The impact of nationally organised efforts on global citizen-science platforms

(my yearly reminder about how cool iNat is)

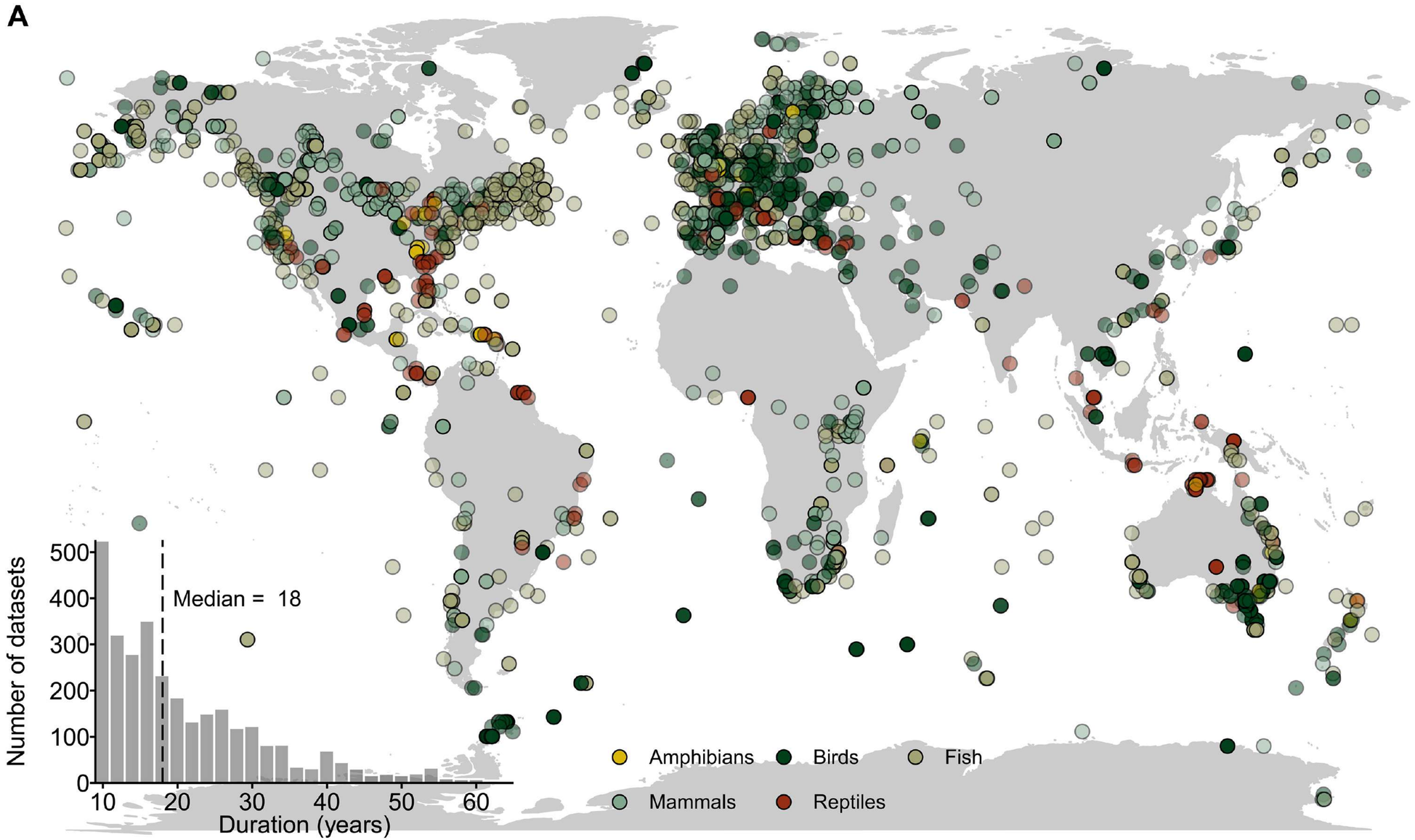
Flo Grattarola 28th May 2026

Faculty of Environmental Sciences

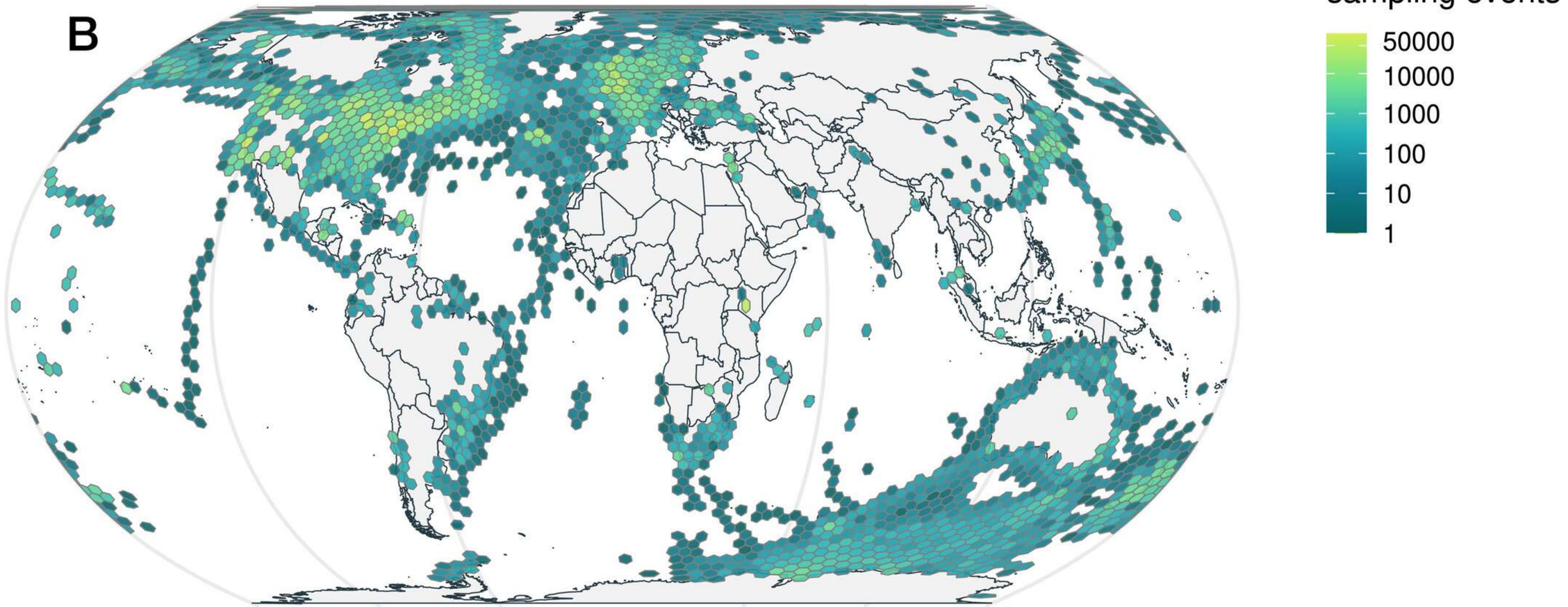
MOBI Lab

Kate Evans/CIFOR-ICRAF


GBIF.org



Living Planet Index



BioTime

Photo by Biodiversidata in Bella Unión (Uruguay)

Documenting local knowledge

People

- Local biodiversity knowledge holders can help fill these gaps - *situated knowledge* (Donna Haraway)

Data collection before: diaries, notebooks

Drawings from Larrañaga of águila coronada, lechuza de campanario and becasa de mar

Encontré varios árboles que no conocía: entre ellos varias Mimosas, una de ellas la llamaban Ñapindá, porque se agarraba a la ropa y su espina no era alesnada sino en forma de uña y corta, arrojando muchas varazones o mimbres; y aun vi una que subía muy alto envuelta en un tronco de otro árbol; aunque esto es raro: observé muchos árboles de Chañal, que había visto en Buenos Aires traídos de Córdoba en donde creí que solamente se encontraban: los árboles están muy arruinados, pero algunos años dan mucho fruto, que comen y son muy exquisitos. Recogí algunas otras plantas y nos retiramos.

