Literature Summary of Watershed Studies Involving AI/ML – Living Resources

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Leveraging Artificial Intelligence and Machine Learning to Advance Chesapeake Bay Research and Management

24-25 February 2025

U.S. Department of the Interior
U.S. Geological Survey

Lots of Literature – a challenge to synthesize

Different terminology

Different ecological disciplines

May be in non-ecological oriented outlets

Different extents

Rapidly evolving field

Let's start by looking at a few key papers

USGS science for a changing world

Many foundational papers

USGS
science for a changing world

Journal of Animal Ecology

Journal of Animal Ecology 2008, 77, 802–813 doi: 10.1111/j.1365-2656.2008.01390.x

A working guide to boosted regression trees

J. Elith[1*], J. R. Leathwick[2] and T. Hastie[3]

[1]School of Botany, The University of Melbourne, Parkville, Victoria, Australia 3010; [2]National Institute of Water and Atmospheric Research, PO Box 11115, Hamilton, New Zealand; and [3]Department of Statistics, Stanford University, CA, USA

Ecology, 81(11), 2000, pp. 3178–3192
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CLASSIFICATION AND REGRESSION TREES: A POWERFUL YET SIMPLE TECHNIQUE FOR ECOLOGICAL DATA ANALYSIS

Glenn De'ath[1] and Katharina E. Fabricius[2]

ECOGRAPHY 29: 129–151, 2006

Novel methods improve prediction of species' distributions from occurrence data

Jane Elith*, Catherine H. Graham*, Robert P. Anderson, Miroslav Dudík, Simon Ferrier, Antoine Guisan, Robert J. Hijmans, Falk Huettmann, John R. Leathwick, Anthony Lehmann, Jin Li, Lucia G. Lohmann, Bette A. Loiselle, Glenn Manion, Craig Moritz, Miguel Nakamura, Yoshinori Nakazawa, Jacob McC. Overton, A. Townsend Peterson, Steven J. Phillips, Karen Richardson, Ricardo Scachetti-Pereira, Robert E. Schapire, Jorge Soberón, Stephen Williams, Mary S. Wisz and Niklaus E. Zimmermann

Received: 1 August 2022 | Accepted: 5 December 2022
DOI: 10.1111/2041-210X.14061

Methods in Ecology and Evolution

REVIEW

Machine learning and deep learning—A review for ecologists

Maximilian Pichler | Florian Hartig

REVIEW

Methods in Ecology and Evolution

Applications for deep learning in ecology

Sylvain Christin[1] | Éric Hervet[2] | Nicolas Lecomte[1]

REVIEW

Methods in Ecology and Evolution

Deep learning as a tool for ecology and evolution

Marek L. Borowiec[1,2] | Rebecca B. Dikow[3] | Paul B. Frandsen[3,4] | Alexander McKeeken[1] | Gabriele Valentini[5] | Alexander E. White[3,6]

Ecology, 88(11), 2007, pp. 2783–2792
© 2007 by the Ecological Society of America

RANDOM FORESTS FOR CLASSIFICATION IN ECOLOGY

D. Richard Cutler,[1,7] Thomas C. Edwards, Jr.,[2] Karen H. Beard,[3] Adele Cutler,[4] Kyle T. Hess,[4] Jacob Gibson,[5] and Joshua J. Lawler[6]

ELSEVIER | Ecological Modelling 135 (2000) 147–186 | ECOLOGICAL MODELLING www.elsevier.com/locate/ecolmodel

Predictive habitat distribution models in ecology

Antoine Guisan [a,*], Niklaus E. Zimmermann [b,1]

[a] Swiss Center for Faunal Cartography (CSCF), Terreaux 14, CH-2000 Neuchâtel, Switzerland
[b] Swiss Federal Research Institute WSL, Zuercherstr. 111, 8903 Birmensdorf, Switzerland

ELSEVIER | Ecological Modelling 154 (2002) 135–150 | ECOLOGICAL MODELLING www.elsevier.com/locate/ecolmodel

Illuminating the "black box": a randomization approach for understanding variable contributions in artificial neural networks

Julian D. Olden *, Donald A. Jackson

Ecological Monographs, 90(4), 2020, e01422
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A translucent box: interpretable machine learning in ecology

Tim C. D. Lucas[1]

Volume 83, No. 2 | THE QUARTERLY REVIEW OF BIOLOGY | June 2008

MACHINE LEARNING METHODS WITHOUT TEARS: A PRIMER FOR ECOLOGISTS

Julian D. Olden

ELSEVIER | Ecological Modelling 120 (1999) 65–73 | ECOLOGICAL MODELLING www.elsevier.com/locate/ecolmodel

Artificial neural networks as a tool in ecological modelling, an introduction

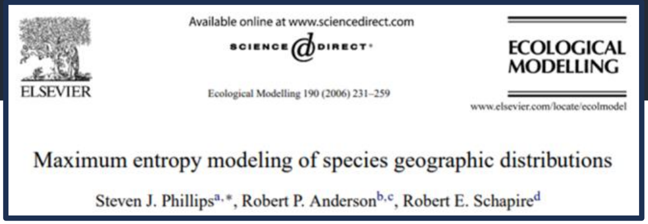
Sovan Lek [a,*], J.F. Guégan [b]

ELSEVIER | Available online at www.sciencedirect.com SCIENCE DIRECT | Ecological Modelling 190 (2006) 231–259 | ECOLOGICAL MODELLING www.elsevier.com/locate/ecolmodel

Maximum entropy modeling of species geographic distributions

Steven J. Phillips[a,*], Robert P. Anderson[b,c], Robert E. Schapire[d]

Phillips 2006 paper Maximum Entropy


Available online at www.sciencedirect.com
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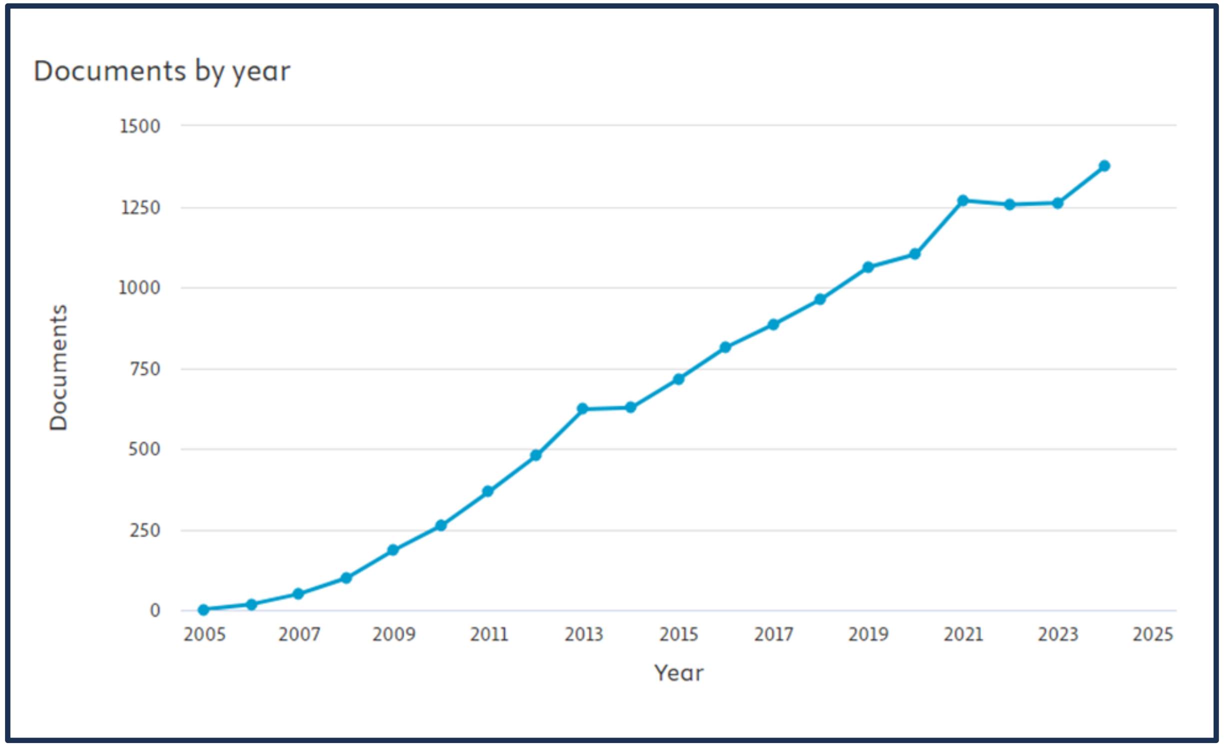
ELSEVIER
Ecological Modelling 190 (2006) 231–259
ECOLOGICAL MODELLING
www.elsevier.com/locate/ecolmodel

