Deep Learning Projects Jurisdiction of New and Proposed Clean Water Act Regulation

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Abstract

Projecting the effects of proposed policy reforms is challenging because no outcome data exist for regulations not yet implemented. Our ex ante deep learning framework projects effects of proposed reforms by mapping past regulatory outcomes to proposed rules. Applied to the US Clean Water Act, ex ante algorithms generate exceptional performance improvements over domain experts, with fourfold higher identification of regulated waters and fiftyfold higher identification of non-jurisdictional waters. Ex post models perform best. The Supreme Court's 2023 *Sackett* decision removes protection from one-third of previously regulated waters, particularly floodplains and pristine fish habitats. The 2025 White House Energy Emergency Order and March Guidance deregulate ~0.5%. Algorithms can effectively project consequences of regulatory reforms before implementation, when projections are both most uncertain and most useful.

Evaluating proposed policy reforms is a critical task, since it can shape both how policymakers choose among alternative possible regulations and how private and public entities adapt to reforms. Government, academic, and private sector analysts generate hundreds of regulatory projections annually (*1*), and proposed legislation would expand government remit to include more environmental impacts (*2*, *3*). The stakes are high—regulatory reforms can generate hundreds of billions of dollars in annual benefits, though also enormous costs (*4*, *5*).

Policy forecasting is also challenging since forecasts are made before a policy is implemented, when uncertainty is greatest. Because no outcome data exist for proposed policies, forecasting typically relies on domain experts like scientists, economists, and engineers. This challenge has led to the concern the existing ex ante evaluation system is "broken, … largely based on faith, rather than evidence" (*6*).

We develop a relabeling methodology that provides among the first deep learning projections of new regulations' effects. To address the absence of training data on proposed regulations, we map past regulatory outcomes ("labels") to proposed rules. We compare performance of this methodology against published projections from domain experts and against ex post algorithms. Analysts increasingly use deep learning to interpret existing energy, environmental, financial, health, judicial, and labor market regulations (*7–10*), though not proposed reforms.

We apply this methodology to study recent and proposed reforms to the 1972 US Clean Water Act (CWA), the cornerstone of federal water pollution control. The CWA protects the "Waters of the United States" (WOTUS) but does not enumerate which streams and wetlands this phrase covers. To determine whether the CWA protects a site, a developer can ask the Army Corps of Engineers (USACE) to evaluate the site and issue an Approved Jurisdictional Determination (AJD), indicating whether the CWA regulates it. USACE may issue permits for jurisdictional sites.

Many stakeholders argue that the CWA and its recent reforms are costly and uncertain. Microsoft's President summarized these permits in congressional testimony on data centers as the "number 1 challenge" in development (*11*). A legal expert described courts modifying the CWA as sometimes "flying blind." (*12*) Media describe the regulatory landscape as "hazy" and "chaos" (*13*).

In addition to implementing ex ante deep learning, we develop and train the ex post Clean Water Act Analysis of Regulation (CLEAR) deep learning model using about 200,000 AJDs. CLEAR provides the first ex post national quantitative analysis of regulation under the Supreme Court's *Sackett* ruling, "one of the most impactful environmental decisions in the Court's history" (*14*).

Compared to algorithmic analysis of earlier CWA regulation (*10*), our deep learning models project effects of proposed regulations; analyze *Sackett*; study floodplains, fish habitat quality, and other ecosystem services; and implement numerous methodological improvements (SM A.1). We project regulation ex ante under *Sackett*, the 2025 White House National Energy Emergency Executive Order, and March 2025 USEPA and USACE Guidance (*15*).

CWA Background

"Regulatory ping pong" (*16*, *17*) under the CWA—frequent reversals in rules between administrations and courts—includes six rules in the last decade, plus others under discussion or implementation (*18*). In the Supreme Court's 2006 *Rapanos* case, Justice Kennedy's concurring opinion found that jurisdictional waters required a significant nexus involving biological, physical, or chemical connections to traditional navigable waters. The 2016 Clean Water Rule (CWR) primarily clarified *Rapanos;* USEPA and USACE repealed CWR in 2019. The 2020 Navigable Waters Protection Rule (NWPR) followed Justice Scalia's *Rapanos* plurality in restricting jurisdiction to relatively permanent waters with a continuous surface water connection to traditional navigable waters, excluding ephemeral streams and isolated wetlands. The 2023 Rule, litigated then enjoined in some areas, resembled *Rapanos*. *Sackett* echoed Justice Scalia's *Rapanos* opinion, removed the significant nexus standard, required a continuous surface water connection, less directly embraced the relatively permanent standard, and excluded certain wetlands separated from navigable waters by barriers. Due to litigation, in September 2023, the USEPA implemented two versions of *Sackett* across states, which we pool given their similarity. In March 2025, the USEPA and USACE issued revised *Sackett* guidance, prompting 115,470 public comments (*19*). The June 2025 PERMIT Act, proposed in the US House, adds further changes; permitting reform currently has bipartisan support and may become a federal legislative priority in 2025-2026 (*20*).

Predictive Models of CWA Jurisdiction

In addition to describing a naïve benchmark assuming no jurisdiction, we compare four types of models. First, domain experts use geophysical data to characterize CWA jurisdiction (*21*, *22*). Geophysical models underpin prominent Supreme Court briefs (*23*) and receive extensive media attention (*24–26*). Using maps of streams and wetlands, these models assume that features with predefined attributes characterize jurisdiction under new rules. We analyze a geophysical rule (*22*) assuming that non-tidal wetlands in the National Wetlands Inventory (NWI) inundated a certain share of the year lose jurisdiction. We also analyze a Connected geophysical rule echoing previous approaches (*21*, *27*) which assumes wetlands within 50 meters of a stream that connects to a navigable water are jurisdictional. SM A.1 provides details.

Second, Relabeled *Sackett* implements ex ante deep learning. We train Relabeled *Sackett* only on AJDs and knowledge preceding *Sackett* implementation, and project *Sackett* as NWPR but with labels changed to reflect *Sackett* (table S1 and SM A.1). We formalized the relabeling in a June 2023 external email and presentation, far before USEPA announced its conforming rule or USACE began implementing it.

Third, the ex post CLEAR deep learning model predicts jurisdiction under each rule. We pre-train deep learning models on AJDs from all rules in the relevant training data, then fine-tune on each rule individually (SM A.1).

Fourth, we project jurisdiction under two ongoing reforms. The National Energy Emergency Executive Order of January 2025 purports to eliminate CWA jurisdiction for fossil fuel and hydroelectric energy sites. This order accelerates permitting ("fast-tracks") for energy projects but does not otherwise change jurisdiction. Using CLEAR-*Sackett* predictions, we deregulate sites around energy infrastructure or high-potential fossil fuel resources (*28*) (SM A.1). To study a second ongoing reform, we relabel NWPR with labels reflecting the March 2025 *Sackett* guidance (*15*) (SM A.1), then train a deep learning model to predict the relabeled AJDs.

As in climate science, a "projection" reflects an assumed future policy scenario. As in machine learning, a "prediction" reflects an algorithmic calculation of what a rule regulates based on data from implementation of that rule (*29*).

Measuring Performance

To measure model performance, we calculate statistics using a held-out test set (SM A.2). We focus on the area under the receiver operating characteristic curve (AUC) given its robustness to class imbalance (19.7% of sites in the test set are jurisdictional), invariance to the decision threshold used to produce binary classifications, and use of the full distribution of calibrated jurisdictional probabilities rather than reliance on a binary cutoff. We also report the F1 score, along with recall, precision, and specificity, given concern with false positives and false negatives; accuracy, given its simple interpretation and common use; and mean absolute error (MAE) nationally and by state, given usefulness for stakeholders. For metrics using binary classifications, we choose optimal thresholds using the validation set (SM A.7). We focus on *Sackett*, since all models have predictions for it, and more briefly discuss the performance of the ex post CLEAR deep learning model on earlier rules.

The Wetness model (*30*) only has predictions for non-vegetated, non-anthropogenically influenced, shallow water non-tidal wetlands connected to jurisdictional streams and rivers. These areas only account for 1.1% of all *Sackett* AJDs, or 36 observations in the test set. We believe this restricted availability is underappreciated and limits applicability of the Wetness model. We therefore report results for this area and two related Wetness model interpretations. One applies to all polygons within the published analysis area (*30*) and assumes other sites are not jurisdictional. The other measures wetness across more NWI polygons (emergent, forested, and palustrine wetlands, representing 23% of the test set) and predict other wetlands as not jurisdictional.

Model Results

A naïve benchmark assuming no sites are jurisdictional has AUC of 0.50 and F1 of 0.000, by construction (table 1A and fig. S1).

The Wetness (*22*) geophysical model provides little improvement (table 1B). The median Wetness criterion has an AUC of 0.498, just below the benchmark, and F1 of 0.007, just above the benchmark. Its recall implies only correctly identifying only 1 in 250 true positives. MAE and accuracy slightly underperform the benchmark. On the full sample, other wetness thresholds have similar performance (table S3). In the non-tidal wetlands sample (N=36), performance varies widely across scenarios, reflecting the small sample. Wetness scenarios 3 and 4, which perform best in the validation sample, have test set AUC of 0.417, well below the benchmark.

The Connected geophysical model (table 1B) predicts no test set AJDs as jurisdictional, since none fall within connected wetlands. This geophysical model therefore has identical predictions and performance as the naïve benchmark.

The ex ante deep learning model, Relabeled *Sackett* (table 1C), outperforms the geophysical models on most metrics. Relabeled *Sackett* has an AUC of 0.693, 0.193 higher than the Wetness or Connected geophysical models, considered an exceptional performance improvement in most algorithmic contexts. Its F1 score of 0.332 is 47 times the median Wetness model performance.

Compared to the Wetness model, Relabeled *Sackett* is four times more likely to identify true positives and fifty times more likely to identify true negatives, though has comparable accuracy.

The ex post CLEAR model substantially outperforms the geophysical models and moderately outperforms ex ante deep learning (table 1D). The ex ante and ex post deep learning models have similar AUC. By this important performance metric, the ex ante model therefore has sufficient insight from relabeling that ex post implementation data do not improve model performance.

Ex post implementation data do improve model performance on metrics other than AUC. On the F1 score, the ex post CLEAR model substantially outperforms other models, due to its avoidance of both false positives and false negatives. CLEAR's national MAE of 0.001 means it almost perfectly projects the actual mean national jurisdiction of test set *Sackett* sites.

CLEAR achieves AUC above 0.80 on the other rules (NWPR, CWR, and *Rapanos*), exceeding levels for *Sackett* (table S4A). *Rapanos* and CWR let CLEAR observe more true positives, increasing recall. NWPR and *Sackett* have fewer true positives, decreasing opportunities to learn to predict positives for these rules. CLEAR national MAE is also near zero for *Rapanos* and NWPR, though much higher for CWR, which has the smallest sample.

Describing Jurisdiction

Geophysical models predict little jurisdiction for *Sackett* (table S2), though their scenarios range widely (table S5). The median Wetness model (*22*) predicts that *Sackett* regulates 2.6% of the US, covering 16.5% of wetland acres and 6.7% of stream miles. The original Wetness scenarios conclude that under *Sackett*, 0 to 80 percent of non-tidal wetlands are jurisdictional, a range wide enough to be "bogged down in mystery" (*31*). Wetness scenarios range widely because the results depend on assumptions about how USACE interprets *Sackett*. Additionally, the Wetness model sample (*30*) excludes many jurisdictional *Sackett* AJDs (fig. S2).

The Connected geophysical model concludes that almost no test set streams or wetlands are jurisdictional. It predicts low jurisdiction rates because its input layers (the National Hydrography—NHD—and NWI) miss many jurisdictional *Sackett* sites.

The ex ante deep learning model, Relabeled *Sackett*, projects that *Sackett* regulates of 13.4% of the contiguous US, 36.0% of stream miles, and 31.4% of wetland acres (table S2). Relative to the median Wetness model, Relabeled *Sackett* predicts four times more regulation of streams and double the regulation of wetlands.

The ex post deep learning model, CLEAR, calculates that *Sackett* regulates 11.5% of the contiguous US, including 24.9% of stream miles and 27.8% of wetland acres (table S2). = *Sackett* is 2.5 times more likely to regulate perennial streams than to regulate intermittent and ephemeral streams. This difference is arguably smaller than one might expect, since *Sackett* largely intends to deregulate ephemeral but not perennial streams, but this statistic may partly reflect misclassification of stream types in NHD. CLEAR indicates that 11.2% of areas not in NHD and 8.7% of areas not in NWI's palustrine wetlands are jurisdictional, further underscoring potential limits of NHD and NWI and geophysical models that exclusively rely on them. Only one-third of floodplains in the US are jurisdictional under *Sackett*, a statistic where the ex post CLEAR-*Sackett* and ex ante Relabeled *Sackett* deep learning models almost perfectly agree.

CLEAR shows that *Sackett* regulates fewer waters than any previous rule (table S6). *Rapanos* regulated 46% of stream miles, 41% of wetland acres, and 18% of contiguous US area. NWPR deregulated 9% of regulated stream miles and deregulated 15% of regulated wetland acres. Compared to *Rapanos*, *Sackett* deregulates one-third of regulated streams and wetlands and 28% of regulated floodplains. This amounts to over 700,000 stream miles and 19 million wetland acres. *Sackett* deregulates the most wetland acres in Florida and Michigan (table S7). The floodplain deregulation may increase development and corresponding risk of flood damage. Our estimates of regulation under NWPR exceed those of prior algorithmic estimates (*10*), partly since we average calibrated probabilities while prior work averages binary jurisdictional predictions (SM B.2).

NWPR and *Sackett* both have a basis in Justice Scalia's *Rapanos* opinion, but the differences are so far largely unquantified. CLEAR finds that *Sackett* regulates systematically less than NWPR, including 20% fewer wetland acres (table S6).

The March guidance and Energy Emergency Order each decrease jurisdiction of streams and wetlands relative to *Sackett* by 0.5 pp (table S2D). Because the March guidance model relabels NWPR AJDs, Relabeled *Sackett* provides our preferred comparison for it. These policy proposals therefore represent far less dramatic jurisdictional changes than other CWA rule changes of the past decade.

Fig. 1 graphs the "regulatory ping pong" of recent CWA regulation. Jurisdiction fluctuated between 2018 and 2020 due to differences between CWR and *Rapanos*. The share of stream and wetland points regulated fell by 15% in 2020 and returned to broader jurisdiction in late 2021. Jurisdiction declined by around a third in 2023. We project that the proposed rules would modestly decrease jurisdiction.

Maps of CLEAR's ex post predictions reveal enormous spatial differences across rules and models (Figs. 2 and S3). Ex ante and ex post deep learning models of *Sackett* predict qualitatively similar spatial patterns, though the ex ante model predicts more regulation in the coastal plans of the mid-Atlantic and near the Pacific coast. The ex post CLEAR model reveals that compared to *Rapanos*, *Sackett* deregulates isolated wetlands in coastal and inland areas, and ephemeral streams across the arid West. *Sackett* deregulates streams and wetlands in almost every state (table S7). Compared to NWPR, *Sackett* primarily deregulates wetlands along the East Coast and in some areas of the Pacific Northwest, but changes jurisdiction little across the Arid West (fig. S3E). The March 2025 guidance further deregulates some Eastern coastal wetlands. The National Energy Emergency Executive Order particularly deregulates the Marcellus and Bakken shales, plus shale and oil fields in Texas.

Case studies highlight local differences across rules and predictions, and agreement between the ex ante and ex post *Sackett* deep learning models (Figs. 3 and S4). In wetland-abundant regions like Michigan's Upper Peninsula and North Carolina's coast, *Sackett* regulates fewer isolated wetlands and small water bodies than *Rapanos*. In drier regions, *Sackett,* NWPR, and the March guidance deregulate ephemeral streams. The wetness model has no predictions in most of these areas, given its restriction to a narrow set of non-tidal wetlands.

Wetlands support ecosystem services including flood mitigation and water filtration, and support CWA goals of decreasing water pollution and improving water-based recreation including fishing. *Sackett* deregulates areas important to all four of these objectives (fig. 4 and table S8). For example, in areas not used for drinking water, *Sackett* has 5 pp lower probability of regulation than *Sackett*; in areas used for drinking water sources, *Sackett* has 10 pp lower probability of regulation. In areas where a large share of waters is too polluted to support intended uses ("impaired"), *Sackett* has 10 pp lower probability of regulation than *Sackett*. The March guidance expands these gaps (fig. S8).

Discussion

Many groups may value accurate projections of the effects of proposed environmental regulations, including politicians, judges, federal and state agency staff, land developers, environmental restoration firms, industrial firms, farmers, and environmental organizations. Relabeling lets deep learning provide such projections. This framework helps address a critical problem of policy analysis—projecting effects of proposed policies before data on exist on outcomes of the proposed reforms—a time period when analysis is both most uncertain and most useful.

Our analysis of recent CWA reforms finds that ex ante deep learning far outperforms expert geophysical projections on most measures of predictive performance. Expert projections provide marginal improvement over a naïve benchmark. Ex post deep learning has the highest predictive performance and describes enormous decreases in wetland and stream jurisdiction under *Sackett*.

Future work can further clarify the potential contributions of deep learning and domain experts to projecting other reforms' effects. Recent or ongoing reforms to wetland protection in Chile, China, the EU, Japan, and elsewhere may provide opportunities for similar analysis (*32–37*). The frequency of regulatory reforms in financial, labor market or other environmental domains provides many opportunities to investigate related methods.

In any setting, the relative performance of ex ante deep learning versus domain experts may depend on the extent to which relabeling effectively characterizes the policy reform. More precise descriptions of proposed reforms, and descriptions which overlap with labels of prior policies, may improve relabeling performance. Agency capacity, evolving interpretations, willingness to enforce policy changes, and voluntary compliance by regulated entities can all vary a regulation's impacts. One interpretation is that in our setting, agencies treat regulatory reforms in a fashion that flexible interpretation from past reforms can effectively project.

While we focus on projecting effects of regulation, a related and important question asks whether agency interpretation of a regulation fits with the intent of a law as written. This represents another area almost exclusively analyzed by domain experts, and where the potential contribution of deep learning remains unknown. More involved human-in-the-loop frameworks, where domain experts and algorithms collaboratively improve an evaluation system's capabilities, may also provide a useful path to integrate relative advantages of both approaches.