Viaje de Montevideo a Paysandú by Dámaso Antonio Larrañaga, 1815

Data collection before: diaries, notebooks

Birdwatchers in Central Park in 1958. Sam Falk/The New York Times

ILLINOIS AUDUBON SOCIET

AREA	Arboretum	Decatur	Evanston	Jasp.-Pulas.	Lake Genev.	Mich. City	Moroc. Ind.	North Ind.	Olney	Spr'gfield	Tri-City	Waukegan	White Pines	TOTALS 1955
Common Loon										1				
Horned Grebe			1			15		1						
Pied-billed Grebe					2									
Double-cr. Cormorant		1				1								
Great Blue Heron		1					1	2			1		1	
Canada Goose				153	1		1,000		60	46			9	1,2
Snow Goose		1												
Blue Goose		3												
Mallard Duck		2,000	103	20	11	27	100,000		78	5,000	39	46	17	107,3
Black Duck		4		45	10	65	500			1,000	1	3		1,(
Gadwall										1				
Baldpate (Widgeon)					2	2		1		3				
Pintail		15				1	8			9				
Green-winged Teal				1							1			
Redhead							1							
Ring-necked Duck		1			2						11	1		
Canvasback		1			2,500	1				17	1	1	2	2,
Greater Scaup Duck			23			1								
Lesser Scaup Duck		10	172	1	18	200	1	10		3	40	170		
American Golden-eye		20	331	1	350	475		18		20	675	26		1,
Bufflehead		7	18		3	375						3		
Old-squaw			426			3,000		1,204				120		4,
White-winged Scoter					1	6								
Ruddy Duck						1								
Hooded Merganser					4	4					4	1		
American Merganser			598		50	410	2	18		30	117	18		1,
Red-breasted Merganser			2,798			17		69			2	7		2,
Goshawk													1	
Sharp-shinned Hawk	2												2	
Cooper's Hawk						1		1	1		1		3	
Red-tailed Hawk		1	1	1		3	4		21	2	12		6	
Krider's red-tailed Hawk					1						1			
Red-shouldered Hawk		1	1	1	1		1	4	15	1	6			
Broad-winged Hawk													1	
Rough-legged Hawk			1		1		1		5		1		6	
Ferruginous rough-leg					1									
Bald Eagle				1							5		1	
Marsh Hawk				3		2	10	3	9	2	2		2	
Sparrow Hawk	3		4			6		10	14	1	7	1	4	
Prairie Chicken							37		1					
Bob-white (Quail)		1		43		21	7		10	12	73			
Ring-necked Pheasant	5		57	3	5	8					37	13	2	
American Coot		2			550	2	1	1	1	7		3	1	
Killdeer		15			1						4			
Wilson's Snipe						2								
Iceland Gull						1								
Herring Gull			704		55	780		673		1	480	300	9	3
Ring-billed Gull		51	234		1	265		476		500	153	3		1
Franklin's Gull			32											
Bonaparte's Gull			1			650						50		
Little Gull						2								
Mourning Dove	39	3	6	4		24	2	2	235	1	38		2	
Barn Owl									1					
Screech Owl								1	1		5			
Great Horned Owl	1		1				1				2			
Snowy Owl											1			
Barred Owl		1							2	1	5		2	
Long-eared Owl	16										4	5		
Saw-Whet Owl	2													
Belted Kingfisher			4			3		1	1		7	1	1	

Illinois Audubon Society. (1973) https://www.biodiversitylibrary.org/bibliography/186801

Data collection now: platforms

ECORUTAS

Irish Butterfly Monitoring Scheme

epicollect5

Indicia

TMD

Turtle crossing
Taiwan Roadkill Observation Network
https://roadkill.tw

customisable form-based systems

off-the-shelf solutions

Infraestructure for data collection (platforms)

project noah

launched in the US in 2015

eco registros

created in Argentina in 2011

lost momentum or never achieved widespread global adoption

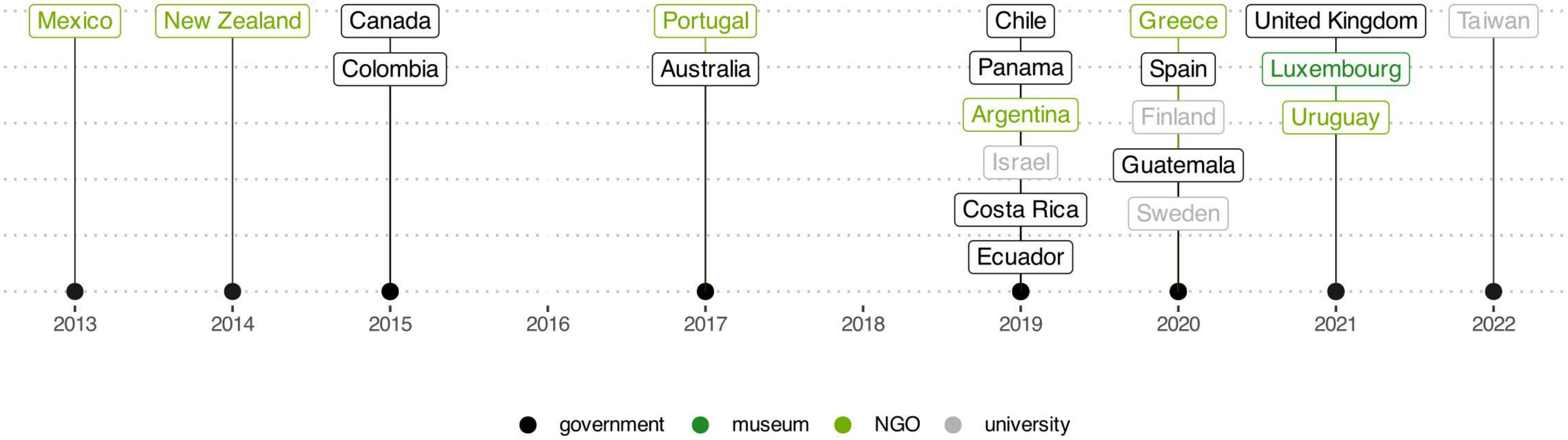
Global successful platforms

	# records in GBIF (May 2026)
eBird	1,775,781,186
iNaturalist	151,728,963
Observation.org	127,703,309


iNaturalistFi
FINLAND
iNaturalist.Se
SWEDEN
iNaturalistUK
UNITED KINGDOM
iNaturalist.ca
CANADA
iNaturalist.LU
LUXEMBOURG
BioDiversity4All
INATURALIST PORTUGAL
iNaturalistGR
GREECE
iNaturalistMX
MEXICO
iNaturalistGT
GUATEMALA
Natusfera
INATURALIST SPAIN
iNaturalistil
ISRAEL
iNaturalistTW
TAIWAN
NaturalistaCR
INATURALIST COSTA RICA
NaturalistaCO
INATURALIST COLOMBIA
iNaturalistPa
PANAMA
iNaturalistEc
ECUADOR
iNaturalistAU
AUSTRALIA
NaturalistaUY
INATURALIST URUGUAY
iNaturalistCL
CHILE
ArgentíNat
INATURALIST ARGENTINA
iNaturalist.NZ
NEW ZEALAND
iNaturalist
GLOBAL NETWORK

The Network

iNaturalist



What drives iNat's success?

Is being part of the network important?

- How per-country iNaturalist numbers (records, users, species, projects, data quality, and derived publications) depend on different explanatory variables, **including the presence or absence of a national node.**

Methods

6 response variables

Variable	Description	Source
n_records	Number of records on iNaturalist in the country	iNaturalist.org
n_users	Number of users that uploaded at least one observation in the country (regardless of their country of residency)	iNaturalist.org
n_species	Number of species recorded in the country	iNaturalist.org
n_projects	Number of projects registered by country	iNaturalist.org
n_literature	Number of peer-reviewed publications indexed by GBIF that use iNaturalist data with a documented geographic focus on the country	GBIF.org
p_research_grade	Proportion of records on iNaturalist in the country that are “Research Grade” (as a proxy for data quality)	iNaturalist.org

8 expanatory variables

Variable	Description	Source	Expectation
has_node	Whether a country has a node on the iNaturalist network	iNaturalist.org	Countries that have an iNaturalist node will have greater country-level iNaturalist metrics
neighbour_has_node	Whether a country has a neighbouring (adjacent) country that has a node on the iNaturalist network	*rnaturalearth* country polygons +	Countries that have a neighbouring country that has an iNaturalist node will have greater country-level iNaturalist
population	Population of the country (number of inhabitants)	World Development Indicators	More populated countries will have greater country-level iNaturalist metrics
area	Area of the country in km^2	World Development Indicators	Larger countries will have greater country-level iNaturalist metrics
gdp_per_capita	Country's GDP per capita (in US dollars)	World Development Indicators	Countries with richer citizens will have greater country-level iNaturalist metrics
gdp_in_research	Percentage of the country's GDP dedicated to research (%)	World Development Indicators	Countries that invest more in science will have greater country-level iNaturalist metrics
latitude	Country's centroid latitude	*rnaturalearth* country polygons	Countries located in lower latitudes will have greater country-level iNaturalist metrics as they usually are more biodiverse
iucn_species	Number of species assessed for threat status in a country	IUCN Red List	Countries with higher numbers of species will have greater country-level iNaturalist metrics