Maximum entropy modeling of species geographic distributions

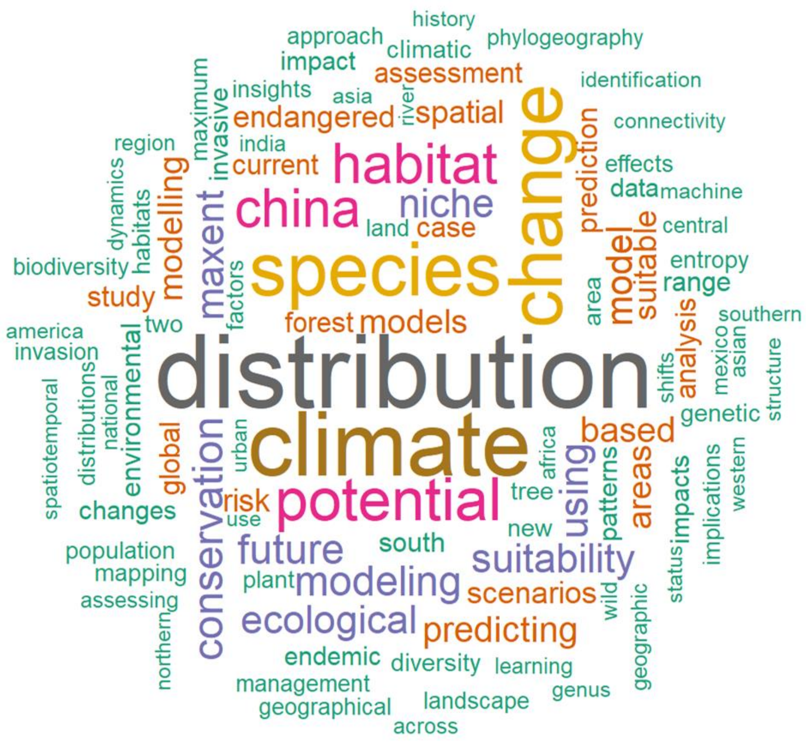
Steven J. Phillips[a,*], Robert P. Anderson[b,c], Robert E. Schapire[d]

Scopus database query 05 Feb 2025

13,415 total citations



Wordcloud based on titles of latest 2,000 citations



Phillips, S.J., Anderson, R.P. and Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. *Ecological modelling*, *190*(3-4), pp.231-259. https://doi.org/10.1016/j.ecolmodel.2005.03.026

Preliminary Information-Subject to Revision. Not for Citation or Distribution

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Cutler 2007 paper Random Forests

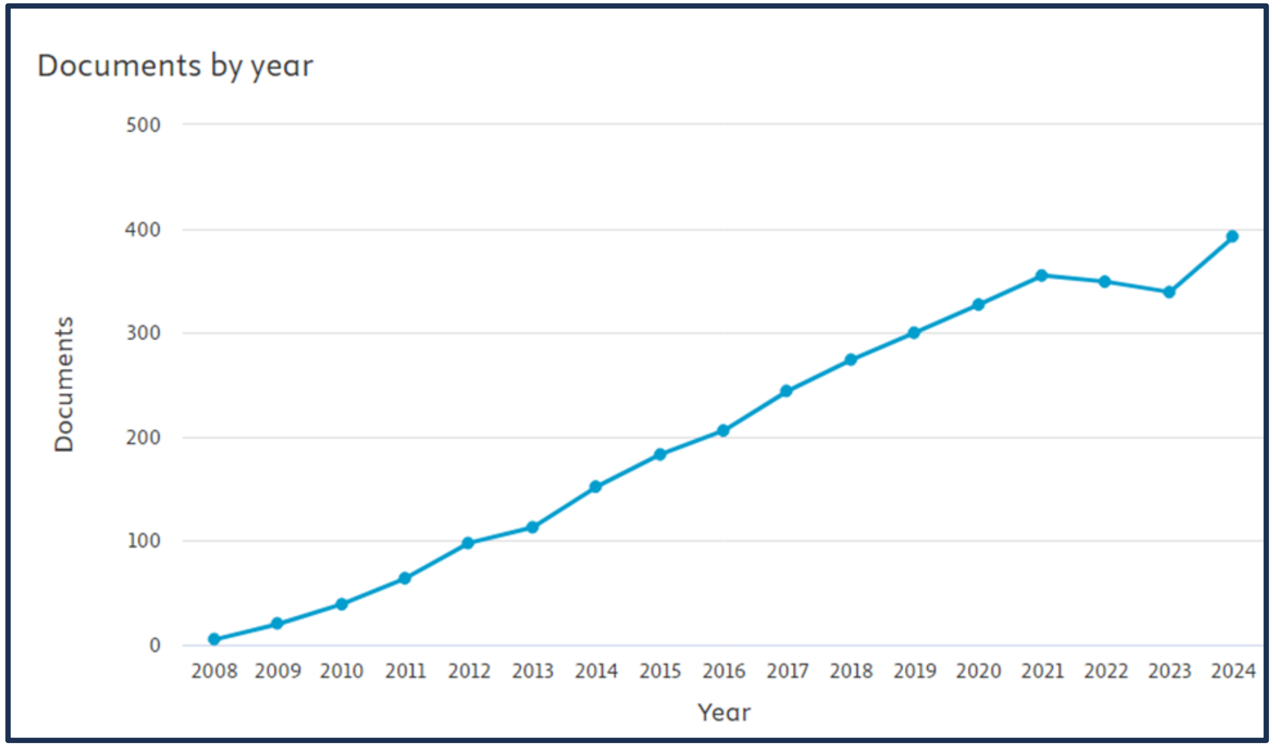

Ecology, 88(11), 2007, pp. 2783–2792
© 2007 by the Ecological Society of America

RANDOM FORESTS FOR CLASSIFICATION IN ECOLOGY

D. Richard Cutler,[1,7] Thomas C. Edwards, Jr.,[2] Karen H. Beard,[3] Adele Cutler,[4] Kyle T. Hess,[4] Jacob Gibson,[5] and Joshua J. Lawler[6]

Scopus database query 05 Feb 2025

3,460 total citations



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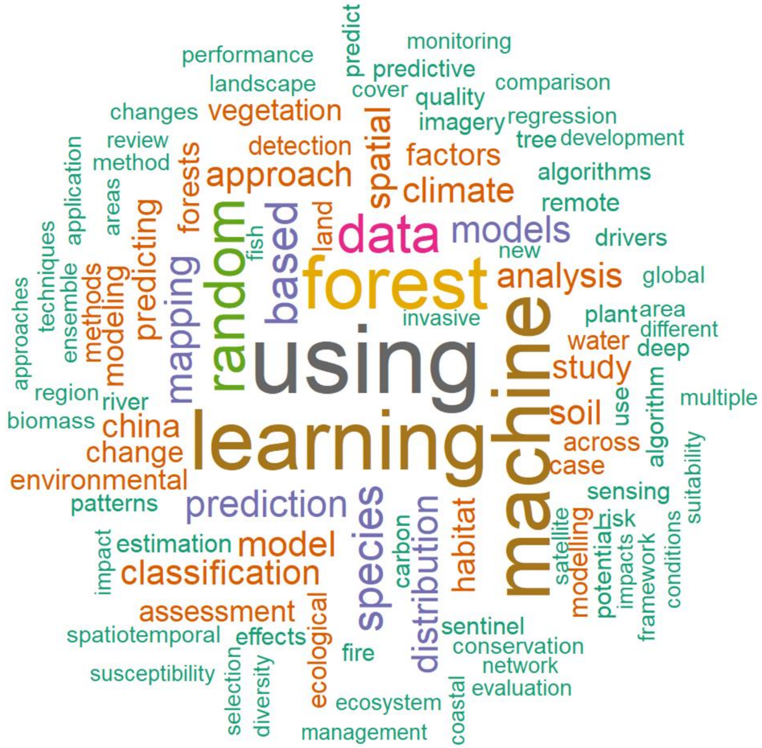

Cutler, D.R., Edwards Jr, T.C., Beard, K.H., Cutler, A., Hess, K.T., Gibson, J. and Lawler, J.J., 2007. Random forests for classification in ecology. Ecology, 88(11), pp.2783-2792. https://doi.org/10.1890/07-0539.1