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Supplementary Materials

This PDF file includes:

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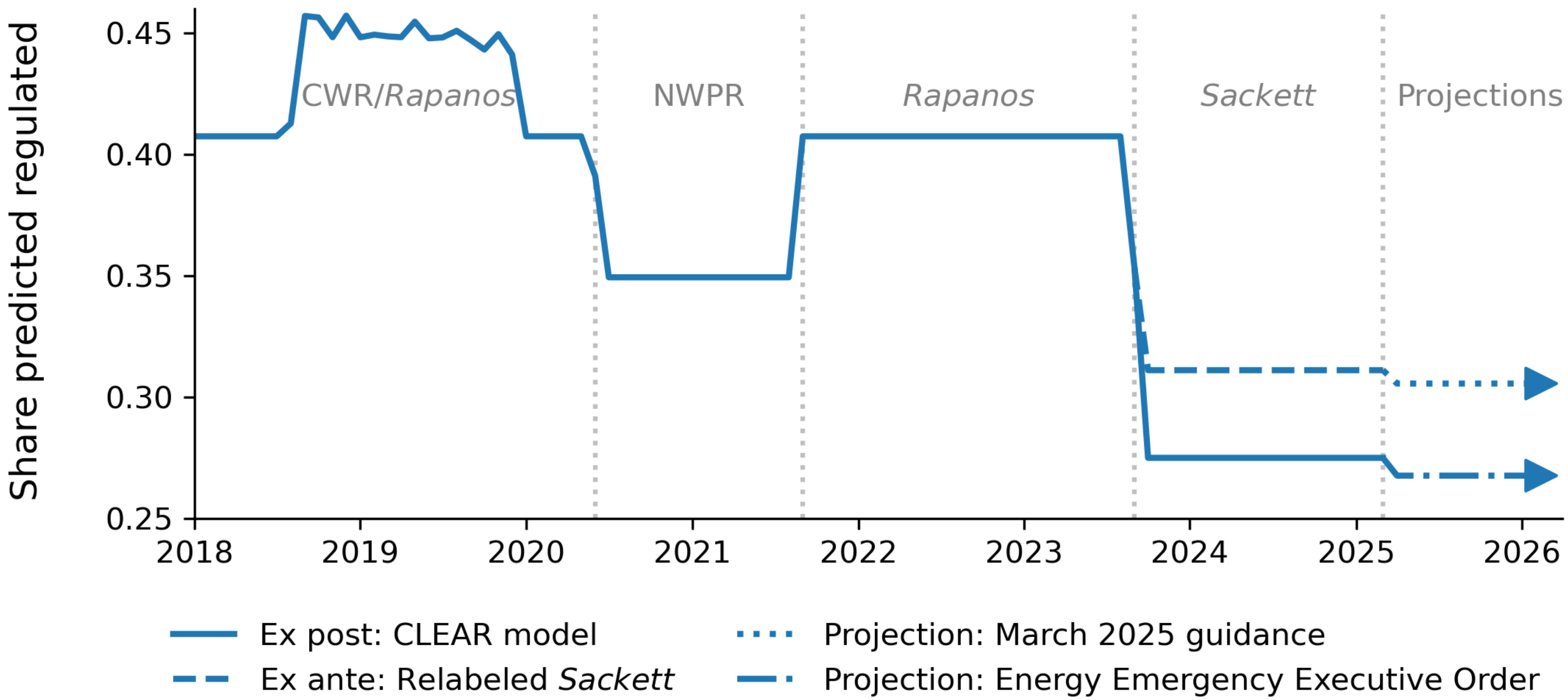

Fig. 1. "Regulatory ping pong" reflects large variation in CWA jurisdiction across rules. The graph shows the share of points within 50 meters of stream or wetland (NHD or NWI) features that are predicted as jurisdictional each month. To determine which rule applied in each month, we use the rule used to decide a majority of AJDs within each state in each month, calculate statistics by state, and average across states, weighting by the number of points in the state. Between January 2018 and August 2019, some states implemented CWR and others implemented *Rapanos*, due to contemporaneous lawsuits challenging CWR. Fluctuations in the share of locations regulated during this period reflect state-level changes in rules applied due to stays on CWR's implementation (*38*). *Rapanos* applied from September 2019 to May 2020. NWPR applied from June 2020 to August 2021. *Rapanos* (defined to include the 2023 rule) applied again from September 2021 to August 2023. *Sackett* applied from September 2023 onwards. The USEPA and USACE are implementing two versions of *Sackett* in different states due to pending litigation, which we pool given their similarity. Between August 2023 and March 2025, the solid line shows the CLEAR-*Sackett* ex post prediction of jurisdiction, and the dashed line shows the ex ante Relabeled *Sackett* prediction. Post March 2025 plots projections. Dash-dotted lines project the 2025 Energy Emergency Executive Order. Dotted lines project March 2025 guidance.

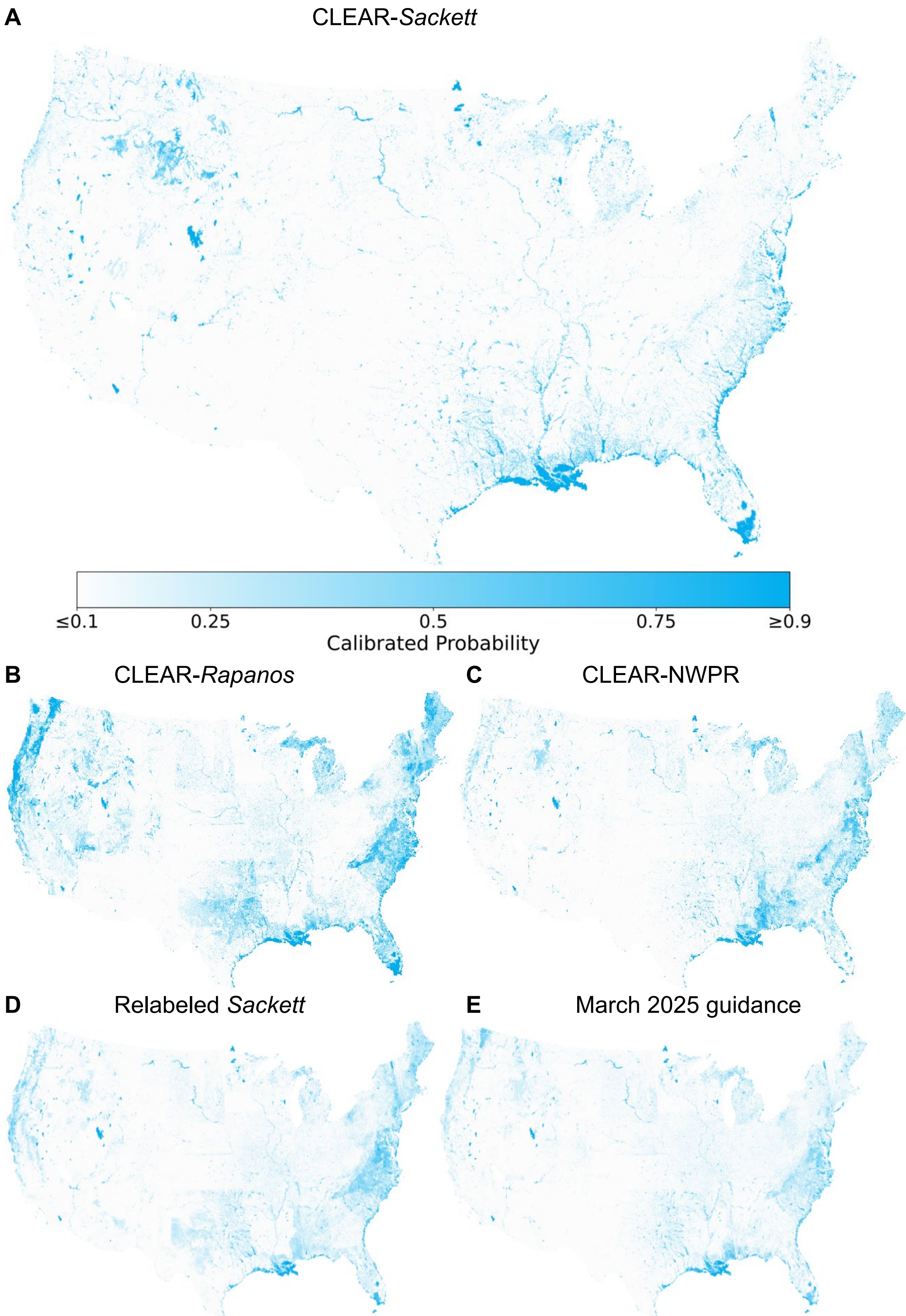

Fig. 2. Maps show that regulation under all rules varies enormously across the US. Panels show calibrated probabilities of CWA regulation under (**A**) *Sackett*, (**B**) *Rapanos*, (**C**)

NWPR, and projections of regulation (**D**) Relabeled *Sackett*, and (**E**) March 2025 Guidance. Maps aggregate the four million prediction points by taking the mean model score in 5 km by 5 km grid cells (~8 prediction points per grid cell). Extreme calibrated probabilities (0.0-0.1; white, 0.9-1.0; blue) are plotted with the same color.

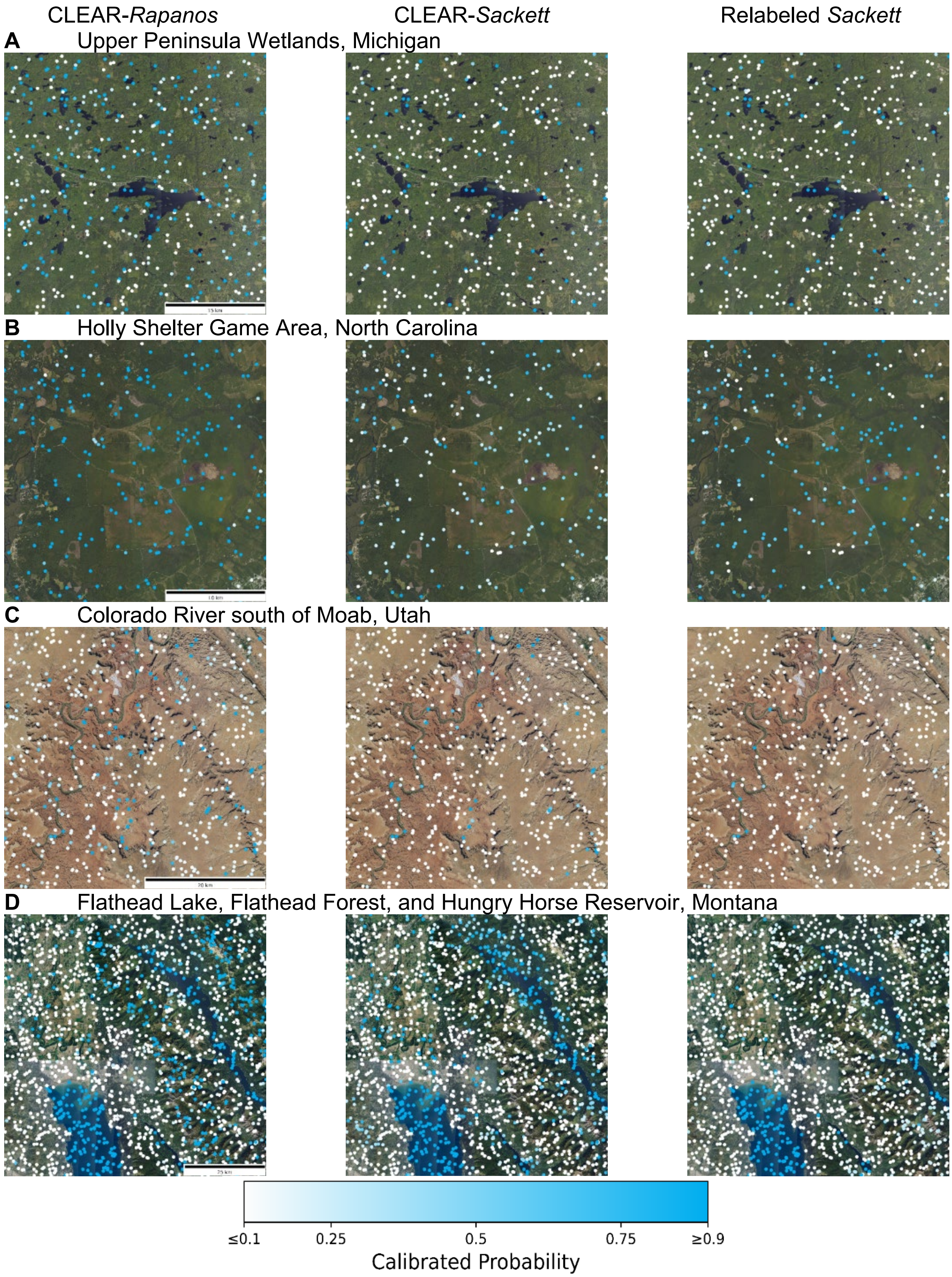

Fig. 3. Case studies reveal performance of relabeling methodology and spatial patterns of jurisdiction. Columns show calibrated model scores for subsets of the 4 million random

prediction points under three different deep learning models. Left column shows CLEAR-*Rapanos*, center column shows CLEAR-*Sackett*, right column shows the ex ante Relabeled *Sackett*. (**A**) Lakes and wetlands in the Upper Peninsula of Michigan. All models predict jurisdiction for large water bodies with high confidence. CLEAR-*Rapanos* predicts regulation across most of the area, CLEAR-*Sackett* predicts less regulation for surrounding wetlands, and Relabeled *Sackett* closely reflects the ex post CLEAR-*Sackett*. (**B**) Holly Shelter Game Area, North Carolina. CLEAR-*Rapanos* predicts jurisdiction across most of this coastal outdoor recreation area. CLEAR-*Sackett* predicts systematically less jurisdiction, and Relabeled *Sackett* is intermediate. (**C**) Colorado River and ephemeral streams south of Moab, Utah. All models classify the Colorado River as jurisdictional. Differences between CLEAR-*Rapanos* and CLEAR-*Sackett* model scores show deregulation of ephemeral streams supplying the river. Relabeled *Sackett* predicts slightly less jurisdiction of ephemeral streams than CLEAR-*Rapanos*. (**D**) Flathead Lake, Flathead Forest, and Hungry Horse Reservoir, Montana. All models classify Flathead Lake in the southwest of the image and the Hungry Horse Reservoir in the northeast corner as jurisdictional. CLEAR-*Rapanos* predicts extensive regulation for areas of Flathead Forest between the water bodies; CLEAR-*Sackett* predicts little regulation, and Relabeled *Sackett* concurs.

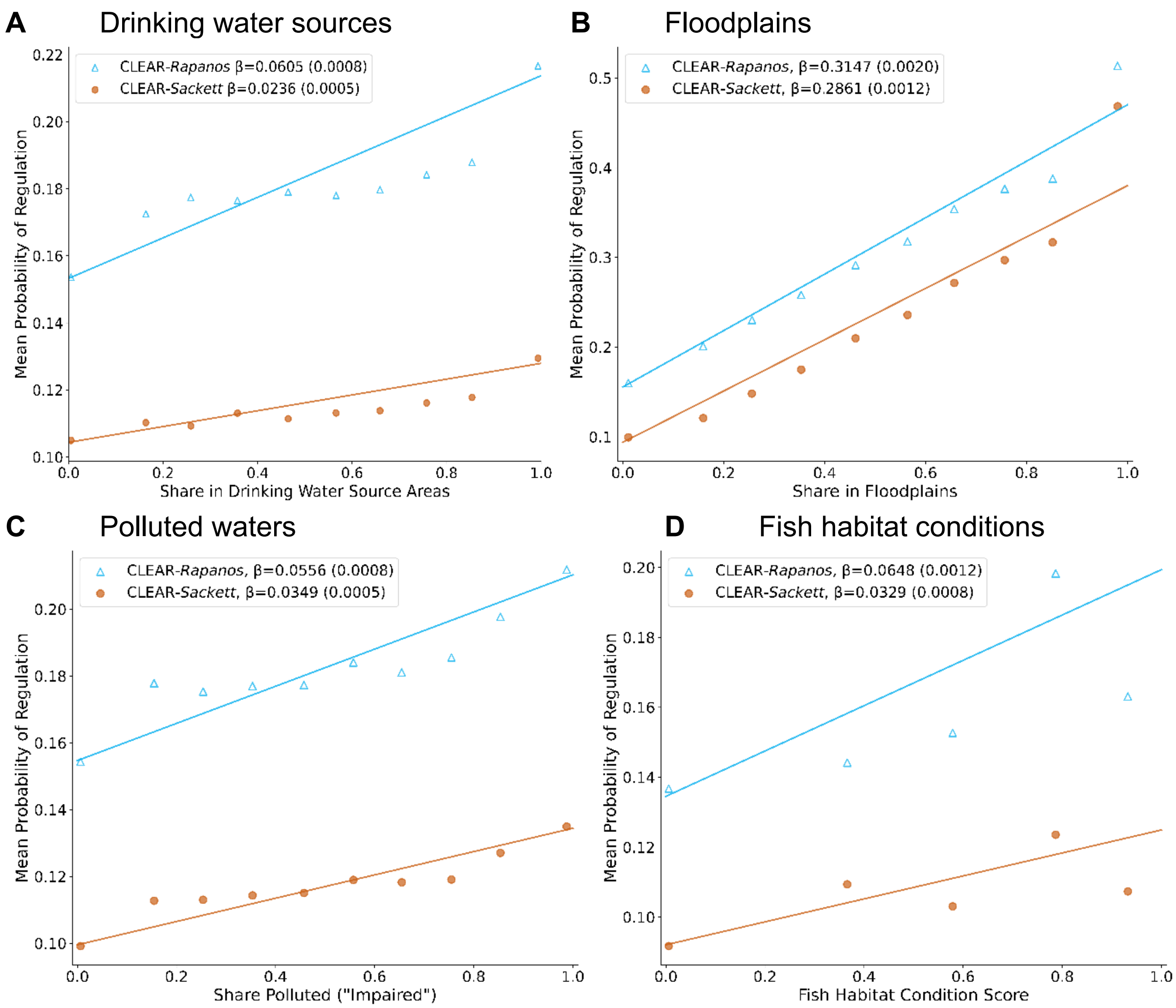

Fig. 4. *Sackett* deregulates areas supporting ecosystem services and areas important for CWA goals. (**A**) Share of points in drinking water source areas. (**B**) Share of points in floodplains. (**C**) Proportion of assessed waters considered "impaired" based on pollution and intended use. (**D**) Fish habitat conditions (0=worst, 1=best). Each panel splits 4 million random points into the 251,975 5km by 5 km grid cells used to plot fig. 2. In each graph, the y-axis shows the mean calibrated probability from CLEAR-*Rapanos* and CLEAR-*Sackett,* and the x-axis shows the mean ecosystem value within the grid cell. The x-axis divides grid cells into equal-width bins (0-1 scale) based on underlying values. The legend shows the grid-level regression coefficient with standard errors in parentheses. In all four panels, a hypothesis test that *Rapanos* and *Sackett* have equal slopes rejects with p-value < 0.000, estimated from the interaction term in a pooled regression including both rules. Impaired waters and fish habitat conditions are measured by 12-digit hydrologic unit code (HUC12) from the EPA's 2025 Restoration and Protection Indicator Database.