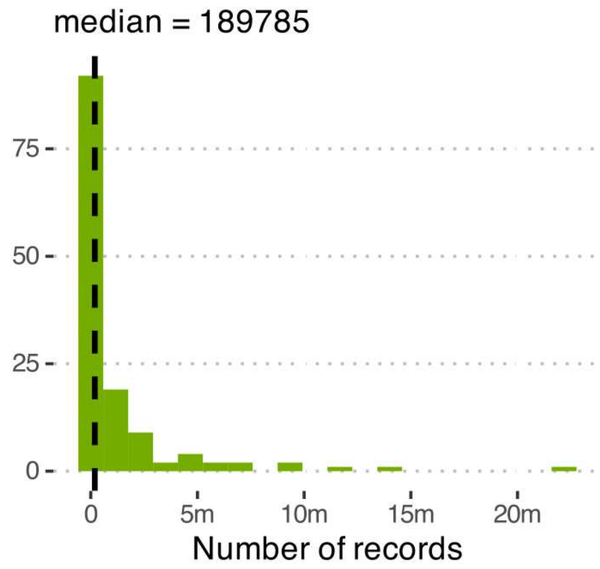
Data download

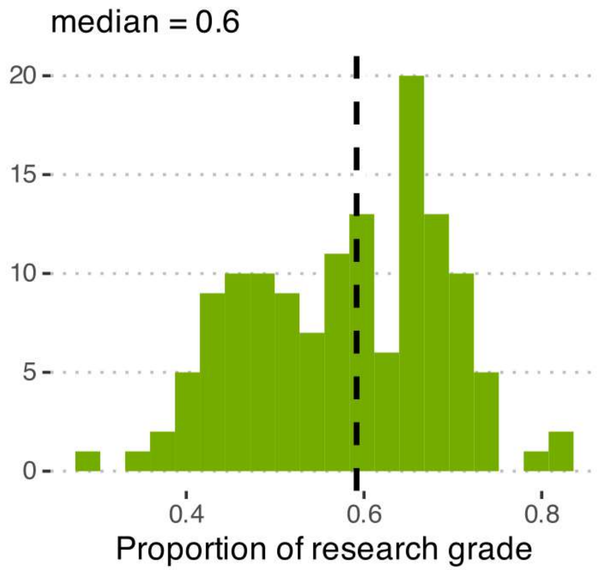
All code available at: https://github.com/bienflorencia/iNat_network_contributions

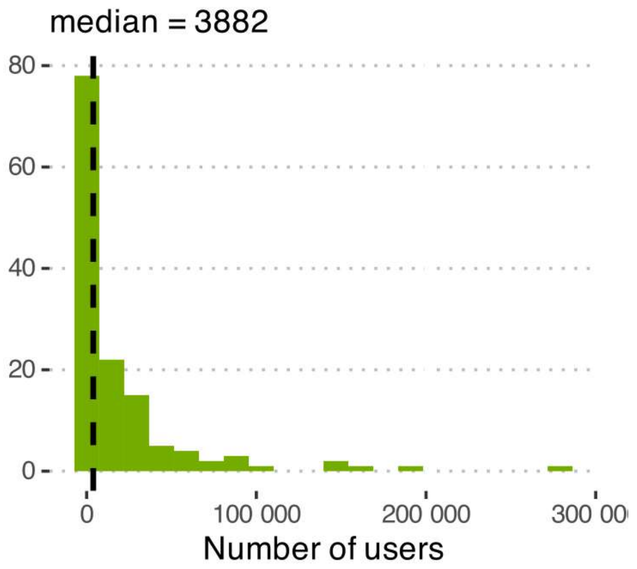
Custom functions that allow programmatic access to sources via APIs. This process facilitates automated data retrieval, ensures reproducibility, and minimises the risk of errors from manual data collection.

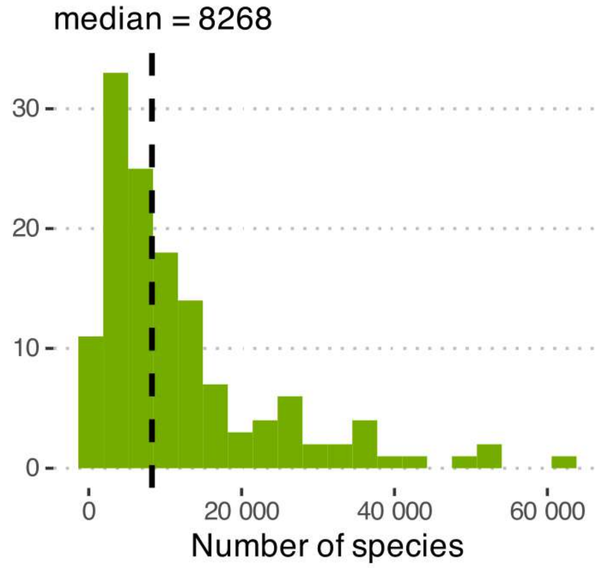
- **iNaturalist API** (https://api.inaturalist.org/v1/docs/),
- **GBIF Literature API** (https://techdocs.gbif.org/en/openapi/v1/literature),
- **World Development Indicators API** (https://datatopics.worldbank.org/world-development-indicators/),
- **IUCN API** (https://api.iucnredlist.org/api-docs/index.html).

