Montana Beaver Dam Census & Beaver Restoration Assessment Tool (BRAT) Verification

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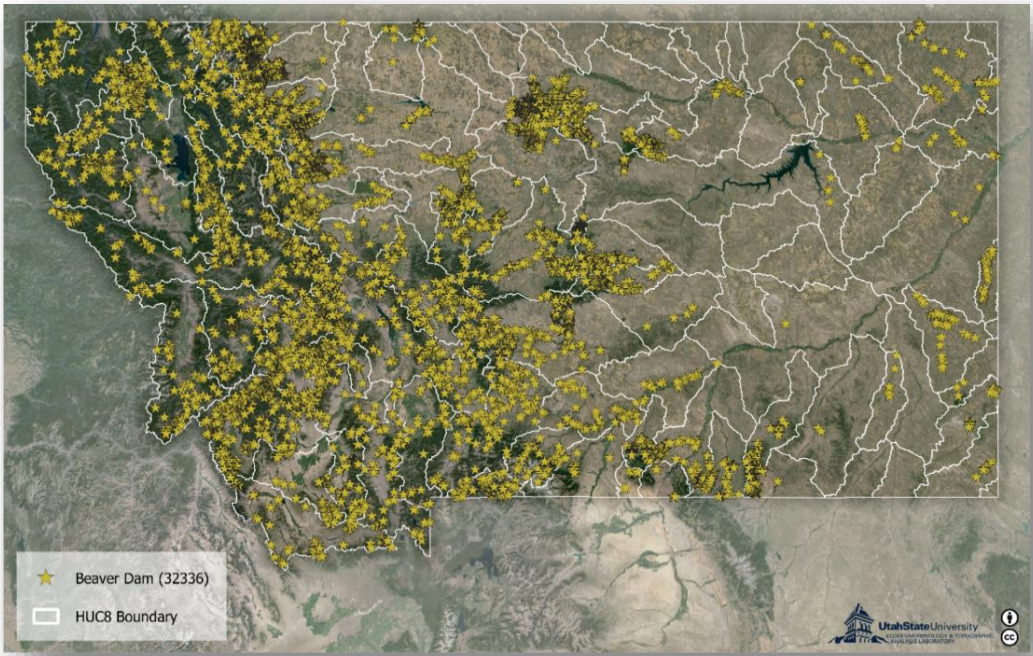

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EXECUTIVE SUMMARY

The focus of this report is on 1) the results of a Montana statewide imagery-based census of beaver dams along the entire perennial stream network and 2) a comparison of the beaver dam census to the Beaver Restoration Assessment Tool (BRAT) estimates of beaver dam capacity.

The Montana statewide imagery-based census took a total of 910-person hours to complete with a total of 32,336 dams recorded. There was a significant variation in the number of beaver dams per 8-digit Hydrologic Unit Code (HUC 8) watershed throughout the state. Specifically, 3 of the 101 watersheds that make up the state showed more than 2,000 dams and are located in western Montana whereas 20 watersheds showed no beaver dams and are located in the eastern portion of the state. The western portion of the state had much higher numbers of dams per watershed.

Since the BRAT capacity model output is beaver dam density, direct comparison to dam densities from the census is a useful form of model verification. As such, we verified the performance of the BRAT existing capacity model estimates in six HUC 8 watersheds using 5,034 beaver dams that met our criteria (less than 30 m from an USGS National Hydrography Dataset (NHD) stream segment and on a reach greater than 100 m in length).

Three forms of model verification were used to assess the performance of the BRAT capacity model:

1. How do dam densities track between predicted and actual?
2. Do the electivity indices increase appreciably from the *none* to the *pervasive* class?
3. Are there surveyed dams where the model predicted existing dam capacity as *none*?

Of the total 2,199 stream segments with verification dam counts only 385 exceeded the capacity estimates indicating that the model effectively segregates the factors controlling beaver dam occurrence and density 82% of the time (Figure 9). Thus, the BRAT model underestimated capacity 18% of the time. Most of the disagreement between the modeled and observed dam densities was due to dam building on floodplains, side-channels and other anabranches which are not included in the input stream network, and thus could not be captured by the model.

The electivity index results show that throughout the perennial streams of the six HUC 8 watersheds, beavers preferentially dam in reaches with higher modelled dam capacity while avoiding those with lower dam capacity. That is, beaver exhibited avoidance of reaches predicted as supporting *none*, *rare* or *occasional* densities, and beaver exhibited preference for areas predicted as having *frequent* or *pervasive* dam densities.

Only 2 dams (0.04%) were found on stream segments where no dams were predicted to occur based on the BRAT capacity model, and both were a result of misattribution of the dam to the NHD channel network.

BACKGROUND

BRAT - Beaver Dam Capacity Model

The BRAT capacity model estimates the upper limits of riverscapes to support beaver dam building. These beaver dam capacity estimates come from seven lines of evidence: (1) a reliable water source; (2) stream bank vegetation conducive to foraging and dam building; (3) vegetation within 100 m of edge of stream to support expansion of dam complexes and maintain large beaver colonies; (4) likelihood that dams could be built across the channel during low flows; (5) the likelihood that a beaver dam on a river or stream is capable of withstanding typical floods; (6) evidence of suitable stream gradient; and (7) evidence that river is too large to allow dams to be built and to persist.

The four primary questions that the BRAT capacity model asks:

1. Is there enough water present to maintain a pond?
2. Are enough and the right types of woody plants present to support dam building?
3. Can beaver build a dam at base flows?
4. Can dams withstand typical floods?

With the BRAT capacity model, approximate quantitative answers to these four questions are calculated using GIS data. For this application, the following publicly available datasets of national extent were used (Table 1) that provide direct approximations for these lines of evidence based on remotely sensed imagery and regionally derived empirical relationships. The beaver dam capacity model is described thoroughly in Macfarlane et al. (2017), and detailed online documentation describing how to run the model is available at http://tools.riverscapes.net/brat. Therefore, in this report, we only briefly describe the capacity model.

The BRAT model estimates the capacity of riverscapes to support dam-building activity by approximating the maximum number of dams that can be sustained, based on vegetation resources and typical stream flows. Model outputs are calibrated to a range of dam densities found in nature and reported in the literature, which locally can be as high as 40 dams per km, or roughly one dam every 25 m. These high densities are only found where multiple colonies maintain large dam complexes, which vary from 3 to 15 dams each (Gurnell, 1998). We express the model output in dams per length (km) because a) it is directly comparable to densities that can be calculated in GIS from field GPS measurements, b) densities can also be approximated with aerial imagery and/or overflights, and c) linear dam density is commonly reported in the literature so there are valid estimates for direct comparison. The output categories are as follows:

- None – 0 dams: *segments deemed not capable of supporting dam building activity*
- Rare – > 0-1 dam/km: *segments barely capable of supporting dam building activity; likely used by dispersing beaver*
- Occasional – > 1-5 dams/km: *segments that are not ideal, but can support an occasional dam or small colony*
- Frequent – > 5-15 dams/km: *segments that can support multiple colonies and dam complexes, but may be slightly resource limited*
- Pervasive – > 15-40 dams/km: *segments that can support extensive dam complexes and many colonies.*

To assess evidence of a stream within a network being a reliable water source for dam-building beaver we use the National Hydrography Dataset (NHD) cartographically derived 1:24 000 drainage network. The NHD network differentiates between perennial, intermittent, and ephemeral watercourses. We use the perennial designation segmented into 300 m long segments because a) this is a reasonable length over which to approximate reach averaged slope from a 10 m DEM, and b) 300 m segments produce a reasonable length along which to sample 30 m LANDFIRE vegetation data within buffers and get a representative sample.

To assess dam building material preferences, [LANDFIRE EVT 2020] (first made available in 2022), a nationwide 30 m Landsat satellite imagery-based landcover classification was used. Based on these preferences, a single numeric suitability value from 0-4 to each of the land cover classes was assigned, with zero representing unsuitable building material and four representing preferred woody building material. The result is a look-up table of LANDFIRE land cover classes and associated beaver preference values that is applied to raster data on a cell-by-cell basis.

Riverscapes with narrow riparian corridors limit beaver dam construction opportunities relative to those with expansive riparian areas and/or adjacent deciduous forests with preferred woody browse (e.g. aspen). To represent this important distinction, we generate two buffers along the drainage network in which we assessed beaver dam-building preference values:

- A 30 m buffer representing the streamside vegetation; and
- A 100 m buffer representing the maximum harvest distance (Figure 1).

Table 1. Input data used to represent the lines of evidence of Montana BRAT beaver dam capacity model.

Input Data	Criteria	Source
Streams and rivers	Perennial water	USGS National Hydrography Dataset http://nhd.usgs.gov/
LANDFIRE 2016 (EVT and BPS)	Riparian vegetation	LANDFIRE land cover data http://www.landfire.gov/
USGS baseflow equations	Dam could be built	Montana StreamStats https://doi.org/10.3133/sir20155019
USGS 2-year peak flow equations	Dam could withstand floods	Montana StreamStats https://doi.org/10.3133/sir20155019
10 m DEM	Evidence of stream gradient	USDA NRCS Geospatial Data Gateway http://datagateway.nrcs.usda.gov/

We based these buffer distances on documented distances from water that beaver typically travel to harvest woody stems for dam and lodge construction, and winter food caches. Many studies indicate that most of the woody species utilized by beaver occur within 30 m of the edge of water and that a majority of foraging occurs within 100 m. To infer whether it is likely that beaver could physically build a dam during low-flow conditions, we calculate stream power ($\Omega = \rho g Q S$) at baseflow. Where Ω is the stream power (in Watts), ρ is the density of water (1000 kg/m3), g is acceleration due to gravity (9.8 m/s2), Q is discharge (m3/s), and S is the channel slope.

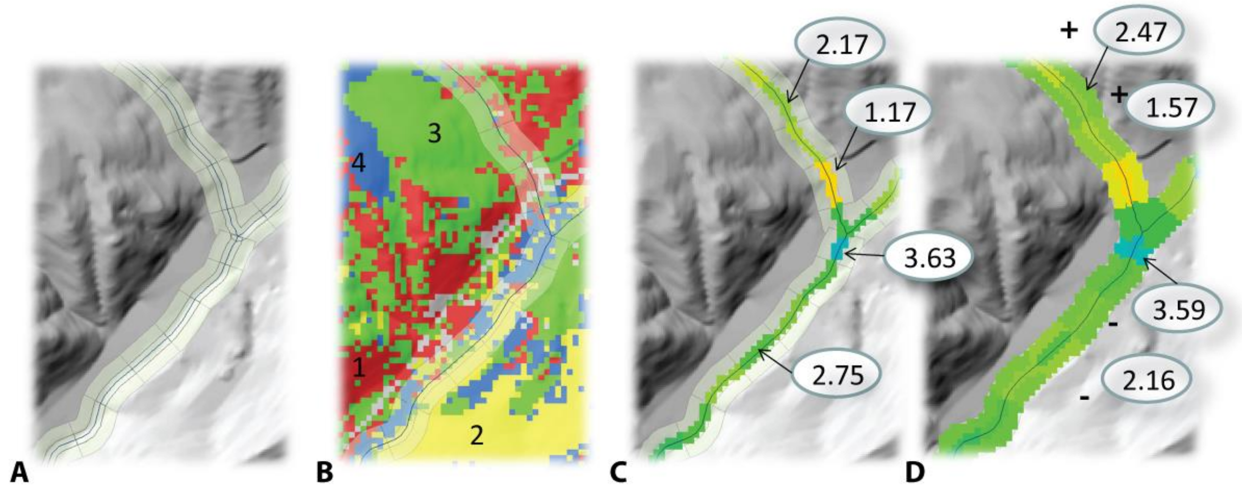

Figure 1. Reach scale illustration of derivation of streamside vs. riparian vegetation scores from 30 vs. 100 m stream network buffers. A shows the 30 m and 100 m buffers, which we used to summarize intersecting pixels from 30 m resolution classified LANDFIRE raster in B. Dam building suitability are shown in B and range from 0 (unsuitable; grey) to 4 (optimal; blue) with red for 1, yellow for 2, and green for 3. C & D contrast the buffer averaged values for the 30 m buffer (C) and the 100 m buffer (D).