	AUC (1)	F1 (2)	Precision (3)	Recall (4)	Specificity (5)	Accuracy (6)	Mean absolute error: US (7)	Mean absolute error: State (8)
A Naïve benchmark								
1. No jurisdiction	0.500	0.000	—	0.000	1.000	0.803	0.197	0.265
B Ex ante geophysical models								
2. Wetness	0.498	0.007	0.118	0.004	0.993	0.798	0.191	0.258
3. Connected	0.500	0.000	—	0.000	1.000	0.803	0.197	0.265
C Ex ante deep learning								
4. Relabeled *Sackett*	0.693	0.332	0.457	0.261	0.930	0.796	0.067	0.166
D Ex post deep learning								
5. CLEAR - *Sackett*	0.691	0.368	0.502	0.290	0.973	0.819	0.001	0.182

Table 1. Geophysical models improve little on naïve benchmark, ex ante Relabeled *Sackett* model does better, ex post CLEAR model has strongest performance. All statistics use AJD test set. AUC: Area under the receiver operating curve. F1: harmonic mean of precision and recall. Precision: TP / (TP + FP), where TP is the count of true positive predictions and FP is the count of false positive predictions. Recall: TP / (TP + FN), where FN is the count of false negative predictions. Precision is undefined if a model makes no positive predictions. Specificity: TN / (TN + FP), where TN is the count of true negative predictions. Accuracy: percent correct. Column (7) equals $|\mathrm{mean}(J_i) - \mathrm{mean}(C_i)|$, where J_i represents AJD jurisdiction and C_i represents model predictions. Column (8) equals $(1/S)\sum_s |mean_i(J_{is}) - mean_i(C_{is})|$, i.e., the mean across states of the mean true jurisdiction rate within each state minus the mean jurisdiction rate of model predictions within each state. Row 1 describes a naïve benchmark that predicts no location is jurisdictional. Row 2 describes the median Wetness model (*22*), "seasonally flooded." Row 3 defines points as jurisdictional if they fall within a National Wetlands Inventory (NWI) polygon that is within 50 meters of a National Hydrography Dataset (NHD) flowline that terminates in a navigable water. Row 4 describes Relabeled *Sackett*, which trains a deep learning model to predict resource types in Navigable Waters Protection Rule (NWPR) AJDs relabeled as an ex ante projection of *Sackett*. Row 5 describes the ex post CLEAR-*Sackett* model. Rows 4 and 5 show performance of calibrated probabilities with thresholds optimized for performance for F1 in columns (2), (3), and (4), accuracy in columns (5) and (6), national mean absolute error (MAE) in column (7), and state MAE in column (8). Column (1) depends on model calibrated probabilities and is independent of threshold choice. Table S13 and fig. S6 show the optimized thresholds. All models describe *Sackett*. Table excludes the Energy Emergency Executive Order and March 2025 guidance since they lack ex post implementation data to evaluate performance. N = 2,777.

Supplementary Materials for

Deep Learning Projects Jurisdiction of New and Proposed Clean Water Act Regulation

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A. Materials and Methods

A.1: Predictive Model Details

Ex Ante Geophysical *Sackett* Models. The Wetness model (*22*) analyzes several inundation frequency scenarios based on Cowardin water regimes reported in the NWI. Ex ante, it is unclear which scenario performs best. The main text reports the median scenario in terms of wetness (scenario 4 out of 8), though we discuss all scenarios (table S3), and mention that scenarios 3 and 4 have the best performance in the validation set. We observe both jurisdictional and non-jurisdictional AJDs in six of the eight water regimes with at least one AJD (fig. S2).

The Connected model identifies as jurisdictional any points within an NWI wetland polygon that is within 50 meters of an NHD flowline terminating in a navigable water. We identify navigable NHD flowlines as those that terminate in the Pacific or Atlantic Oceans, the US border, or manually identified navigable lakes such as the Great Lakes or Humboldt Lake, reflecting previous work (*21*, *27*). Additionally, we consider a series of geophysical models that use individual layers to predict jurisdiction (see SM B.1 and table S4).

Ex Ente Relabeled *Sackett* Model. AJD data include rule-specific legal classifications ("resource types") for each water body. Under NWPR, for example, USACE AJDs classify some sites as "adjacent wetlands" and others as "non-adjacent wetlands." Table S1 presents our relabeling scheme for the Relabeled *Sackett* model. This relabeling scheme assumes that relative to NWPR, *Sackett* deregulates wetlands separated from navigable waters by artificial structures and natural features. We believe these specific relabeling choices follow directly from majority opinion in *Sackett*. We chose them in June 2023, before USEPA announced a conforming rule or USACE announced associated guidance. We use these relabeled AJDs to fine-tune a deep learning model. We pre-train the deep learning model on all non-*Sackett* AJDs. SM B.5 of Greenhill et al. (*10*) mentions the concept of changing labels in old data to describe new rules, though questions the potential performance of this approach and does not implement it.

Although we apply our relabeling methodology to a computer vision problem, the approach builds on the tradition of weak and indirect supervision in natural language processing (*39*–*41*). Whereas many weak supervision techniques generate labels for unlabeled data using heuristics or knowledge bases, our approach transforms a corpus of already-labeled data into a new label space. Unlike ex post deep learning models (*9*, *10*), which are trained using true labels from the target task, or simulation-based methods (*42*), which project outcomes using process-based environmental models, our relabeling methodology derives target-task labels by mapping historical decisions to the criteria of a new regulation. This allows deep learning projections before any true target-task data exist, enabling ex ante projection and ex post validation under real policy changes.

Compared to algorithmic analysis of CWA regulation (*10*), methodological improvements in the current paper are to use synthetic training data; fine-tune on individual rules; fuse image and tabular data; and incorporate model score calibration and optimal classification thresholds

Ex Post CLEAR Model. We fine-tune deep learning models to predict jurisdiction for each of the four main rules enforced since 2018—CWR, *Rapanos*, NWPR, and *Sackett*. We pre-train on AJDs from all rules, then fine-tune using only AJDs from one rule, resulting in one model per rule. The next section describes deep learning architecture and training details.

The deep learning models can predict jurisdiction for any coordinate in the contiguous US. They therefore avoid a predetermined decision between a framework only designed to analyze streams (*43*) or only designed to analyze non-tidal wetlands (*22*); each of these categories covers a small fraction of all AJDs.

Ex Ante Projections. The National Energy Emergency Executive Order does not change the process of determining jurisdiction under *Sackett*. Instead, it allows development of energy projects to avoid the CWA regulatory process. We identify US area currently used for energy projects with information from the Energy Information Agency (*44*). We also identify area primed for future development from Bartik et al. (*28*). We take CLEAR-*Sackett* calibrated probabilities, and reset the calibrated probability to zero in three separate cases: if the location is (1) within 100 meters of an energy facility (e.g., power plants, refineries, market hubs), (2) within 10 meters of an energy transmission line or pipeline, or (3) within a "high prospectivity" county as defined by Bartik et al. (*28*) and considered not developed nor used for agriculture by NLCD. This projection abstracts from legal actions that could modify or delay implementation of this order.

To project the impact of the March 2025 guidance on jurisdiction, we relabel NWPR with jurisdictional labels changed to reflect the new guidance, labeling wetlands without a "continuous surface connection" as not regulated (table S1) (*15*). We then fine-tune a deep learning model on the relabeled NWPR AJDs, starting from a model pre-trained on all AJDs. We relabel NWPR AJDs to project jurisdiction under the March 2025 guidance because resource types in the NWPR AJDs identify wetlands separated by artificial structures, flooding, or natural resources, and these categories are relevant to our relabeling for the March 2025 guidance. We do not relabel *Sackett* or *Rapanos* AJDs to project jurisdiction under March 2025 guidance because the AJD resource types used in these rules lack the information required for this relabeling (tables S9, S10).

A.2: Model Architecture

The relabeling and CLEAR deep learning models use a multimodal deep learning architecture that integrates both raster and tabular data to predict CWA jurisdiction. The model outputs a score between 0 and 1 reflecting the model's predicted likelihood that a site is jurisdictional under a given CWA rule.

The model's primary branch is a ResNet-18 backbone (*45*) pre-trained on ImageNet (*46*). The features extracted from the ResNet-18 after the final global average pooling operation are concatenated with a vector of tabular features. These concatenated raster and tabular features are then passed through a two-layer perceptron with a final sigmoid activation to produce the model score. This multimodal design allows for greater computational efficiency than the pure convolutional neural network approach of Greenhill et al. (*10*), which required rasterizing the tabular data.

The raster branch of the model has 29 input layers: color and near infrared aerial imagery; the locations and characteristics of streams and wetlands; elevation; summary statistics of long-run average precipitation, temperature, dewpoint temperature, vapor pressure deficit, solar radiation, and cloudiness; soils data; and land cover data. SM A.5 provides additional details about input layers. Twenty-eight of these layers were used in Greenhill et al. (*10*); we add land cover data from the Coastal-Change Analysis Program (C-CAP) due to its resolution and quality, while recognizing that C-CAP covers only coastal areas. The model takes in 512-by-512 pixel rasters centered at the location whose jurisdictional status is being evaluated, corresponding to an area of 308-by-308 meters. These inputs provide a detailed snapshot of ground conditions affecting the probability of CWA jurisdiction and include the main national layers that USACE reports using in AJDs.

We experimented with a geo-foundation model in the validation set that used embedding fields (*48*) but found that it modestly decreased performance, perhaps because other layers had similar information and due to the sample size. The Clean Water Act Analysis of Regulation (CLEAR) model therefore does not use these embedding fields data.

Train-Test Split. We divide the 202,295 AJDs into disjoint training, validation, and test data sets, avoiding footprint overlap to prevent leakage across folds (fig. S5). We train each algorithm using 80% of the data, then tune hyperparameters and choose model design using the validation set, with 10% of the data. All performance statistics here represent a held-out 10% test set.

CLEAR uses the train, test, and validation split rules from Greenhill et al. (*10*) (SM, lines 33-43), with a few extensions. When assigning groups for new Approved Jurisdictional Determinations (AJDs), we first create footprint groups for AJDs whose footprints overlap. If a new AJD's footprint group overlaps with multiple footprint groups of AJDs used in the original model, the new AJDs take the split of the AJD it overlaps with. If the new footprint groups connect AJDs that the original model put in separate groups, we assign or reassign all to the same split. If an AJD from the original model is in the train split, we assign all connecting AJDs to training, then testing, and finally validation. We split all new AJDs that do not overlap following the procedure in (*10*).

A.3: Synthetic Data

AJDs focus on ambiguous cases and contain few locations with unambiguous jurisdiction (e.g., few sites in the middle of the Great Lakes or Mississippi River, or on desert mountain peaks). Augmenting the AJD data with locations where expert knowledge suggests unambiguous jurisdiction may improve model generalizability. Adding unambiguous examples to the training set may also improve the model's performance on the AJD test set if the unambiguous examples provide relevant information to AJD jurisdiction, by helping the model learn features that predict both the unambiguous examples and the AJDs.

We therefore add synthetic AJDs to the training and validation sets. We generate jurisdictional synthetic AJD points in perennial streams that terminate in navigable waters and in the largest 98 inland lakes that are deep enough for boat access. We generate non-jurisdictional synthetic AJDs in isolated wetlands (prairie potholes, playas, West Coast vernal pools, and salt flats) and along hydrologic region (HUC2) boundaries (table S11, table S12). This hand-labeling procedure represents a case of human-in-the-loop machine learning, where algorithms and human feedback collaboratively improve performance (*47*).

We develop separate procedures for identifying unambiguously jurisdictional and non-jurisdictional locations, as detailed below. Figs. S5a and S5b map the results.

Synthetic Data: Jurisdictional Locations. We generate jurisdictional synthetic training data within National Hydrography Dataset (NHD) (*49*) area stream, river, sea, and ocean polygons that connect to NHD flowlines terminating at navigable waters. All NHD flowlines list their terminal feature. We identify all NHD flowlines whose terminal feature is coastal, a large inland lake such as the Great Lakes or Humboldt lake, or at the US border; these are potentially navigable. To ensure completeness, we manually investigate the jurisdictional status of terminal features not meeting the criteria above that serve as a terminus for over 1000 other flowlines.

We keep all NHD area polygons classified as streams/rivers (fcode: 46006) or sea/ocean (fcode: 44500) that spatially intersect with a flowline identified above. To ensure we select coordinates inside the water body, we generate a 10 meter buffer inside the boundary of each NHD area polygon. Finally, we randomly select coordinates from these polygons. Fig. S5a shows this primarily selects traditional navigable waters.

Synthetic Data: Non-Jurisdictional Locations. We draw two sets of non-jurisdictional synthetic data: isolated wetlands and hydrologic unit code (HUC2) boundaries.

Synthetic Non-Jurisdictional Data: Isolated Wetlands. We identify wetlands that are not jurisdictional under *Sackett* or NWPR following the classification of Tiner (*50*). For each isolated wetland type in Table 1 and Figure 3 of Tiner (*50*), we identify the US region with that type of isolated wetlands. Tables S11 and S12 describe our mapping from Tiner (*50*) wetland types to geographic regions. In some cases, one wetland type spans multiple geographic regions. We were unable to link about half of the Tiner categories to specific US regions, and therefore do not generate synthetic non-jurisdictional training data for these areas.

We then identify isolated wetlands separately for each region and isolated wetland type. We take all National Wetland Inventory (NWI) (*51*) polygons at least 100 meters from any navigable water, where navigable waters are defined as above.

To identify wetland types for non-jurisdictional synthetic data, we tabulate all AJDs with the identified NWI polygons satisfying the criteria of the previous paragraph, separately by Cowardin code (table S12). We require that AJDs within wetlands of that Cowardin code must satisfy the following additional criteria:

1. We must observe at least 25 AJDs falling within wetlands of that Cowardin code;
2. Across all rules, no more than 10% of AJDs within these wetlands can be jurisdictional;
3. No more than 5% of Navigable Waters Protection Rule (NWPR) and *Sackett* AJDs within these wetlands can be non-jurisdictional.

As one test of whether this procedure effectively identifies isolated wetlands, among the *Sackett* AJDs satisfying these criteria, we find that the Army Corps of Engineers (USACE) classifies resource codes for 97% as isolated wetlands. Other rules lack a distinct resource type for isolated wetlands, so we cannot report comparable statistics from AJDs for other rules. We generate synthetic non-jurisdictional training data for NWPR and *Sackett* only, as the jurisdictional status of these types of wetlands is ambiguous under other rules.

Synthetic Non-Jurisdictional Data: HUC2 Boundaries. We generate additional synthetic non-jurisdictional training data along hydrologic region boundaries. The US Geological Survey defines a HUC as land area within which surface water drains to a point. We focus on the 21 HUC2 water resource regions, which define the drainage areas of one or multiple major rivers. HUC2 boundaries are typically uplands, since they demarcate one drainage region from another, and thus are not jurisdictional. For example, the Pacific Northwest constitutes one HUC2, bounded by several mountain ranges (Pacific Coast, Siskiyou, Absaroka, and others). The Continental Divide and Great Basin distinguish parts of other HUC2 boundaries. One could oversimplify a HUC2 boundary as a mountain ridge where one side has streams flowing to the East and the other side has streams flowing to the west, though many HUC2 boundary areas in the Midwest and South are in the high portion of low-elevation, gently sloped areas.

To generate synthetic training data along HUC2 boundaries, we randomly sample points satisfying the following criteria:

1. Within 50 meters of HUC2 boundaries
2. Not within 50 kilometers of international borders
3. Not within 50 meters of any NHD flowline that NHD indicates terminates in an ocean, large inland lake, or US border
4. Not within 50 meters of any NHD area polygon intersecting such NHD flowlines.

We exclude areas within 50 kilometers of international borders since some HUC2 boundaries coincide with oceans and Great Lakes.

As one test of whether this strategy accurately identifies non-jurisdictional areas, we examine the 69 true AJDs satisfying all these criteria. Among these AJDs, 37 were completed under *Rapanos*, 7 under the Clean Water Rule, 7 under NWPR, and 18 under *Sackett*. USACE concluded that none of these 69 AJDs are jurisdictional.

Synthetic Data: Model Training. In model development, we experimented with including different quantities of synthetic data, between about 500 synthetic points up to 100,000. We found that AJD validation set performance was maximized around 1,000 points of each synthetic type (i.e., 1,000 synthetic jurisdictional points, 1,000 synthetic non-jurisdictional points from HUC2 boundaries, and 1,000 of each of the synthetic non-jurisdictional isolated wetland types).

Synthetic data improve model performance both for traditional navigable waters and more ambiguous cases. The model has near-perfect accuracy on synthetic data. Additionally, including synthetic data improves model accuracy on AJDs by 2 to 3 percentage points in the validation set, as well as improving both precision and recall by 6 to 7 percentage points each. This suggests that including synthetic points helps the model distinguish between ambiguous and unambiguous decisions, and so reduces the rate at which the model produces both false positive and false negative predictions.

A.4 AJD PDF Files

We obtain labels from tabular data that USACE and USEPA provide online (52) and downloaded on March 24, 2025. For each AJD, USACE staff complete a document listing jurisdiction of each potential water resource in the project, and USACE and USEPA then separately hand-enter the

AJD content into the tabular data we use as labels. These AJD documents are available for a limited subset of sites, while the tabular data are available for all.

To assess potential classification errors in the labels, we manually compare labels in the tabular data and the AJD documents. We find that labels in the AJD documents disagree with labels in the tabular data for 3.4% of AJDs, and have coordinates differing by more than 217.8 meters, meaning that the input data tile does not include the location evaluated by the AJD, for 19.4% of AJDs. The percentage of differential coordinates partially reflects many project PDFs listing the project centroid, rather than the centroid of the relevant water feature. We do not use the AJD document labels or coordinates as ground truth data because the documents are only available for 7,556 of over 40,000 projects in our sample; because a single document often reports labels for many potential water resources within a development project and correctly mapping each water feature's label to the water features within the project can introduce additional error; and few AJD documents list coordinates for individual water resources, while many list coordinates for the project centroid.

A.5 Input Layers

Our deep learning models take as inputs 29 raster layers and 89 tabular features. Twenty-eight of the raster layers are identical to those used in Greenhill et al. (*10*): three-band color and near infrared aerial imagery from the National Agricultural Imagery Program (NAIP) (*53*); wetland types from NWI (*51*); river and stream feature codes, stream order, seasonal high and low flows, and path lengths from NHD; elevation from the 3D Elevation Program; land cover data from the National Land Cover Dataset (NLCD) (*54*); soil taxonomic class, hydric rating, water table depth, flooding frequency, and ponding frequency from the Gridded National Soil Survey Geographic Database (gNATSGO) (*55*); average annual total precipitation, average daily minimum temperature, average daily maximum temperature, average daily mean temperature, average daily dew point temperature, average daily minimum vapor pressure deficit (VPD), average daily maximum VPD, average daily clear sky and total solar radiation, and average daily atmospheric transmittance (cloudiness), all for 1990-2021, from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) 30-year normal (*56*); and level IV Ecoregions (*57*). Further details about these layers are available in Table S4 of Greenhill et al. (*10*). We also include land cover data from the Coastal Change Analysis Program (C-CAP) (*58*), which has higher native resolution and is believed to be more accurate than NLCD. Because C-CAP covers only coastal areas, we retain NLCD. All raster inputs are resampled from their original resolution to match the resolution of the 0.6 meter NAIP imagery, resulting in 512 by 512 pixel rasters centered at the location being evaluated, covering an area of approximately 308 by 308 meters. Several raster input layers are available only in the contiguous US, so we restrict our analysis to this region. We selected raster input layers based on the datasets that USACE engineers most frequently cited in the PDF files accompanying AJDs (*10*).