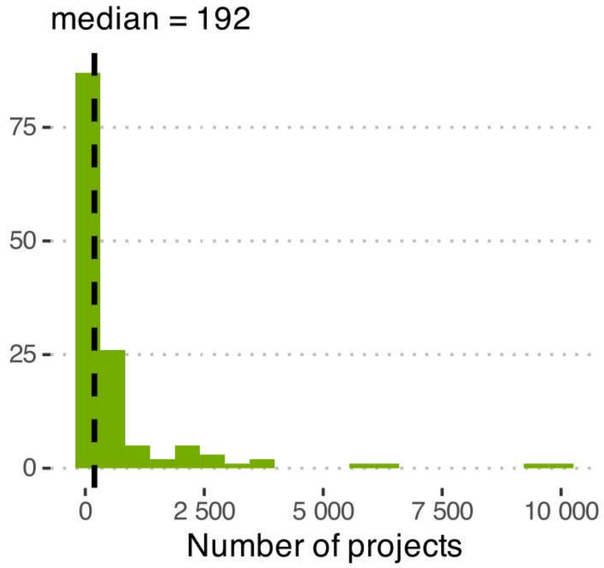
response variables

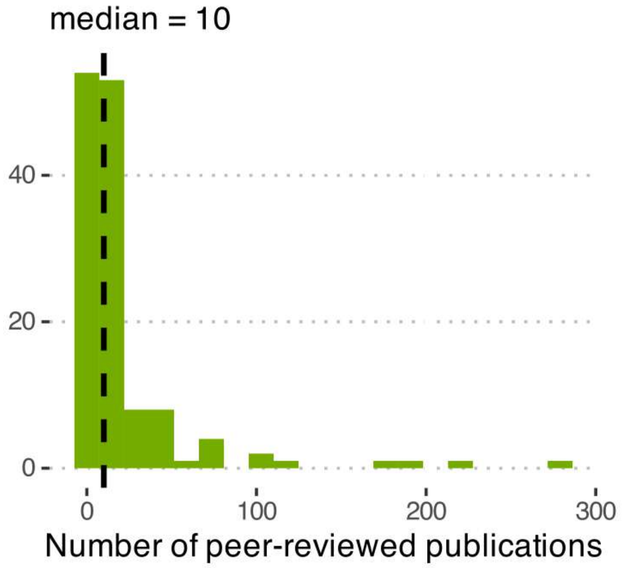




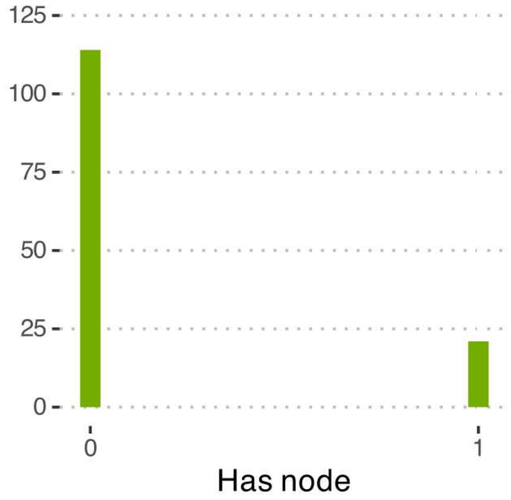


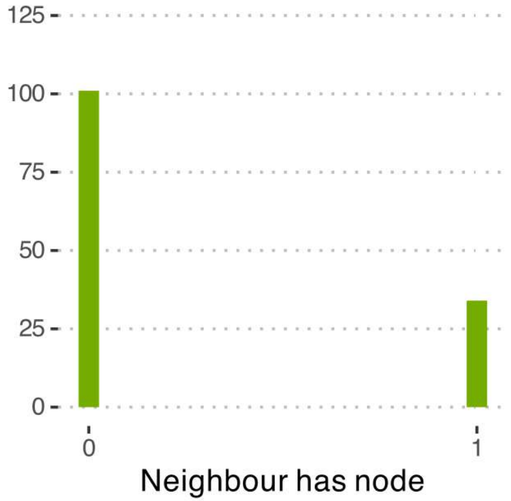


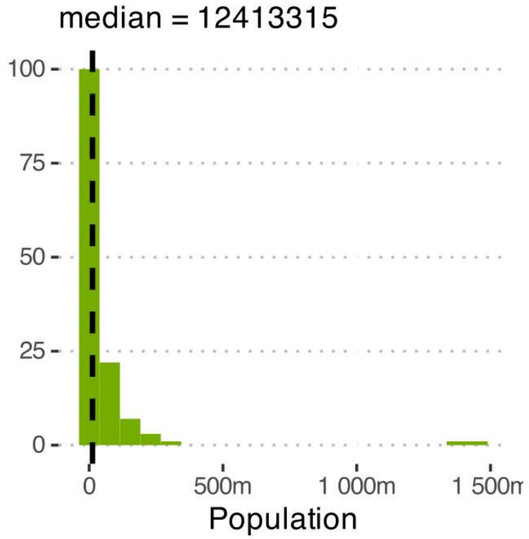


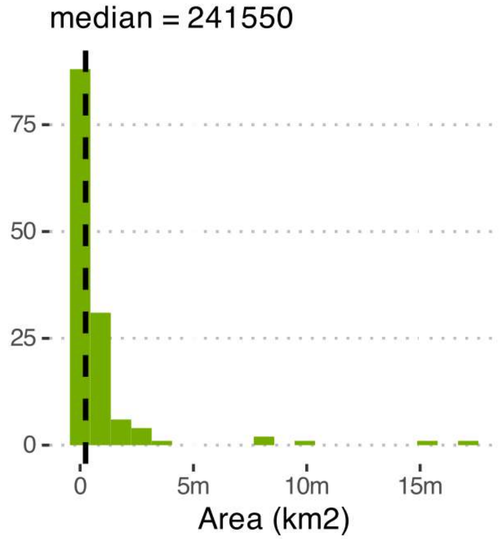


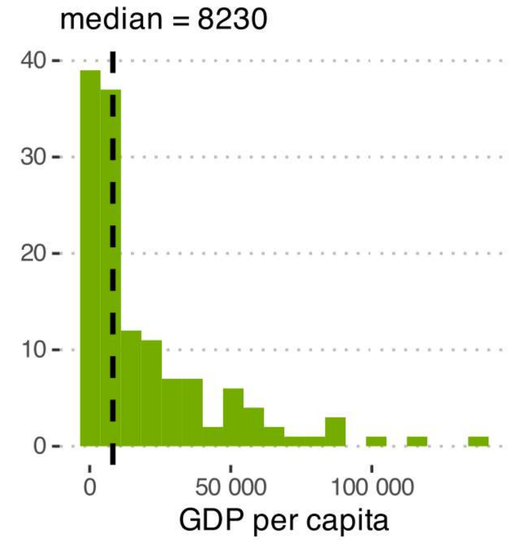
expanatory variables

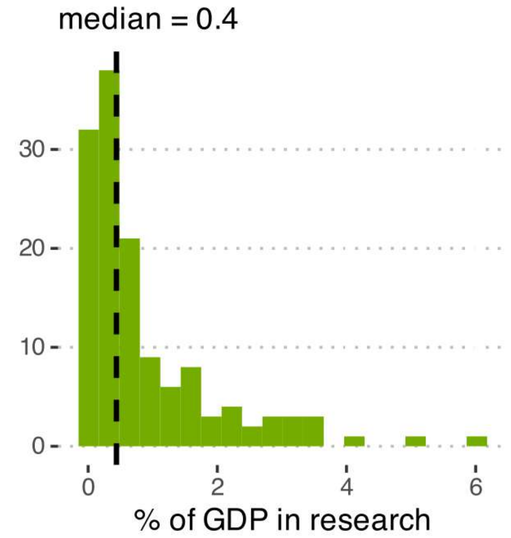


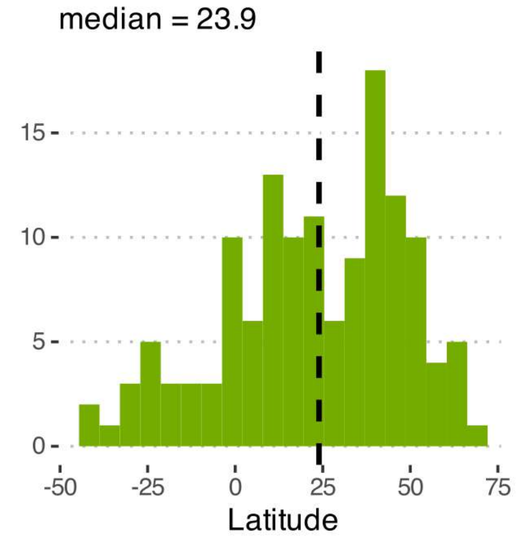


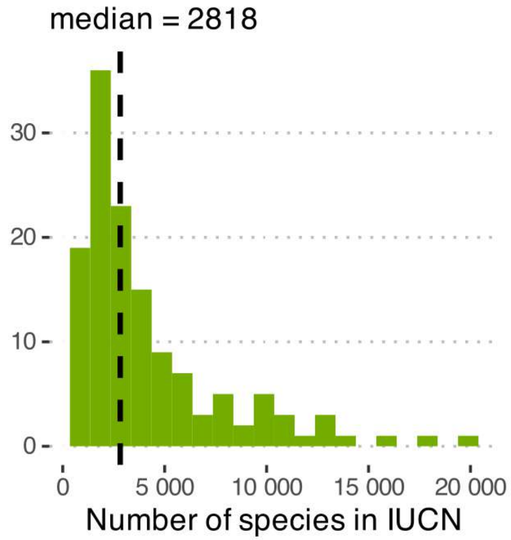




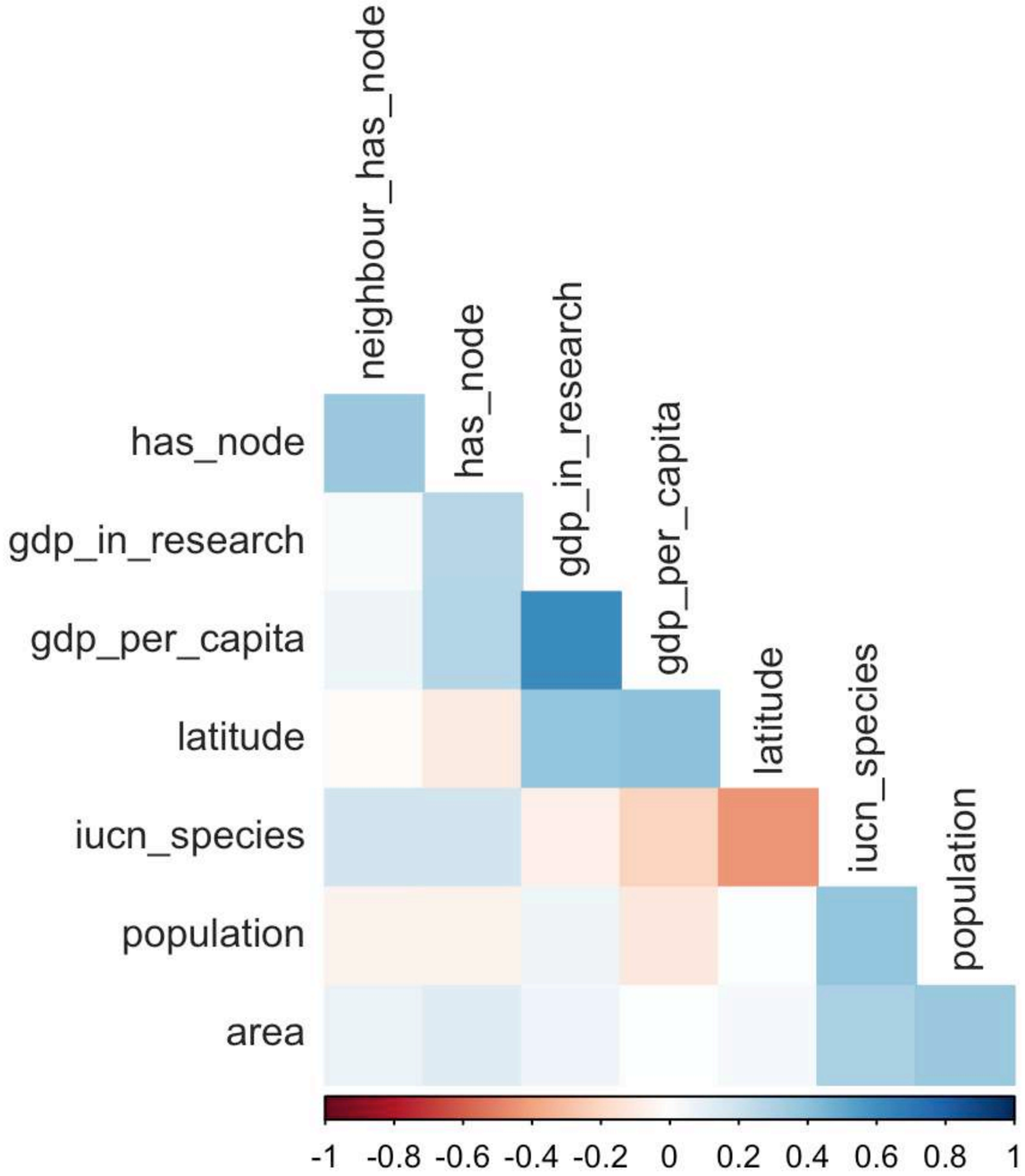








expanatory variables

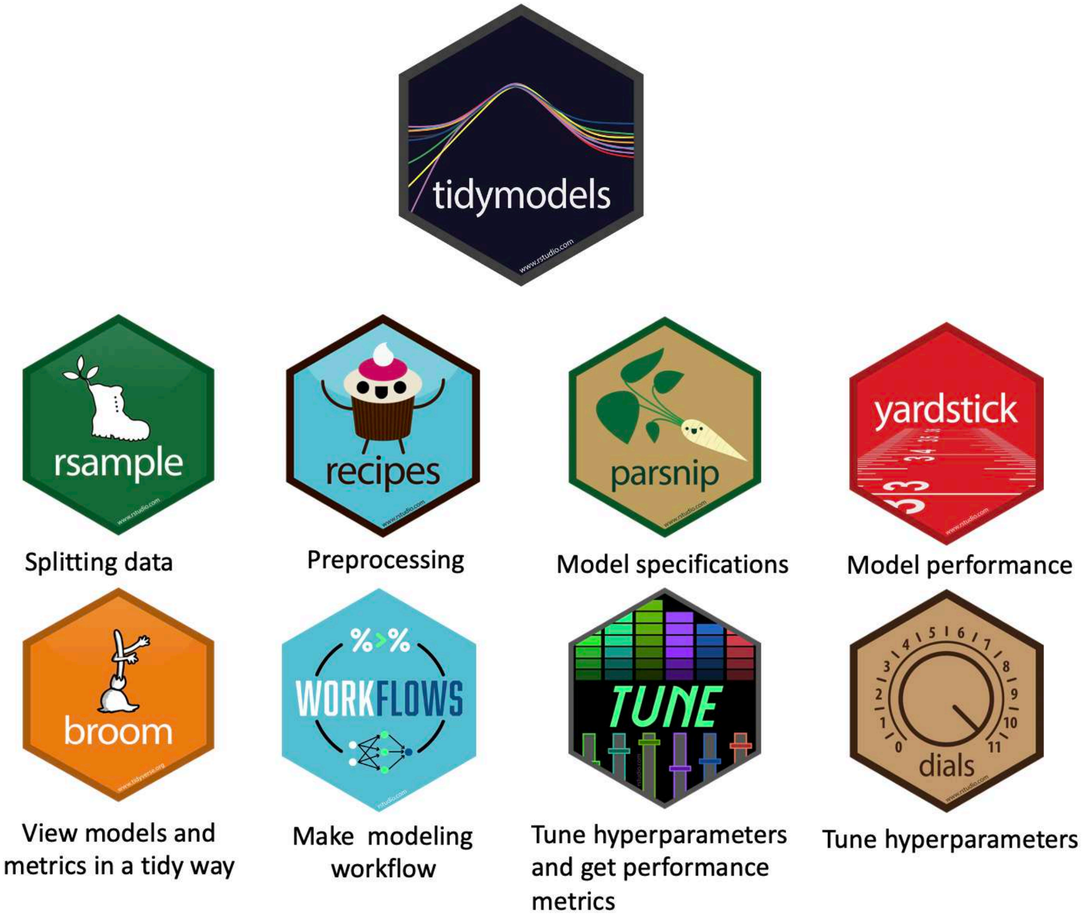


Random Forests

Using tidymodels

flexibles!