Preliminary Information-Subject to Revision. Not for Citation or Distribution

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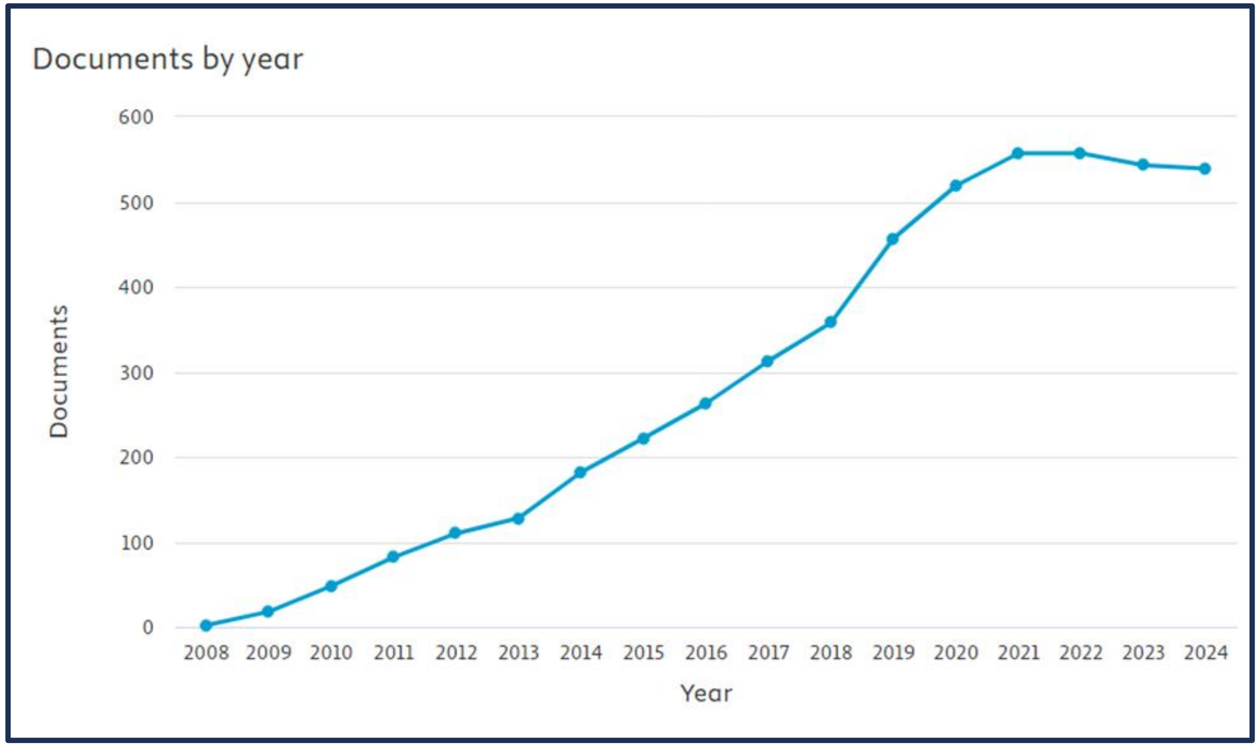
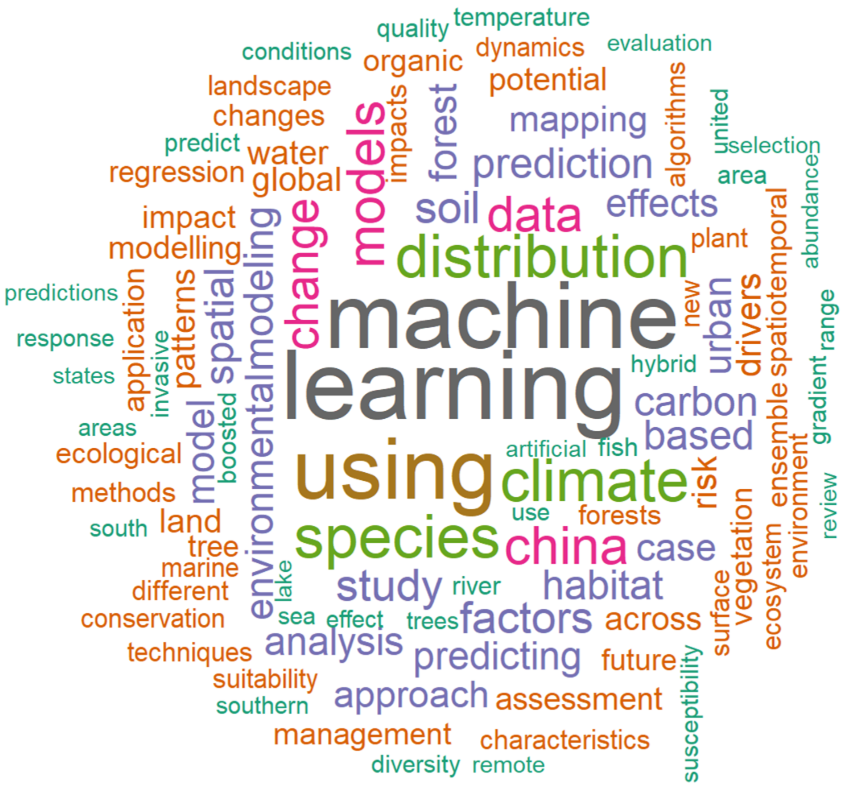
Elith 2008 paper Boosted Reg. Trees

Scopus database query 05 Feb 2025

4,899 total citations



Wordcloud based on titles of latest 2,000 citations



Elith, J., Leathwick, J.R. and Hastie, T., 2008. A working guide to boosted regression trees. Journal of animal ecology, 77(4), pp.802-813. https://doi.org/10.1111/j.1365-2656.2008.01390.x

Preliminary Information-Subject to Revision. Not for Citation or Distribution

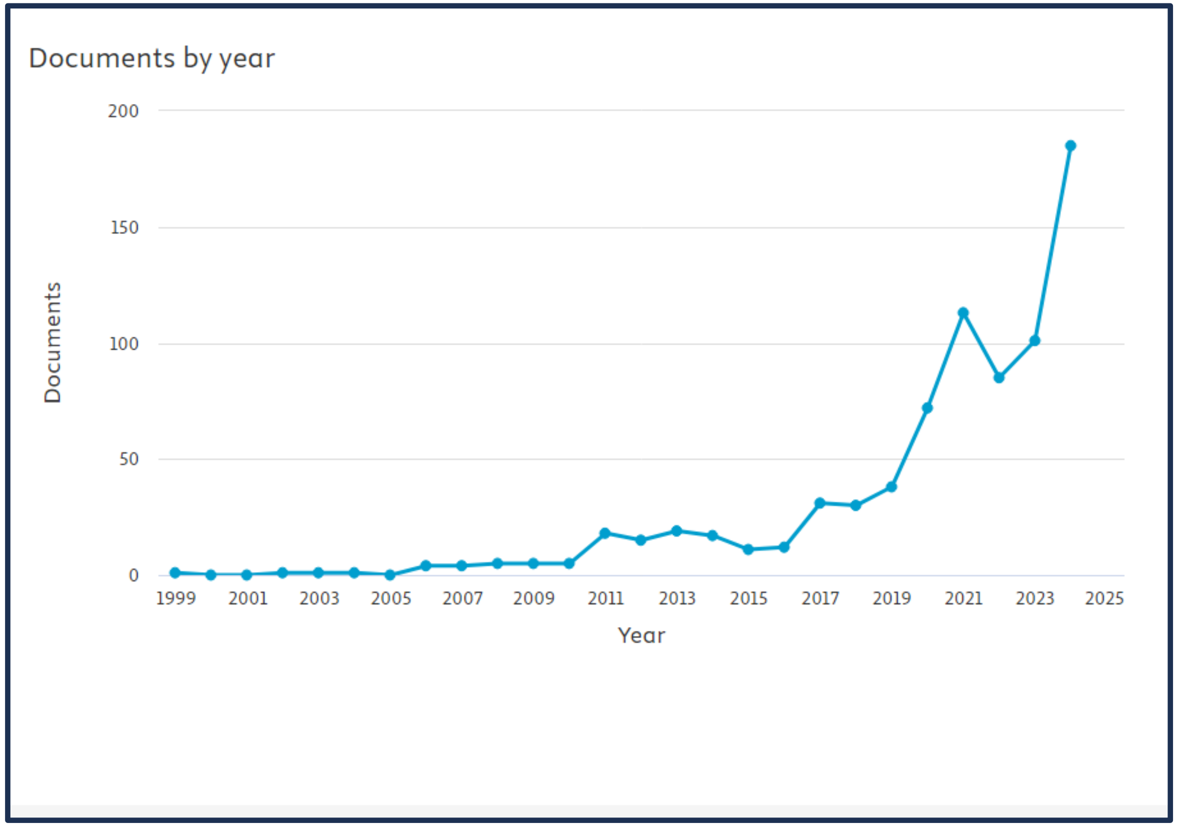
USGS science for a changing world

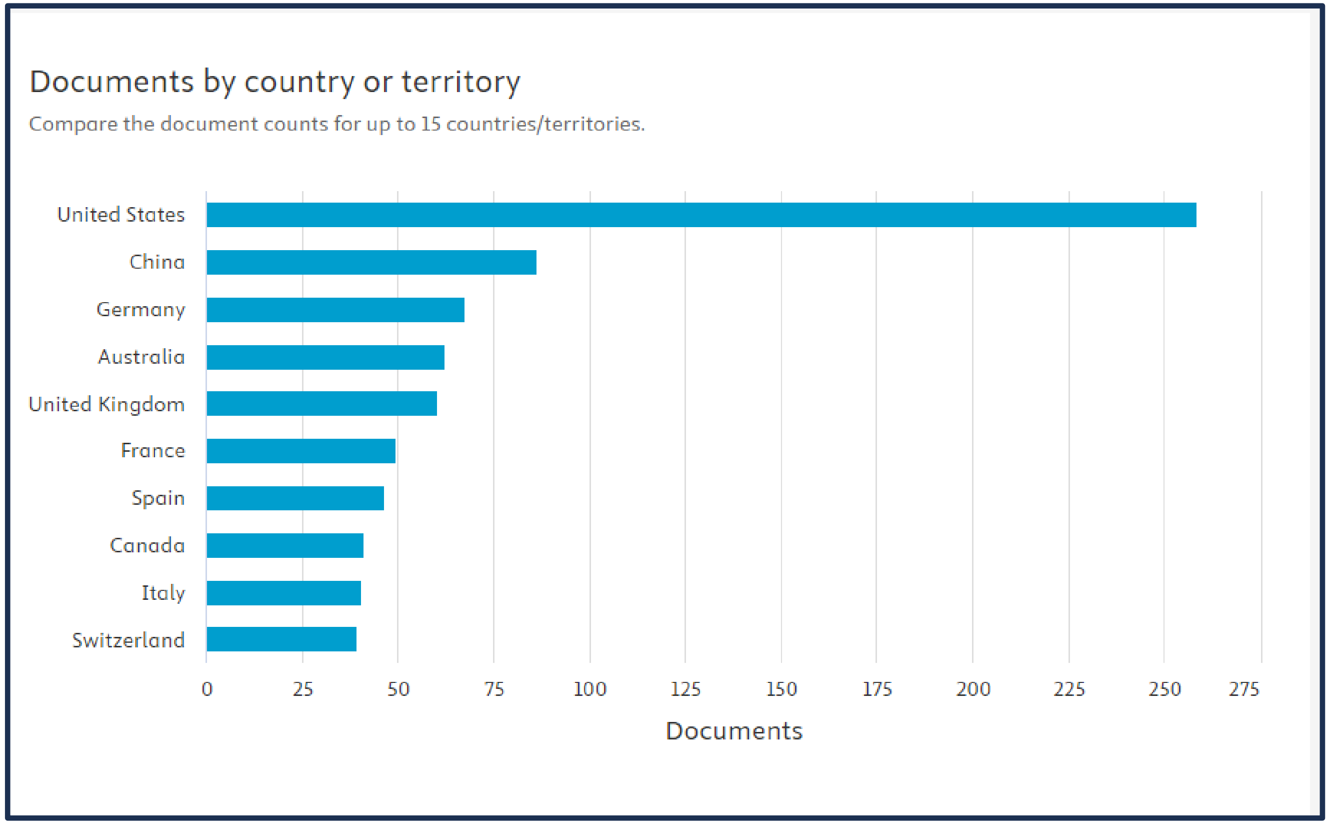
Scopus database query of AI/ML and species distribution