To infer the likelihood that a beaver dam will persist once built, the two-year recurrence interval peak flood (Q_2) stream power is calculated for each reach based on drainage area and USGS regional curves. To calculate reach slope, we use the NHD network segmented into 300 m long reaches and extract elevations at top and bottom of each reach based on the DEM and divide by reach length. The two slope values that matter for the BRAT capacity model are < 0.5 percent slope because dam density goes down in very flat areas and > 23% slope because dams cannot be built and sustained in very steep reaches. All seven lines of evidence (described above) are combined within a fuzzy inference system (FIS) to estimate the maximum beaver dam density (dams/km) of riverscapes (Figure 2).

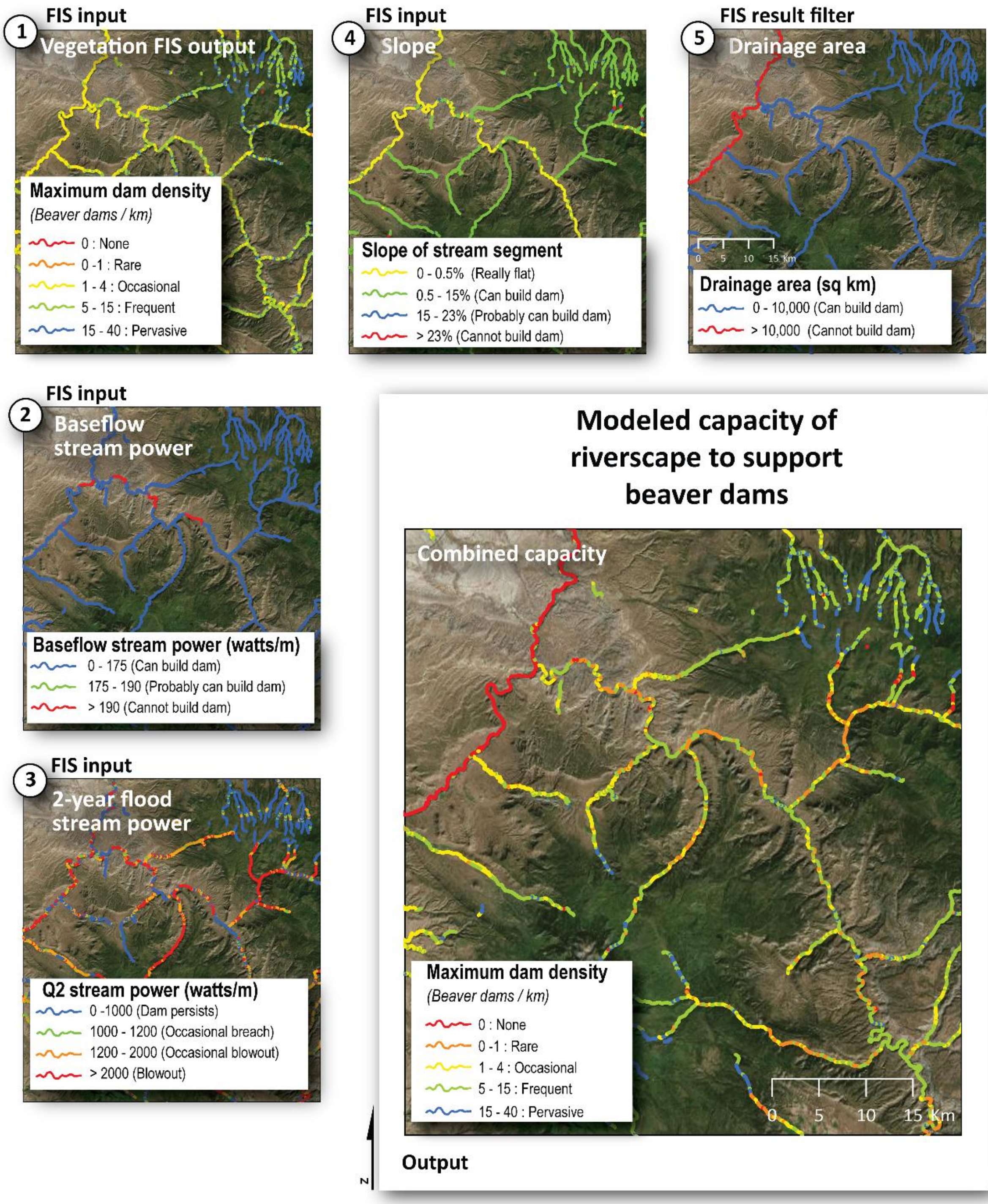

Figure 2. Methodological illustration of inputs (1-5) and output for the combined capacity model of riverscapes capacity to support beaver dam-building activity. Model output is expressed as dam density (dams/km).

METHODS

Imagery-based Beaver Dam Census

We utilized current and historic satellite imagery available in Google Earth Pro (GE) and from Esri's ArcGIS Online platform to identify beaver dam locations.

Survey Design

Desktop surveys were conducted on a per-watershed basis. A perennial stream network was derived from the USGS National Hydrography Dataset (NHD) and was split by each 8-digit Hydrologic Unit Code (HUC 8) watershed in Montana. The individual stream networks were then exported to ArcGIS Online as Web Maps for each corresponding watershed. ArcGIS Survey123—a program that allows users to develop interactive "smart" forms—was utilized to facilitate data collection. Simple forms were generated via the Survey123 Connect desktop application with general questions about observation points (Table 2). The forms were added to the web maps, and ArcGIS Online web apps were subsequently created to provide an interface for engaging with the surveys.

Table 2. Survey123 form structure and explanation.

Variable	Assessments	Explanation
Dam Certainty	Low, Medium, High	The confidence level on whether or not the observation is a beaver dam
Feature Type	Active Dam, Inactive Dam, Relic	The condition of the dam at the time of imagery capture.
Feature Type Certainty	Low, Medium, High	The confidence level on whether the observation is of a certain dam type
Imagery	Google Earth, Esri	The source of the imagery for the observation
Year of Imagery	Year	The year associated with the imagery capture date

Survey Process

Observers surveyed the stream network in GE at a digital altitude of approximately 200 – 800 meters above the Earth's surface. The 'time slider" within GE was used to explore current and historic satellite imagery. Imagery preference was decided based on capture date and clarity, with the most recent high-resolution imagery taking priority (i.e., able to clearly visualize dams). When a potential beaver dam was identified, lines of visual evidence were evaluated to determine validity (pond shape, crest structure, riparian harvest, skid trails, and lodges). When evidence of beaver activity was determined to be likely, an observation point was placed on the crest of the potential beaver dam, and the observer answered the survey form questions through the web app (Figure 3). By using current and historic satellite imagery in GE in conjunction with a Survey123 and ArcGIS Online web applications, potential dams were identified using multiple sets of imagery and multiple lines of evidence (e.g., observations of dam crests, ponding, lodges).

Figure 3. Recording beaver dam observations within the Survey123 web application.

After all beaver dam point locations were collected and their attributes were recorded per HUC 8 watershed, the data was reviewed for quality by the project's Principal Investigator who either "signed off" on the census or provided feedback on how the census should be modified.

BRAT Capacity Model Verification

The most up-to-date Montana BRAT run available in the Riverscapes Data Exchange (https://data.riverscapes.net) was an 'uncalibrated' version (i.e., run using default hydrologic functions and vegetation suitability classification without quality control and calibration of these values). In the process of running the validation code that compares BRAT existing capacity estimates to beaver dam densities from our dam census, it became evident that the model was poorly calibrated in landscapes where BRAT has not previously been validated (e.g., the plains regions of Eastern Montana). Because beaver are generalists, vegetation preferences and utilization may vary based on what is available, and as a result, the vegetation inputs to the BRAT model runs should be calibrated regionally. We, therefore, performed some initial calibration of vegetation preferences within each of the six Level III EPA Ecoregions (Northern Rocky Mountains, Canadian Rocky Mountains, Middle Rocky Mountains, Northwestern Great Plains, Northwestern Glaciated Plains and, Idaho Batholith; see Figure 8) in Montana. Within each ecoregion, we selected one HUC 8 watershed with high observed dam counts (in order to have a large sample size for validation) and ran the BRAT model to perform validation.

Since the BRAT capacity model output is dam density, direct comparison to dam densities from our census is a useful form of model verification. We used three forms of model verification to assess the performance of the BRAT capacity model:

1. How do dam densities track between predicted and actual?
2. Are there surveyed dams where the model predicted existing dam capacity as *none?*
3. Do the electivity indices increase appreciably from the *none* to the *pervasive* class?

First, beaver dam locations from the imagery-based beaver dam census were used to calculate densities and these dam densities were compared to modeled dam capacity estimates. Specifically, beaver dam census data were plotted against predicted existing capacity counts and a quantile regression was performed on the 50th, 75th, and 90th percentiles of these data. Quantile regression using upper percentiles (i.e., 75th, 90th) is used to evaluate habitat models because many of these systems have low surveyed dam densities. Upper percentiles represent the highest levels of surveyed dam density which correspond most closely with true capacity, which is what BRAT is modeling.

Our census mapped beaver dams that occurred on floodplains and secondary anabranches, as well as on the main channel. In many cases, these secondary channels are not included in the NHD channel network (Figure 4). Attributing these values to the nearest channel segment, therefore, can result in artificially high densities for a given reach. Similarly, if beaver dams are mapped in an area *without* an associated NHD channel reach, snapping them to the nearest reach will result in high dam densities inappropriately attributed to a channel reach. Additionally, short channel segments can drive artificially high beaver dam densities by using a short length value in the denominator of the calculation. For example, in the Big Sandy watershed an isolated NHD segment with a length of only 7.7 meters had two dams attributed to it, resulting in an extremely high density of 259.8 dams per kilometer (Figure 4). To account for these factors, we only used dams that were within 30 m of an NHD stream segment, and segments with length greater than 100 m for our validation analyses.

Second, model outputs were used to confirm whether or not the predictions seemed reasonable (e.g. places with no evidence of beaver dams are modeled with a capacity equal to 0 dams/km). An observed dam density one dam higher than the modeled capacity is a small error in a reach estimated to have pervasive capacity relative to a reach modeled to have 'rare' capacity. We also characterized potential errors in the capacity estimates, therefore, by calculating the proportion of reaches with dams that have observed densities below predicted capacity, below 150% of the predicted capacity, and below 200% above predicted capacity.