The 89 tabular features consist of one-hot encoded identifiers for the state and USACE district of the location being evaluated, the distance to district headquarters, and one-hot encoded information on the WOTUS rule under which the location's jurisdictional status is being evaluated. State and USACE district boundaries have an important influence on jurisdictional rates. Similarly, distance to district headquarters may influence the likelihood that a site receives a field visit, which may also affect jurisdictional determinations (*10*). Including one-hot encoded rule information allows us to capture differences across rules and produce model predictions for the same locations under different rules.

Our visual review of spatial patterns in the 4 million prediction points reveals that CLEAR predictions occasionally display discontinuities within a water body. Investigation indicates that discontinuities in input layers, typically the National Agricultural Imagery Program (NAIP) (*53*) and the Gridded National Soil Survey Geographic Database (gNATSGO) (*55*) drive these patterns. In all examples we investigated, the algorithm itself does not generate these discontinuous patterns except insofar as the inputs have them. The infrequent abrupt changes in NAIP inputs that we identified reflect cloud cover affecting processing of remote sensing data. gNATSGO combines the Soil Survey Geographic Database (SSURGO), State Soil Geographic Database version 2, and the Raster Soil Survey data. Analysts create SSURGO by stitching together soil survey areas. One survey area may cover one or several entire counties or parts of counties. This stitching process occasionally produces discrete spatial changes in gNATSGO inputs.

A.6: Agriculture

The CWA excludes prior converted cropland from jurisdiction, but many AJD coordinates fall within NLCD's cropland layer. To understand this contrast, an additional analysis manually investigated a sample of 88 jurisdictional AJDs from *Rapanos*, NWPR, and *Sackett* which have coordinates within NLCD's cropland layer. For each AJD where a document was available, this analysis checked the coordinate in the USEPA-USACE tabular data against the coordinate in the document. This analysis inspected Google Earth imagery from these coordinates and compared against any maps in the AJD document. This analysis found that only 12.5% of the sample of AJDs (11 AJDs) within NLCD's cropland layer represented agricultural activity. For these AJDs, the AJD documents contained insufficient information to determine why the AJD was jurisdictional and was not excluded as prior converted cropland. For example, it is possible these sites became cropland recently so were not "prior." Of the remaining AJDs, 48.9% were near agriculture but not on a field (e.g., a pond or house next to cropland), 29.5% appeared to have slight reporting error in the coordinate, and 9.1% had incorrect labels, as SM A.4 discusses.

A.7: Model Calibration and Decision Threshold Choice

Raw CLEAR model scores have imperfect calibration, i.e., model scores do not reflect the probability that a point is regulated. To improve model calibration, we fit an isotonic regression on the training set, then use the fitted isotonic regression model to calibrate out of sample predictions. This procedure improves model calibration, especially for calibrated probabilities below 0.6. The Brier score on the test set is 0.178 before calibration and 0.148 after calibration. For calibrated probabilities above 0.3, the average predicted probability of jurisdiction in each bin is higher than the observed probability in the test set.

Geophysical models primarily generate binary predictions of whether a site is jurisdictional. Deep learning models produce continuous model scores, which we calibrate to describe the probability that a site is regulated. Deep learning models can also generate a binary jurisdictional prediction indicating whether the site's calibrated probability exceeds a given threshold (e.g., 0.5). To use all information from the model, to estimate the share of an area that is jurisdictional, we average calibrated probabilities rather than averaging binary jurisdictional predictions.

Different stakeholders may value different model performance metrics and may thus prefer different thresholds for binary jurisdictional classification. AUC aggregates across all possible thresholds. For other metrics, Table 1 reports model performance for classification thresholds that differ by performance metric, each chosen to optimize the performance metric. We use the validation set to choose optimal thresholds. To evaluate the sensitivity of threshold choice to validation set sampling variation, we implemented threshold selection using five-fold cross validation and observed minimal variation in the selected thresholds.

Fig. S6 shows how performance metrics vary across decision thresholds in the validation set. Optimal thresholds are chosen based on performance in the validation set, and then applied to the test set. Table S13 reports all test set performance metrics at the optimal threshold for each metric. AUC is invariant to threshold choice. Thresholds near 0.25 optimize F1 score and state MAE. A lower threshold, 0.17, optimizes national MAE. A decision threshold near 0.50 maximizes overall accuracy. Much of the threshold domain has flat curves, suggesting that threshold choice has only a marginal impact on overall performance. Furthermore, during model development we implemented five-fold cross validation for threshold selection on the validation set and found that optimal thresholds and the corresponding metrics did not change significantly across folds.

Histograms show the distribution of the calibrated probabilities (fig. S7). CLEAR has high confidence——few sites have a score near 50% and most have calibrated probabilities below 20% or above 80%. To use all information from the model to estimate the share of an area that is jurisdictional, we average calibrated probabilities rather than averaging binary jurisdictional predictions.

A.8: Prediction Points

We report model predictions on groups of sites. We randomly select 4 million points across the contiguous US, using the same set of locations analyzed by Greenhill et al. (*10*). These are gathered by dividing the contiguous US into approximately 80,000 0.1 by 0.1 degree grid cells, then randomly sampling 50 points in each cell. This large number of points allows us to produce high resolution maps (Fig. 2), case studies (Fig. 3), and report on predicted regulation overall and at specific locations of interest (table S2). We separately report predictions for streams, wetlands, agricultural sites, floodplains, developed urban areas, and areas likely to see urban growth in the future. We identify these areas using NHD (*49*), NWI (*51*), the National Land Cover Dataset (NLCD) (*54*), and the National Flood Insurance Program (NFIP) (*59*), and Integrated Climate and Land Use Scenarios (ICLUS) (*60*).

We report the mean calibrated probability for the 4 million prediction points and for subsets of these points in important areas, including within 5 m of NWI wetlands or NHD streams (table S2). Because we average across points, we interpret these in terms of stream miles and wetland acres.

B. Supplementary Text

B.1: Geophysical Model Projections

Table S4B presents models using one geophysical input layer at a time to determine jurisdiction. For example, the presence of hydric soils is often taken as an indicator of historic wetlands (*61*). A prediction relying on whether a site has hydric soils has an AUC of only 0.492, which is worse than the naïve benchmark, and F1 of 0.295. Row 9 shows that a model assuming sites with water table depth less than 10 m are jurisdictional also performs poorly. The CWA excludes prior converted cropland and urban developed areas from jurisdiction, so rows 10 and 11 use crop cover and built-up area classes in the NLCD. Again, these rules perform poorly.

The Connected Wetlands model reported in Table 1 assumes that only NWI wetlands that are within 50 meters of a NHD stream that terminates in a navigable water are regulated. These wetlands are uncommon, and thus the Connected model predicts low regulation rates. The Connected model performs poorly in part due to low predicted regulation.

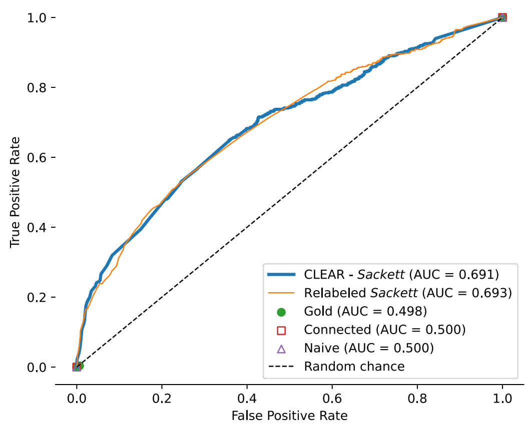
B.2: Projections Using Probabilities Versus Binary Jurisdictional Predictions

As discussed in the main text, to estimate jurisdiction across groups of sites, Table S2 and Table S5 average calibrated probabilities. These tables use the calibrated probabilities since binary jurisdictional predictions discard information by discretizing each site to an indicator for whether the calibrated probability exceeds a threshold. For example, if all sites in an area had a calibrated probability of 0.20, averaging the calibrated probabilities would indicate that 20% of sites are jurisdictional, while averaging the binary jurisdictional predictions would indicate that 0% of sites are jurisdictional.

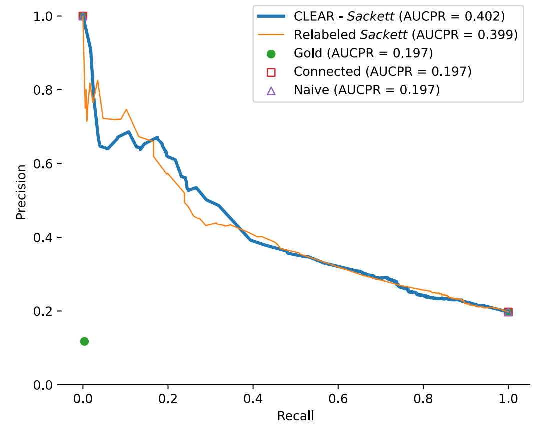
To understand the consequences of this choice, we re-estimated Table S5 by averaging the binary jurisdictional predictions. Averaging the binary predictions would imply that 11.6% of all sites are jurisdictional under *Rapanos* and 5.8% under NWPR. These are far below the values that average calibrated probabilities. Averaging the binary predictions rather than averaging the calibrated probabilities mostly decreases the estimated share of points that are jurisdictional for NWPR, and for points without streams or wetlands. This occurs because, as in the example from the previous paragraph, binary jurisdictional predictions adjust sites with low calibrated probabilities to zero, but the calibrated probabilities retain some non-zero estimated probability of regulation for such sites. This also helps explain why Table S5 estimates higher regulation rates for *Rapanos* and NWPR than Greenhill et al. (*10*) do, since they average binary jurisdictional predictions but do not average calibrated probabilities.

Fig. S1. CLEAR and Relabeled *Sackett* outperform geophysical models.

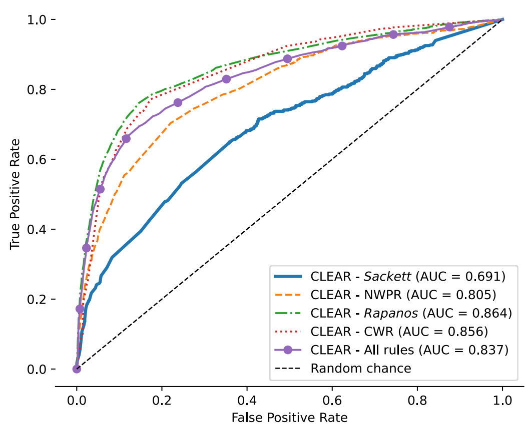
A Receiver operating curves – *Sackett*



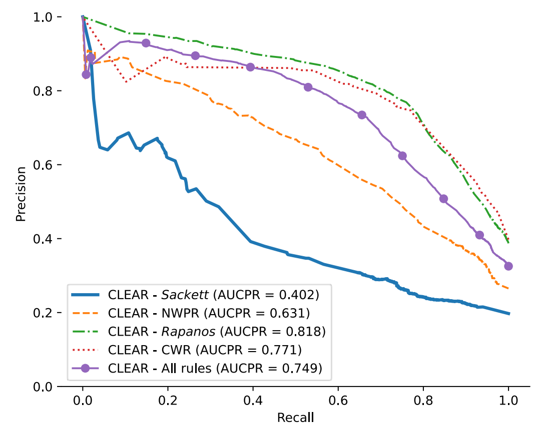
B Precision-recall curves – *Sackett*



C Receiver operating curves – comparing rules

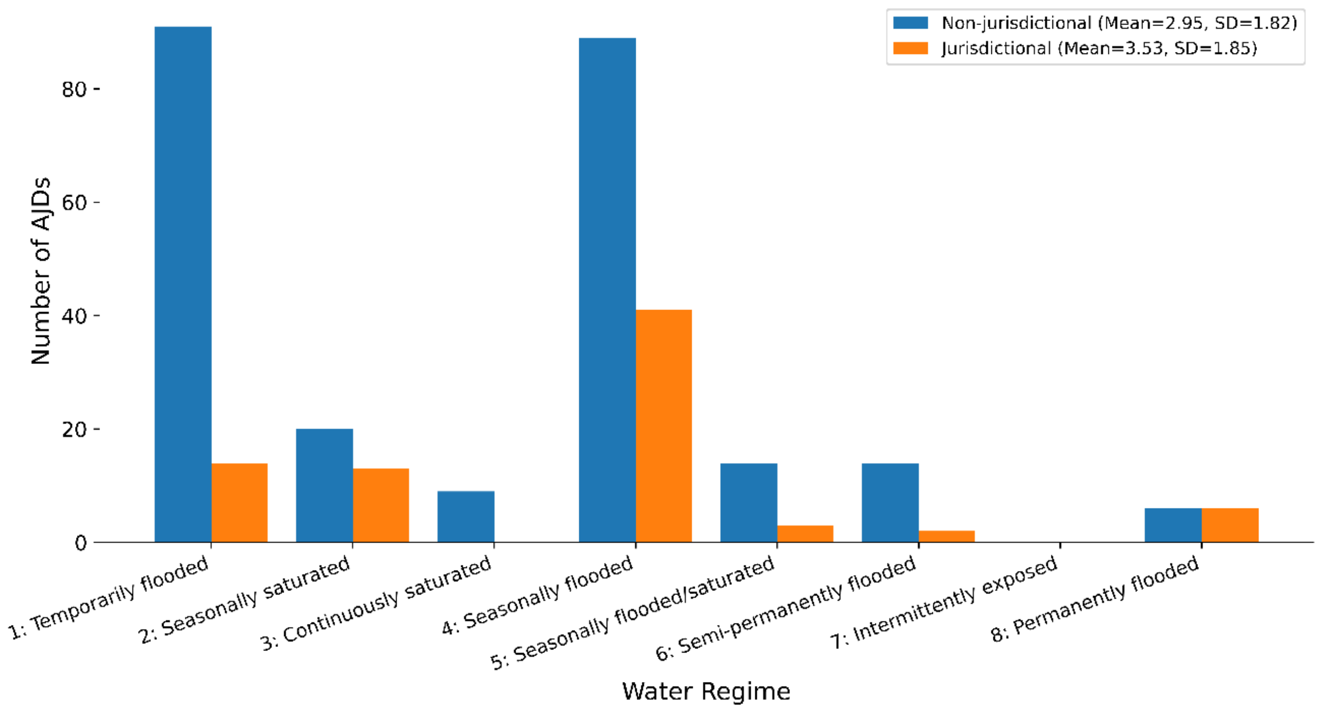


D Precision-recall curves – comparing rules



(**A**) and (**C**) show the Receiver operating curve (ROC), and the Area Under the Curve (AUC). The ROC plots the True Positive Rate (share of correctly identified positives) against the False Positive Rate (share of negatives incorrectly identified as positive) across all classification thresholds. For example, the left-most point corresponds to a threshold above one, predicting no positives. The right-most point corresponds to a threshold below zero, predicting all positives. CLEAR-*Sackett* has 69.1% probability of ranking a randomly chosen jurisdictional AJD higher than a randomly chosen non-jurisdictional AJD. AUC = 0.5 is random chance, AUC-ROC = 1 is perfect. On all rules, CLEAR has a 0.837 AUC. (**B**) and (**D**) show the Precision-Recall (PR) Curve and the Area Under the Curve (AUCPR). The PR curve plots precision (share of predicted positives that are true positives) against recall (share of true positives identified) across all classification thresholds. The AUCPR averages precision across all recall levels. A random classifier has an AUC-PR of 0.197 since 19.7% of *Sackett* AJDs are jurisdictional. CLEAR-*Sackett*'s AUCPR of 0.402 means the model identifies positive cases with about twice the precision as a random classifier, indicating strong performance in detecting jurisdictional AJDs despite class imbalance. Across all rules, a random classifier has an AUCPR of 0.325 since 32.5% of AJDs are jurisdictional. Also across all rules, CLEAR's AUCPR of 0.749 means the model identifies positive cases with over twice the precision as random guessing, indicating strong performance in detecting jurisdictional AJDs despite class imbalance. The PR curves focus on positive-class performance and are more informative under class imbalance. Curves are constructed by using all unique calibrated model scores as thresholds. All curves are independent of any chosen classification cutoff. Because Gold (*22*), Connected, and the Naïve models have binary model scores, these are plotted as points rather than lines.

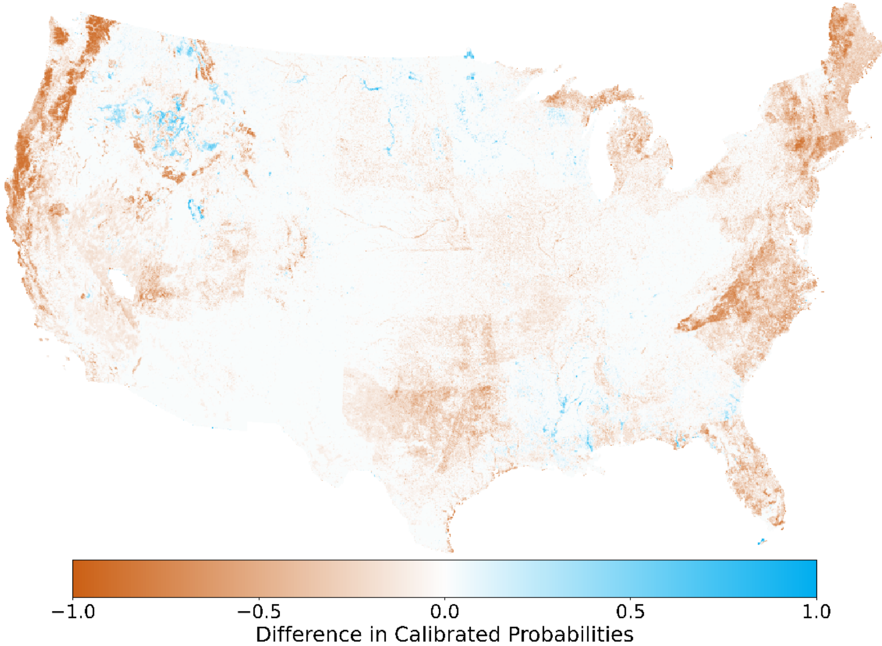
Fig. S2. NWI Wetness values for *Sackett* AJDs noisily measure jurisdiction.



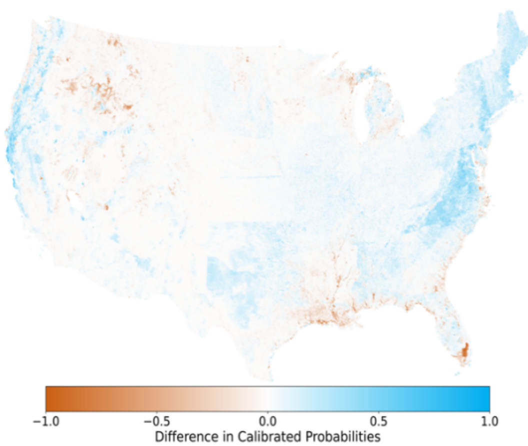
NWI "Water Regime" values differ across both non-jurisdictional and jurisdictional *Sackett* AJDs. Some jurisdictional AJDs have relatively low wetness, and some non-jurisdictional AJDs have relatively high wetness. This figure plots the water regime value, which describes "Wetness" in Gold (*22*) scenarios, for all 322 *Sackett* AJDs that fall within a NWI polygon in Gold (*22*). Dark blue bars display non-jurisdictional AJDs; light orange bars display jurisdictional AJDs. SD is standard deviation.