“Machine learning” and “Species Distribution” or “Artificial Intelligence” and “Species Distribution”

Scopus database query 06 Feb 2025

774 total citations



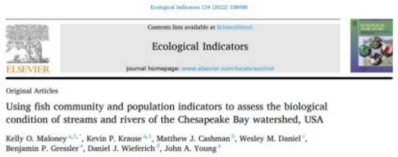


Case Studies – Regional and Chesapeake Bay

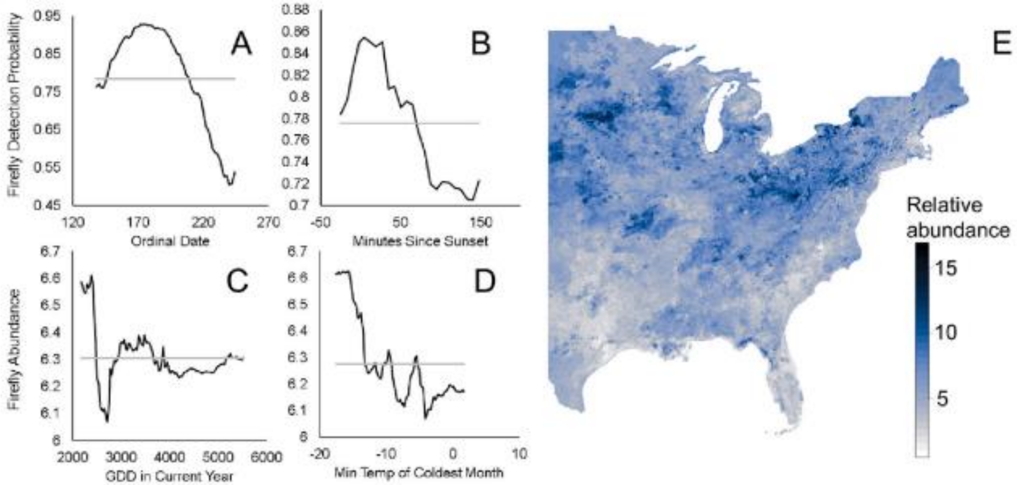

Science of the Total Environment
Illuminating patterns of firefly abundance using citizen science data and machine learning models
Darin J. McNeil, Sarah C. Goslee, Melanie Kammerer, Sarah E. Lower, John F. Tooker, Christina M. Grozinger

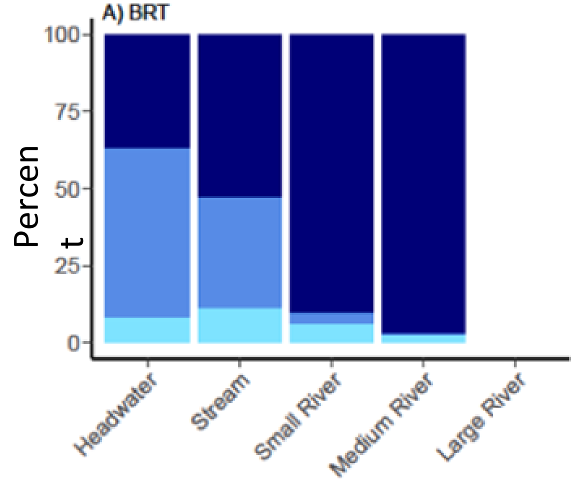
https://doi.org/10.1016/j.scitotenv.2024.172329

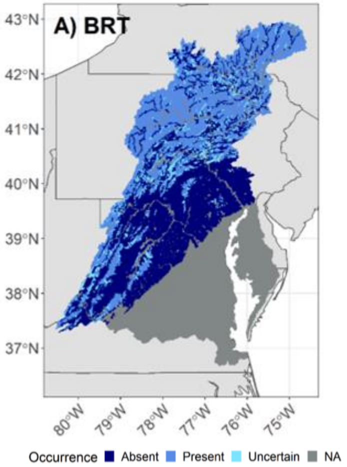
Species Distribution
Fireflies and Fish
McNeill et al. 2024, Maloney et al. 2022


Ecological Indicators
Original Articles
Using fish community and population indicators to assess the biological condition of streams and rivers of the Chesapeake Bay watershed, USA
Kelly O. Maloney, Kevin P. Krause, Matthew J. Cashman, Wesley M. Daniel, Benjamin P. Gressler, Daniel J. Wieferich, John A. Young

https://doi.org/10.1016/j.ecolind.2021.108488

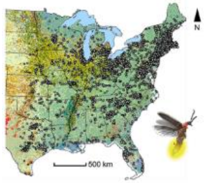






Data set: Firefly Watch

Response: Presence/absence & Relative abundance



Extent: Eastern US

Method: Random Forests

Example Result: "…variation in firefly abundance was explained by complex interactions among soil conditions, weather, and land cover characteristics…"

Take home: "…results support hypotheses related to factors threatening firefly populations, especially habitat loss, and suggest that climate change may pose a greater threat than appreciated in previous assessments"

Data set: Chesapeake Fish data set

Response: Presence/absence

Extent: Chesapeake Bay watershed

Method: Random Forests

Example Result: Predicted presence centered north and central portions and more often in headwaters and streams.

Take home: "…Random forests ML enable predictions of brook trout occurrence with uncertainty and enabled identification of key habitats (and change through time (not shown))…."

Case Studies – Regional and Chesapeake Bay


Ecological Applications, 0(0), 2017, pp. 1–19

Predictive mapping of the biotic condition of conterminous U.S. rivers and streams

Ryan A. Hill,[1,3] Eric W. Fox,[1] Scott G. Leibowitz,[1] Anthony R. Olsen,[1] Darren J. Thornbrugh,[1,2] and Marc H. Weber[1]

https://doi.org/10.1002/eap.1617

Habitat Assessments
Stream Condition
Hill et al. 2017, Maloney et al. 2022

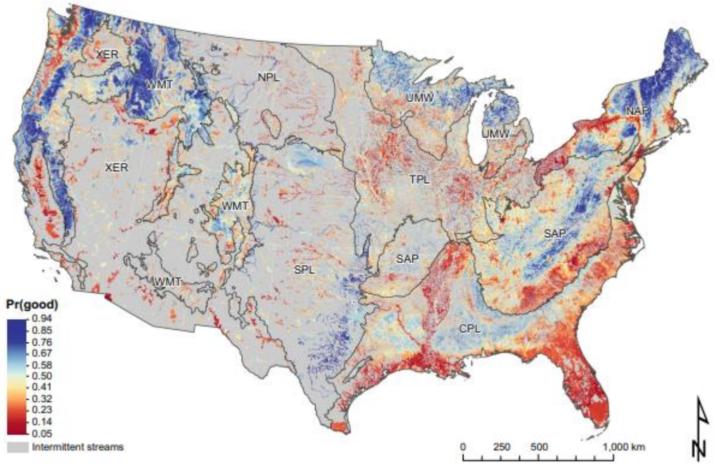

Journal of Environmental Management 322 (2022) 116068
Contents lists available at ScienceDirect
Journal of Environmental Management
journal homepage: www.elsevier.com/locate/jenvman

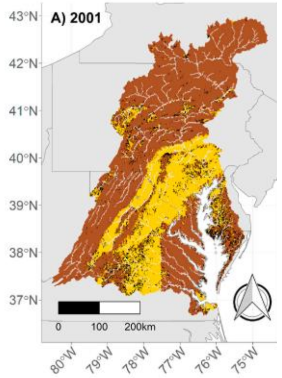
Research article

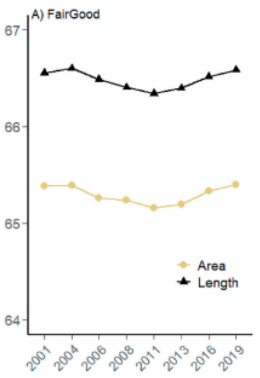
Explainable machine learning improves interpretability in the predictive modeling of biological stream conditions in the Chesapeake Bay Watershed, USA

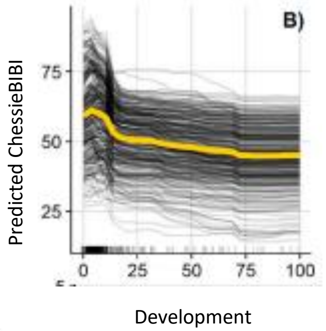
Kelly O. Maloney, Claire Buchanan, Rikke D. Jepsen, Kevin P. Krause, Matthew J. Cashman, Benjamin P. Gressler, John A. Young, Matthias Schmid

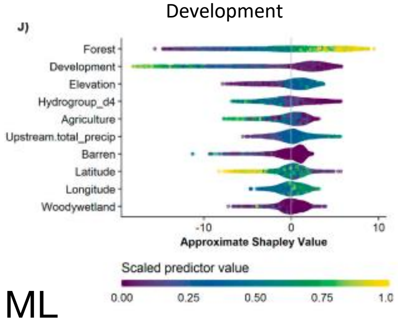
https://doi.org/10.1016/j.jenvman.2022.116068











Data set: USEPA 2008-09 NRSA

Response: Benthic MMI, Probability of Good

Extent: CONUS

Method: Random Forests

Example Result: Probability of Good had low correlations with %Agr and %Urb with non-linear functions.