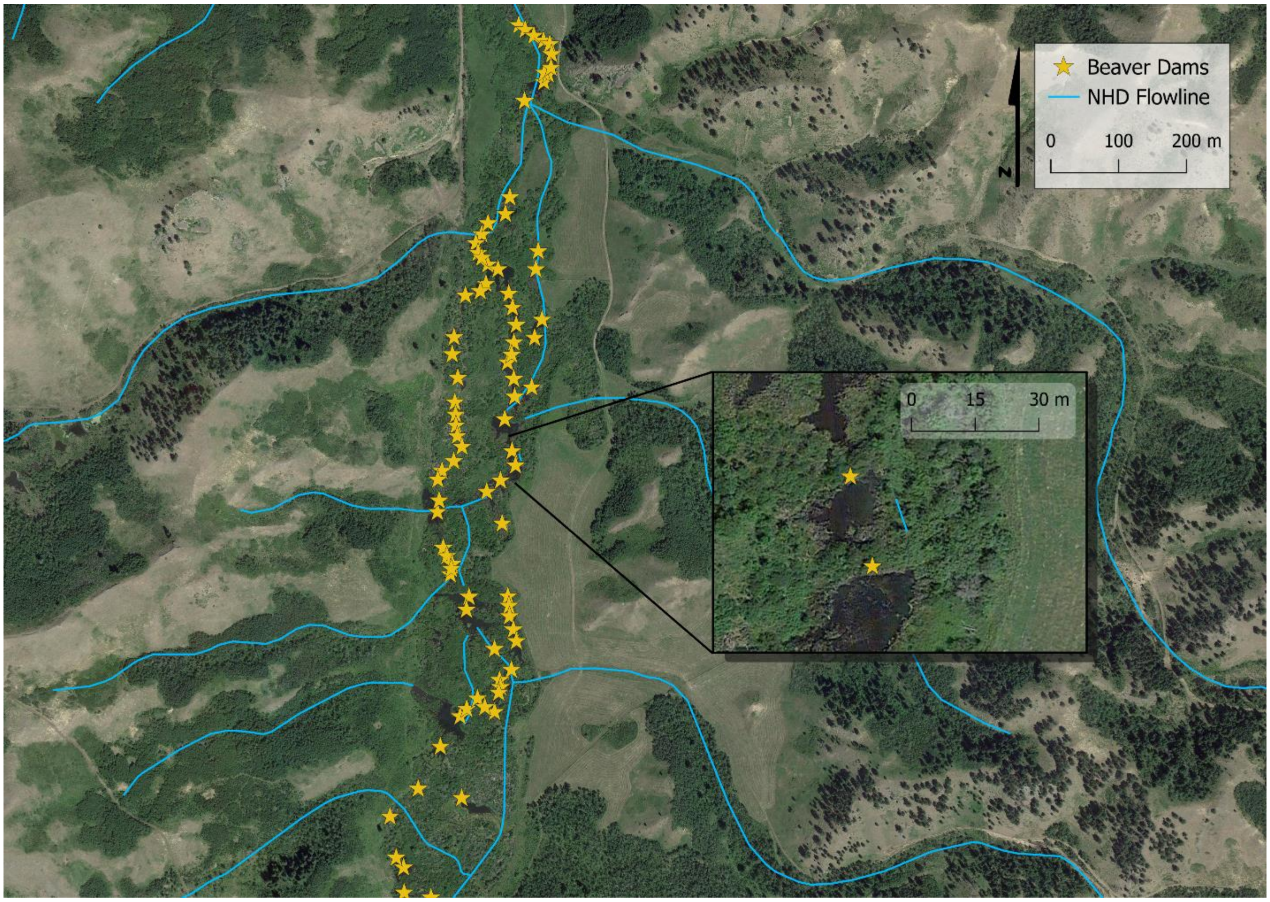

Figure 4. Observed dam locations and the NHD flowline channel network. Note the dams mapped along secondary channels for which there is no NHD flowline. The inset shows where two dams were attributed to a very short segment resulting in an artificially high-density value.

Lastly, to assess whether or not beaver dam-building was preferentially taking place in reaches with higher capacity estimates, an electivity index (EI) was calculated. This logic, follows conceptually from the 'ideal free distribution' (Fretwell & Lucas, 1970), such that the distribution of beaver dams (in this case) should match the distribution of resources to support such construction and maintenance activities. Following Pasternack (2011) an *EI*, was calculated for each segment type (*i*):

$EI_i=(n_i/\sum n_i)(l_i/\sum l_i)$

Where n_i is the number of beaver dams surveyed in segment type *I* and l_i is the length of that segment type. The *EI* essentially normalizes utilization by availability such that i) an *EI* value of one indicates utilization of available habitat without preference or avoidance, ii) an *EI* value less than one indicates avoidance of a particular habitat, whereas iii) an *EI* value greater than one indicates preference for a habitat. The segment types (*i*) are a classification that corresponds to the linguistic categories used in the BRAT capacity model FIS. If the capacity model is effectively segregating actual dam densities, we would expect an *EI* close to zero for the *none* and *rare* classes, less than one for the *occasional* class, greater than one for the *frequent* class, and much greater than one for the *pervasive* class.

RESULTS

Imagery-based Beaver Dam Census

The Montana statewide imagery-based census took a total of 910-person hours to complete with a total of 32,336 dams recorded across the 101 HUC 8s that make up the state of Montana. This equates to on average 9.1 hours per HUC 8 watershed, 35.5 dam locations per hour or 1.7 minutes per dam location. Figure 5 shows the spatial distribution of 32,336 beaver dams across the 101 HUC 8 watersheds that were identified throughout Montana. There is significant variation in the number of beaver dams per watershed, with some having no dams and others having over 2,000 dams per watershed (Figure 6).

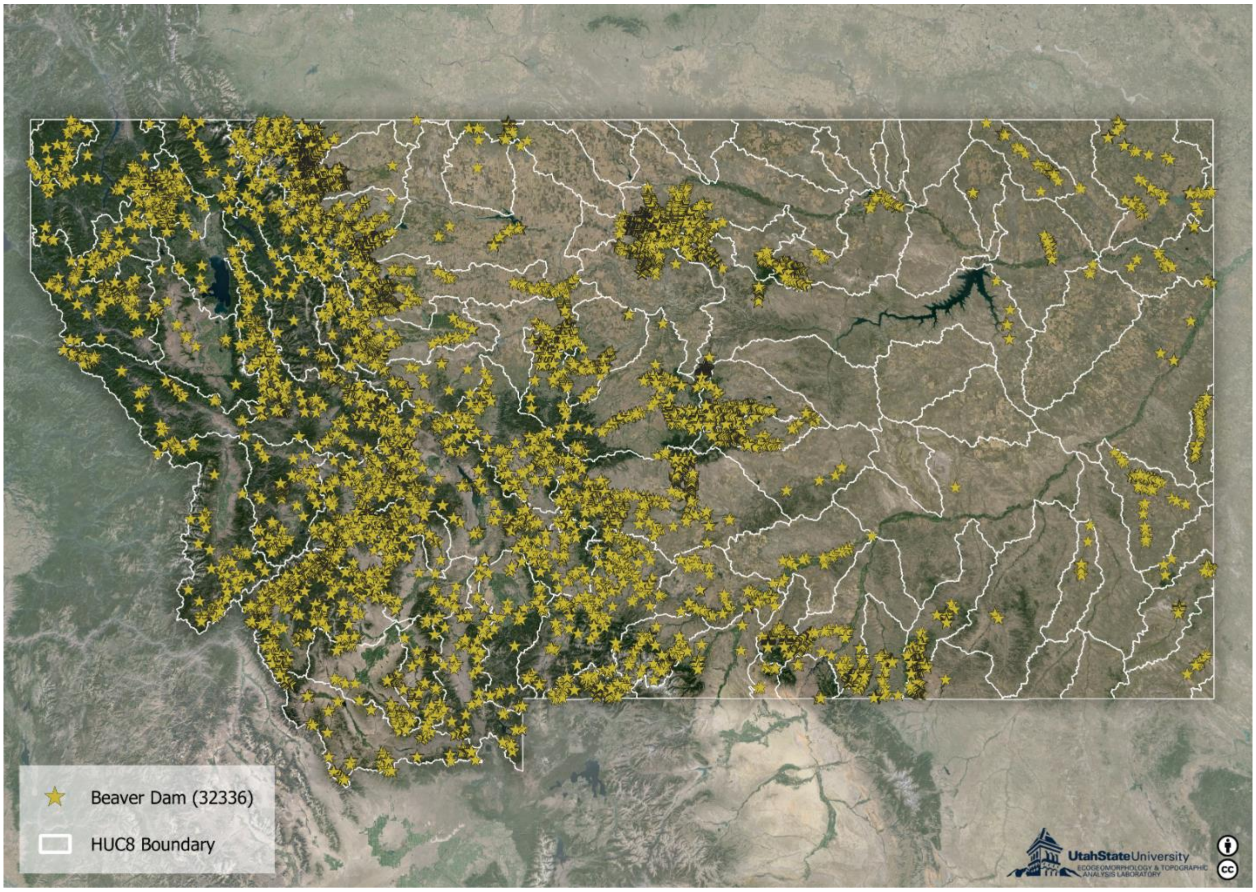

Figure 5. Beaver dam locations based on Montana statewide imagery-based beaver dam census.

Specifically, a total of 20 of the 101 HUC 8 watersheds showed no beaver dams and are primarily located in the eastern portion of the state (Figure 6). An additional 20 watersheds had fewer than 50 dams and were also concentrated in the eastern portion of the state. The western portion of the state had much higher numbers of dams per watershed. Beaver dam densities per watershed had a similar spatial pattern to number of dams across the state (Figure 7).

We also generated 3 different versions (points, cluster points and choropleth) of an atlas of beaver dam locations across the state at the HUC 8 level which can be found here. The GIS data layers for beaver dam locations are also available as KMZ and shapefile format. Statewide data can be found here and HUC 8 level data can be found here.

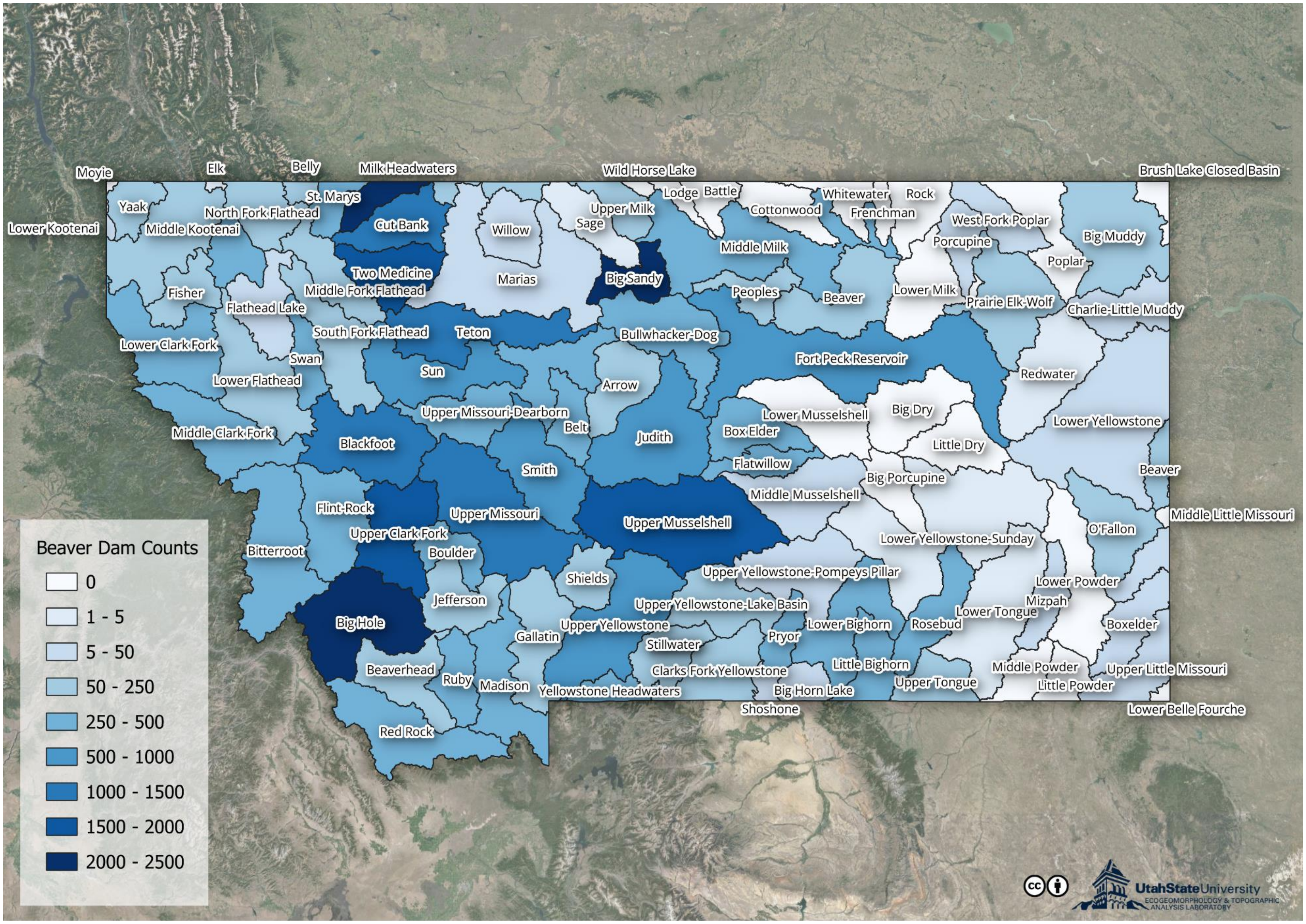

Figure 6. The number of beaver dams per USGS HUC 8 watershed based on imagery-based census.