Fig. S3. Maps show large spatial differences in regulation across rules and models.

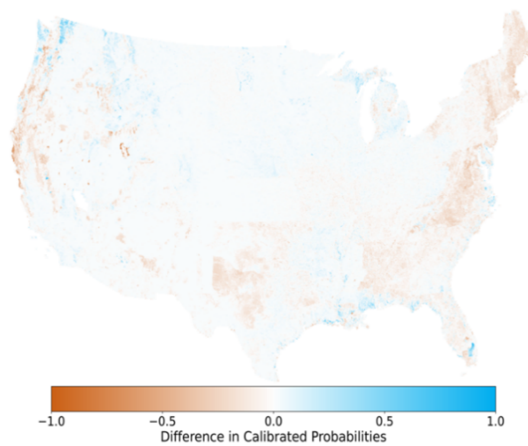
A CLEAR-*Sackett* – CLEAR-*Rapanos*



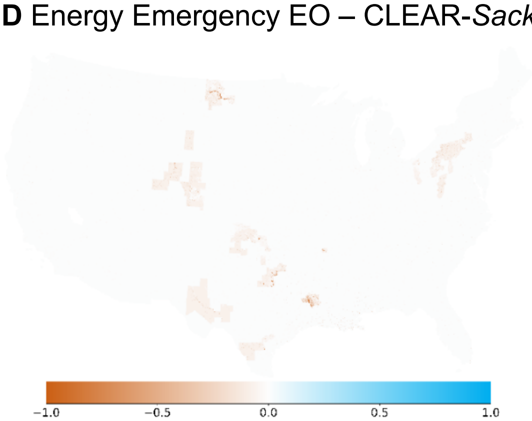
B Relabeled *Sackett* – CLEAR-*Sackett*



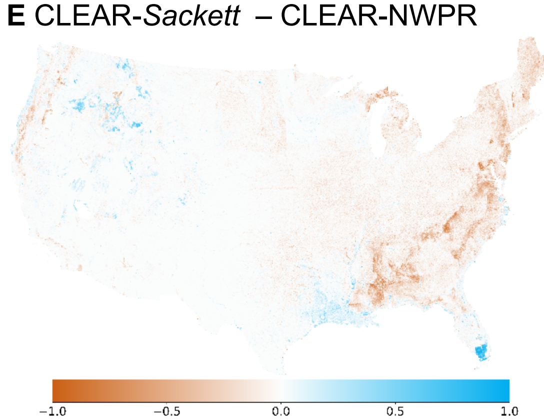
C March 2025 Guidance – Relabeled *Sackett*



D Energy Emergency EO – CLEAR-*Sackett*

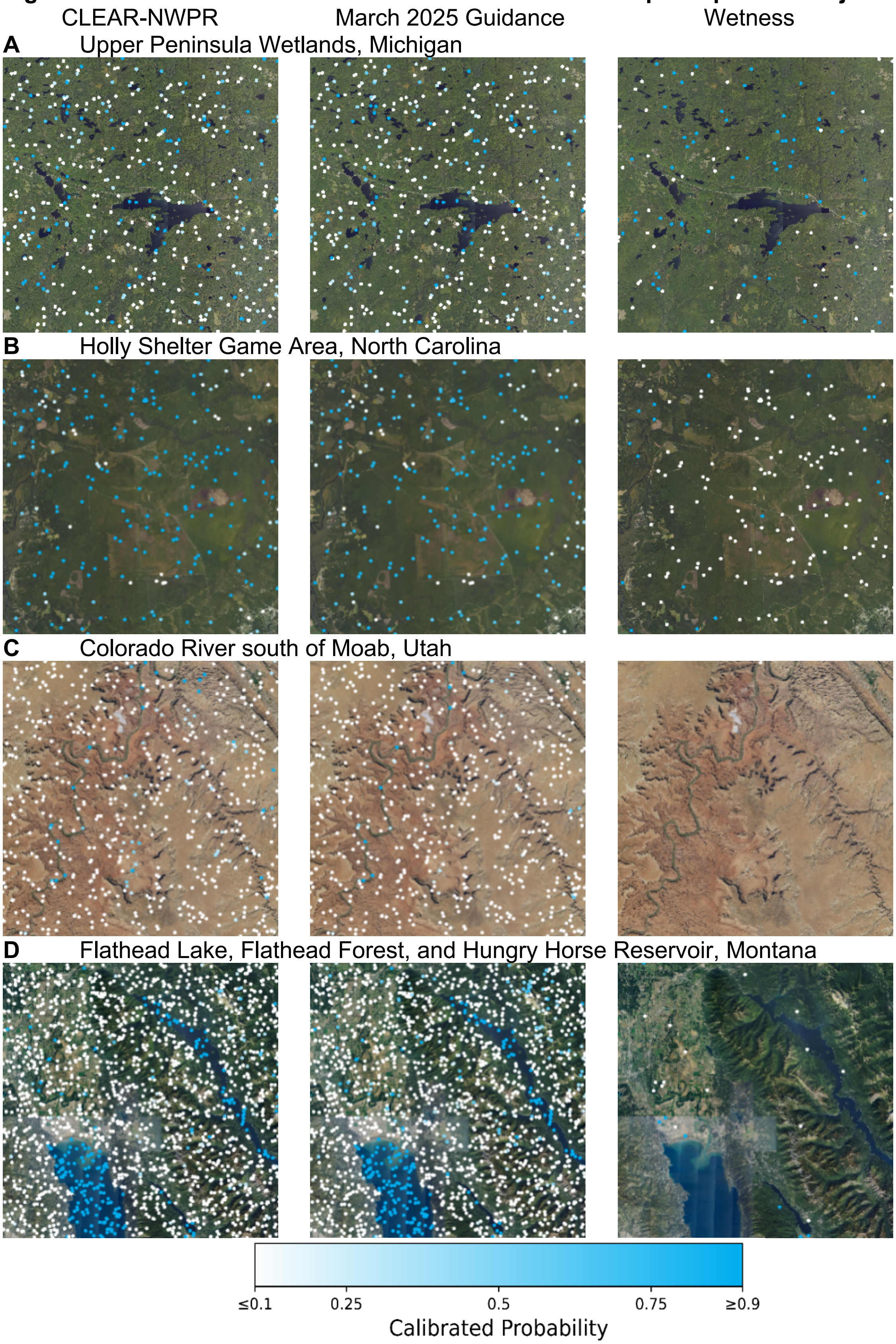


E CLEAR-*Sackett* – CLEAR-NWPR



Brown represents newly deregulated, blue represents newly regulated. Maps show: (**A**), changes from CLEAR-*Rapanos* to CLEAR-*Sackett*; (**B**), CLEAR-*Sackett* to Relabeled *Sackett*; (**C**), Relabeled *Sackett* to March 2025 Guidance, since both relabel NWPR AJDs; (**D**), CLEAR-*Sackett* to Energy Emergency Executive Order (EO); and (**E**), CLEAR-NWPR to CLEAR-*Sackett*. Maps aggregate the four million prediction points by taking the mean model score in 5 km by 5 km grid cells (~8 prediction points per grid cell).

Fig. S4. Case studies show differences across rules and spatial patterns of jurisdiction.

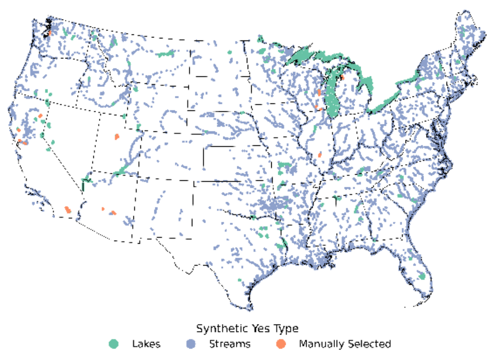


Columns show calibrated model scores for prediction points under three different models, two deep learning and one geophysical. The first column shows CLEAR-NWPR, the second column shows the

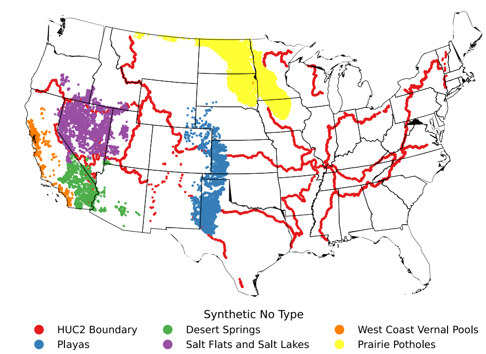
March 2025 guidance, and the third column shows the Wetness (*22*) model (seasonally flooded scenario). The Wetness model only shows prediction points within wetlands used in Gold (22, 30) which lack information for most prediction points. (**A**), Lakes and wetlands in the Upper Peninsula of Michigan. CLEAR-NWPR and the March Guidance predict little jurisdiction for surrounding wetlands, and the Wetness model predicts jurisdiction for different surrounding wetlands and information for many points. (**B**), Holly Shelter Game Area, North Carolina. CLEAR-NWPR classifies most points as jurisdictional in this coastal outdoor recreation area. The March Guidance predicts less jurisdiction for most points in the region, and the Wetness model predicts little jurisdiction. (**C**), Colorado River and ephemeral streams south of Moab, Utah. CLEAR-NWPR and the March Guidance predict no jurisdiction for ephemeral streams upstream of the river, the Wetness model has no information for any points. (**D**), Flathead Lake, Flathead Forest, and Hungry Horse Reservoir, Montana. CLEAR-NWPR and the March Guidance classify the lake in the southwest corner and the reservoir in the northeast corner as jurisdictional, but do not regulate the Flathead Forest. The Wetness model has almost no information on sites in the area.

Fig. S5. Synthetic and true training data span most US regions.

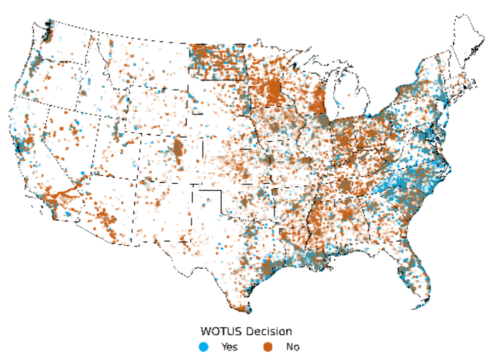
A Synthetic jurisdictional points



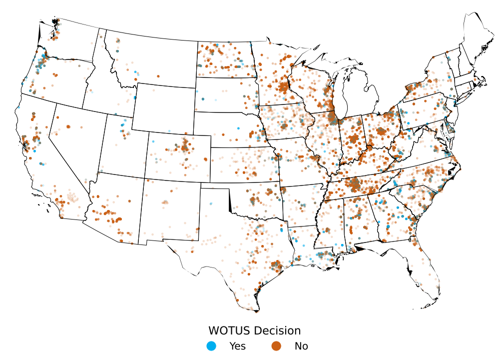
B Synthetic non-jurisdictional points



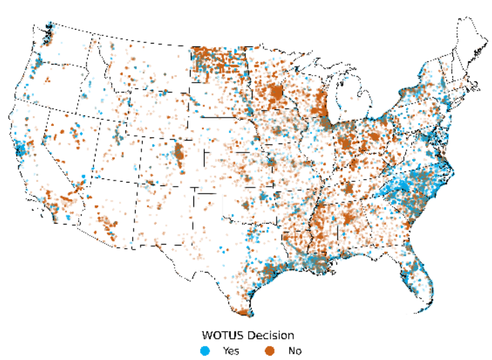
C True AJDS



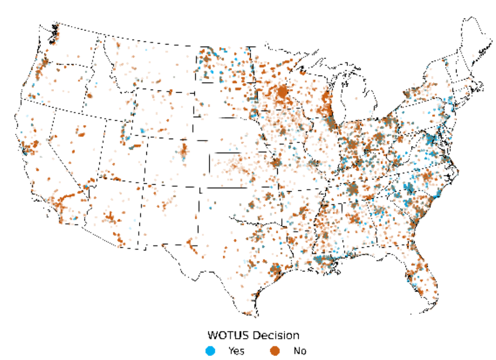
D *Sackett* AJDs



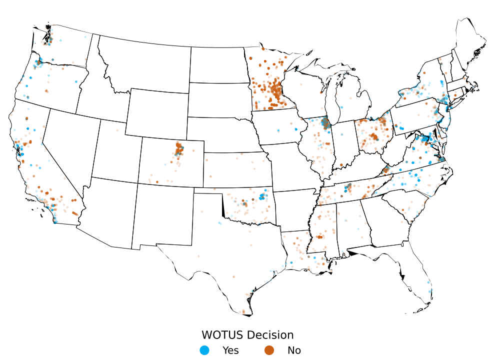
E *Rapanos* AJDs



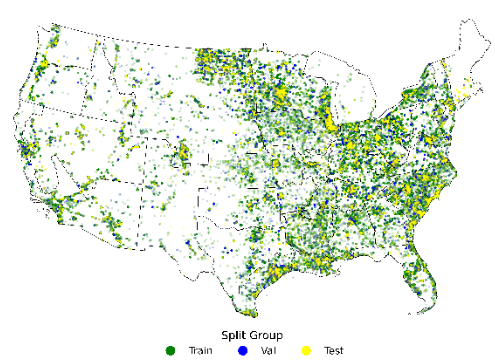
F NWPR AJDs



G CWR AJDs



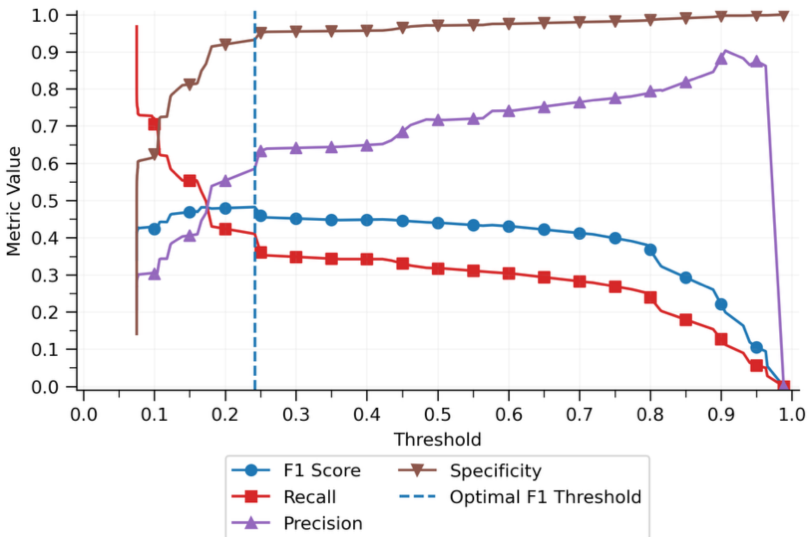
H True AJDs, by split



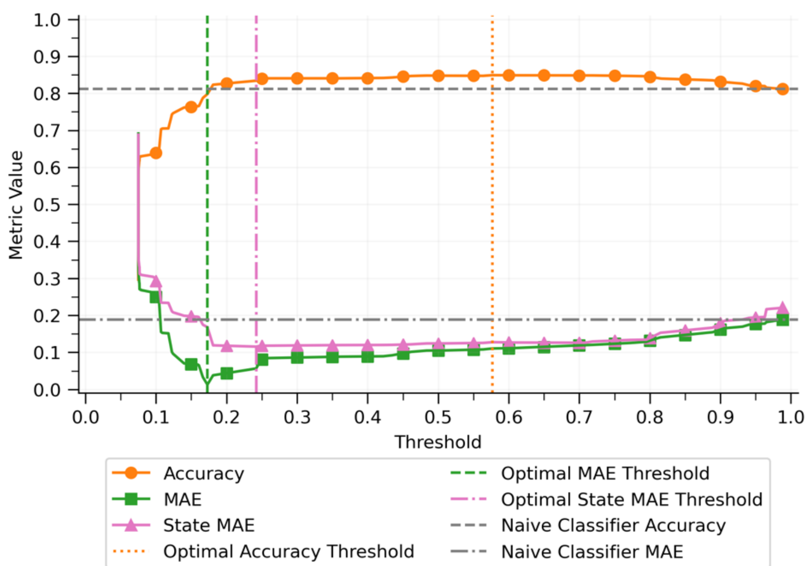
(**A**), synthetic jurisdictional AJDs and **(B**), synthetic non-jurisdictional AJDs, both colored by water resource type. (**C**)**,** true (non-synthetic) AJDs, colored by label. (**D**)-(**G**) separate true AJDs by rule. (**H**) colors true AJDs by split. Lines in (**A**)-(**F**) show states; lines in (**H**) show Army Corps (USACE) districts.

Fig. S6. Jurisdictional thresholds optimize model performance for each metric.

A F1-Score, Precision, Recall, and Specificity



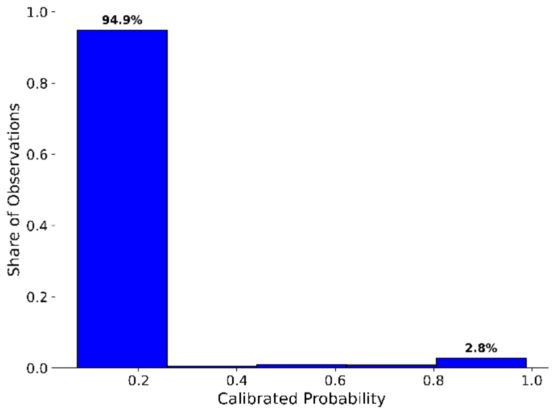
B Accuracy, Overall Mean Absolute Error (MAE), and State MAE



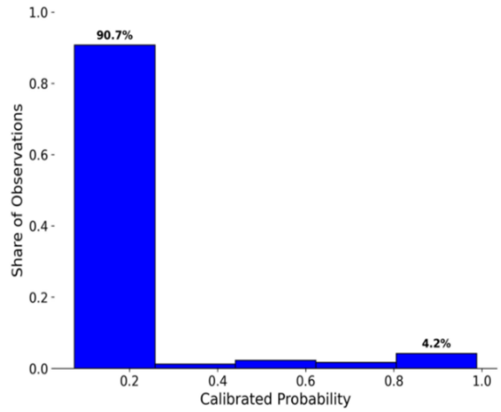
The CLEAR-*Sackett* model predicts a site as jurisdictional if its calibrated probability exceeds the relevant threshold. The y-axis in each graph shows the model's performance on the metric of interest if the model uses the threshold indicated on the x-axis. Each line with markers shows a different performance metric. (**A**), the blue line with circles shows F1; the red line with squares shows recall; the purple line with triangles shows precision; and the brown line with inverted triangles shows specificity. The vertical dashed blue line shows the threshold which maximizes F1. (**B**), the orange line with circles shows accuracy, the green line with squares shows MAE, and the pink line with triangle shows state MAE. Each vertical line shows the threshold which maximize the performance metric with matching color (e.g., the dashed green line shows the threshold which maximizes MAE, which is also shown in green). The horizontal dashed lines show performance of a naïve benchmark that assumes no sites are jurisdictional.