Take home: "This study provides an important proof-of-concept and approach for using this type of survey data to predict stream condition at large scales with geospatial information."

Data set: Chessie BIBI

Response: Probability of Fair/Good

Extent: Chesapeake Bay watershed

Method: Random Forests, explainable ML

Example Result: stream length/catchment area in FairGood condition decreased/increased over 19 yrs. xML shows negative influence of Dev and Agr at local (Shapley) and model average (PD) levels.

Take home: a random forests model predicted trends in stream biological conditions over a 19-year period; xML improved interpretability of global and local effects.

Case Studies – Regional and Chesapeake Bay

Species Distribution- Birds – CONUS
Causal Inference Double Machine Learning
Fink et al. 2023

Received: 21 December 2022 | Accepted: 26 June 2023
DOI: 10.1111/2041-210X.14186
RESEARCH ARTICLE
Methods in Ecology and Evolution

A Double machine learning trend model for citizen science data

Daniel Fink[1] | Alison Johnston[2] | Matt Strimas-Mackey[1] | Tom Auer[1] | Wesley M. Hochachka[1] | Shawn Ligocki[1] | Lauren Oldham Jaromczyk[1] | Orin Robinson[1] | Chris Wood[1] | Steve Kelling[1] | Amanda D. Rodewald[1]

Data set: citizen science eBird

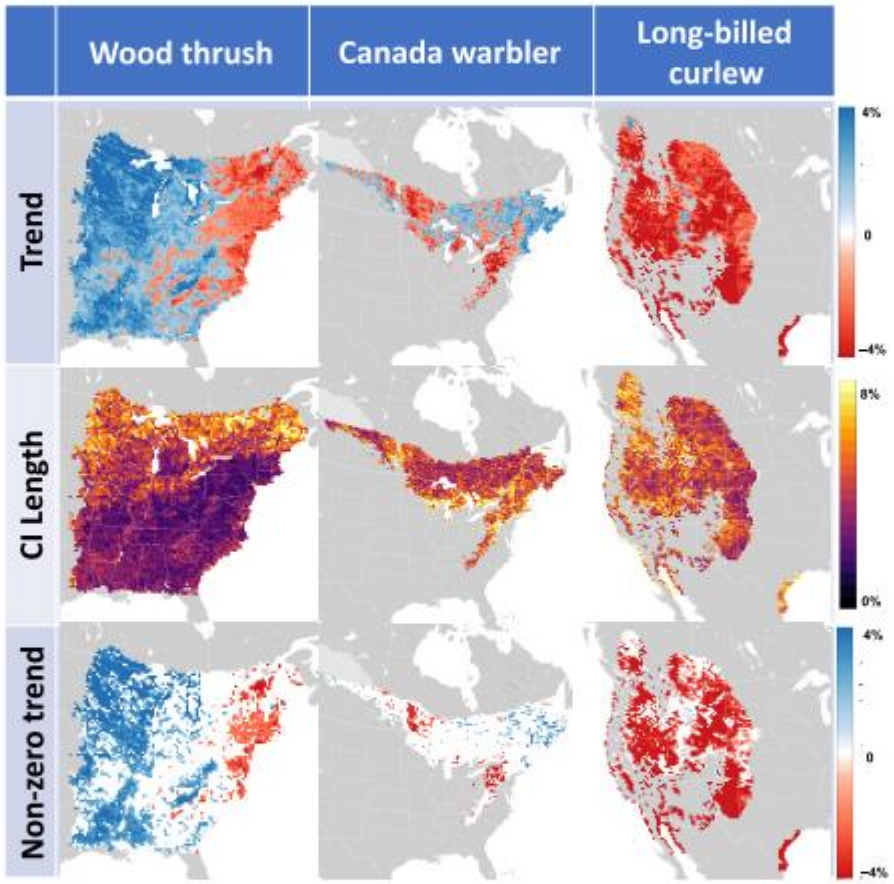
Response: abundance and trends of Wood Thrush, Canada Warbler, and Long-Biller Curlew.

Extent: North America

Method: Double machine learning

Example Result: Wood Thrush shows steep declines in the northeast and increases in the southwest of its breeding season population.

Take home: "The results show that DML can be used to reduce confounding bias leading to more accurate estimates and stronger associative inferences."



Fink, D., Johnston, A., Strimas-Mackey, M., Auer, T., Hochachka, W.M., Ligocki, S., Oldham Jaromczyk, L., Robinson, O., Wood, C., Kelling, S. and Rodewald, A.D., 2023. A double machine learning trend model for citizen science data. *Methods in Ecology and Evolution*, *14*(9), pp.2435-2448. https://doi.org/10.1111/2041-210X.14186

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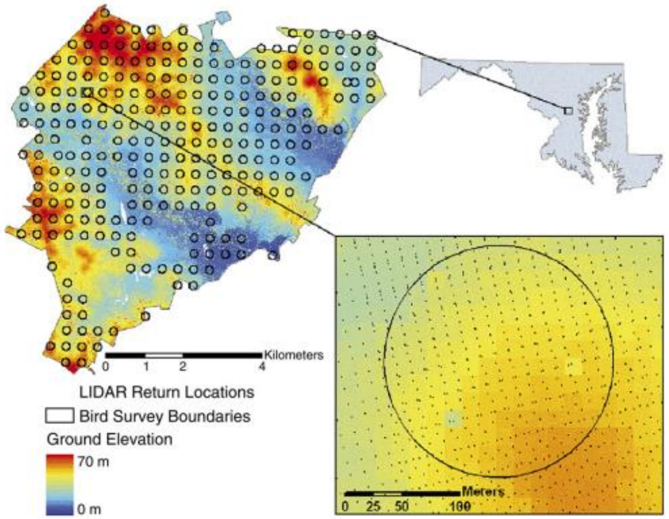
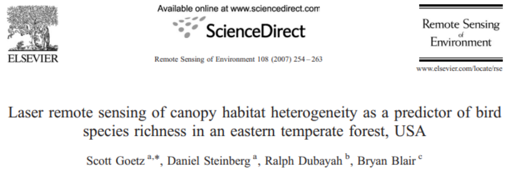
Case Studies – Chesapeake Bay Examples



Species Distribution
Bird Richness – PNWR
Goetz et al. 2007

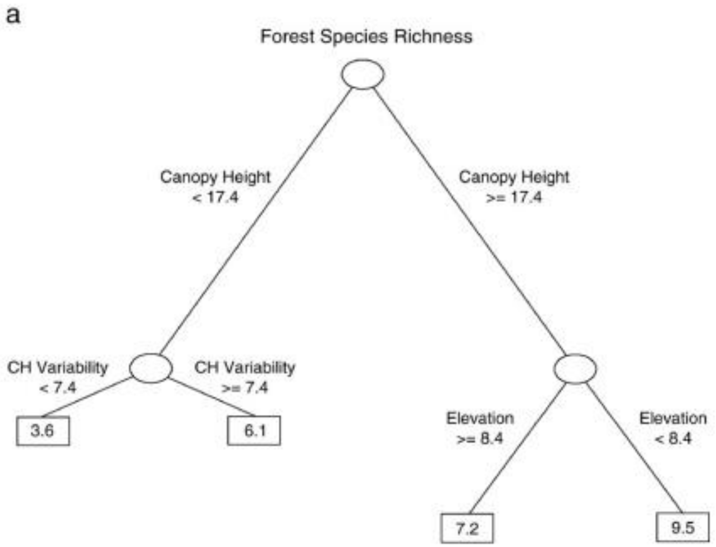


Available online at www.sciencedirect.com
ScienceDirect
Remote Sensing of Environment 108 (2007) 254–263
Remote Sensing of Environment
www.elsevier.com/locate/rse

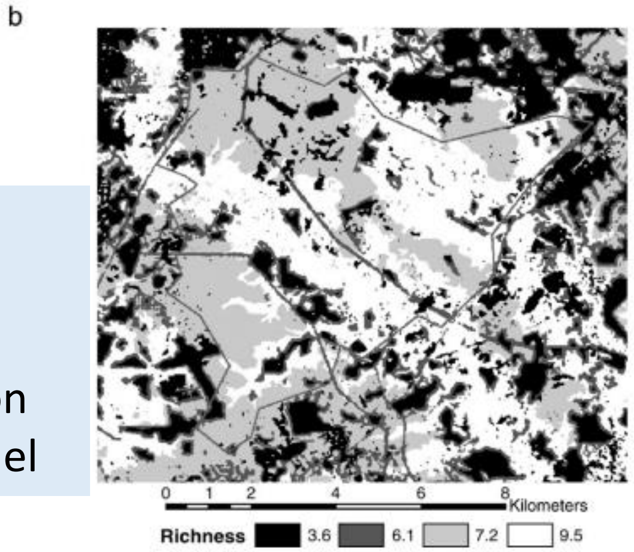
Laser remote sensing of canopy habitat heterogeneity as a predictor of bird species richness in an eastern temperate forest, USA

Scott Goetz [a,*], Daniel Steinberg [a], Ralph Dubayah [b], Bryan Blair [c]

Point abundance of species within 100m radius



Predicted richness using the Regression Tree model



Data set: USGS Breeding Bird Survey, LIDAR & Optical image

Response: Richness and abundance

Extent: Patuxent National Wildlife Refuge, MD

Method: MLR, GAMs, Regression Trees

Example Result: Best model explained 45% of variation in species richness, more typically 30-40%.

Take home: Found little advantage of Regression Trees or GAMs over MLR, attributed to not including interactions or limited tree depth.

