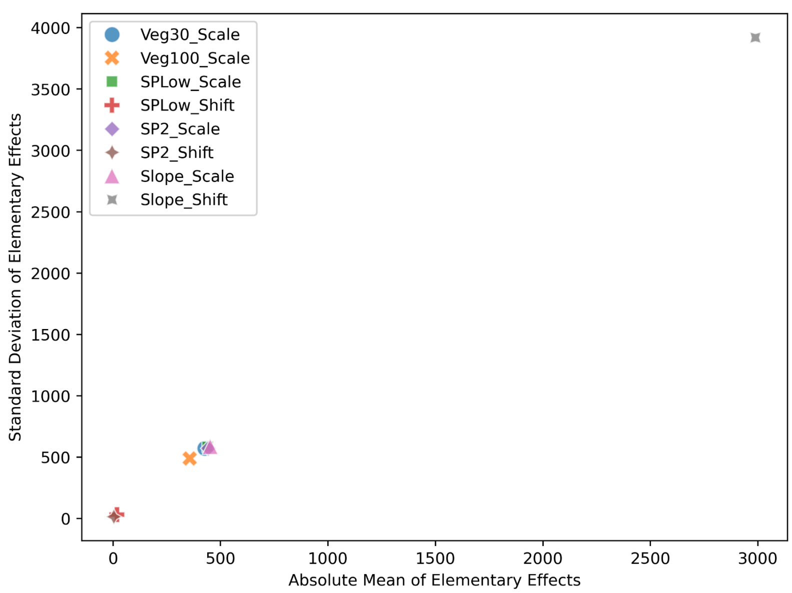


Figure 30. Simulation 2 (Siletz) Morris Elementary Effects for Adjustments. Visual representation of Table 12.

The Pearson correlation coefficients and the Morris Elementary Effects for Simulation 2 differ a bit more than in Simulation 1. They both agree with slope shifts being the dominant adjustment by far. However, correlation coefficients put both vegetation suitabilities as the next most sensitive factors and rates hydrologic scales as not significant or not very sensitive. The Elementary Effects, on the other hand, rank all other scale adjustments fairly evenly. More investigation could be needed, but conclusions about slope shifts stand. We give preference to the Pearson Correlation Coefficients in our comparative analysis.

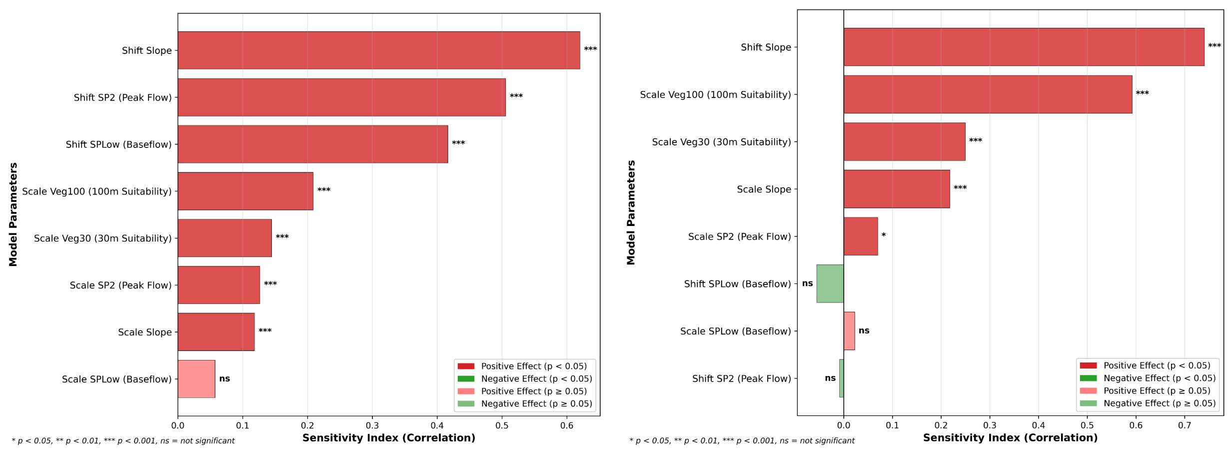


Figure 31. Model Sensitivity of Simulations 1 and 2. Sim1 on the left, Sim2 on the right.

The results of Simulation 2 (Siletz) agree with Simulation 1 (Uniform) on some metrics, but differ on others. Firstly and most clearly, shifting the slope is once again the dominant adjustment for output sensitivity. However, when using Siletz-sampled inputs, outputs become much more sensitive to vegetation and much less sensitive to baseflow and peak flow adjustments. This makes sense, since the Siletz watershed does not suffer from extreme baseflow or even peak flow values; slope is the limiting hydrologic factor. This means the model’s internal structure sensitivity is consistent with the standard output analysis.

Because the Monte Carlo method is a form of global sensitivity analysis, it allows for the investigation of combination effects — e.g. where two parameters interact with an emergent effect on outputs. This was tentatively explored using 3D surface plots, but ultimately determined to be less meaningful and out of the scope of this project. The model is fairly straightforward and adjustment impacts are generally linear. We do not believe there are any significant compound effects of adjustments beyond what is intuitive: e.g. shifting *and* scaling the slope MFs will increase capacity even more than doing one or the other.

3.3 Community Engagement

3.3.1 Data Collection Survey

A Qualtrics survey was designed to collect validation data from Siletz community members. Questions were designed to be clear and accessible but also result in standardized data collection of beavers, dams, or evidence of past activity. A Google Maps interactive window was included to record the coordinates of observations so that evidence could be compared to BRAT outputs in the future.

3.3.2 BRAT Maps

Two maps were prepared to be printed for community engagement efforts. The first showed all BRAT outputs within the Siletz watershed boundary with a satellite background. The second showed the NHD Streams with labels for the Siletz watershed boundary. Despite the digital basis of the model, physical print-outs will greatly aid community engagement and make the model more accessible to those less comfortable with technology.

4. Conclusion

Sensitivity analysis improves our confidence in the robustness of a model. Our tests show that BRAT is indeed robust and conservative. While field validation is needed, we can conclude that BRAT is resilient to small or singular adjustments to its structure. It takes adjustments that are compound or extreme to cause significant change in model outputs. Additionally, we are satisfied with the design of BRAT's Fuzzy Inference System, particularly the reasonable choices of membership function intersections at y=0.5 and linear shapes.

That said, outputs are clearly sensitive to the model's harsh slope cutoffs. With both uniform inputs and inputs representative of the Siletz watershed, BRAT was more sensitive to changes to its slope membership functions than any other adjustment we tested. Beyond slope, for watersheds with gentle baseflow and peak flow such as Siletz, vegetation emerges as the second-most influential factor.

Future work should continue to validate BRAT, exploring not only adjustments to its structure and input values, but also input sources and performance in different regions. Nonetheless, BRAT is an effective tool that should continue to be applied to watersheds and restoration efforts across the US and beyond.

Appendix

A. GitHub

A GitHub repository, forked from Riverscapes' open source tools, houses all the code and scripts used to perform analysis, process data, generate figures, etc. Scripts are built on top of BRAT, preserving the original functionality, and documented with the hope that they could be used or modified in the future. https://github.com/Hydroinformatics/riverscapes-tools-fork.

B. sqlBRAT Installation Instructions

A dedicated file containing sqlBRAT installation instructions and information can be found on the GitHub repository. Here is a direct link:

https://github.com/Hydroinformatics/riverscapes-tools-fork/blob/master/BRAT%20Installation%20%26%20Setup%20Instructions%202025.md

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