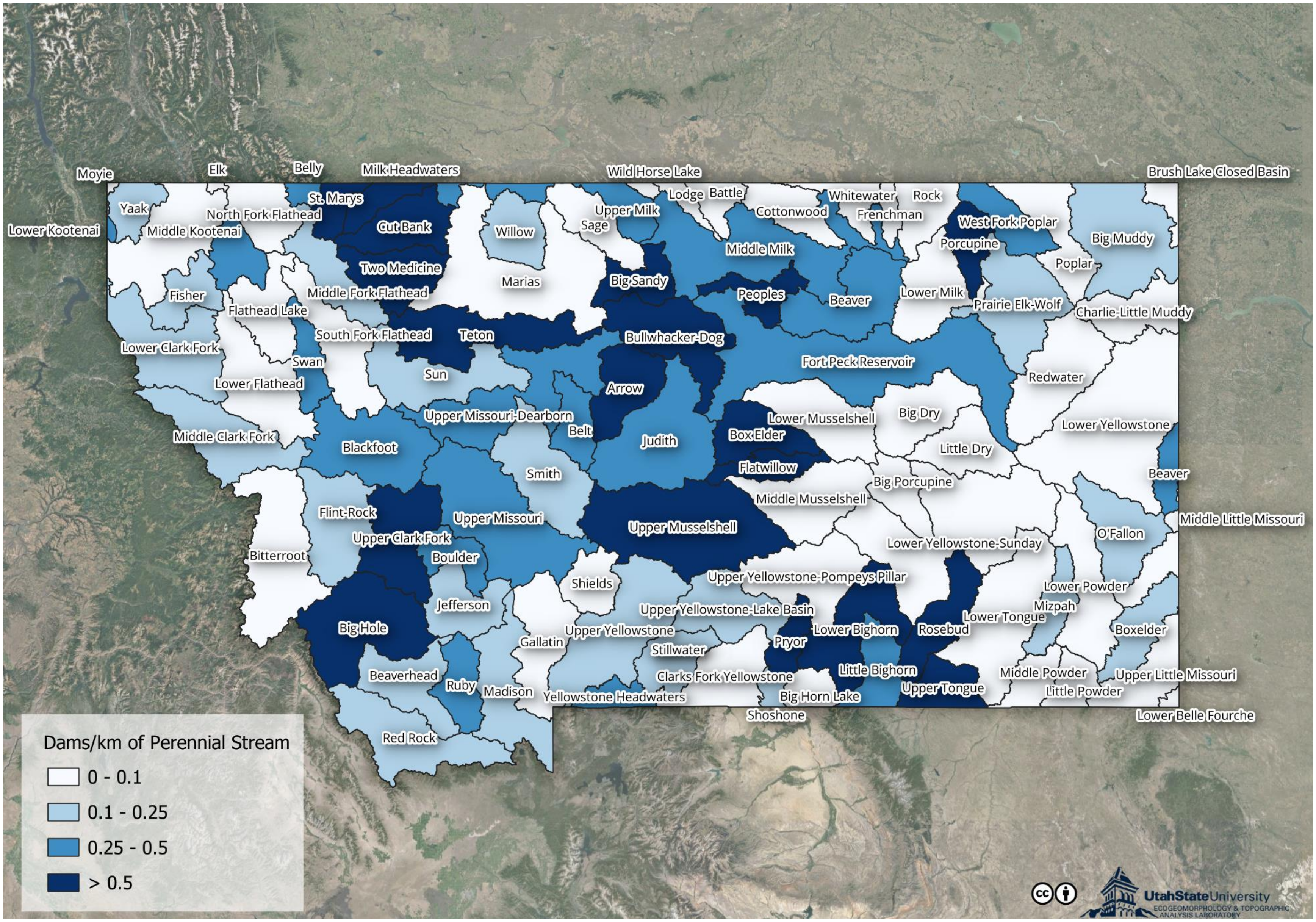

Figure 7. Dams per kilometer of perennial stream based on individual dam census data and NHD perennial stream network.

Three watersheds had over 2000 dams recorded: Milk Headwaters at 2481 dams, Big Hole at 2461 dams, and the Big Sandy at 2156 dams (Table 3). Big Sandy and Milk Headwaters also had by far the highest dam densities with 6.89 and 6.19 dam per km respectively whereas the Big Hole's density was quite low at 0.64 dams per km of perennial streams (Table 3). The next highest observed dam densities, other than Big Sandy and Milk Headwaters, were Cut Bank with a dam density of 1.75 followed by Two Medicine with a density of 1.33 (Table 3).

The Middle Rockies ecoregion had the highest number of beaver dams pers ecoregion with 11009 dams (Figure 8). Whereas the Northwestern Glaciated Plains Ecoregion had the second largest number of dams with 9263 and by far the highest density of dam per km of perennial stream at 0.8 dams per km with the next closest ecoregion – Middle Rockies at 0.3 dams per km (Table 4).

Table 3. The top 10 HUC 8 for number of dams recorded by the imagery-based census. Table shows the number of beaver dams and associated dam density per HUC 8 watershed.

HUC 8	Number of Dams	Dams per km of perennial stream
Milk Headwaters	2481	1.32
Big Hole	2461	0.57
Big Sandy	2156	6.97
Two Medicine	1922	1.33
Upper Clark Fork	1806	0.76
Upper Musselshell	1654	0.56
Teton	1386	1.05
Blackfoot	1264	0.43
Cut Bank	1235	1.75
Upper Missouri	1037	0.36

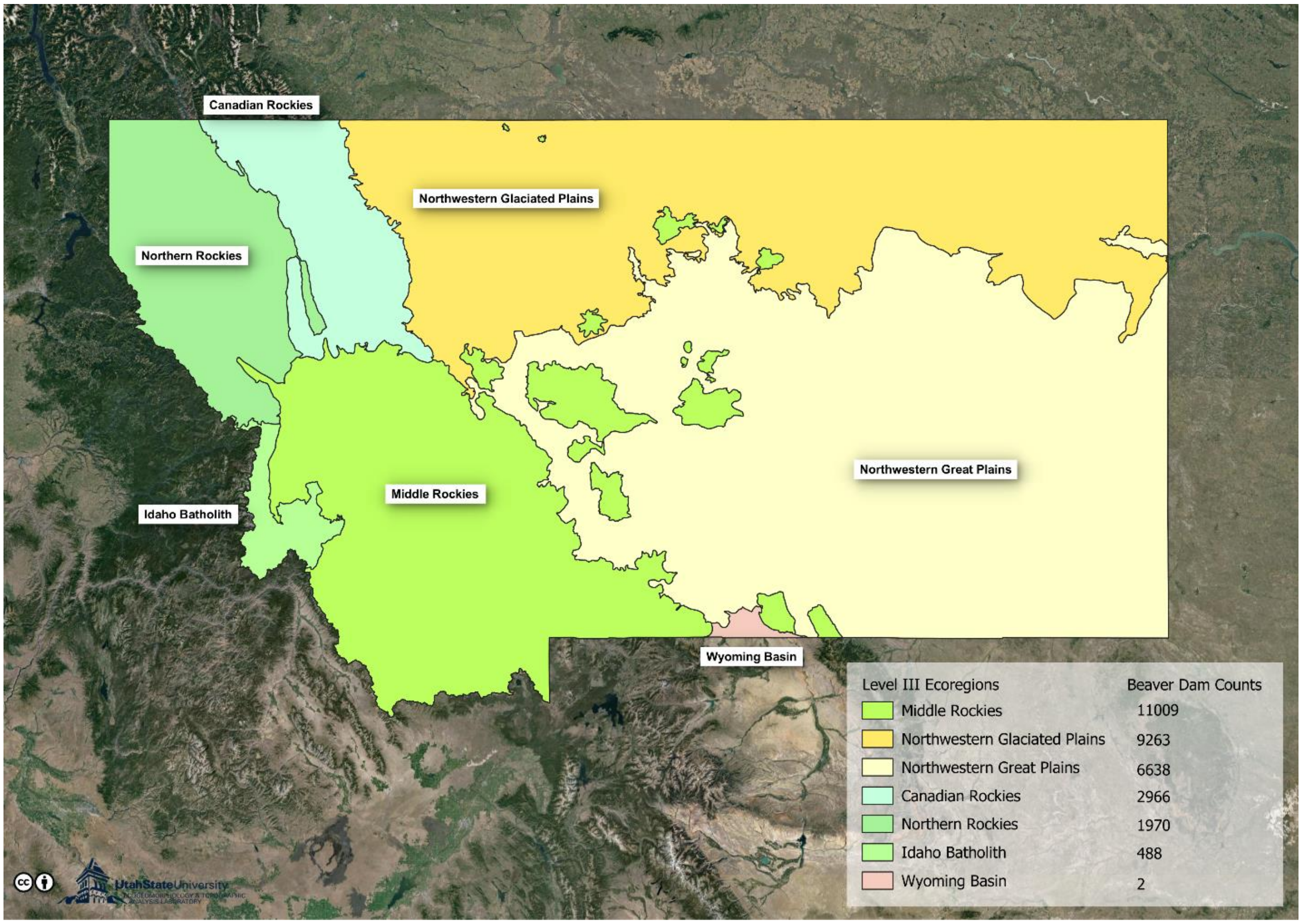

Figure 8. This map shows number of beaver dams per EPA Level III Ecoregion.

Table 4. Estimated beaver dam density per Level III Ecoregion based on imagery-based census.

Ecoregions	Number of Dams	Dams per km of perennial stream
Middle Rockies	11009	0.30
Northwestern Glaciated Plains	9263	0.80
Northwestern Great Plains	6638	0.29
Canadian Rockies	2966	0.24
Northern Rockies	1970	0.17
Idaho Batholith	488	0.14
Wyoming Basin	2	0.01

When we intersect the beaver dam location data with landownership interesting patterns emerge. For instance, tribal lands have by far the highest beaver dam densities at 1.16 dams per km, the next highest densities are local government at 0.88, followed by state government at 0.49 (Table 5).

Table 5. Beaver dam density per land ownership category.

Ownership	Length (km)	Dam count	Dams per km perennial stream
Nontribal	88709.95	24199	0.27
Tribal	7006.05	8137	1.16
Private	45673.74	15673	0.34
USFS	32986.34	5447	0.17
State Government	4253.05	2087	0.49
Tribal	7006.05	8137	1.16
BLM	1984.23	178	0.09
NPS	2850.38	536	0.19
USFWS	402.33	65	0.16
Local Government	236.87	208	0.88

Out of the three dam types recorded in the survey (active, inactive, and relic), 88% were recorded as active (Table 6). Out of the dam certainty types (high, medium and low), 62% were recorded as high certainty (Table 6). The year of imagery from which dam locations were collected range from 2009 to 2024 (a 15-year time period), with most dams being recorded in 2014 (Table 7).

Table 6. Dam type and certainty total counts and the proportion of the total number of records.

Dam Type	Count	Proportion
Active	28410	87.9%
Inactive	3413	10.6%
Relic	512	1.6%

Dam Certainty	Count	Proportion
High	20151	62.3%
Medium	8929	27.6%
Low	3255	10.1%

Table 7. Distribution of years of imagery used in census and total dam counts for each year with proportion of total dam count.