Goetz, S., Steinberg, D., Dubayah, R. and Blair, B., 2007. Laser remote sensing of canopy habitat heterogeneity as a predictor of bird species richness in an eastern temperate forest, USA. *Remote Sensing of Environment*, *108*(3), pp.254-263. https://doi.org/10.1016/j.rse.2006.11.016

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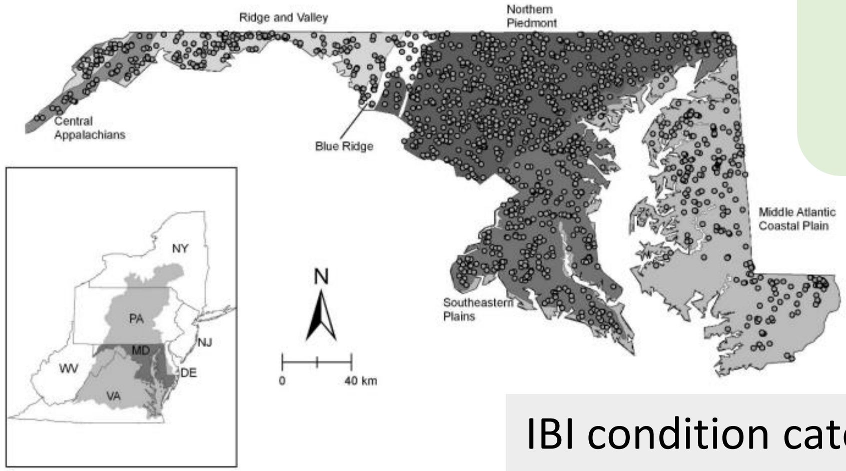
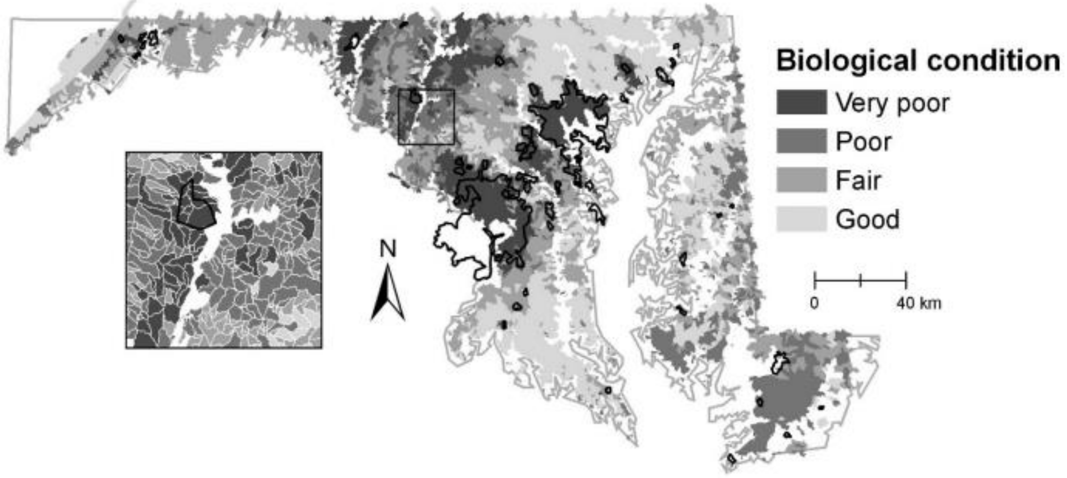
Case Studies – Chesapeake Bay Examples



Assessment
Maryland IBI
Maloney et al. 2009



IBI condition categories based on benthic macroinvertebrates

Data set: Maryland Biological Stream Survey

Response: Index of Biotic Integrity

Extent: Maryland portion of the Chesapeake Bay watershed

Method: Regression Trees, condition Regression Trees, Random Forests, conditional Random Forests, Ordinal Logistic Regression

Example Result: RF and cRF most accurate, select cRF due to bias in variable selection with RF, which predicted 33.8% of streams in fair, 29.9% in good, 22.7% in poor, and 13.6% in very poor biological condition

Take home: Both forests ML approaches were best at prediction of stream condition, but some biases were found with RF.

Used cRF model to predict stream biological condition for non-tidal streams


J. N. Am. Benthol. Soc., 2009, 28(4):869–884
© 2009 by The North American Benthological Society
DOI: 10.1899/08-142.1
Published online: 29 September 2009

Classifying the biological condition of small streams: an example using benthic macroinvertebrates

Kelly O. Maloney[1] AND Donald E. Weller[2]
Smithsonian Environmental Research Center (SERC), 647 Contees Wharf Rd., P.O. Box 28, Edgewater, Maryland 21037-0028 USA

Marc J. Russell[3]
Gulf Ecology Division, US Environmental Protection Agency, 1 Sabine Island Dr., Gulf Breeze, Florida 32561 USA

Torsten Hothorn[4]
Institut für Statistik, Ludwig-Maximilians-Universität, Ludwigstraße 33, D-80539 München, Germany

Maloney, K.O., Weller, D.E., Russell, M.J. and Hothorn, T., 2009. Classifying the biological condition of small streams: an example using benthic macroinvertebrates. *Journal of the North American Benthological Society*, *28*(4), pp.869-884. https://doi.org/10.1899/08-142.1

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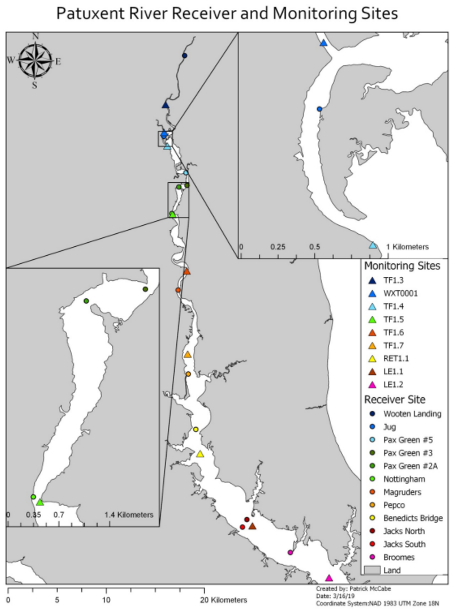
Case Studies – Chesapeake Bay Examples



Invasive Species
Blue Catfish in Patuxent River
McCabe 2019 Master's

Patrick McCabe, 2019, Habitat Modeling of Invasive Blue Catfish in the Patuxent River, Chesapeake Bay, Master's degree Duke University, https://dukespace.lib.duke.edu/items/87838f61-7d55-4b08-ba39-28c5e4a5a236

Data set: acoustic telemetry, tagging

Response: Presence/Absence, monthly

Extent: Patuxent River, Chesapeake Bay watershed

Method: Boosted Regression Trees

Example Result: "..highest presence probability is confined to the channels and deep holes from Nottingham to Pepco, .."

Take home: "This study identified abiotic environmental variables most essential to blue catfish habitat and demonstrate seasonal habitat and movement patterns of blue catfish within the Patuxent."

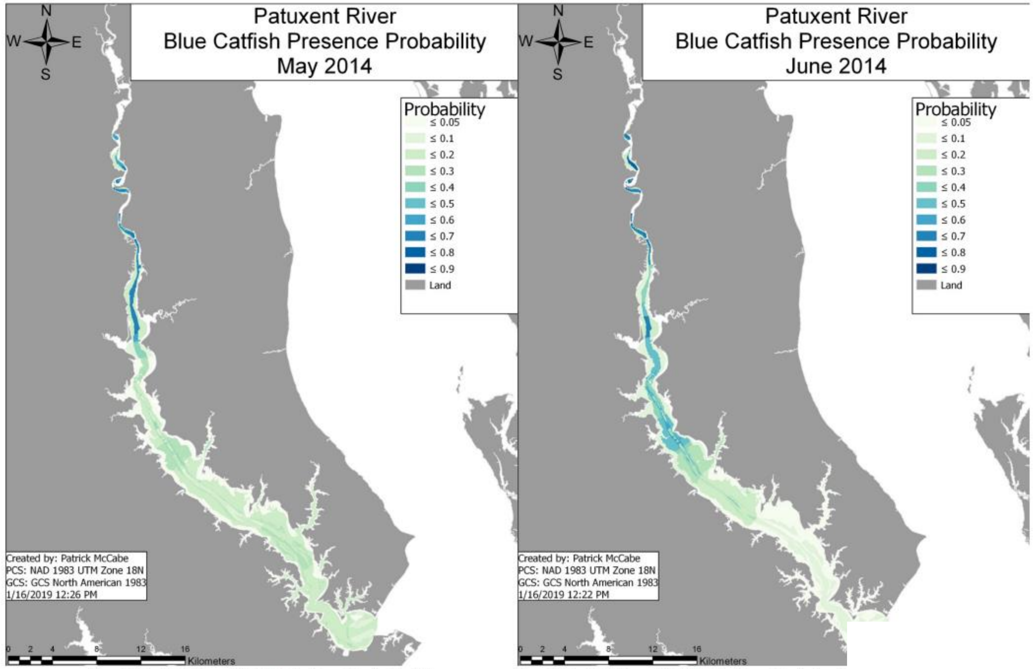
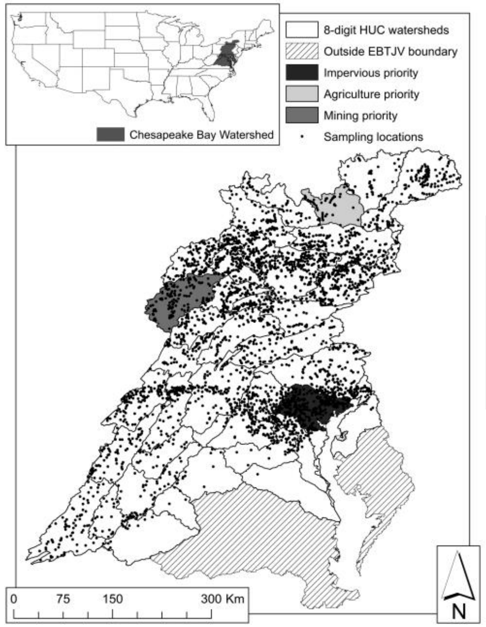