Fig. S7. Distribution of calibrated probabilities of regulation differ by rule and sample, though concentrate below 0.2 or over 0.8.

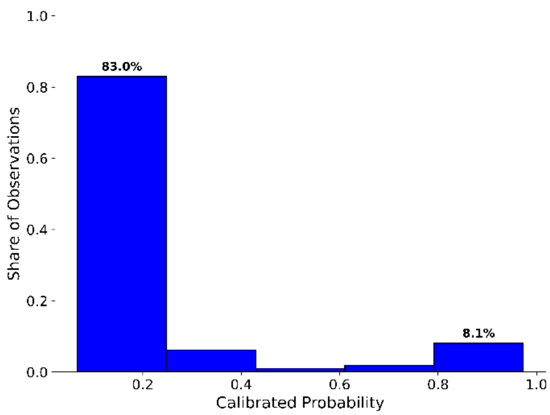
A CLEAR-*Sackett* – 4 million points



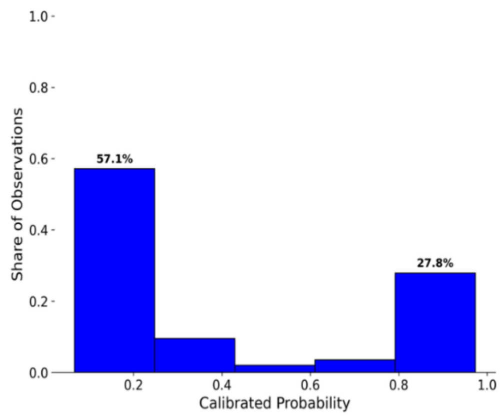
B CLEAR-*Sackett* – test set



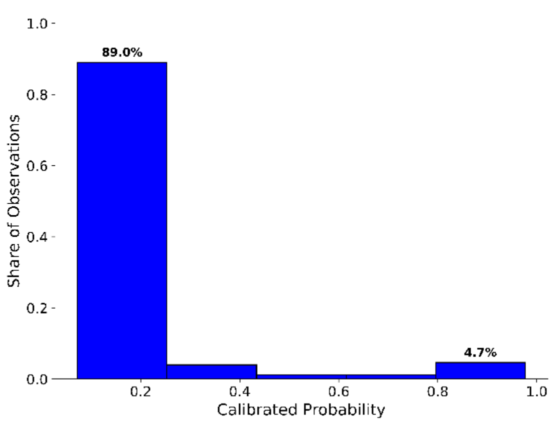
C CLEAR-*Rapanos* – 4 million points



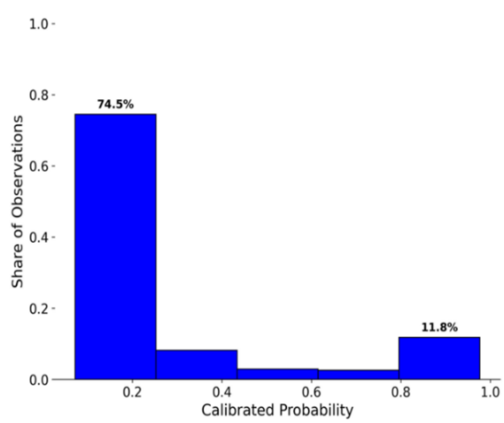
D CLEAR-*Rapanos* – test set



E CLEAR-NWPR – 4 million points



F CLEAR-NWPR – test set



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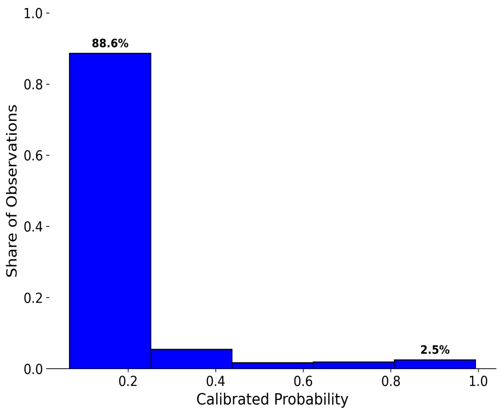
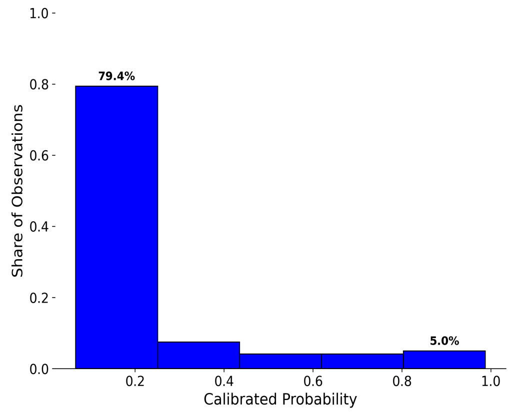
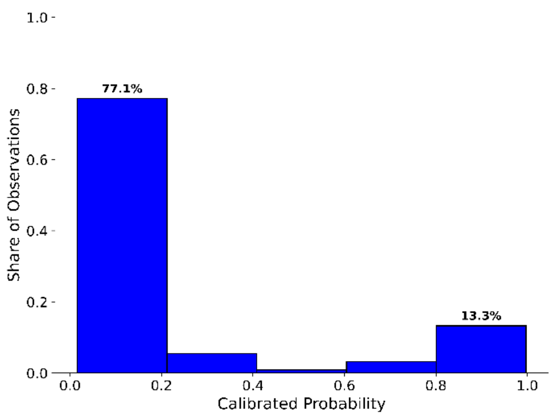
G Relabeled *Sackett* – 4 million points



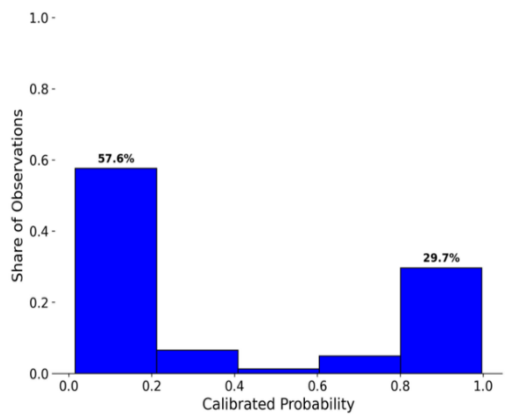
H Relabeled *Sackett* – test set



I CLEAR-CWR – 4 million points

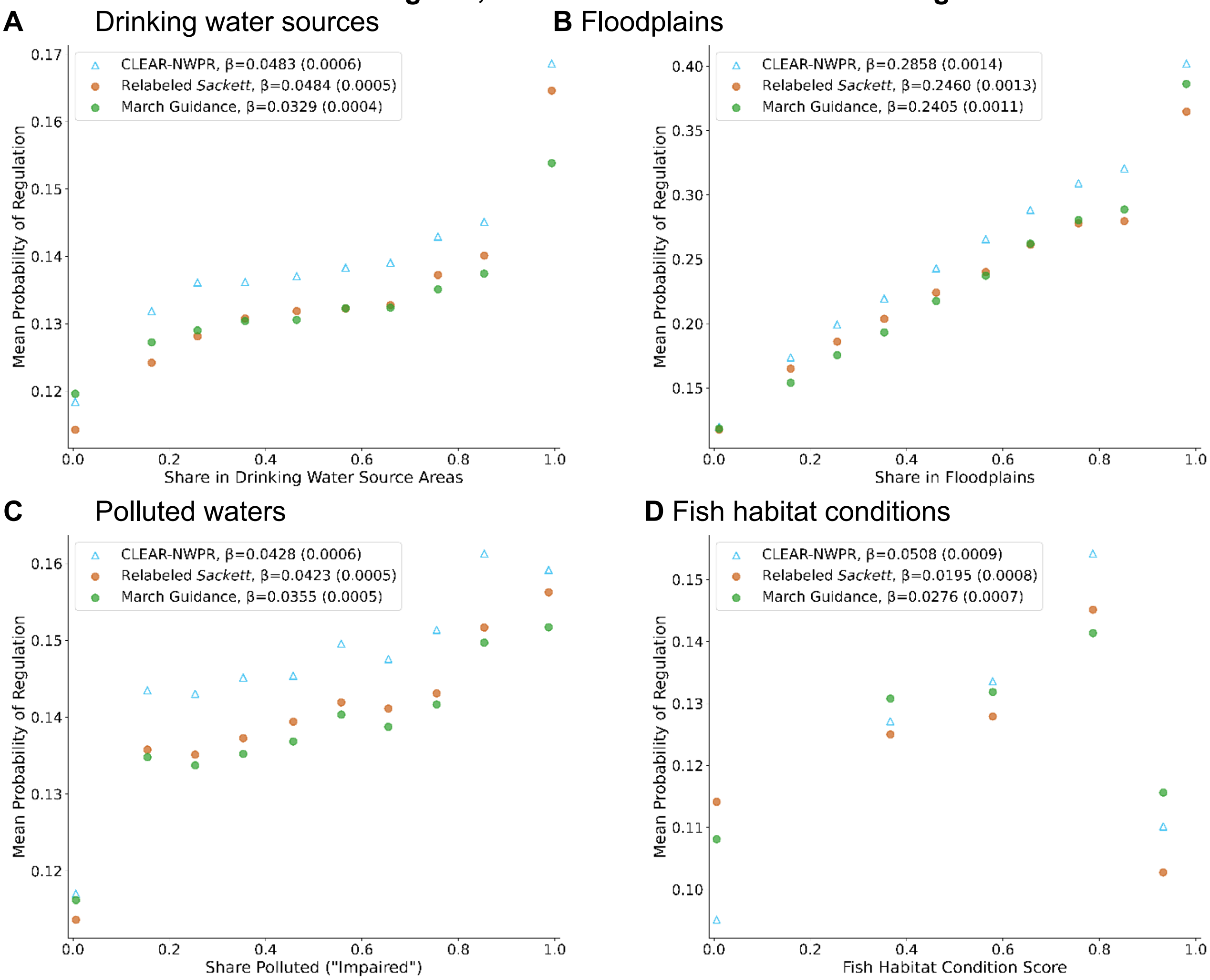


J CLEAR-CWR – test set



For each rule and for either the 4 million prediction points or the test set, each graph shows the share of points with a calibrated probability in one of five evenly sized bins spanning 0.0 to 1.0. Across all rules, and in both the 4 million random prediction points and the test set, around 90 percent of sites have calibrated probabilities below 0.2 or above 0.8, indicating that the model has high confidence. The test set has higher jurisdictional probabilities than the 4 million random prediction points because AJDs disproportionately represent sites with potential water resources.

Fig. S8. Relabeling captures *Sackett*'s deregulation of areas with concentrated ecosystem services and relevant to CWA goals, and March Guidance further deregulates these areas.



(**A**) Share of points in drinking water source areas. (**B**) Share of points in floodplains. (**C**) Proportion of assessed waters considered "impaired" based on ambient pollution and relevant standards. (**D**) Fish habitat condition score. Each panel splits 4 million random points into the 251,975 5km by 5 km grid cells used to plot Fig. 2. In each graph, the y-axis shows the mean calibrated probability from CLEAR-NWPR, Relabeled *Sackett*, and the March 2025 Guidance, and the x-axis shows the mean value within the grid cell. The x-axis divides grid cells into equal-width bins (0-1 scale) based on underlying values. The legend shows the grid-level regression coefficient with standard errors in parentheses. Impaired waters and fish habitat conditions measured by 12-digit hydrologic unit code (HUC12) from the EPA's 2025 Restoration and Protection Indicator Database.

Table S1. Relabeling NWPR AJDs allows training of Relabeled *Sackett* and March 2025 Guidance models.

	Definition	Share of AJDs	Jurisdictional under NWPR	Relabeled *Sackett*	March 2025 Guidance
	(1)	(2)	(3)	(4)	(5)
A1TNW10	(a)(1) Water is also subject to Sections 9 or 10 of the Rivers and Harbors Act - RHA Tidal water is subject to the ebb and flow of the tide	0.0035	Yes	Yes	Yes
A1TNWCOMM	(a)(1) Water is currently used, was used in the past, or may be susceptible to use in interstate or foreign commerce (CWA Section 404 only)	0.00067	Yes	Yes	Yes
A1TNWFED	(a)(1) A federal court has determined the water is navigable in fact under federal law	0.00011	Yes	Yes	Yes
A1TNWSEAS	(a)(1) Territorial Seas	6.4E-05	Yes	Yes	Yes
A2TRIBINT	(a)(2) Intermittent tributary contributes surface water flow directly or indirectly to an (a)(1) water in a typical year	0.072	Yes	Yes	Yes
A2TRIBPER	(a)(2) Perennial tributary contributes surface water flow directly or indirectly to an (a)(1) water in a typical year	0.039	Yes	Yes	Yes
A3LPIFLOOD	(a)(3) Lake/pond or impoundment of a jurisdictional water inundated by flooding from an (a)(1)-(a)(3) water in a typical year	0.0013	Yes	Yes	Yes
A3LPIFLOW	(a)(3) Lake/pond or impoundment of a jurisdictional water contributes surface water flow directly or indirectly to an (a)(1) water in a typical year	0.0057	Yes	Yes	Yes
A4WETABUT	(a)(4) Wetland abuts an (a)(1)-(a)(3) water	0.11	Yes	Yes	Yes
A4WETARTSEP	**(a)(4) Wetland separated from an (a)(1)-(a)(3) water only by an artificial structure allowing a direct hydrologic surface connection between the wetland and the (a)(1)-(a)(3) water in a typical year**	**0.0076**	**Yes**	**No**	**No**
A4WETFLOOD	**(a)(4) Wetland inundated by flooding from an (a)(1)-(a)(3) water in a typical year**	**0.0081**	**Yes**	**Yes**	**No**
A4WETNATSEP	**(a)(4) Wetland separated from an (a)(1)-(a)(3) water only by a natural feature**	**0.0027**	**Yes**	**No**	**No**
B10STORM	(b)(10) Stormwater control feature constructed or excavated in upland or in a non-jurisdictional water to convey, treat, infiltrate, or store stormwater runoff	0.02	No	No	No
B11REUSE	(b)(11) Groundwater recharge, water reuse, or a wastewater recycling structure constructed or excavated in upland or in a non-jurisdictional water	0.00024	No	No	No
B12WTS	(b)(12) Waste treatment system	0.0018	No	No	No

(Continued next page)

Table S1. Relabeling NWPR AJDs allows training of Relabeled *Sackett* and March 2025 Guidance models. (Continued)

	Definition	Share of AJDs	NWPR	Relabeled *Sackett*	March 2025 Guidance
			Jurisdictional under		
	(1)	(2)	(3)	(4)	(5)
B1EXCLUDEDOTH	(b)(1) Water or water feature that is not identified in (a)(1)-(a)(4) and does not meet the other (b)(1) sub-categories	0.011	No	No	No
B1LPINOSCFLD	(b)(1) Lake/pond or impoundment that does not contribute surface water flow directly or indirectly to an (a)(1) water and is not inundated by flooding from an (a)(1)-(a)(3) water in a typical year	0.014	No	No	No
B1SWCNOSC	(b)(1) Surface water channel that does not contribute surface water flow directly or indirectly to an (a)(1) water in a typical year	0.0078	No	No	No
B1WETNONADJ	(b)(1) Non-adjacent wetland	0.31	No	No	No
B2GRNDWATER	(b)(2) Groundwater, including groundwater drained through subsurface drainage systems	0.00011	No	No	No
B3EPHEMERAL	(b)(3) Ephemeral feature, including an ephemeral stream, swale, gully, rill, or pool	0.22	No	No	No
B4SHEETFLOW	(b)(4) Diffuse stormwater run-off over upland or directional sheet flow over upland	0.0016	No	No	No
B5DITCH	(b)(5) Ditch that is not an (a)(1) or (a)(2) water, and those portions of a ditch constructed in an (a)(4) water that do not satisfy the conditions of (c)(1)	0.094	No	No	No
B6PCC	(b)(6) Prior converted cropland	0.0053	No	No	No
B7ARTIRR	(b)(7) Artificially irrigated area, including fields flooded for agricultural production, that would revert to upland should application of irrigation water to that area cease	0.0013	No	No	No
B8LPIART	(b)(8) Artificial lake/pond constructed or excavated in upland or a non-jurisdictional water, so long as the artificial lake or pond is not an impoundment of a jurisdictional water that meets (c)(6)	0.028	No	No	No
B9DEPPIT	(b)(9) Water-filled depression constructed/excavated in upland/non-jurisdictional water incidental to mining/construction or pit excavated in upland/non-jurisdictional water to obtain fill/sand/gravel	0.0058	No	No	No
DRYLAND	The review area is comprised entirely of dry land (i.e. There are no waters or water features, including wetlands, of any kind in the entire review area)	0.034	No	No	No
RHA10NAV	RHA Non-tidal water is on the district's Section 10 waters list	0.00045	No	No	No

(Continued next page)

Table S1. Relabeling NWPR AJDs allows training of Relabeled *Sackett* and March 2025 Guidance models. (Continued)

	Definition	Share of AJDs	Jurisdictional under NWPR	Relabeled *Sackett*	March 2025 Guidance
	(1)	(2)	(3)	(4)	(5)
RHAB10STORM	Rivers and Harbors Act Section 10 water excluded from the CWA as a (b)(10) stormwater control feature constructed or excavated in upland or in a non-jurisdictional water to convey, treat, infiltrate, or store stormwater runoff	0.00010	No	No	No
RHAB1EXCLUDEDOTH	Rivers and Harbors Act Section 10 water excluded from the CWA as a (b)(1) water or water feature that is not identified in (a)(1)-(a)(4) and does not meet the other (b)(1) sub-categories	0.000016	No	No	No
RHAB1LPINOSCFLD	Rivers and Harbors Act Section 10 water excluded from the CWA as a (b)(1) lake/pond or impoundment that does not contribute surface water flow directly or indirectly to an (a)(1) water and is not inundated by flooding from an (a)(1)-(a)(3) water in a typical year	0.000016	No	No	No
RHAB1WETNONADJ	Rivers and Harbors Act Section 10 water excluded from the CWA as a (b)(1) non-adjacent wetland	0.0014	No	No	No
RHAB3EPHEMERAL	Rivers and Harbors Act Section 10 water excluded from the CWA as a (b)(3) ephemeral feature, including an ephemeral stream, swale, gully, rill, or pool	0.00032	No	No	No
RHAB6PCC	Rivers and Harbors Act Section 10 water excluded from the CWA as (b)(6) prior converted cropland	0.000016	No	No	No
RHATIDAL	RHA Tidal water is subject to the ebb and flow of the tide	0.00075	No	No	No

Each row describes one NWPR resource type. Relabeled *Sackett* or March 2025 Guidance relabel resource types appear in bold. Column (2) shows non-synthetic AJDs for each resource type as a share of all NWPR AJDs.

Table S2. CLEAR and ex ante models project that *Sackett* regulates relatively few water resources.