Year	Count	Proportion
2009	2	0%
2010	43	0.1%
2011	95	0.3%
2012	12	0%
2013	613	1.9%
2014	12975	40.1%
2015	4006	12.4%
2016	1762	5.4%
2017	1267	3.9%
2018	9	0%
2019	355	1.1%
2020	460	1.4%
2021	584	1.8%
2022	5321	16.5%
2023	4818	14.9%
2024	13	0%

BRAT Capacity Model Verification

For validation, we compared observations of dam locations from our imagery-based census with BRAT existing capacity outputs from six HUC 8 watersheds (one within each EPA Level III Ecoregions): 10020004 (Big Hole), 10030201 (Two Medicine), 10040201 (Upper Musselshell), 10050004 (Middle Milk), 17010205 (Bitterroot) and 17010213 (Lower Clark Fork). A total of 7,149 beaver dams were mapped representing 5% of the 687 km of perennial streams with beaver dam capacity. Of those, we used 5,034 beaver dams that met our criteria (less than 30 m from an NHD segment and on a reach greater than 100 m in length) to verify the performance of the BRAT existing capacity model.

How do dam densities track between predicted and actual?

Of the total 2,199 stream segments with verification dam counts 385 exceeded the capacity estimates indicating that the model effectively segregates the factors controlling beaver dam occurrence and density 82% of the time (Figure 9). Thus, the BRAT model underestimated capacity 18% of the time (Figure 9). 90% of the dammed reaches had observed capacities within 150% of the modeled capacity (i.e. 1.5 times the modeled capacity value), and 94% of the reaches had observed capacities under 200% of the modeled capacity (i.e., double the modeled capacity value). Some of the underestimation of capacity may be a result of including some dams on secondary channels, even after using the filtering criteria previously described (see Discussion). Beaver dams identified in the imagery-based census were concentrated in reaches where the BRAT capacity model estimated frequent and pervasive dam densities. In all of our validation watersheds, the 75th and 90th percentile regression lines were similar to the 1:1 line, indicating that model is effectively discriminating capacity values (Figure 9).

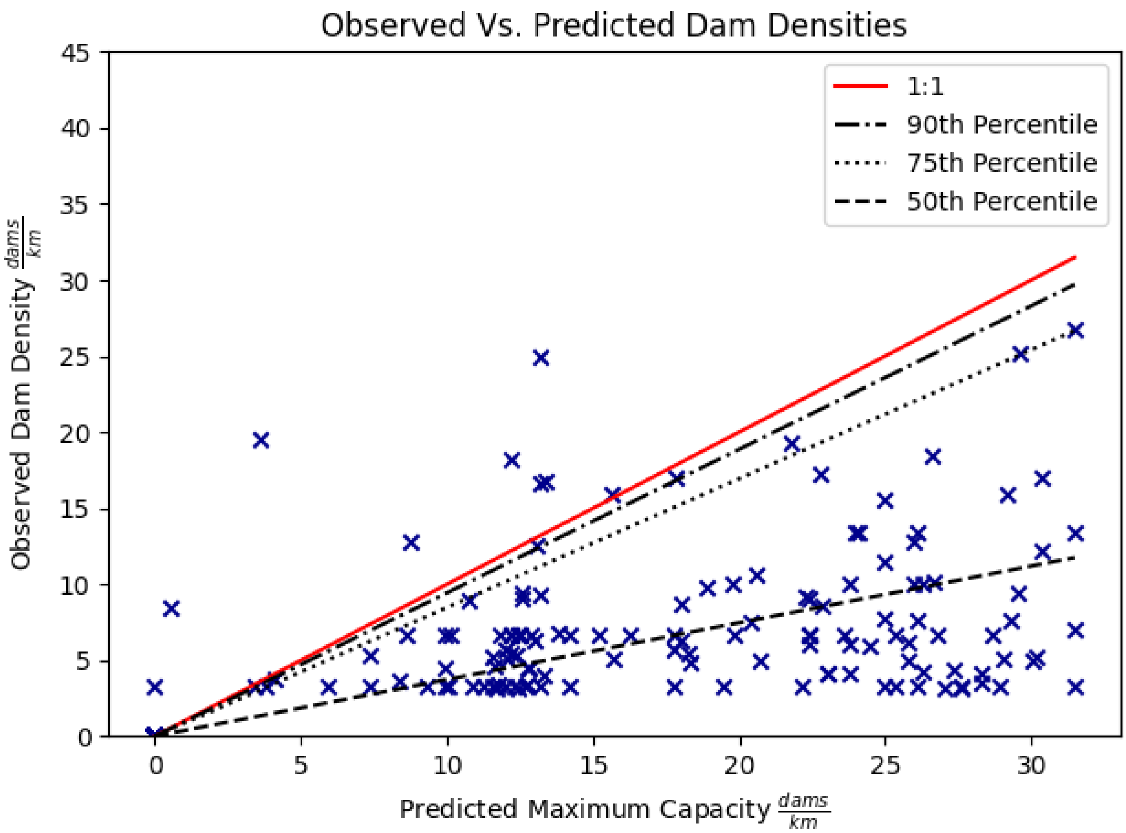

Figure 9. An example of quantile regression outputs; predicted vs. observed dam counts (per reach) for HUC 17010213 (Lower Clark Fork). The red line is the line of perfect agreement (1:1 relationship), dash-dot line is the 90th percentile regression, dotted line is the 75th percentile regression, and dashed line is the 50th percentile regression. The nearer the higher percentile regression is to the 1:1 ratio, the better the model is performing.

Are there surveyed dams where none are predicted?

Only 2 beaver dams (0.04%) were found where the model predicted no dams could be supported. Additionally, of the 385 reaches where capacity was underestimated, 129 reaches (6%) had a discrepancy of 100% (i.e. was different by a factor of 2) or more. All of these had higher densities than predicted by the model due to floodplain and side channel dam building, or issues with the input channel network position (see Discussion).

Do the electivity indices increase appreciably from the none to the pervasive class?

The electivity indices results shown in Table 8 indicate that throughout the perennial streams of the six validation watersheds, beavers preferentially build dams in reaches with higher modelled dam capacity while avoiding those with lower capacity. That is, beaver exhibited avoidance of reaches predicted as supporting *none*, *rare* or *occasional* densities, and beaver exhibited preference for areas predicted as having *frequent* or *pervasive* dam densities.

Table 8. Number of dams (based on imagery-based census) compared to BRAT modeled capacity estimates for six HUC 8 watersheds in Montana.

Segment Type	Stream Length	Percent of Drainage Network	Surveyed Dams	BRAT Estimated Capacity	Average Surveyed Dam Density	Average Predicted Capacity	Percent of Modeled Capacity	Electivity Index
	km	%	# of dams	# of dams	dams/km	dams/km	%	
None	1762	11%	2	0	0.001	0.00	N/A	0.004
Rare	400	2%	10	238	0.025	0.60	4%	0.083
Occasional	4813	29%	337	17240	0.07	3.53	2%	0.232
Frequent	7262	44%	2051	73381	0.282	10.25	3%	0.936
Pervasive	2439	15%	2634	55540	1.080	22.45	5%	3.578
Total	**16691**	**100%**	**5034**	**146399**	**0.302**	**7.36**	**3%**	**N/A**

Individual validation results for each of the six watersheds can be found in APPENDIX B.

DISCUSSION

Imagery-based Beaver Dam Censusing: Caveats

We refer to this approach of collecting dam locations as ‘censusing’ because the entire perennial network is sampled. However, it is important to point out that this is not a complete census of beaver dams, it is a sample from a “snap shot” in time based on the date of imagery. Moreover, this imagery-based method generally under-samples total dams, especially in forested ecosystems where it is difficult to see the stream through the forest canopy.

The quality of the imagery used for identifying beaver dams varied significantly across imagery acquisition dates. Often more recently acquired imagery suffered from poor quality due to factors such as low resolution and clarity, issues with color and contrast levels, and obscuration of streams from clouds or shadows (Figure 10). Consequently, observers frequently resorted to utilizing historical imagery to collect their beaver dam locations. The acquisition dates of the historical imagery ranged from a few years to over a decade. This raises the concern that the data captured from these images may not represent the current condition of these riverscapes. Ground truthing could be an effective way to improve the accuracy of the dam observations but would prove costly due to the large number of observations and area covered.

a) Imagery Date: 9/11/2015 b) Imagery Date: 8/3/2021

Figure 10. Comparison between older and newer satellite imagery. In this area, the only imagery acquired after 2015 contained thick cloud cover, obscuring potential dams and limiting observation potential.

It is also important to note that although the perennial network was the focus, if dams on an intermittent or ephemeral stream were found within the view frame, they were also marked. For instance, there were many dams in the Big Sandy watershed specifically that were not on a perennial stream and are skewing the metric of dams per kilometer of perennial stream.

Another caveat to mention is the issue of mistaking “land bridges” as beaver dams. We define land bridges as exposed, channel spanning bars that are perpendicular to the stream channel and are found in many low elevation, low gradient watersheds. Several watersheds in eastern Montana had many land bridges, which often pool water, making them easy to mistake as a beaver dam. Hence, we established a protocol to distinguish between land bridges and beaver dams, but there are likely some land bridges that were still marked as beaver dams.

NHD Flowlines: Limitations

Even after selecting only dams within 30 m of a stream segment longer than 100 m, in some cases, dams were still retained that occurred on secondary channels not included in the NHD channel network (Figure 11). This was the case for the majority of the segments where observed densities were significantly higher than predicted densities. If our methodology could more effectively segregate between dams associated with and NHD channel segment and dams that are not, or if NHD consistently and accurately mapped secondary anabranches, instances of underestimates of capacity would be reduced.

Figure 11. An illustration of exaggerated dam densities due to dams occurring on multiple anabranches where only a single channel is mapped by NHD.

Dams on Segments with No Modeled Capacity

Two dams occurred on segments predicted to have no capacity. However, upon investigation neither dam actually occurred on the channel where no capacity was modeled. In one case, the dam was mapped more closely to a small, steep tributary with no capacity than to the correct associated channel in the NHD network. As a result, the dam was attributed to the wrong stream segment in the validation code (Figure 12). In the other case, the dam was a floodplain dam across a road (which intersects the floodplain) from the main channel.