Figure 18. Blue Catfish Presence Probability in the Patuxent River for May 2014.
Figure 19. Blue Catfish Presence Probability in the Patuxent River for June 20

Case Studies – Chesapeake Bay Examples



Distribution & Assessment
Merriam et al. 2019
Brook Trout

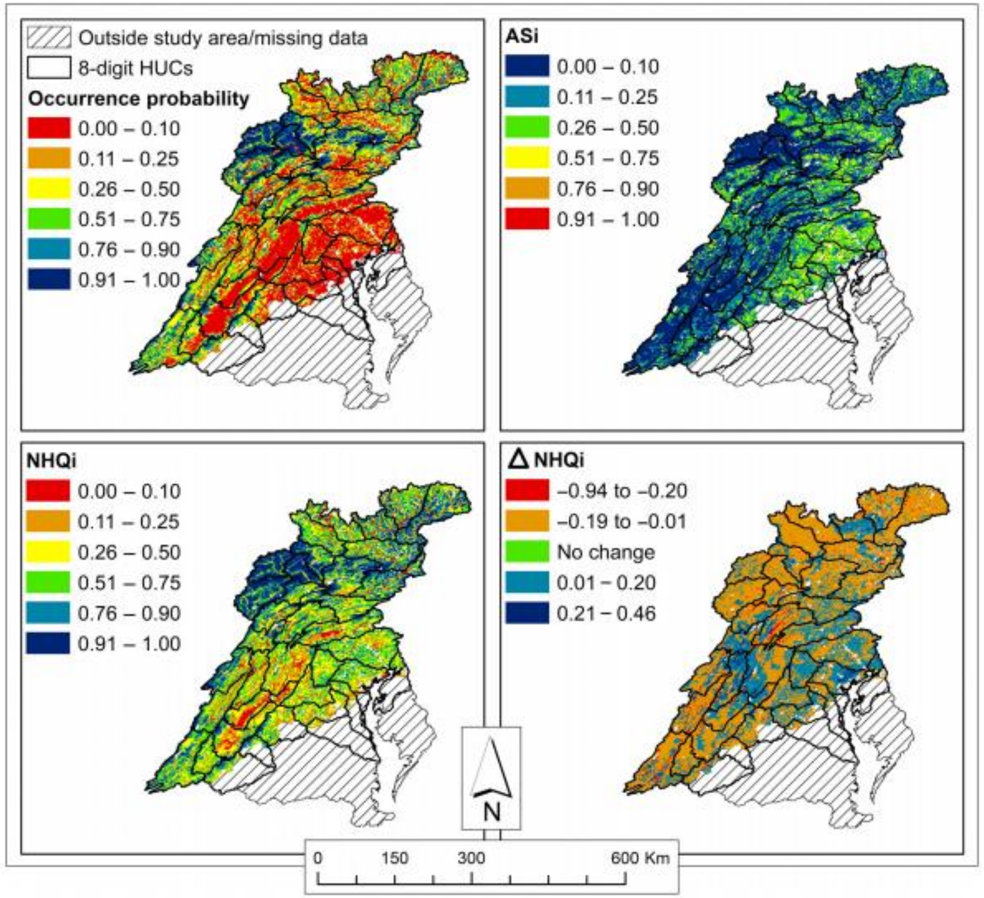
Modeled occurrence of Brook Trout

esa ECOSPHERE

Conservation planning at the intersection of landscape and climate change: brook trout in the Chesapeake Bay watershed

Eric R. Merriam,[1,3] J. Todd Petty,[1,†] and Jason Clingerman[2]

Predicted occurrence, overall anthropogenic stress index (ASi), natural habitat quality (NHQi) and potential change in fishery to future climate (ΔNHQi)



Data set: Compiled Brook Trout dataset

Response: Occurrence

Extent: Chesapeake Bay watershed

Method: Boosted Regression Trees

Example Result: Current land use predicted loss of occurrence in 11,000 stream segments (40% suitable habitat) climate change projected 3,000 additional segments (19% current).

Take home: "Our results suggest that land use activities interact strongly with water temperature and precipitation and how we manage this interaction likely will determine the fate of brook trout populations throughout this region."

Merriam, E.R., Petty, J.T. and Clingerman, J., 2019. Conservation planning at the intersection of landscape and climate change: brook trout in the Chesapeake Bay watershed. Ecosphere, 10(2), p.e02585. https://doi.org/10.1002/ecs2.2585

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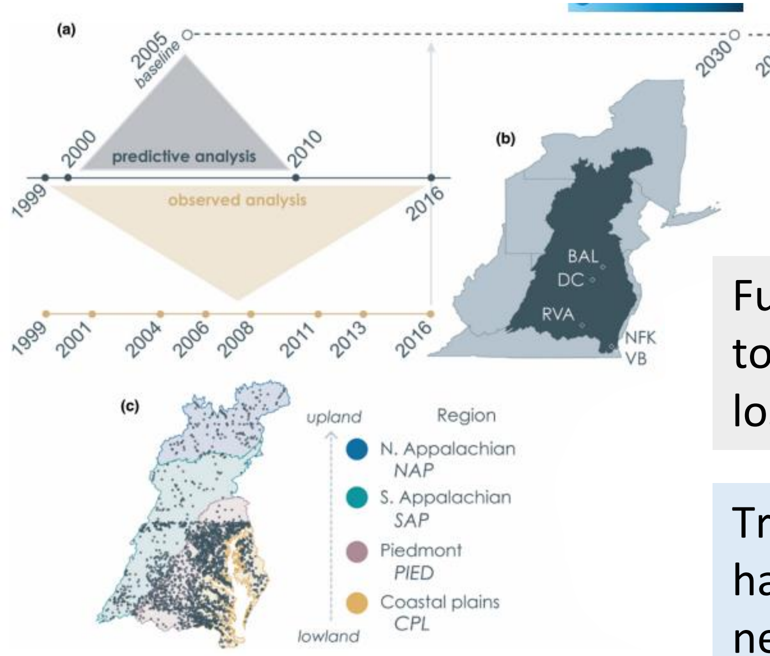
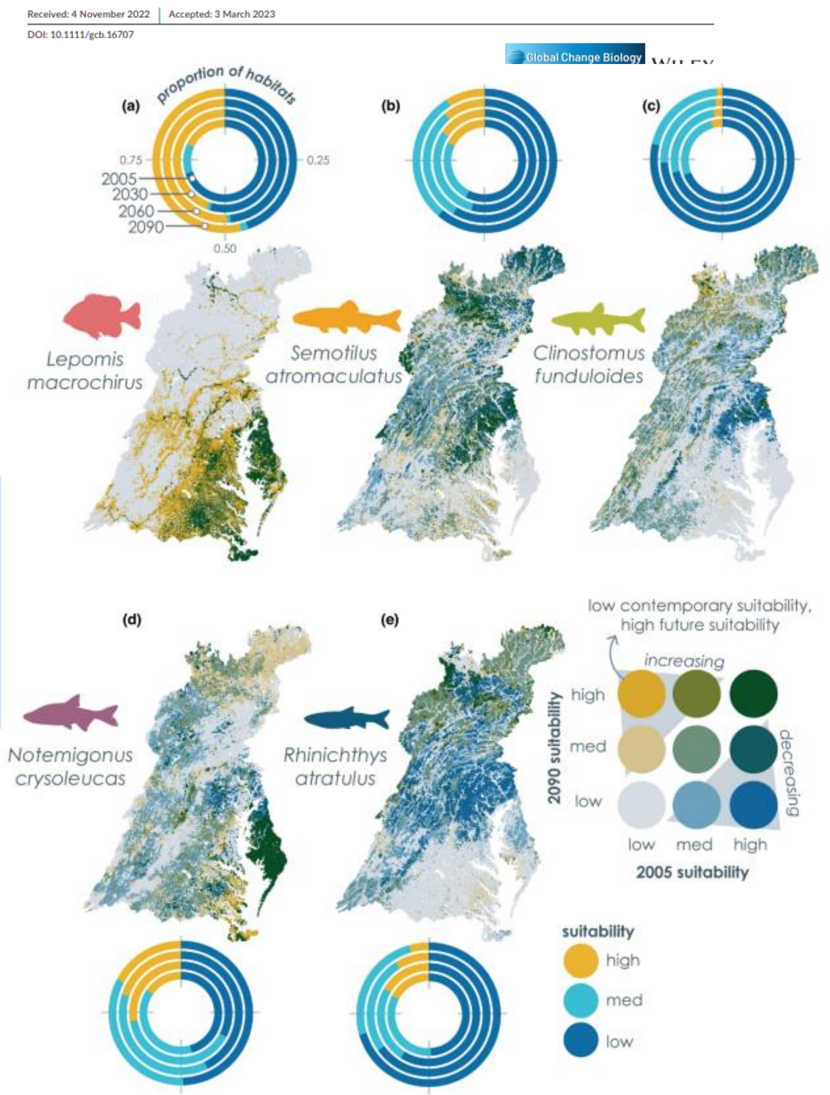
Case Studies – Chesapeake Bay Examples



Distribution & Assessment
Woods et al. 2023
Fish Traits

Functional traits groups to identify winner and loser traits

Traits preferences for warm water, pool habitats, fine or vegetated substrates, nest-guarding reproductive strategies, and carnivores may gain suitable habitat.