		Ex ante geophysical		Ex ante DL	Ex post	Other projections	
	Naïve benchmark (1)	Wet-ness (Gold) (2)	Connected (3)	Re-labeled *Sackett* (4)	CLEAR-*Sackett* (5)	Energy emergency (6)	March 2025 Guidance (7)
A General groups of points							
All 4 million points	0.000	0.026	0.000	0.134	0.115	0.111	0.133
AJD test set	0.000	0.006	0.001	0.204	0.161	0.156	0.197
B Rivers and streams							
All (NHD all)	0.000	0.067	0.002	0.360	0.249	0.239	0.370
Perennial	0.000	0.122	0.002	0.502	0.347	0.336	0.500
Intermittent or ephemeral	0.000	0.033	0.001	0.232	0.137	0.131	0.252
None (not in NHD)	0.000	0.025	0.000	0.129	0.112	0.108	0.129
C Wetlands							
All (NWI palustrine)	0.000	0.165	0.002	0.314	0.278	0.271	0.307
Non-tidal wetlands	0.000	0.524	0.002	0.286	0.318	0.315	0.310
Emergent (NWI)	0.000	0.348	0.001	0.194	0.199	0.194	0.211
Forested (NWI)	0.000	0.330	0.002	0.291	0.284	0.280	0.298
None (not in NWI palustrine)	0.000	0.001	0.000	0.102	0.087	0.083	0.103
D Rivers, streams, and wetlands							
All (NWI all, NHD all)	0.000	0.161	0.002	0.311	0.275	0.268	0.306
None (not in NWI or NHD)	0.000	0.001	0.000	0.102	0.086	0.083	0.102
E Other important groups of points							
Cropland and pasture (NLCD)	0.000	0.008	0.000	0.098	0.082	0.082	0.104
Floodplains (NFIP)	0.000	0.179	0.002	0.353	0.333	0.326	0.347
Urban growth areas (ICLUS)	0.000	0.017	0.000	0.133	0.093	0.090	0.121
Urban developed (NLCD)	0.000	0.007	0.000	0.116	0.087	0.086	0.111

Values represent share of points regulated. Columns (4)-(7) average calibrated probabilities. Column (1) describes a naïve model where no points are jurisdictional. Column (2) describes the median scenario from the original wetness model (*22*), “seasonally flooded.” Column (3) defines points as jurisdictional in NWI polygons within 50 m of an NHD flowline terminating in navigable waters. Column (4) describes Relabeled *Sackett*, which relabels resource types in NWPR AJDs. Column (5) describes ex post CLEAR-*Sackett*. Column (6) describes the January 2025 Energy Emergency Executive Order, by deregulating CLEAR-*Sackett* predictions around energy infrastructure. Column (7) describes the March 2025 Guidance, by relabeling NWPR resource types. (**B**)-(**E**) describe subsets of the four million prediction points. NHD includes areas within 5 m of perennial, intermittent, and ephemeral flowline feature codes (fcodes) 46006, 46003, and 46007. Non-tidal wetlands include wetlands analyzed in the original wetness model (*30*). NHD is National Hydrography Dataset, NWI is National Wetlands Inventory, NLCD is National Land Cover Dataset, NFIP is National Insurance Program, ICLUS is Integrated Climate and Land-Use Scenarios, DL is deep learning.

Table S3. Ex ante and ex post deep learning outperform different wetness scenarios

	AUC	F1	Precision	Recall	Specificity	Accuracy	Mean absolute error	
							US	State
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A All sites (N=2,777)								
1 Temporarily flooded	0.499	0.021	0.167	0.011	0.987	0.794	0.184	0.254
2 Seasonally saturated	0.501	0.021	0.214	0.011	0.990	0.797	0.187	0.256
3 Continuously saturated	0.498	0.007	0.118	0.004	0.993	0.798	0.191	0.258
4 Seasonally flooded	0.498	0.007	0.118	0.004	0.993	0.798	0.191	0.258
5 Seasonally flooded/saturated	0.498	0.004	0.083	0.002	0.995	0.799	0.193	0.259
6 Semi-permanently flooded	0.500	0.004	0.250	0.002	0.999	0.802	0.196	0.262
7 Intermittently exposed	0.501	0.004	0.500	0.002	1.000	0.803	0.197	0.264
8 Permanently flooded	0.501	0.004	0.500	0.002	1.000	0.803	0.197	0.264
9 Naïve	0.500	0.000	0.000	0.000	1.000	0.803	0.197	0.265
10 Connected	0.500	0.000	0.000	0.000	1.000	0.803	0.197	0.265
11 Relabeled *Sackett*	0.693	0.332	0.457	0.261	0.940	0.802	0.066	0.166
12 CLEAR-*Sackett*	0.691	0.368	0.502	0.290	0.973	0.819	0.001	0.182
B Non-tidal NWI (Emergent, Forested, Pond) (N=640)								
1 Temporarily flooded	0.502	0.030	0.250	0.016	0.988	0.800	0.181	0.244
2 Seasonally saturated	0.503	0.031	0.286	0.016	0.990	0.802	0.183	0.245
3 Continuously saturated	0.496	0.000	0.000	0.000	0.992	0.800	0.188	0.248
4 Seasonally flooded	0.496	0.000	0.000	0.000	0.992	0.800	0.188	0.248
5 Seasonally flooded/saturated	0.497	0.000	0.000	0.000	0.994	0.802	0.189	0.250
6 Semi-permanently flooded	0.500	0.000	0.000	0.000	1.000	0.806	0.194	0.248
7 Intermittently exposed	0.500	0.000	0.000	0.000	1.000	0.806	0.194	0.248
8 Permanently flooded	0.500	0.000	0.000	0.000	1.000	0.806	0.194	0.248
9 Naïve	0.500	0.000	0.000	0.000	1.000	0.806	0.194	0.248
10 Connected	0.500	0.000	0.000	0.000	1.000	0.806	0.194	0.248
11 Relabeled *Sackett*	0.703	0.370	0.487	0.298	0.948	0.820	0.056	0.154
12 CLEAR-*Sackett*	0.724	0.424	0.568	0.339	0.969	0.825	0.003	0.175

(Continued next page)

Table S3. Ex ante and ex post deep learning outperform different wetness scenarios (continued)

	AUC	F1	Precision	Recall	Specificity	Accuracy	Mean absolute error	
							US	State
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C Non-tidal wetlands (*30*) (N=36)								
1 Temporarily flooded	0.500	0.286	0.167	1.000	0.000	0.167	0.833	0.823
2 Seasonally saturated	0.633	0.353	0.214	1.000	0.267	0.389	0.611	0.504
3 Continuously saturated	0.417	0.174	0.118	0.333	0.500	0.472	0.306	0.361
4 Seasonally flooded	0.417	0.174	0.118	0.333	0.500	0.472	0.306	0.361
5 Seasonally flooded/saturated	0.400	0.111	0.083	0.167	0.633	0.556	0.167	0.302
6 Semi-permanently flooded	0.533	0.200	0.250	0.167	0.900	0.778	0.056	0.218
7 Intermittently exposed	0.567	0.250	0.500	0.167	0.967	0.833	0.111	0.177
8 Permanently flooded	0.567	0.250	0.500	0.167	0.967	0.833	0.111	0.177
9 Naïve	0.500	0.000	0.000	0.000	1.000	0.833	0.167	0.177
10 Connected	0.500	0.000	0.000	0.000	1.000	0.833	0.167	0.177
11 Relabeled *Sackett*	0.819	0.200	0.250	0.167	0.933	0.806	0.000	0.149
12 CLEAR-*Sackett*	0.947	0.625	0.500	0.833	0.967	0.917	0.139	0.250

MAE: mean absolute error in predicted share jurisdictional in US or state. AUC-ROC: Area under the receiver operating curve. F1: harmonic mean of precision and recall. Precision: TP / (TP + FP), where TP is the count of true positive predictions and FP is the count of false positive predictions. Recall: TP / (TP + FN), where FN is the count of false negative predictions. Specificity: TN / (TN + FP), where TN is the count of true negative predictions. Accuracy: percent correct. Column (7) equals $|\mathrm{mean}(J_i) - \mathrm{mean}(C_i)|$, where J_i represents AJD jurisdiction and C_i represents jurisdiction of Clean Water Act Analysis of Regulation (CLEAR) predictions. Column (8) equals $(1/S)\sum_s |mean_i(J_{is}) - mean_i(C_{is})|$, i.e., the mean across states of the mean jurisdiction rate of validation Approved Jurisdictional Determinations (AJDs) within each state minus the mean jurisdiction rate of model predictions. Each panel describes jurisdiction predicted by scenarios analyzed in Gold (*30*). Each scenario indicates how "wet" a wetland must be to be protected under the Clean Water Act. In other words, in scenario 4, all AJDs within wetlands (*30*) at least as wet as "seasonally flooded" are predicted as WOTUS; all others are predicted as non-WOTUS. The median scenario ex-ante, Scenario 4, is used as the wetness model throughout the rest of the paper. (**A**), N=2,777. (**B**), N=640. (**C**), N=36.

Table S4. For all rules, CLEAR performs well but individual input layers perform poorly.

	AUC (1)	F1 (2)	Precision (3)	Recall (4)	Specificity (5)	Accuracy (6)	Mean absolute error: US (7)	Mean absolute error: State (8)	N (9)
A CLEAR model, by rule									
1. All rules	0.837	0.665	0.787	0.575	0.925	0.811	0.088	0.132	20,844
2. *Sackett*	0.691	0.368	0.502	0.290	0.973	0.819	0.001	0.182	2,777
3. Rapanos	0.864	0.761	0.737	0.786	0.889	0.819	0.005	0.095	10,187
4. NWPR	0.805	0.603	0.561	0.652	0.947	0.801	0.010	0.120	6,373
5. CWR	0.856	0.748	0.756	0.740	0.843	0.802	0.101	0.131	1,507
B Individual input layers—*Sackett*									
5. Wetland (NWI)	0.502	0.253	0.199	0.349	0.655	0.595	0.148	0.198	2,777
6. Stream (NHD)	0.492	0.058	0.146	0.036	0.948	0.768	0.148	0.230	2,777
7. Wetland or stream	0.499	0.253	0.196	0.354	0.644	0.587	0.158	0.205	2,777
8. Hydric soil (gNATSGO)	0.492	0.295	0.194	0.624	0.361	0.413	0.439	0.384	2,777
9. Water table <10m (gNATSGO)	0.506	0.327	0.200	0.898	0.115	0.269	0.690	0.637	2,777
10. Cropland and pasture (NLCD)	0.496	0.308	0.195	0.728	0.263	0.355	0.538	0.485	2,777
11. Urban developed (NLCD)	0.491	0.303	0.193	0.701	0.281	0.364	0.518	0.479	2,777

(**A**), performance of CLEAR calibrated probabilities with thresholds optimized for performance for F1 in columns (2), (3), and (4), accuracy in columns (5) and (6), national mean absolute error (MAE) in column (7), and state MAE in column (8). Column (1) depends on model calibrated probabilities and is independent of threshold choice. (**B**), forecasting based on individual layers on for *Sackett* AJDs. MAE: mean absolute error in predicted share jurisdictional in US or state. AUC-ROC: Area under the receiver operating curve. F1: harmonic mean of precision and recall. Precision: TP / (TP + FP), where TP is the count of true positive predictions and FP is the count of false positive predictions. Recall: TP / (TP + FN), where FN is the count of false negative predictions. Recall is not defined if a model makes no positive predictions. Specificity: TN / (TN + FP), where TN is the count of true negative predictions. Accuracy: percent correct. Column (7) equals $|\mathrm{mean}(J_i) - \mathrm{mean}(C_i)|$, where J_i represents AJD jurisdiction and C_i represents jurisdiction of Clean Water Act Analysis of Regulation (CLEAR) predictions. Column (8) equals $(1/S)\sum_s |mean_i(J_{is}) - mean_i(C_{is})|$, , i.e., the mean across states of the mean jurisdiction rate of test set Approved Jurisdictional Determinations (AJDs) within each state minus the mean jurisdiction rate of CLEAR model predictions. Row 5 predicts regulation if within 5 m of a NWI wetland; row 6 if within 5 m of an NHD stream; row 7 if within 5 m of either an NWI wetland or NHD stream; row 8 if the area has a hydric soil according to the Gridded National Soil Survey Geographic Database (gNATSGO). Row 9 predicts no regulation if the water table is less than 10 meters deep, and regulation everywhere else. Rows 10 and 11 predict no regulation in cropland and pasture, and urban developed areas, respectively, and regulation everywhere else. NWPR is the Navigable Waters Protection Rule. CWR is the Clean Water Rule.

Table S5. Wetness models project a wide range of jurisdiction.

	1 Temporarily flooded	2 Seasonally saturated	3 Continuously saturated	4 Seasonally flooded	5 Seasonally flooded /saturated	6 Semi-permanently flooded	7 Intermittently exposed	8 Permanently flooded
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A General groups of points								
All 4 million points	0.049	0.036	0.030	0.026	0.010	0.008	0.003	0.003
AJD test set	0.013	0.01	0.006	0.006	0.004	0.001	0.001	0.001
B Rivers and streams								
All (NHD all)	0.129	0.077	0.070	0.067	0.020	0.012	0.003	0.003
Perennial	0.221	0.139	0.126	0.122	0.040	0.020	0.005	0.005
Intermittent or ephemeral	0.075	0.039	0.034	0.033	0.005	0.004	0.000	0.000
None (not in NHD)	0.047	0.036	0.030	0.025	0.010	0.008	0.003	0.003
C Wetlands								
All (NWI palustrine)	0.307	0.231	0.192	0.165	0.069	0.052	0.019	0.019
Non-tidal wetlands(*30*)	0.994	0.742	0.622	0.524	0.213	0.163	0.059	0.059
Emergent (NWI)	0.546	0.401	0.376	0.348	0.118	0.099	0.013	0.013
Forested (NWI)	0.711	0.534	0.412	0.330	0.122	0.077	0.007	0.007
None (not in NWI palustrine)	0.004	0.002	0.002	0.001	0.000	0.000	0.000	0.000
D Rivers, streams, and wetlands								
All (NWI all, NHD all)	0.300	0.226	0.188	0.161	0.067	0.051	0.019	0.018
None (not in NWI or NHD)	0.003	0.002	0.002	0.001	0.000	0.000	0.000	0.000
E Other important groups of points								
Cropland and pasture (NLCD)	0.016	0.009	0.008	0.008	0.003	0.002	0.002	0.002
Floodplains (NFIP)	0.276	0.198	0.181	0.179	0.085	0.078	0.033	0.033
Urban growth areas (ICLUS)	0.034	0.023	0.018	0.017	0.005	0.004	0.002	0.002
Urban developed (NLCD)	0.012	0.008	0.007	0.007	0.002	0.001	0.001	0.001

Each column shows one scenario from the Wetness model (*22*). Table shows the share of points each framework estimates are regulated. Panels B through D describe subsets of the four million prediction points. NHD only refers to flowlines. NFIP is the National Flood Insurance Program and ICLUS is the Integrated Climate and Land Use Scenarios.

Table S6. *Sackett* regulates less than earlier CWA rules.

	CWR	*Rapanos*	NWPR	*Sackett*
	(1)	(2)	(3)	(4)
A General groups of points				
All 4 million points	0.230	0.179	0.138	0.115
AJD test set	0.402	0.383	0.246	0.161
B Rivers and streams				
All (NHD all)	0.524	0.463	0.427	0.249
Perennial	0.713	0.615	0.602	0.347
Intermittent or ephemeral	0.373	0.336	0.287	0.137
None (not in NHD)	0.225	0.173	0.133	0.112
C Wetlands				
All (NWI palustrine)	0.567	0.410	0.351	0.278
Non-tidal wetlands(*30*)	0.689	0.463	0.389	0.318
Emergent (NWI)	0.509	0.343	0.234	0.199
Forested (NWI)	0.702	0.455	0.400	0.284
None (not in NWI palustrine)	0.172	0.139	0.101	0.087
D Rivers, streams, and wetlands				
All (NWI all, NHD all)	0.561	0.407	0.349	0.275
None (not in NWI or NHD)	0.171	0.138	0.100	0.086
E Other important groups of points				
Cropland and pasture (NLCD)	0.147	0.124	0.098	0.082
Floodplains (NFIP)	0.611	0.459	0.386	0.333
Urban growth areas (ICLUS)	0.244	0.169	0.135	0.093
Urban developed (NLCD)	0.211	0.139	0.110	0.087

Table shows the share of points each framework estimates are regulated. Columns (1)-(4) average calibrated probabilities from CLEAR. Column (1) describes regulation under the Clean Water Rule (CWR). Column (2) describes regulation under *Rapanos*. Column (3) describes regulation under NWPR. Column (4) duplicates column (5) from Table S2. (**B**)-(**D**) describe subsets of the four million prediction points. NHD only refers to flowlines. NFIP is the National Flood Insurance Program and ICLUS is the Integrated Climate and Land Use Scenarios.

Table S7. Regulated stream miles and wetland acres, by state.