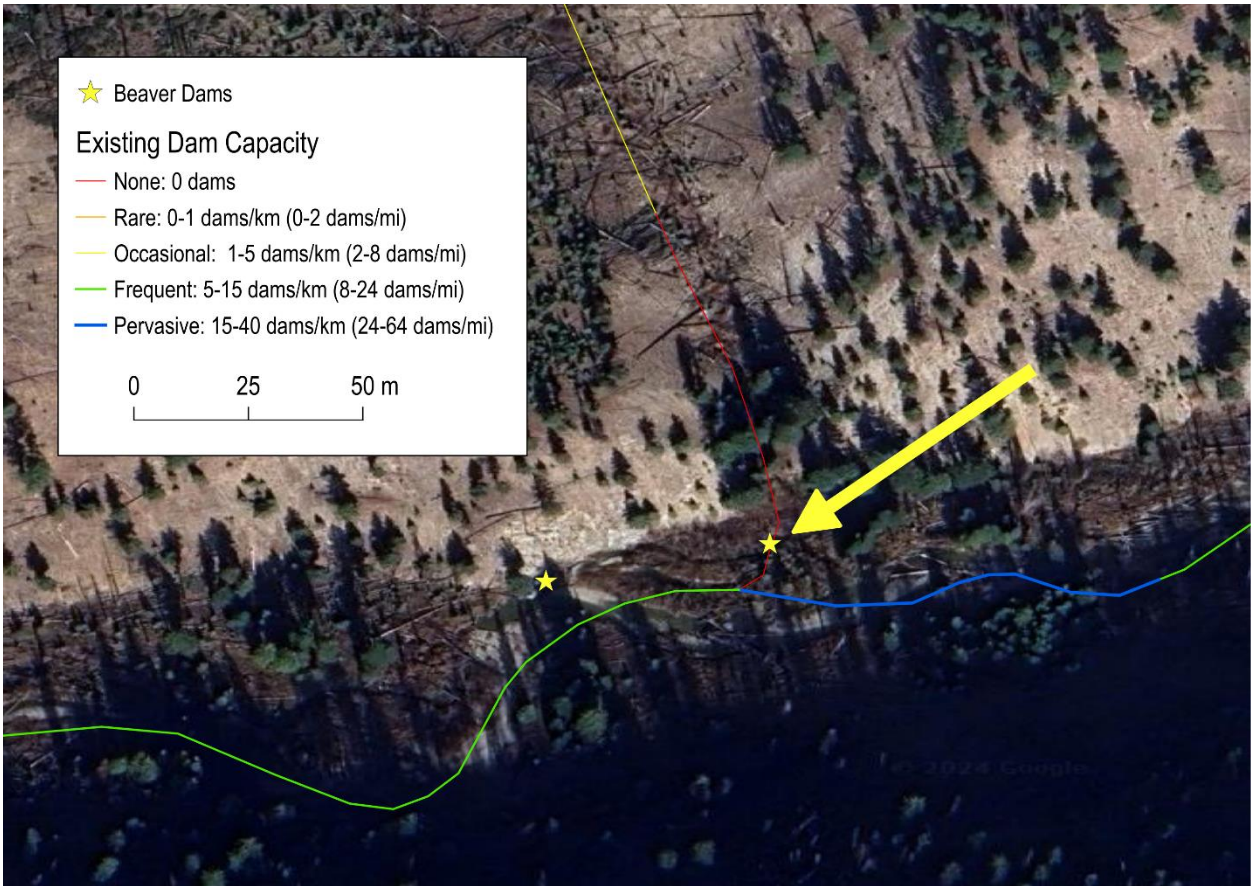

Figure 12. An example of a dam indicated by the arrow being attributed to a tributary with no capacity when it is actually built on the main channel.

BRAT Capacity Model: Limitations

As with any model, the outputs are only as good as the inputs. Though the logic of the capacity model and model performance is robust, the BRAT capacity model is limited by the coarseness of the freely available data used as input, including the vegetation mapping, digital elevation models (DEM), and drainage network (stream position) mapping. In the case of the Montana the investigation of the input vegetation data compared to aerial imagery shows that narrow riparian zones are often missed by the 30-meter resolution vegetation data, and therefore capacity is underestimated in these areas. Eastern Montana contains a lot of narrow riparian corridors.

The low resolution and poor delineation of the NHD network is a major limiting factor for the BRAT model. However, in some cases, other inputs may cause the model to struggle to predict dam capacity accurately. In Figure 13, a stream with no visible side channels in the Bitterroot watershed has a range of predictions for nearby reaches from no dams to pervasive. This is driven by high reach-to-reach variability in stream power due to varying slope values, suggesting that the DEM input for the model in this specific area is of relatively poor quality.

Figure 13. West Fork Bitterroot River showing the maximum range of dam density estimations from none to pervasive, with a dam on the 'none' segment.

CONCLUSIONS

The imagery-based beaver dam census produced by this project reveals important patterns of beaver dam building across the riverscapes of Montana. For instance, the census shows that portions of many western Montana watersheds have dam building at or near capacity, while other similar watersheds with favorable vegetation and hydrology for pervasive levels of dam building have very limited dam building and are only at a small percent of capacity thus revealing where beaver conservation as well as promoting dam building by beaver should take place.

Regardless of the known challenges related to the imagery-based beaver dam census, the NHD flowline data, and the BRAT capacity model, BRAT performed well in the six HUC 8 watersheds we used for validation. Our results indicate that the model effectively segregates the factors controlling beaver dam occurrence and density 82% of the time and the electivity indices indicated that beavers are preferentially building dams in areas where BRAT shows high levels of dam-building capacity, while avoiding areas with low levels of dam-building capacity.

Thus, the statewide beaver dam location data and BRAT capacity model outputs should provide the Montana Fish, Wildlife and Parks staff with the information they need to better manage dam building beaver and to identify opportunities for using beaver in riverscape restoration and conservation at the stream reach level as well as at the watershed scale and throughout Montana.

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APPENDIX A: Full table of all 101 HUC 8s and their beaver dam metrics.

Name	HUC Number	Dam Count	Length of Perennial Stream (km)	Dams per km of Perennial Stream
Big Sandy	10050005	2156	313.15	6.89
Milk Headwaters	10050001	2481	401.07	6.19
Cut Bank	10030202	1235	706.22	1.75
Two Medicine	10030201	1922	1447.45	1.33
Teton	10030205	1386	1330.83	1.04
Peoples	10050009	235	240.53	0.98
Pryor	10070008	336	416.96	0.81
Box Elder	10040204	379	471.18	0.80
Upper Clark Fork	17010201	1806	2317.29	0.78
Arrow	10040102	250	328.25	0.76
Big Hole	10020004	2461	3842.00	0.64
Bullwhacker-Dog	10040101	337	529.69	0.64
St. Marys	9040001	418	678.83	0.62
Porcupine	10050016	7	11.49	0.61
Flatwillow	10040203	337	563.15	0.60
Rosebud	10100003	302	517.66	0.58
Upper Musselshell	10040201	1654	2961.90	0.56
Upper Tongue	10090101	124	223.60	0.56
Lower Bighorn	10080015	496	976.97	0.51
Beaver	10050014	227	467.92	0.49
Little Bighorn	10080016	256	530.13	0.48
Fort Peck Reservoir	10040104	599	1265.58	0.47
Beaver	10110204	100	212.13	0.47
Stillwater	17010210	441	941.05	0.47
Blackfoot	17010203	1264	2947.46	0.43
Belt	10030105	332	776.44	0.43
Upper Milk	10050002	126	297.13	0.42
Yellowstone Headwaters	10070001	266	640.71	0.42
Middle Milk	10050004	488	1183.15	0.41
Ruby	10020003	439	1135.64	0.39
Boulder	10020006	359	953.83	0.38
Judith	10040103	650	1824.60	0.36
Upper Missouri	10030101	1037	2921.87	0.36
Belly	9040002	109	348.98	0.31
Lower Kootenai	17010104	24	77.51	0.31
West Fork Poplar	10060004	41	145.80	0.28

Swan	17010211	266	1029.26	0.26
Upper Missouri-Dearborn	10030102	413	1630.59	0.25
Smith	10030103	530	2157.62	0.25
Sun	10030104	634	2783.09	0.23
Flint-Rock	17010202	435	1976.57	0.22
O'Fallon	10100005	82	381.01	0.22
Red Rock	10020001	425	2081.85	0.20
Middle Clark Fork	17010204	430	2220.64	0.19
Fisher	17010102	116	601.76	0.19
Lower Clark Fork	17010213	368	2127.84	0.17
Big Muddy	10060006	102	653.97	0.16
Madison	10020007	347	2223.39	0.16
Stillwater	10070005	223	1428.63	0.16
Mizpah	10090210	16	105.24	0.15
Boxelder	10110202	29	193.29	0.15
Upper Yellowstone	10070002	555	3787.16	0.15
Upper Yellowstone-Lake Basin	10070004	139	981.44	0.14
Beaverhead	10020002	185	1341.32	0.14
Prairie Elk-Wolf	10060001	57	415.08	0.14
Jefferson	10020005	161	1296.49	0.12
Willow	10030204	13	104.64	0.12
Shoshone	10080014	12	115.85	0.10
Middle Fork Flathead	17010207	217	2122.70	0.10
Yaak	17010103	79	781.26	0.10
Gallatin	10020008	208	2255.25	0.09
Middle Kootenai	17010101	199	2201.95	0.09
Shields	10070003	124	1549.78	0.08
North Fork Flathead	17010206	118	1577.83	0.08
Bitterroot	17010205	256	3864.89	0.07
Big Horn Lake	10080010	34	531.36	0.06
Redwater	10060002	4	64.24	0.06
Charlie-Little Muddy	10060005	28	500.49	0.06
Marias	10030203	49	917.53	0.05
South Fork Flathead	17010209	143	2701.64	0.05
Upper Yellowstone-Pompeys Pillar	10070007	37	695.19	0.05
Flathead Lake	17010208	49	951.01	0.05
Clarks Fork Yellowstone	10070006	64	1476.85	0.04
Upper Little Missouri	10110201	16	385.70	0.04
Lower Flathead	17010212	51	1514.82	0.03

Elk	17010106	2	76.08	0.03
Lower Yellowstone	10100004	19	769.67	0.03
Sage	10050006	1	54.32	0.02
Middle Musselshell	10040202	6	348.97	0.02
Lower Tongue	10090102	5	720.71	0.01
Lower Yellowstone-Sunday	10100001	1	837.91	0.00
Battle	10050008	0	73.96	0
Big Dry	10040105	0	2.72	0
Big Porcupine	10100002	0	11.48	0
Brush Lake Closed Basin	10060007	0	2.53	0
Cottonwood	10050010	0	37.76	0
Frenchman	10050013	0	138.05	0
Little Dry	10040106	0	0.60	0
Little Powder	10090208	0	232.35	0
Lodge	10050007	0	28.69	0
Lower Belle Fourche	10120202	0	4.88	0
Lower Milk	10050012	0	358.08	0
Lower Musselshell	10040205	0	153.09	0
Lower Powder	10090209	0	306.75	0
Middle Little Missouri	10110203	0	0.00	0
Middle Powder	10090207	0	143.45	0
Moyie	17010105	0	57.80	0
Poplar	10060003	0	245.83	0
Rock	10050015	0	126.08	0
Whitewater	10050011	0	23.73	0
Wild Horse Lake	10050003	0	6.70	0

APPENDIX B: Individual validation results for each of the six validation watersheds

HUC: 10020004 (Big Hole)

Table B1. Electivity Index

Capacity	Stream Length	% of Drainage Network	Surveyed Dams	BRAT Estimated Capacity	Average Surveyed Dam Density	Average Predicted Capacity	% of Modeled Capacity	Electivity Index
	km	*%*	*# of dams*	*# of dams*	*dams/km*	*dams/km*	*%*	
None	243	5.6	0	0	0	0	NA	0
Rare	9	0.2	0	5	0	0.63	0	0
Occasional	1127	25.9	41	4172	0.036	3.7	0.98	0.09
Frequent	2019	46.4	403	20406	0.2	10.11	1.97	0.51
Pervasive	954	21.9	1246	22376	1.305	23.44	5.57	3.36
Total	**4352**	**100**	**2461**	**47019**	**0.563**	**10.78**	**3.6**	**NA**