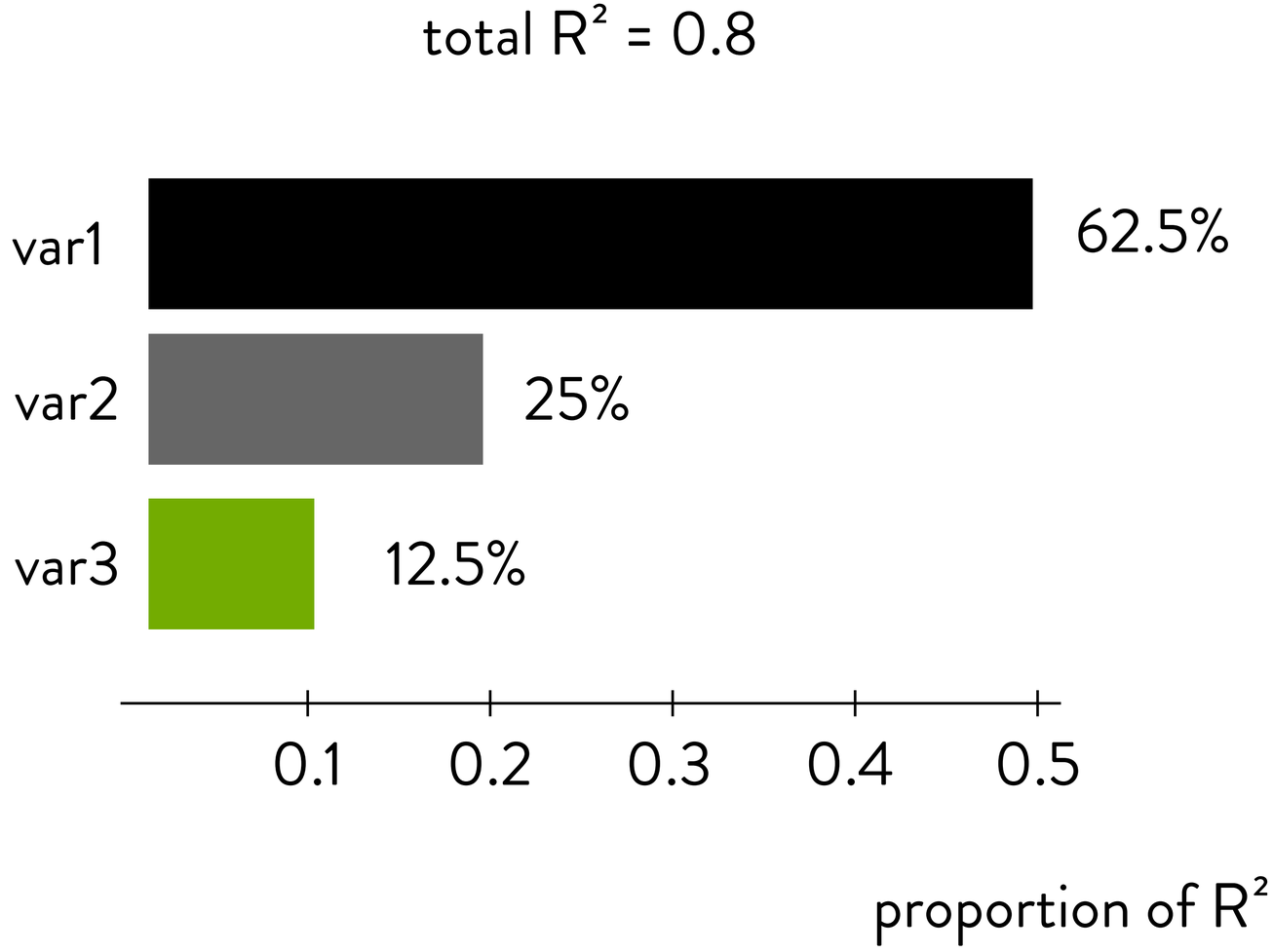
- **Randomly split** into training (75% of the countries) and test (25% of the countries), stratified by the response variables.
- **Hyperparameter tuning** using a single 10-fold random cross-validation on the training data (1,000 trees, node size = 2, 5, 10, 15, and 20, and mtry from 2 to 8.
- **Model evaluation** using 10-fold cross-validation on the training data and a final fit on a separate test dataset.



Random Forests

Using tidymodels

- **Variable importance** as the importance of each variable to the final models by permutation (standardised by the R^2 of each model).