Data set: Cbay watershed fish data set

Response: Functional Traits to enable winner vs. loser analysis

Extent: Chesapeake Bay watershed

Method: Random Forests, land use and climate futures

Example Result: "At the assemblage level, models projected decreasing habitat suitability for cold-water, rheophilic, and lithophilic individuals but increasing suitability for carnivores in the future across all regions."

Take home: "…highlight the complexity of global change impacts across broad landscapes that likely relate to differences in assemblages' intrinsic sensitivities and external exposure to stressors."

Woods, T., Freeman, M.C., Krause, K.P. and Maloney, K.O., 2023. Observed and projected functional reorganization of riverine fish assemblages from global change. *Global Change Biology*, *29*(13), pp.3759-3780. https://doi.org/10.1111/gcb.16707

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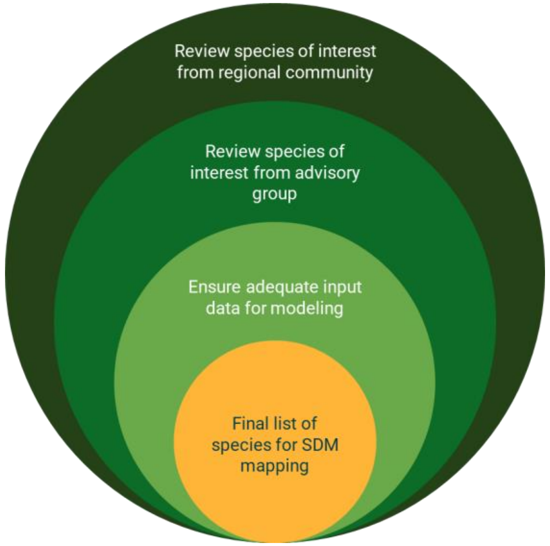
Distribution & Assessment
Kiser, Young, Mainali et al. In Progress
Multi-species Biodiversity Mapping



Data set: multiple species, Cbay24k predictors

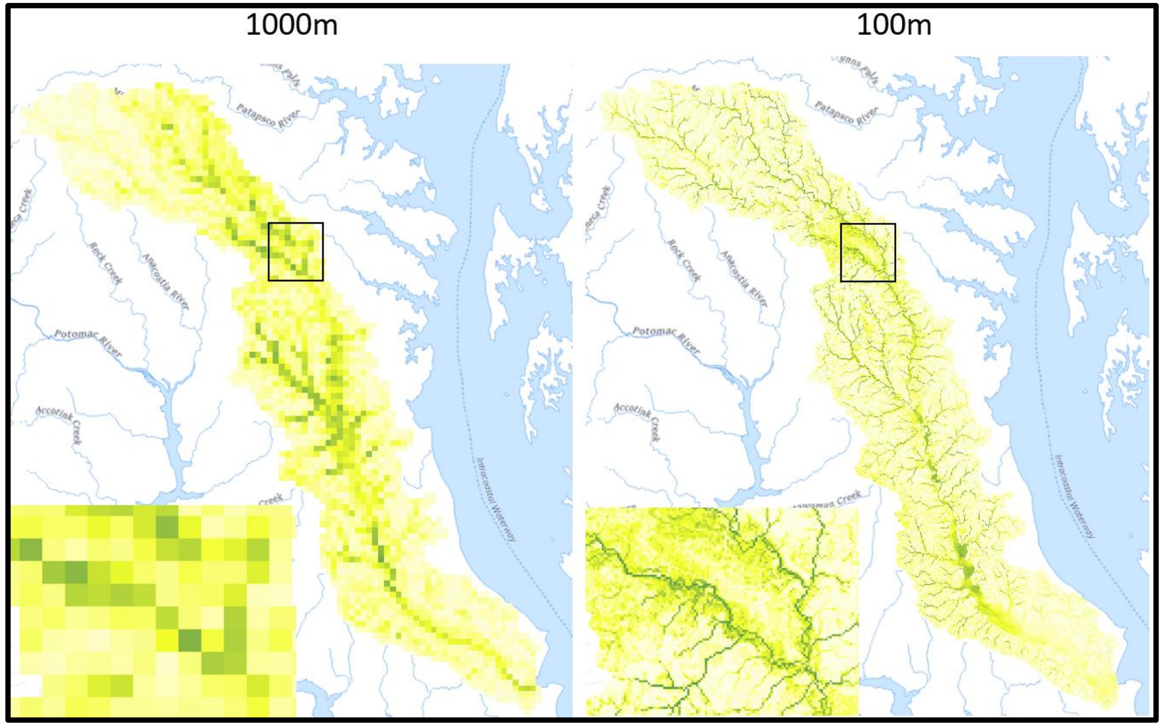
Response: Presence/Absence, Presence only

Extent: Chesapeake Bay watershed

Method: Ensemble and Nested Modeling Approach - Random Forests, Gradient Boosting (Boosted Regression Trees), MaxEnt

Example Result: In Progress

Take home: In Progress



Probability of occurrence of American eel at two spatial scale

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Kumar Mainali (Cbay Conservancy) - kmainali@chesapeakeconservancy.org

Preliminary Information-Subject to Revision. Not for Citation or Distribution

Chesapeake Conservancy

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Case Studies – Collaboration with Statisticians

Building Cross-Disciplinary Collaborations Outside the Ecological or Life Sciences Field

CONUS – used USEPA National Lakes Assessment Survey data, developed a RF ML method for bounded outcomes, %Ephemeroptera

JOURNAL OF COMPUTATIONAL AND GRAPHICAL STATISTICS
2020, VOL. 29, NO. 3, 639–658
https://doi.org/10.1080/10618600.2019.1705310

Taylor & Francis
Taylor & Francis Group

Check for updates

A Random Forest Approach for Bounded Outcome Variables

Leonie Weinhold[a], Matthias Schmid[a], Richard Mitchell[b], Kelly O. Maloney[c], Marvin N. Wright[d], and Moritz Berger[a]

Maryland – used MBSS IBI data, developed a proportional odds model for ordinal outcomes with a functional gradient boosting approach for estimation.

Environ Ecol Stat
DOI 10.1007/s10651-010-0158-4

Geoadditive regression modeling of stream biological condition

Matthias Schmid · Torsten Hothorn · Kelly O. Maloney · Donald E. Weller · Sergej Potapov

We have excellent data sets and interesting questions.

Combined Expertise

Statisticians often faced with challenging questions and have expertise to develop novel techniques.

Achieving interpretable machine learning by functional decomposition of black-box models into explainable predictor effects

David Köhler[1] David Rügamer[2,3] Lindsey J. Boyle[4] Kelly O. Maloney[4] Matthias Schmid[1]

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Currently In Review

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Case Studies – Some Review Papers

Benos, L., Tagarakis, A.C., Dolias, G., Berruto, R., Kateris, D. and Bochtis, D., 2021. Machine learning in agriculture: A comprehensive updated review. *Sensors*, *21*(11), p.3758. https://doi.org/10.3390/s21113758

Crisci, C., Ghattas, B. and Perera, G., 2012. A review of supervised machine learning algorithms and their applications to ecological data. Ecological Modelling, 240, pp.113-122. https://doi.org/10.1016/j.ecolmodel.2012.03.001

Jordan, M.I. and Mitchell, T.M., 2015. Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), pp.255-260. https://doi.org/10.1126/science.aaa8415

Karpatne, A. I. Ebert-Uphoff, S. Ravela, H. A. Babaie and V. Kumar, "Machine Learning for the Geosciences: Challenges and Opportunities," in IEEE Transactions on Knowledge and Data Engineering, vol. 31, no. 8, pp. 1544-1554, 1 Aug. 2019. https://doi.org/10.1109/TKDE.2018.2861006

Liakos, K.G., Busato, P., Moshou, D., Pearson, S. and Bochtis, D., 2018. Machine learning in agriculture: A review. *Sensors*, *18*(8), p.2674. https://doi.org/10.3390/s18082674

Liu, Z., Peng, C., Work, T., Candau, J.N., DesRochers, A. and Kneeshaw, D., 2018. Application of machine-learning methods in forest ecology: recent progress and future challenges. Environmental Reviews, 26(4), pp.339-350. https://doi.org/10.1139/er-2018-0034

Pichler, M. and Hartig, F., 2023. Machine learning and deep learning—A review for ecologists. Methods in Ecology and Evolution, 14(4), pp.994-1016. https://doi.org/10.1111/2041-210X.14061

Recknagel, F., 2001. Applications of machine learning to ecological modelling. *Ecological modelling*, *146*(1-3), pp.303-310. https://doi.org/10.1016/S0304-3800(01)00316-7

Stupariu, M.S., Cushman, S.A., Pleşoianu, A.I., Pătru-Stupariu, I. and Fuerst, C., 2022. Machine learning in landscape ecological analysis: a review of recent approaches. Landscape Ecology, 37(5), pp.1227-1250. https://doi.org/10.1007/s10980-021-01366-9

Tuia, D., Kellenberger, B., Beery, S. *et al.* Perspectives in machine learning for wildlife conservation. *Nat Commun* **13**, 792 (2022). https://doi.org/10.1038/s41467-022-27980-y

Wäldchen, J. and Mäder, P., 2018. Machine learning for image based species identification. Methods in Ecology and Evolution, 9(11), pp.2216-2225. https://doi.org/10.1111/2041-210X.13075

Zhu, J.J., Yang, M. and Ren, Z.J., 2023. Machine learning in environmental research: common pitfalls and best practices. *Environmental Science & Technology*, *57*(46), pp.17671-17689. https://doi.org/10.1021/acs.est.3c00026?urlappend=%3Fref%3DPDF&jav=VoR&rel=cite-as

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Thank you!

Funding:

U.S. Geological Survey Land Management Research Program – Priority Landscapes: Chesapeake Bay

Chesapeake Research Consortium for lodging