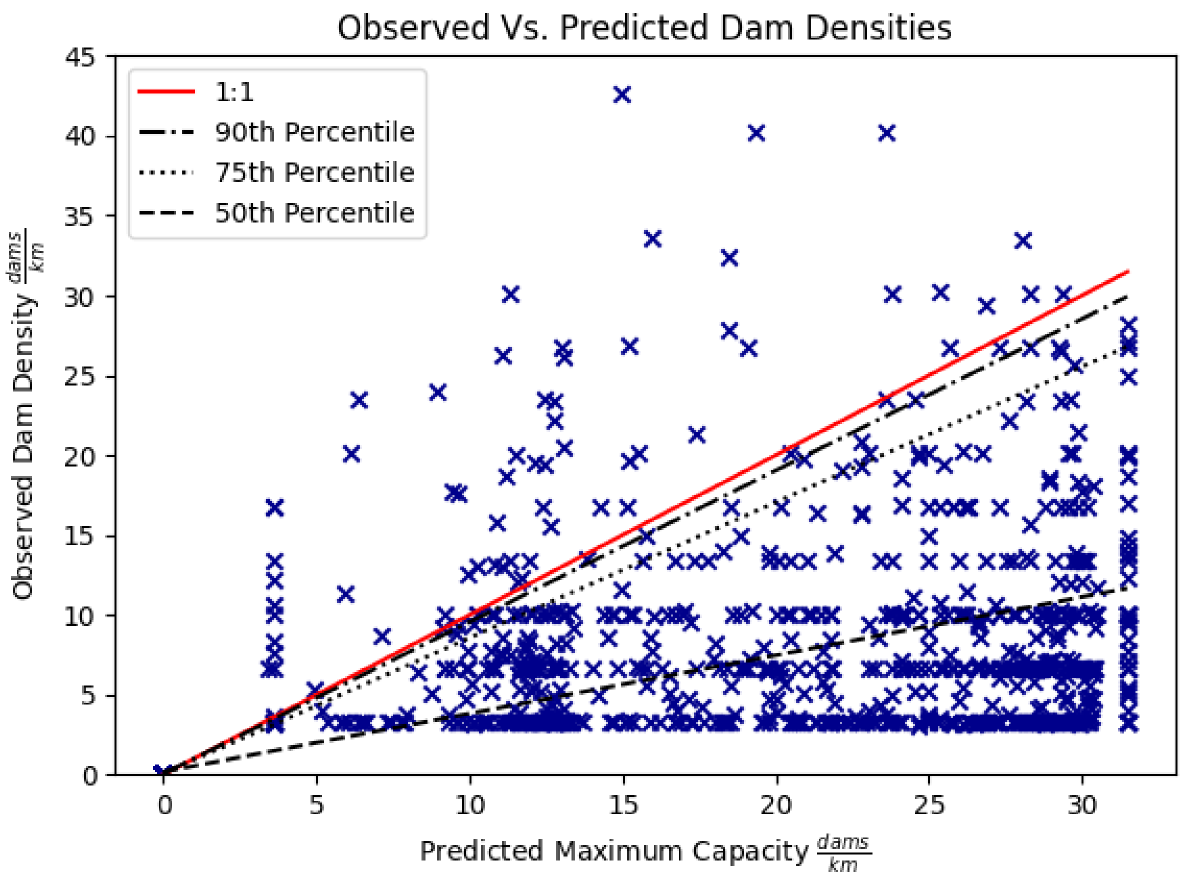

Figure B1. Quantile Regressions

HUC: 10030201 (Two Medicine)

Table B2. Electivity Index

Capacity	Stream Length	% of Drainage Network	Surveyed Dams	BRAT Estimated Capacity	Average Surveyed Dam Density	Average Predicted Capacity	% of Modeled Capacity	Electivity Index
	km	*%*	*# of dams*	*# of dams*	*dams/km*	*dams/km*	*%*	
None	87	5.9	0	0	0	0	NA	0
Rare	47	3.2	3	28	0.063	0.59	10.66	0.07
Occasional	270	18.4	118	902	0.436	3.33	13.08	0.49
Frequent	687	46.6	623	7575	0.906	11.02	8.22	1.02
Pervasive	377	25.6	562	8487	1.489	22.48	6.62	1.68
Total	**1468**	**100**	**1922**	**17101**	**0.886**	**11.53**	**7.69**	**NA**

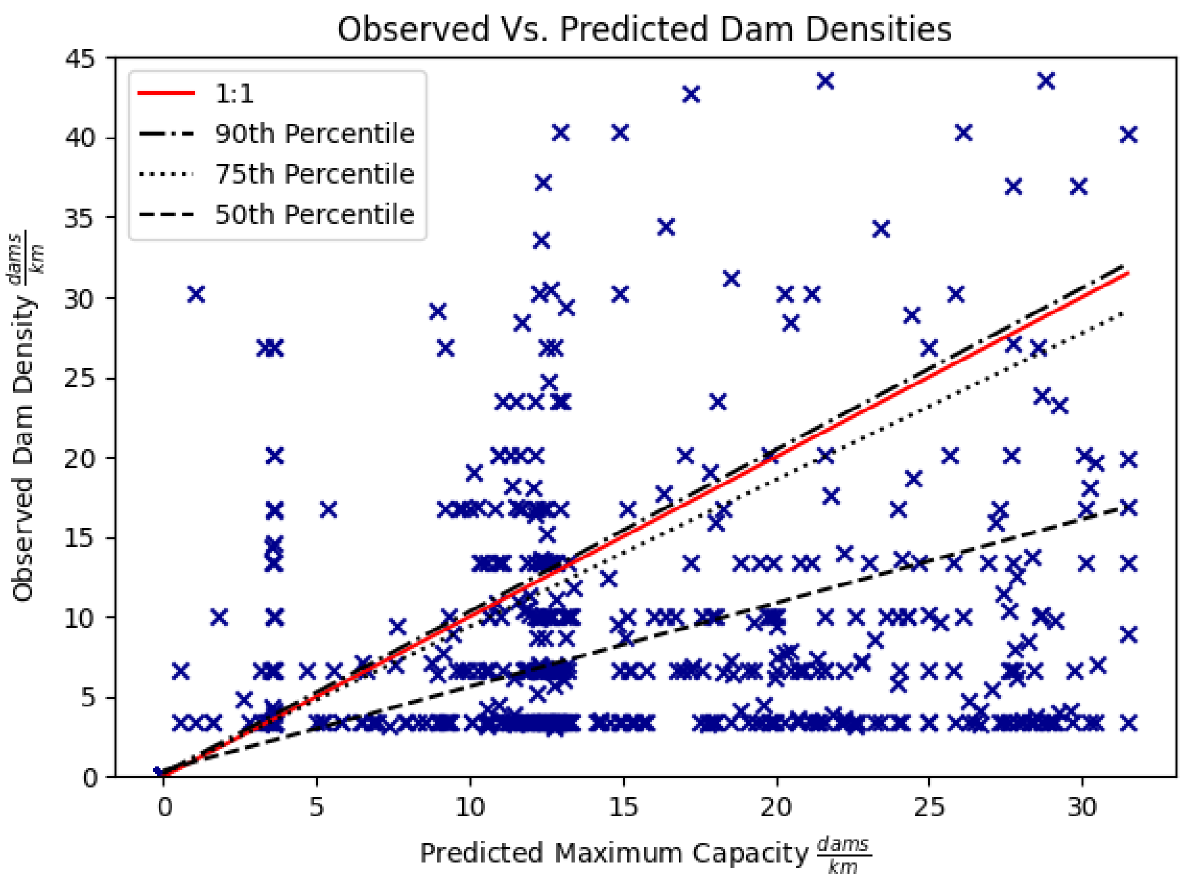

Figure B2. Quantile regressions

HUC: 10040201 (Upper Musselshell)

Table B3. Electivity Index

Capacity	Stream Length	% of Drainage Network	Surveyed Dams	BRAT Estimated Capacity	Average Surveyed Dam Density	Average Predicted Capacity	% of Modeled Capacity	Electivity Index
	km	*%*	*# of dams*	*# of dams*	*dams/km*	*dams/km*	*%*	
None	17	0.6	0	0	0	0	NA	0
Rare	29	1	0	18	0	0.63	0	0
Occasional	1267	43.4	103	4353	0.081	3.43	2.37	0.2
Frequent	1254	43	608	12819	0.485	10.22	4.74	1.18
Pervasive	338	11.6	485	7419	1.435	21.94	6.54	3.49
Total	**2905**	**100**	**1654**	**24659**	**0.41**	**8.43**	**4.86**	**NA**

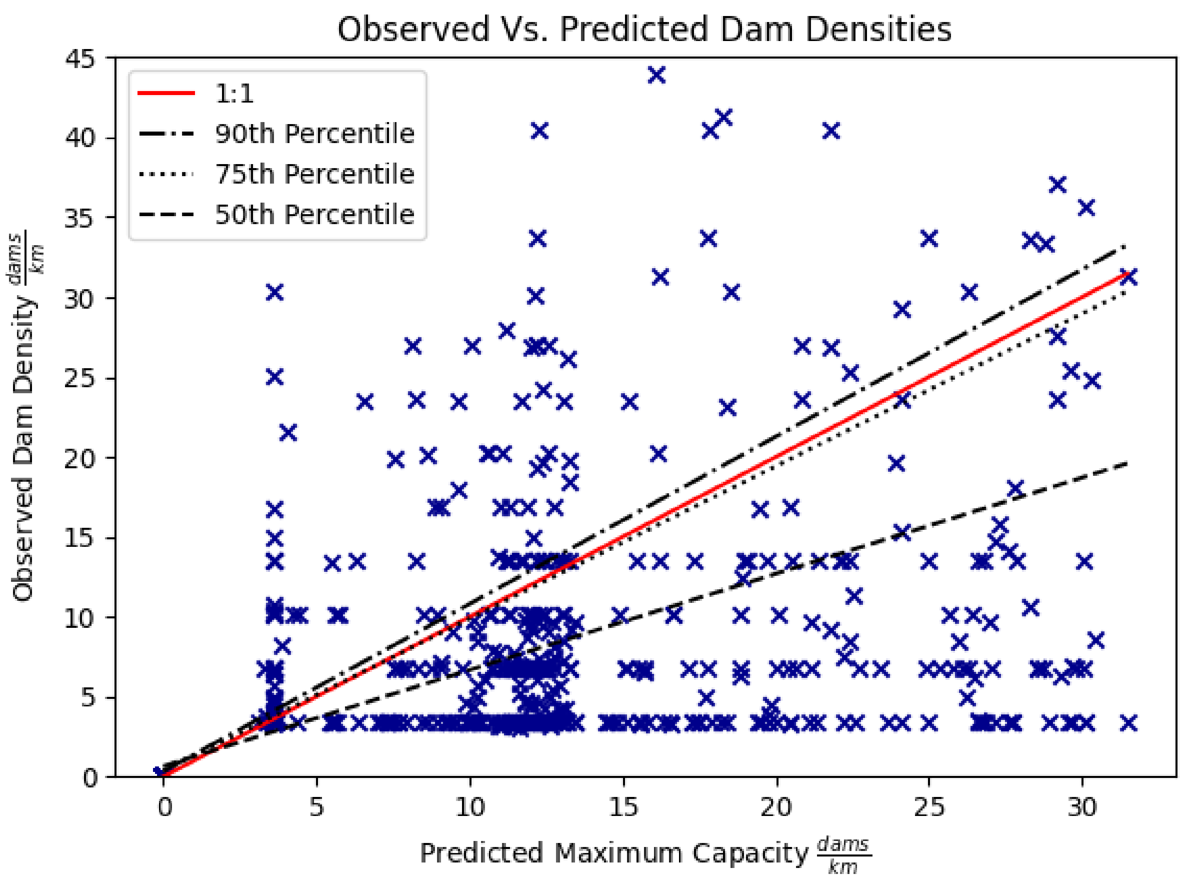

Figure B3. Quantile regressions

HUC: 10050004 (Middle Milk)

Table B4. Electivity Index

Capacity	Stream Length	% of Drainage Network	Surveyed Dams	BRAT Estimated Capacity	Average Surveyed Dam Density	Average Predicted Capacity	% of Modeled Capacity	Electivity Index
	km	*%*	*# of dams*	*# of dams*	*dams/km*	*dams/km*	*%*	
None	513	41	0	0	0	0	NA	0
Rare	35	2.8	3	20	0.085	0.58	14.63	0.22
Occasional	258	20.7	82	868	0.317	3.36	9.44	0.81
Frequent	331	26.5	269	3486	0.811	10.51	7.72	2.08
Pervasive	79	6.4	134	1753	1.678	21.96	7.64	4.31
Total	**1252**	**100**	**488**	**6129**	**0.39**	**4.89**	**7.96**	**NA**