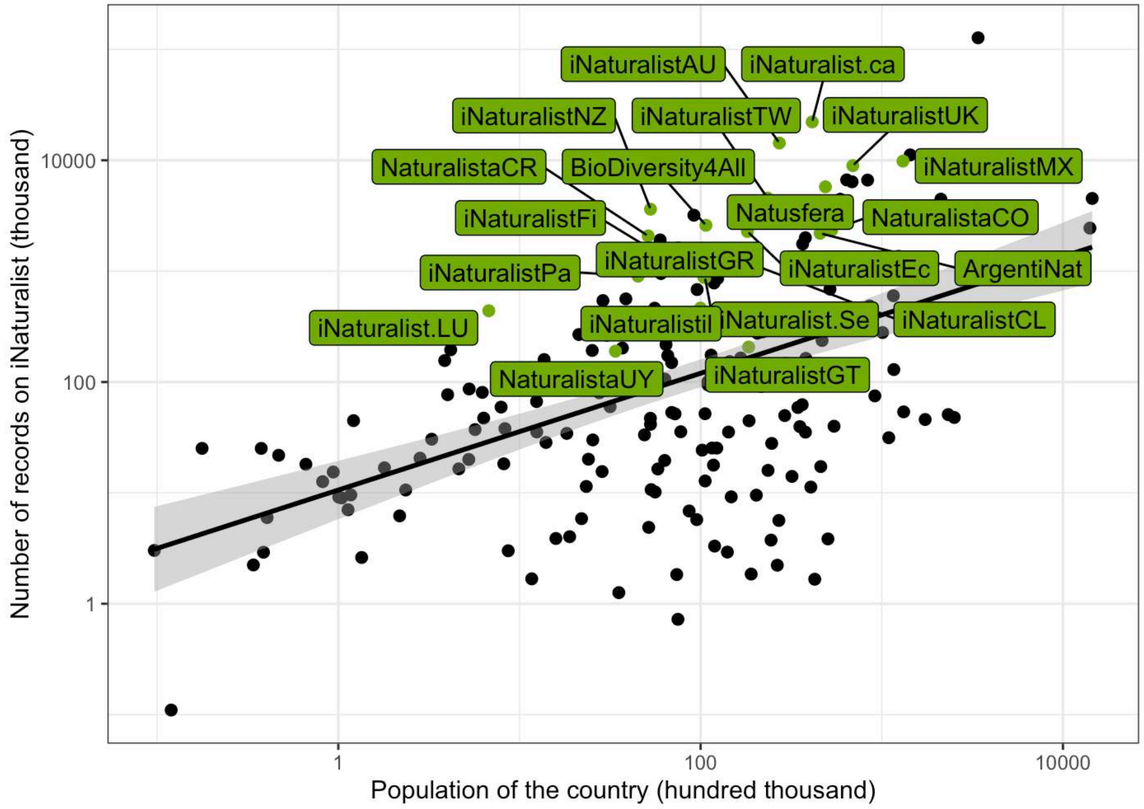


Linear models

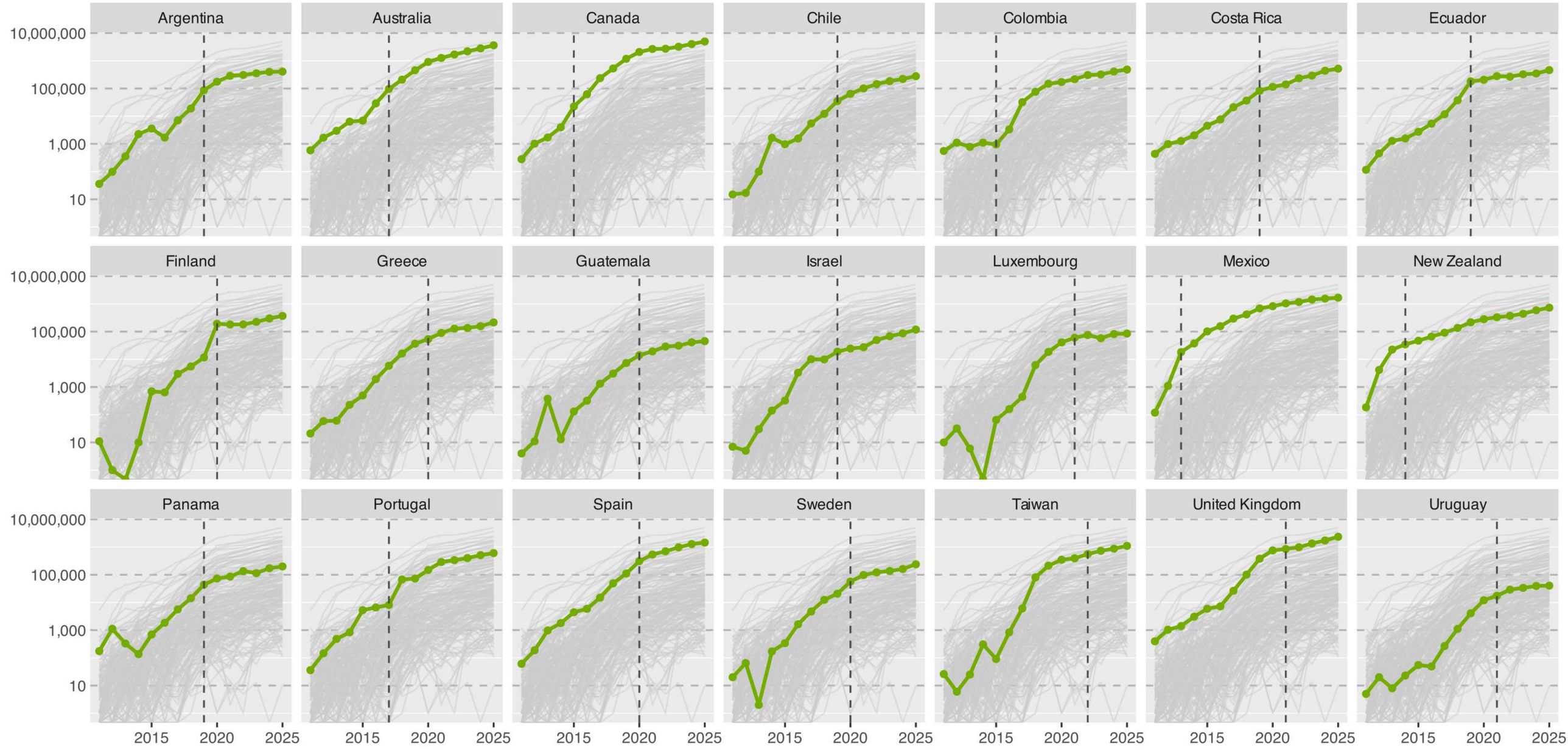
Using lm

not as flexibles

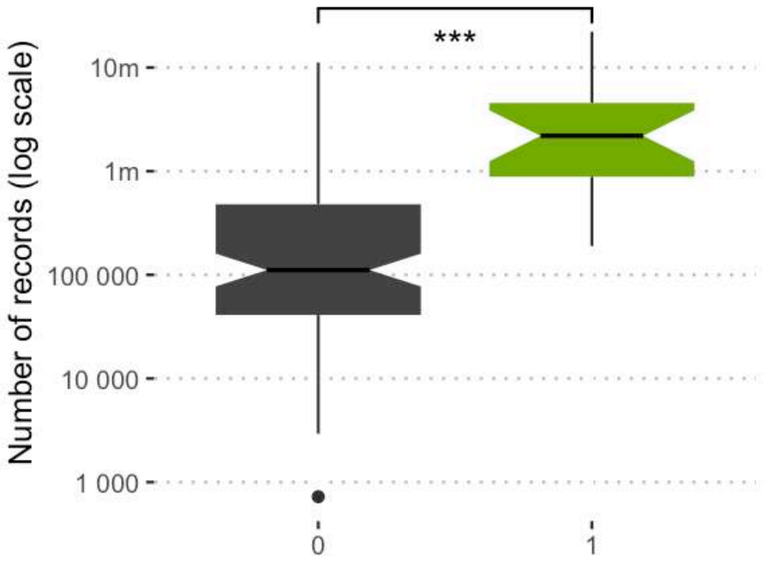
- We fitted linear models (to the same data and using the same model formulas as in the Random Forest analysis) to quantify the specific effect of node membership **while controlling for the remaining predictors**.



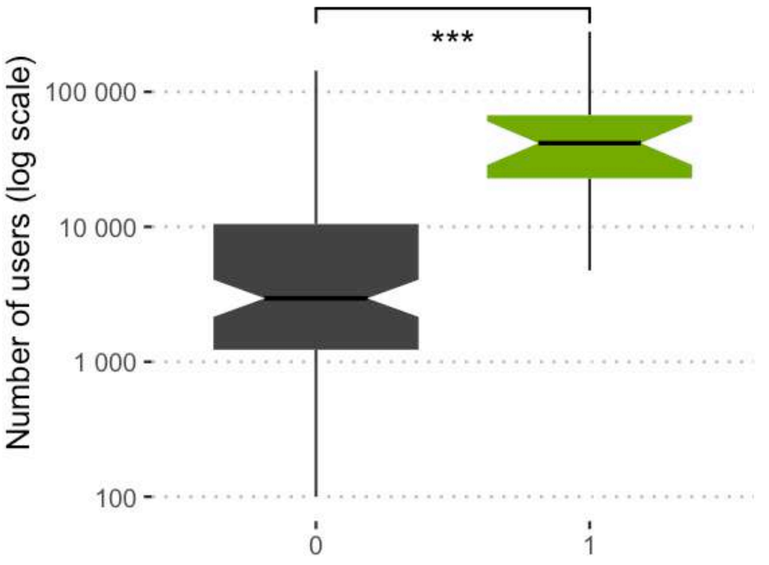
Results


Argentina
Australia
Canada
Chile
Colombia
Costa Rica
Ecuador
Finland
Greece
Guatemala
Israel
Luxembourg
Mexico
New Zealand
Panama
Portugal
Spain
Sweden
Taiwan
United Kingdom
Uruguay
10,000,000
100,000
1,000
10
2015
2020
2025
year the
iNaturalist
node was created