State	Total Stream Miles	Total Wetland Acres	Stream Miles Regulated			Wetland Acres Regulated		
			Rapanos (%)	*Sackett* (%)	Difference *Sackett - Rapanos*	*Rapanos* (%)	*Sackett* (%)	Difference *Sackett - Rapanos*
(1)	(2)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
National	3,154,478	119,825,265	-	-	-705,047	-	-	-19,321,637
Alabama	72,650	4,043,348	0.49	0.35	-10,752	0.41	0.38	-109,170
Arizona	139,281	262,281	0.16	0.09	-9,610	0.32	0.18	-36,457
Arkansas	78,496	2,558,428	0.48	0.25	-18,525	0.39	0.30	-235,375
California	173,028	2,789,804	0.40	0.15	-42,565	0.39	0.15	-694,661
Colorado	93,255	1,522,952	0.28	0.14	-13,056	0.25	0.13	-184,277
Connecticut	5,215	304,750	0.94	0.41	-2,717	0.84	0.19	-196,259
Delaware	2,234	290,940	0.79	0.30	-1,097	0.59	0.30	-84,954
Florida	22,385	12,681,770	0.76	0.60	-3,604	0.68	0.45	-2,916,807
Georgia	64,833	6,396,737	0.45	0.36	-5,381	0.28	0.27	-6,397
Idaho	94,753	1,119,249	0.45	0.38	-6,254	0.51	0.33	-194,749
Illinois	67,074	1,271,986	0.60	0.18	-27,970	0.56	0.21	-443,923
Indiana	24,066	1,008,100	0.51	0.16	-8,543	0.29	0.13	-160,288
Iowa	67,717	1,014,174	0.62	0.17	-30,473	0.45	0.14	-323,522
Kansas	118,236	1,349,856	0.30	0.11	-23,293	0.24	0.09	-206,528
Kentucky	45,616	430,781	0.17	0.09	-3,786	0.23	0.16	-27,139
Louisiana	43,096	8,092,819	0.59	0.59	-259	0.64	0.68	283,249
Maine	24,974	2,569,961	0.73	0.18	-13,961	0.63	0.14	-1,256,711
Maryland	10,263	863,198	0.88	0.43	-4,680	0.80	0.44	-308,162
Massachusetts	7,273	775,106	0.75	0.23	-3,767	0.54	0.15	-302,291
Michigan	47,861	7,712,081	0.86	0.36	-24,122	0.68	0.32	-2,814,909
Minnesota	60,103	9,973,334	0.16	0.13	-1,623	0.09	0.09	-9,973
Mississippi	77,386	4,534,181	0.40	0.32	-5,881	0.38	0.45	321,927
Missouri	95,347	1,388,966	0.63	0.16	-44,813	0.43	0.18	-352,797
Montana	166,847	1,589,844	0.28	0.23	-8,843	0.30	0.20	-163,754
Nebraska	72,506	549,755	0.33	0.14	-13,269	0.30	0.14	-87,961
Nevada	143,616	1,003,174	0.33	0.11	-30,878	0.44	0.18	-258,819
New Hampshire	9,374	384,706	0.71	0.19	-4,790	0.55	0.12	-163,115
New Jersey	7,128	1,019,092	0.90	0.40	-3,557	0.73	0.30	-440,248
New Mexico	109,260	383,873	0.11	0.10	-983	0.14	0.12	-9,213
New York	48,756	2,651,158	0.67	0.21	-22,428	0.43	0.13	-816,557

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Table S7. Regulated stream miles and wetland acres, by state. (Continued)

North Carolina	56,673	4,679,517	0.92	0.50	-23,916	0.84	0.50	-1,600,395
North Dakota	59,514	2,442,160	0.45	0.24	-12,379	0.18	0.11	-180,720
Ohio	54,736	715,219	0.36	0.11	-13,465	0.27	0.13	-99,415
Oklahoma	75,615	1,274,713	0.67	0.19	-35,766	0.56	0.22	-432,128
Oregon	102,984	1,803,096	0.46	0.26	-20,185	0.50	0.22	-497,655
Pennsylvania	51,477	588,835	0.77	0.31	-23,782	0.72	0.35	-219,047
Rhode Island	978	86,061	0.88	0.19	-679	0.64	0.14	-43,203
South Carolina	29,372	4,238,935	0.82	0.48	-9,898	0.67	0.39	-1,191,141
South Dakota	96,965	3,529,693	0.54	0.24	-29,283	0.27	0.13	-465,919
Tennessee	59,244	1,148,777	0.26	0.13	-7,820	0.36	0.23	-153,936
Texas	176,194	5,551,483	0.56	0.25	-54,973	0.59	0.36	-1,276,841
Utah	82,724	624,397	0.44	0.15	-23,494	0.37	0.24	-83,045
Vermont	7,100	287,628	0.47	0.11	-2,542	0.29	0.09	-56,375
Virginia	49,280	1,682,396	0.83	0.43	-19,909	0.79	0.55	-408,822
Washington	68,964	1,297,395	0.42	0.23	-13,034	0.45	0.29	-206,286
West Virginia	30,572	81,858	0.40	0.13	-8,193	0.57	0.19	-30,942
Wisconsin	53,370	7,610,528	0.34	0.23	-5,550	0.14	0.13	-22,832
Wyoming	106,082	1,646,169	0.25	0.17	-8,699	0.25	0.16	-153,094

Total stream miles in column (2) is from NHD stream and river flowline features. Total wetland acres in column (3) is from NWI. Regulation rates in columns (3), (4), (6), and (7) display calibrated probabilities from CLEAR-*Sackett* and CLEAR-*Rapanos*, applied to the subset of four million prediction points that are within 5 meters of NHD or NWI features. The difference in column (5) is measured in stream miles, and in column (8) in wetland acres.

Table S8. Recent rules deregulate drinking water sources.

	CLEAR-*Rapanos*	CLEAR-NWPR	CLEAR-*Sackett*	Energy EO	March 2025 Guidance
	(1)	(2)	(3)	(4)	(5)
A Share Regulated					
1. All points	0.243	0.187	0.144	0.141	0.156
2. NHD or NWI points	0.523	0.448	0.366	0.361	0.404
3. NHD points	0.628	0.578	0.350	0.340	0.468
4. NWI points	0.525	0.449	0.369	0.364	0.407
B Pop. Served Weighted					
1. All points	0.262	0.180	0.139	0.136	0.150
2. NHD or NWI points	0.593	0.463	0.391	0.384	0.429
3. NHD points	0.637	0.565	0.355	0.349	0.454
4. NWI points	0.596	0.465	0.394	0.387	0.433

A 12-digit hydrologic unit code (HUC12) or subwatershed is the finest polygon delineation of watershed boundaries the US Geological Survey defines, corresponding to about 80,000 HUC12s. This table considers active 2019 community water systems (CWS). (**A**), share of prediction points within HUC12 areas that serve as drinking water inputs for an active 2019 CWS predicted as jurisdictional under each regime. (**B**), same share weighted by the population served by each CWS. EO is Executive Order. NWPR is the Navigable Waters Protection Rule.

Table S9. ***Sackett*** **divides AJDs into resource types corresponding to different legal categorizations of waters.**

	Definition	**Share of AJDs**	**Share juris-dictional**
	(1)	(2)	(3)
A Pre-2015-Post-Sackett			
A1.TNW-404	(a)(1) Traditional Navigable Water (Section 404 Only)	0.00076	1.00
A1.TNW-404.10	(a)(1) Traditional Navigable Water, also subject to Sections 9 or 10 of the Rivers and Harbors Act (Section 10/404)	0.0027	1.00
A2.INTSTATE-404	(a)(2) Interstate Waters (Section 404 Only)	0.00025	1.00
A4.IMPDT-404	(a)(4) Impoundments of waters otherwise defined as "waters of the United States"	0.0052	1.00
A5.TRIB-404	(a)(5) Tributaries of waters identified in paragraph (a)(1) through (4), where the tributary is a relatively permanent, standing or continuously flowing body of water	0.094	1.00
A7-AJD.WETL-404	(a)(7) Wetland adjacent to a non-wetland water identified in (a)(1) - (a)(6)	0.095	1.00
DRY.LAND	Dry Land - The review area is comprised entirely of dry land (i.e. there are no aquatic features, including wetlands, of any kind in the entire review area)	0.055	0.00
EXCL-PCC	(a)(8) Prior converted cropland	0.0027	0.00
EXCL-WTS	(a)(8) Waste treatment systems, including treatment ponds or lagoons, designed to meet the requirements of the Clean Water Act	0.0081	0.00
NON-JD - PREAMBLE - ART.IRR	Preamble water - Artificially irrigated areas which would revert to upland if the irrigation ceased	0.0024	0.00
NON-JD - PREAMBLE - ART.LAKE.POND	Preamble water - Artificial lake/pond created by excavating/diking dry land, used exclusively for purposes such as stock watering, irrigation, settling basins, or rice growing	0.04	0.00
NON-JD - PREAMBLE - ART.REF.SWIM.ORN	Preamble water - Artificial reflecting or swimming pools or other small ornamental bodies of water created by excavating and/or diking dry land to retain water for primarily aesthetic reasons	0.0023	0.00
NON-JD - PREAMBLE - NON-TIDAL.DITCH-DRY.LAND	Preamble water -Non-tidal drainage and irrigation ditches excavated on dry land	0.0033	0.00
NON-JD - PREAMBLE - WATERFILLED.DEP-PITS	Preamble water - Waterfilled depression created in dry land and pits excavated in dry land unless and until the operation is abandoned and resulting body of water meets definition of WOTUS	0.012	0.00

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Table S9. *Sackett* divides AJDs into resource types corresponding to different legal categorizations of waters. (Continued)

	Definition	Share of AJDs	Share juris-dictional
	(1)	(2)	(3)
NON-JD - RAPANOS.GUIDE - DITCH	*Rapanos* Guidance - Ditches (including roadside ditches) excavated wholly in and draining only uplands and that do not carry a relatively permanent flow of water	0.09	0.00
NON-JD - RAPANOS.GUIDE - SWALE.EROSION	*Rapanos* Guidance - Swales or erosional features (e.g., gullies, small washes, characterized by low volume, infrequent, or short duration flow)	0.073	0.00
NON-WOTUS-LAKE.POND.NEGATIVE-A5	NON-WOTUS - Intrastate Lake or Pond that is not a tributary to a water identified in paragraphs (a)(1) through (4)	0.023	0.00
NON-WOTUS-STREAM.NEGATIVE-A5	NON-WOTUS - Intrastate Stream that is not a tributary to a water identified in paragraphs (a)(1) through (4)	0.021	0.00
NON-WOTUS-TRIB.NEGATIVE-A5	NON-WOTUS: Tributary to a water identified in paragraphs (a)(1) through (4), where the tributary is not a relatively permanent, standing or continuously flowing body of water	0.19	0.00
NON-WOTUS-WETL.NEGATIVE-A7	NON-WOTUS: Wetland that is not adjacent to a water identified in paragraph (a)(1) through (6)	0.28	0.00
RHA-10NAV	RHA - Non-tidal water is on the district's Section 10 waters list (Section 10 Only)	0.00025	1.00
RHA-10TIDAL	RHA - Tidal water is subject to the ebb and flow of the tide (Section 10 Only)	0.00013	1.00
B Amended-2023-Rule			
A1-1.TNW-404	(a)(1)(i) Traditional Navigable Water (Section 404 Only)	0.0083	1.00
A1-1.TNW-404.10	(a)(1)(i) Traditional Navigable Water, also subject to Sections 9 or 10 of the Rivers and Harbors Act (Section 10/404)	0.0033	1.00
A1-2.TERSEAS-404.10	(a)(1)(ii) Territorial Seas, also subject to Sections 9 or 10 of the Rivers and Harbors Act (Section 10/404)	0.0001	1.00
A1-3.INTSTATE-404	(a)(1)(iii) Interstate Waters (Section 404 Only)	0.0002	1.00
A2.IMPDT-404	(a)(2) Jurisdictional Impoundment (Section 404 Only)	0.0027	1.00
A3.TRIB-404	(a)(3) Tributary (Section 404 Only)	0.061	1.00
A4-1.ADJ.WET.A1-INTSTATE-404	(a)(4)(i) Adjacent Wetland, adjacent to (a)(1))(iii) Interstate Water	0.0006	1.00
A4-1.ADJ.WET.A1-TERSEAS-404	(a)(4)(i) Adjacent Wetland, adjacent to (a)(1)(ii) Territorial Sea	0.0002	1.00
A4-1.ADJ.WET.A1-TNW-404	(a)(4)(i) Adjacent Wetland, adjacent to (a)(1)(i) TNW	0.013	1.00
A4-2.ADJ.WET.A2&A3-404	(a)(4)(ii) Adjacent Wetland, adjacent to a relatively permanent paragraph (a)(2) Impoundment or (a)(3) Tributary (Section 404 Only)	0.067	1.00

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Table S9. *Sackett* divides AJDs into resource types corresponding to different legal categorizations of waters. (Continued)

A5.INTSTATE.LKPND-404	(a)(5) Intrastate Lake or Pond not Identified in Paragraphs (a)(1) through (4), that is a relatively permanent, standing or continuously flowing body of water (Section 404 Only)	0.0023	1.00
B1-EXCL-WTS	(b)(1) Waste Treatment System (Excluded)	0.0088	0.00
B2-EXCL-PCC	(b)(2) Wetland Excluded as Prior Converted Cropland designated by USDA (Excluded)	0.0007	0.00
B3-EXCL-DITCH	(b)(3) Ditches (including roadside ditches) excavated wholly in and draining only dry land and that do not carry a relatively permanent flow of water (Excluded)	0.11	0.00
B4-EXCL-ART.IRR	(b)(4) Artificially irrigated areas that would revert to dry land if the irrigation ceased (Excluded)	0.0022	0.00
B5-EXCL-ART.LK	(b)(5) Artificial lakes or ponds created in dry land, used exclusively for specific purposes (Excluded)	0.031	0.00
B6-EXCL-ART.REF	(b)(6) Artificial reflecting/swimming/ornamental pools; created by excavating or diking dry land to retain water for primarily aesthetic reasons (Excluded)	0.0036	0.00
B7-EXCL-WTF.DEP	(b)(7) Waterfilled depressions created in dry land incidental to construction activity and pits excavated in dry land, until abandoned (Excluded)	0.012	0.00
B8-EXCL-SWAL.EROS	(b)(8) Swales and erosional features (e.g., gullies, small washes) characterized by low volume, infrequent, or short duration flow (Excluded)	0.027	0.00
DRY.LAND	Dry Land - The review area is comprised entirely of dry land (i.e. there are no aquatic features, including wetlands, of any kind in the entire review area)	0.035	0.00
NON-WOTUS-INTSTATE-LKPND.NEGATIVE.A5	NON-WOTUS - Intrastate lake or pond not identified in paragraphs (a)(1 - 4) that is not relatively permanent or does not have a continuous surface connection to (a)(1) or (3) water	0.015	0.00
NON-WOTUS-INTSTATE-STRM.NEGATIVE.A3	NON-WOTUS - Intrastate stream that does not connect to a paragraph (a)(1) or (a)(2) water	0.011	0.00
NON-WOTUS-TRIB.NEGATIVE.A3	NON-WOTUS - Tributary evaluated under (a)(3) and determined to not be a relatively permanent water with a continuous surface connection to paragraph (a)(1) or (a)(3) water	0.18	0.00
NON-WOTUS-WET.NEGATIVE.A4	NON-WOTUS - Wetland that does not have a continuous surface connection to a paragraph (a)(1) water or to a relatively permanent paragraph (a)(2) impoundment or paragraph (a)(3) tributary	0.4	0.00
RHA-10NAV	RHA - Non-tidal water is on the district's Section 10 waters list (Section 10 Only)	0.0003	1.00

Each row lists a *Sackett* resource type from the AJD data. Column (1) describes the resource type, column (2) lists the share of all *Sackett* AJDs the resource type accounts for, and column (3) shows the share of the resource type AJDs that are jurisdictional.

Table S10. *Rapanos* divides AJDs into resource types corresponding to different legal categorizations of waters.

	Definition	Share of AJDs	Share jurisdictional
	(1)	(2)	(3)
IMPNDMNT	Impoundment of Jurisdictional Waters	0.011	0.71
ISOLATE	Isolated (interstate or intrastate) waters	0.34	0.000025
NRPW	Non-relatively Permanent Water that flows directly or indirectly into Traditional Navigable Water	0.052	0.63
NRPWW	Wetland Adjacent to Non-relatively Permanent Water that flows directly or indirectly into Traditional Navigable Water	0.029	0.87
RPW	Relatively Permanent Water that flows directly or indirectly into Traditional Navigable Water	0.098	1.00
RPWWD	Wetlands Directly Abutting Relatively Permanent Water that flows directly or indirectly into Traditional Navigable Water	0.11	1.00
RPWWN	Wetlands Adjacent but not Directly Abutting Relatively Permanent Water that flows directly or indirectly into Traditional Navigable Water	0.037	0.94
TNW	Traditional Navigable Water	0.032	1.00
TNWRPW	Traditional Navigable Water - Relatively Permanent Water	0.0007	0.99
TNWW	Wetlands Adjacent to Traditional Navigable Water	0.038	1.00
UPLAND	Uplands	0.26	0.000064

Each row lists a *Rapanos* resource type from the AJD data**.** Column (1) describes the resource type, column (2) lists the share of all *Rapanos* AJDs the resource type accounts for, and column (3) shows the share of the resource type AJDs that are jurisdictional.

Table S11. Tiner (2003) categorizes many types of isolated wetlands.

	Geographic Region
	(1)
Tiner (2003) Wetland Types	
Alvar wetlands	Level IV ecoregions 50ab (Cheboygan Lake Plain)
Channeled Scablands wetlands	Level IV ecoregion 10a (Channeled Scablands)
Cypress domes	None -- area is too large/no specific agreement
Delmarva pothole wetlands	Level IV ecoregion 63f (Delmarva uplands)
Desert spring wetlands	Level III ecoregions 14 (Mojave Basin and Range)
Fens	None -- area is too large/no specific agreement
Geysers	None -- area is too large/no specific agreement
Inactive floodplain wetlands	None -- area is too large/no specific agreement
Interdunal and intradunal wetlands	None -- area is too large/no specific agreement
Kettle hole wetlands	None -- area is too large/no specific agreement
Mid- and South Atlantic Wetlands	Mid- and South Atlantic Wetlands
Natural ponds	None -- area is too large/no specific agreement
Playas	Level III ecoregion 25 (High Plains)
Prairie potholes	Mann (1974) Prairie Pothole Region
Rainwater basin wetlands	Level IV ecoregion 27f (Rainwater Basin Plains)
Rock pool wetlands	None -- area is too large/no specific agreement
Salt flats and salt lake wetlands	Level III ecoregions 13 (Central Basin and Range)
Sandhills wetlands	Level III ecoregion 44 (Nebraska Sand Hills)
Seepage slope wetlands	None -- area is too large/no specific agreement
Sinkhole wetlands	Level IV ecoregions 69c (Greenbriar Karst), 71e
Tarn wetlands	None -- area is too large/no specific agreement
Volcanic-formed wetlands	Level IV ecoregions 1d (Coast Range Volcanics)

Table shows isolated wetland types from Tiner (*50*). Column (1) shows mapping to geographic regions.

Table S12. We generate synthetic non-jurisdictional training data within several categories of isolated wetlands from Tiner (2003).

	Geographic Region	Tiner (2003) Wetland Type(s)
	(1)	(2)
Cowardin Code		
PABG	Palustrine wetland, aquatic bed, intermittently exposed	Prairie potholes
PEM1A	Palustrine emergent persistent wetland, temporarily flooded	Playas; prairie potholes
Pf	Palustrine wetland, farmed	Prairie potholes
PUBFx	Palustrine wetland, unconsolidated bottom, semi-permanently flooded, excavated	Playas; prairie potholes
PUBHx	Palustrine wetland, unconsolidated bottom, permanently flooded, excavated	West Coast vernal pools
R4SBJ	Riverine wetland, surface flooding, intermittent	Desert spring wetlands; salt flats and salt lake wetlands

Table shows Cowardin codes selected for non-jurisdictional synthetic training data, by Tiner (*50*) wetland type. See SM A.3 under “Synthetic Non-Jurisdictional Data: Isolated Wetlands.” Column (1) describes associated geographic regions and column (2) lists associated Tiner wetland types.

Table S13. Optimal thresholds for each metric allow calculation of model performance.

		Performance Metrics							
								MAE	
Metric optimized	**Threshold** (1)	**AUC** (2)	**F1** (3)	**Precision** (4)	**Recall** (5)	**Specificity** (6)	**Accuracy** (7)	**US** (8)	**State** (9)
MAE	0.173	0.691	0.393	0.392	0.394	0.850	0.760	**0.001**	0.153
State MAE	0.242	0.691	0.368	0.502	0.290	0.929	0.803	0.083	**0.182**
Accuracy	0.577	0.691	0.297	0.635	0.193	0.973	**0.819**	0.137	0.205
F1 Score	0.242	0.691	**0.368**	0.502	0.290	0.929	0.803	0.083	0.182

Table shows CLEAR-*Sackett* model performance. In each row, we choose the threshold which maximizes the performance metric indicated. AUC does not depend on threshold choice so it is identical across cases. Column (1) lists the resulting threshold. Columns (2)-(9) show all performance metrics. Values in bold show the optimized performance values. Selection of thresholds in column (1) uses the validation set. Performance metrics in columns (2)-(9) use the *Sackett* test set AJDs. MAE is mean absolute error.