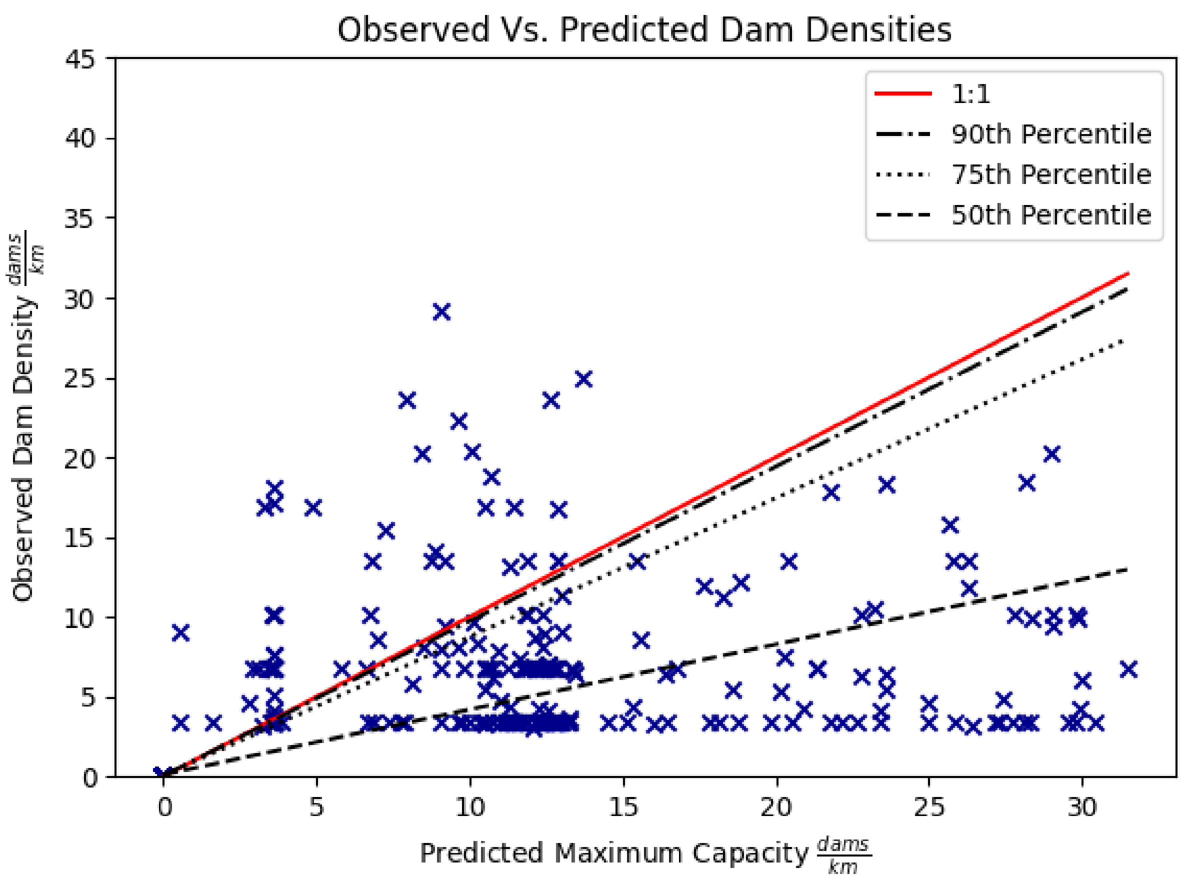

Figure B4. Quantile regressions

HUC: 17010205 (Bitterroot)

Table B5. Electivity Index

Capacity	Stream Length	% of Drainage Network	Surveyed Dams	BRAT Estimated Capacity	Average Surveyed Dam Density	Average Predicted Capacity	% of Modeled Capacity	Electivity Index
	km	*%*	*# of dams*	*# of dams*	*dams/km*	*dams/km*	*%*	
None	574	13.1	1	0	0.002	0	NA	0.03
Rare	215	4.9	11	129	0.051	0.6	8.5	0.87
Occasional	1259	28.8	8	4620	0.006	3.67	0.17	0.11
Frequent	1911	43.7	114	18628	0.06	9.75	0.61	1.02
Pervasive	396	9.1	122	8845	0.308	22.33	1.38	5.26
Total	**4375**	**100**	**256**	**32224**	**0.059**	**7.36**	**0.79**	**NA**

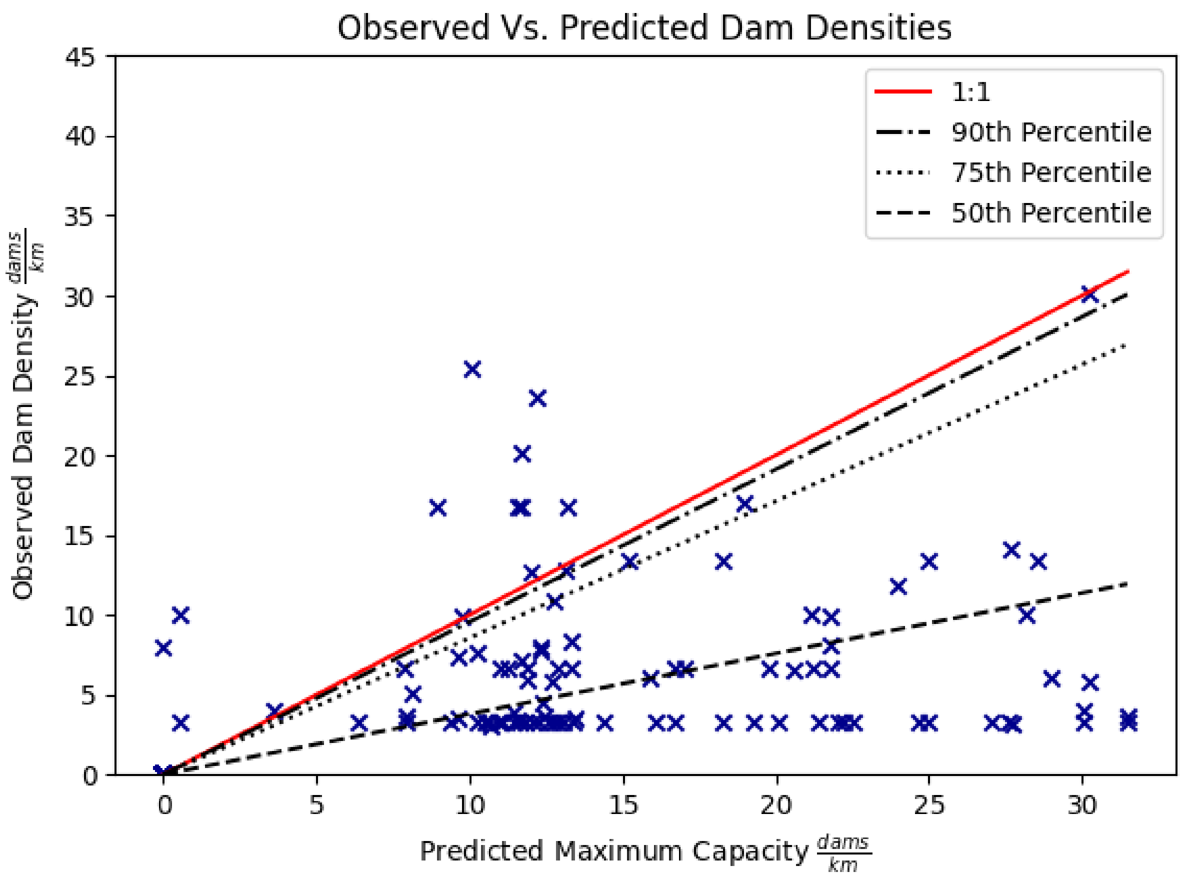

Figure B5. Quantile regressions

HUC: 17010213 (Lower Clark Fork)

Table B6. Electivity Index

Capacity	Stream Length	% of Drainage Network	Surveyed Dams	BRAT Estimated Capacity	Average Surveyed Dam Density	Average Predicted Capacity	% of Modeled Capacity	Electivity Index
	km	*%*	*# of dams*	*# of dams*	*dams/km*	*dams/km*	*%*	
None	328	13.7	1	0	0.003	0	NA	0.03
Rare	65	2.7	1	38	0.015	0.59	2.59	0.15
Occasional	632	26.5	7	2329	0.011	3.68	0.3	0.11
Frequent	1061	44.4	87	10472	0.082	9.87	0.83	0.79
Pervasive	296	12.4	153	6672	0.517	22.53	2.29	4.96
Total	**2382**	**100**	**249**	**19524**	**0.104**	**8.16**	**1.28**	**NA**

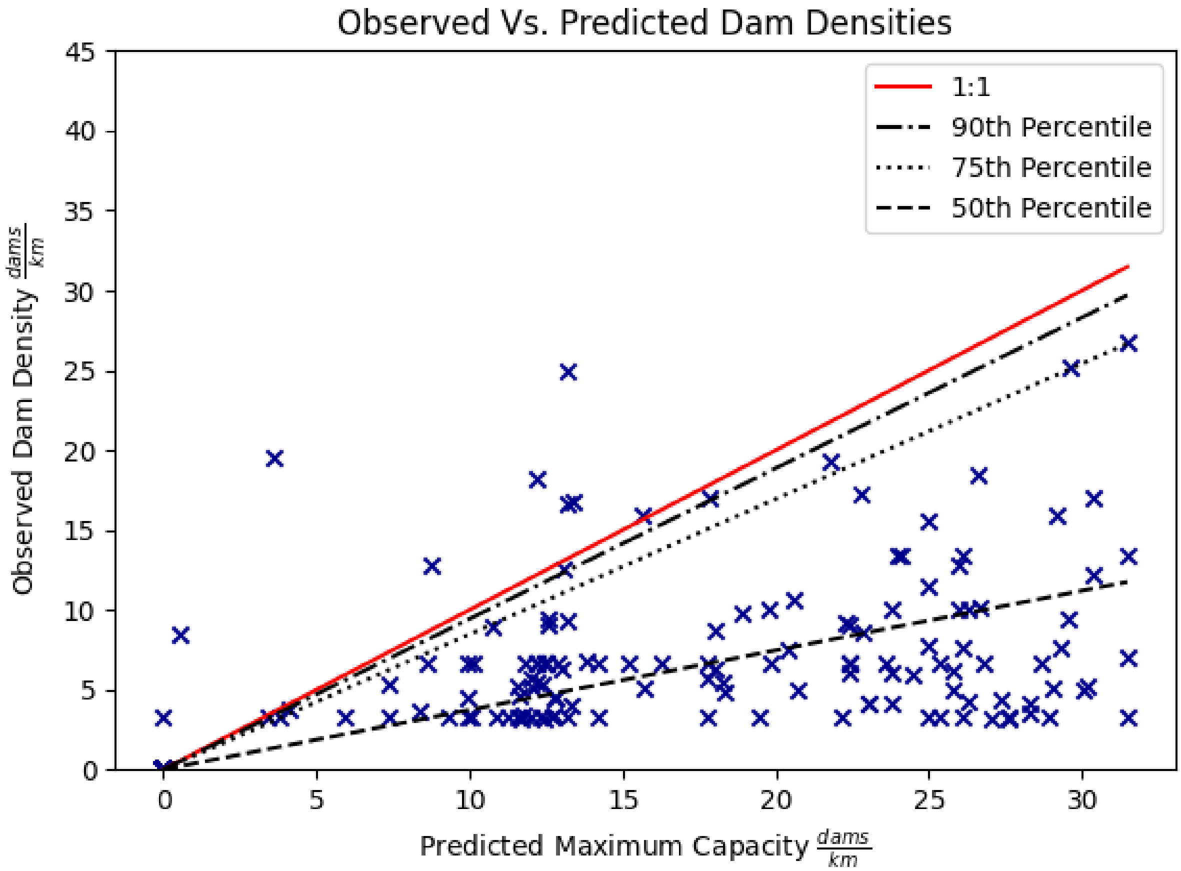

Figure B6. Quantile regressions