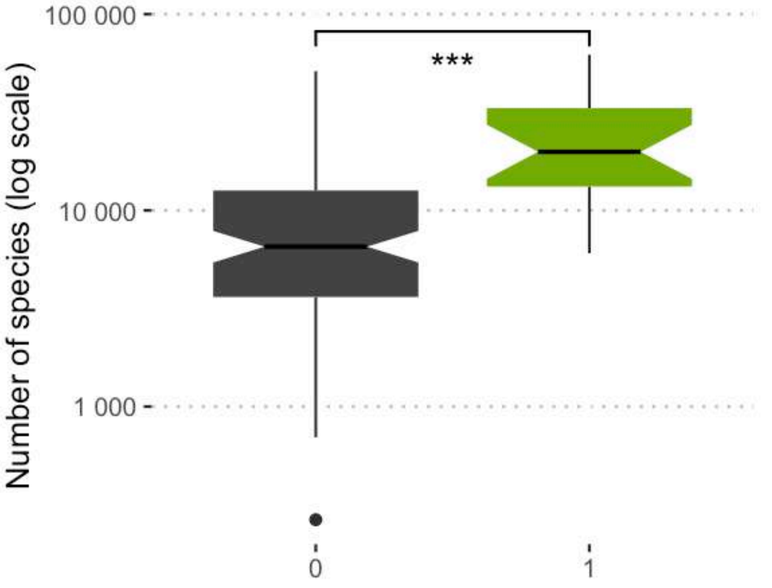
records



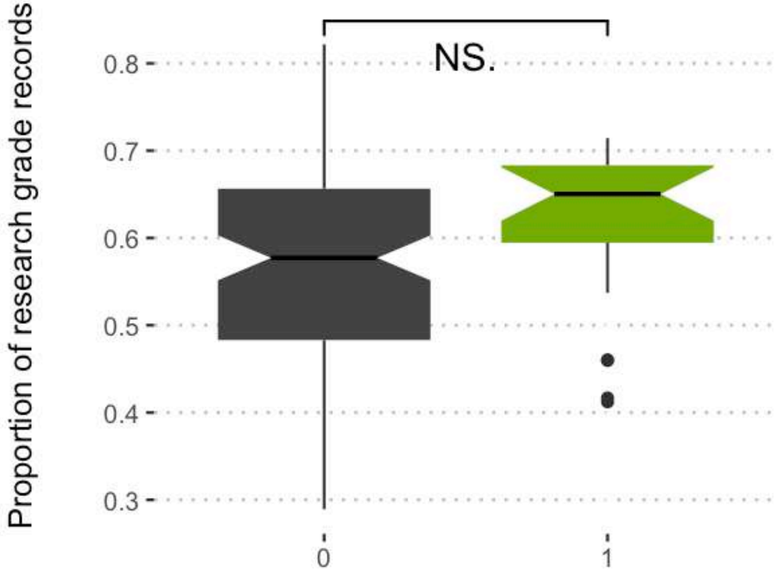
users



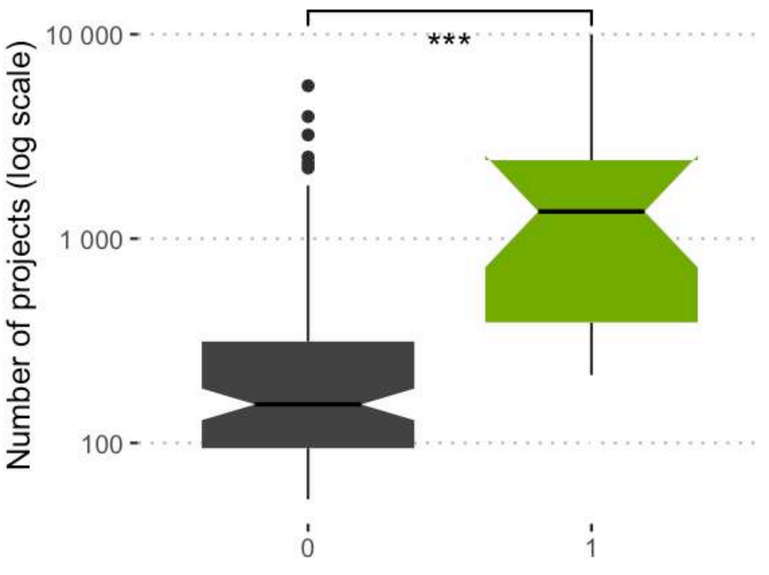
species



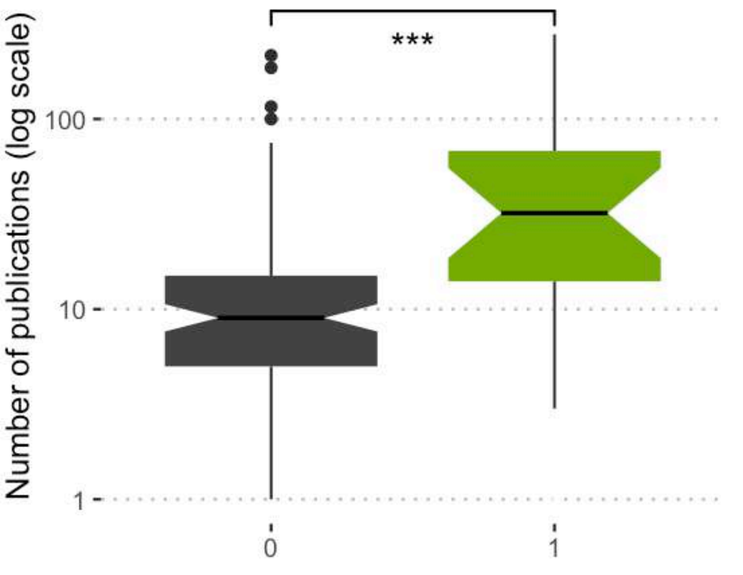
proportion of RG



projects



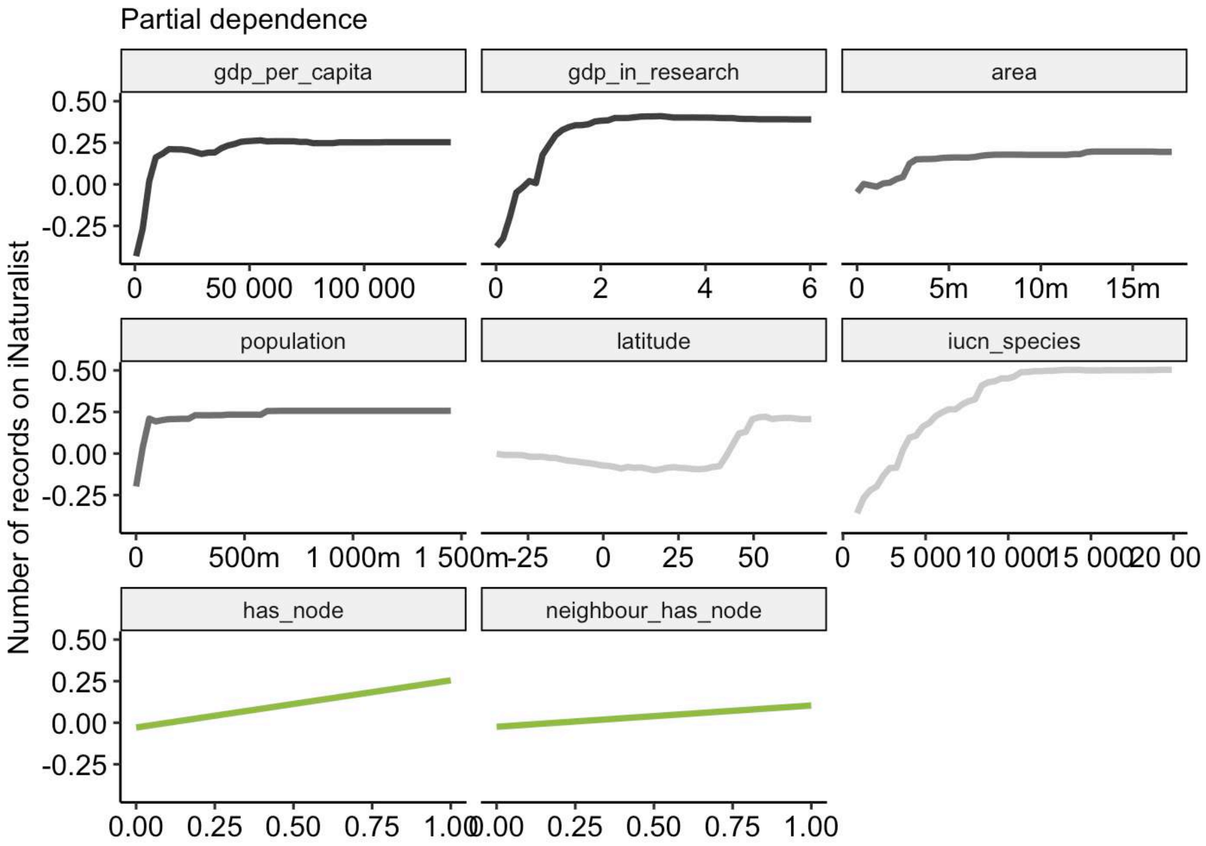
publications

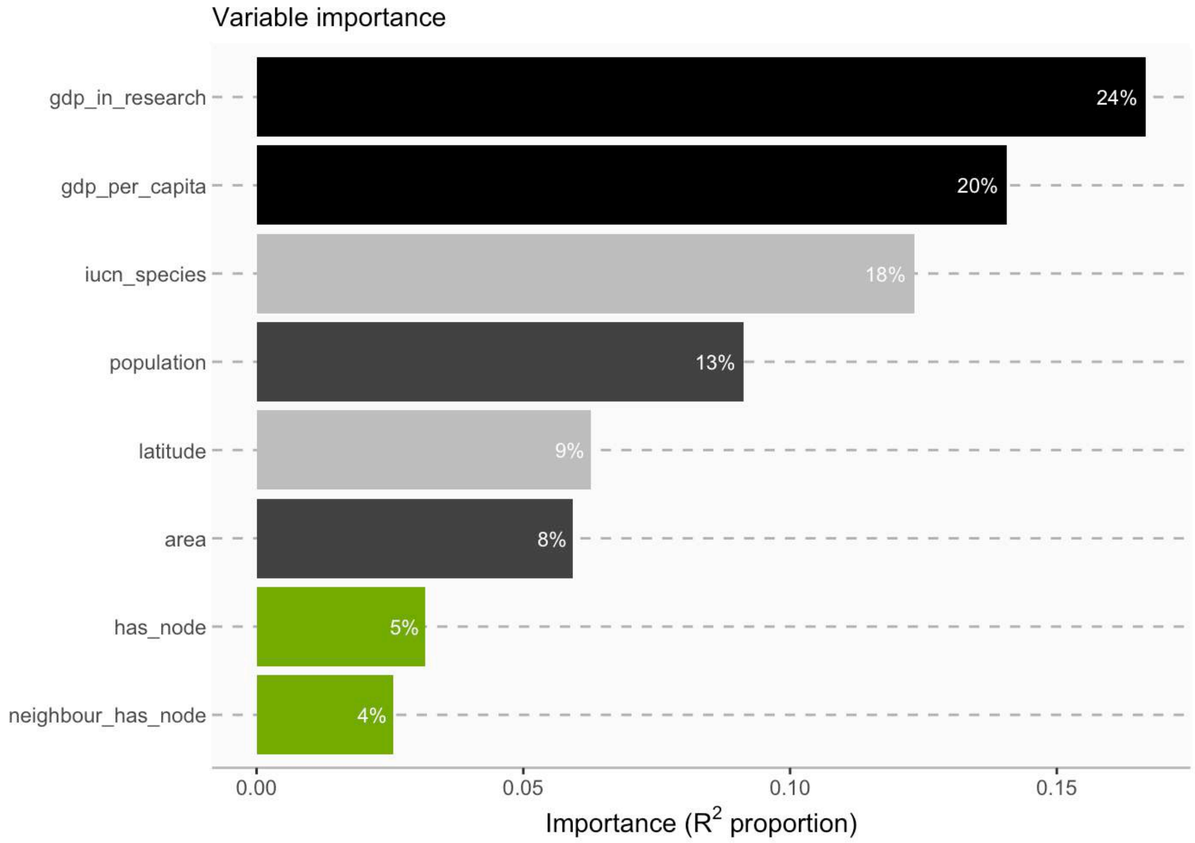


Random forest

model performance	R^2
train	0.967
test	0.701
cross-validation	0.651

number of records

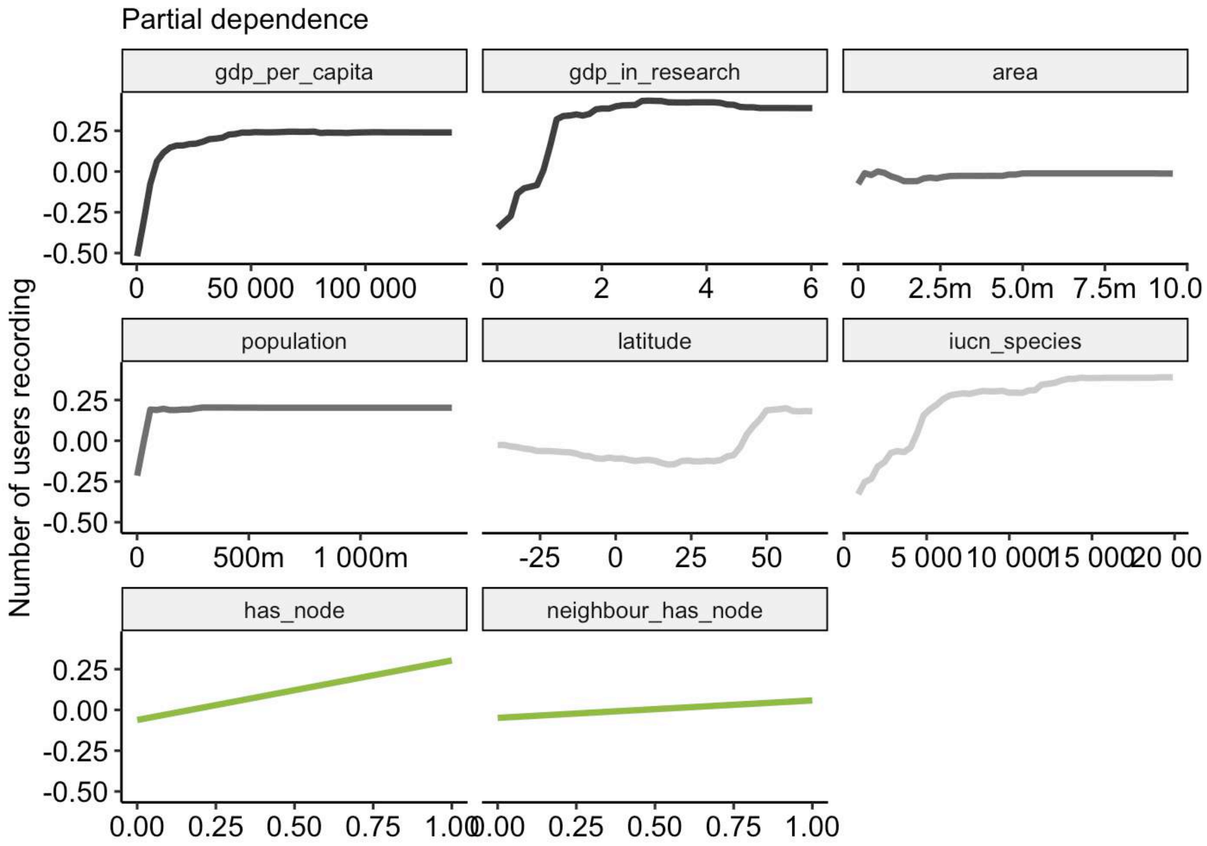


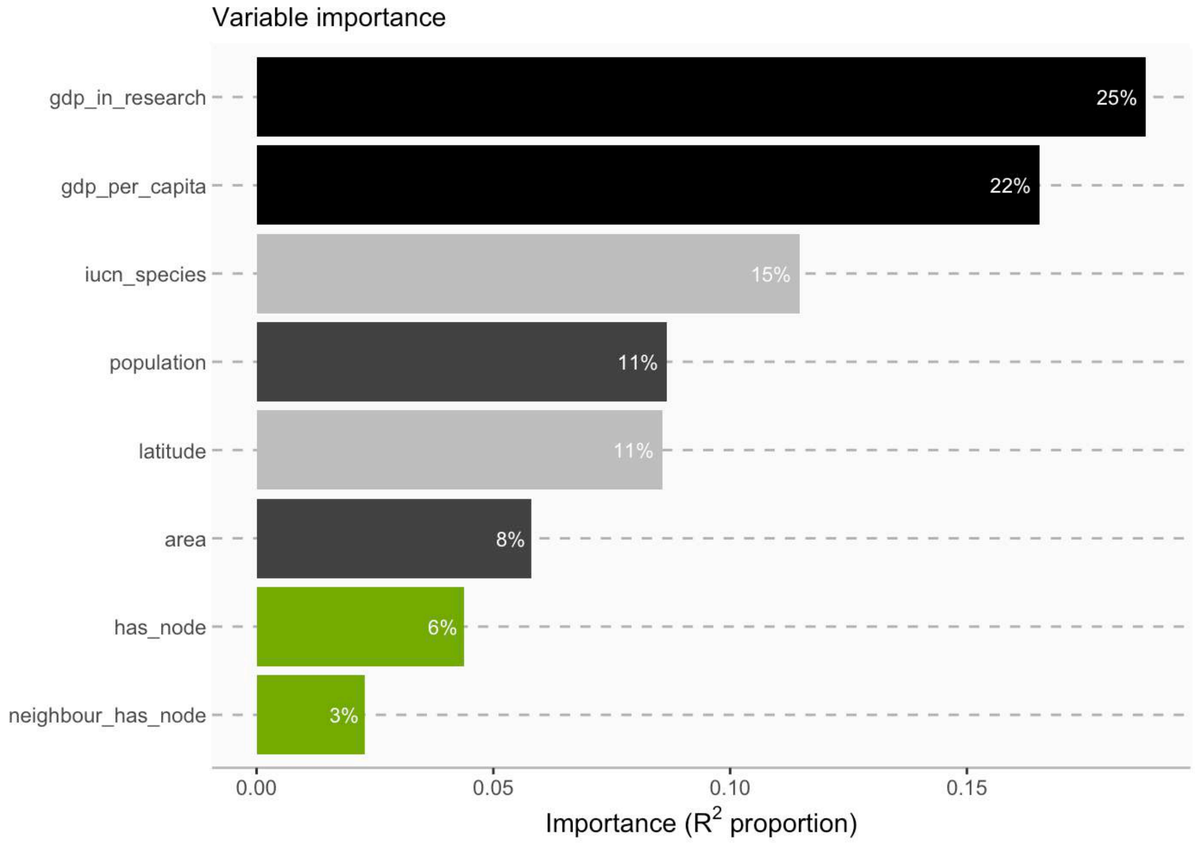


Random forest

model performance	R^2
train	0.972
test	0.765
cross-validation	0.708

number of users

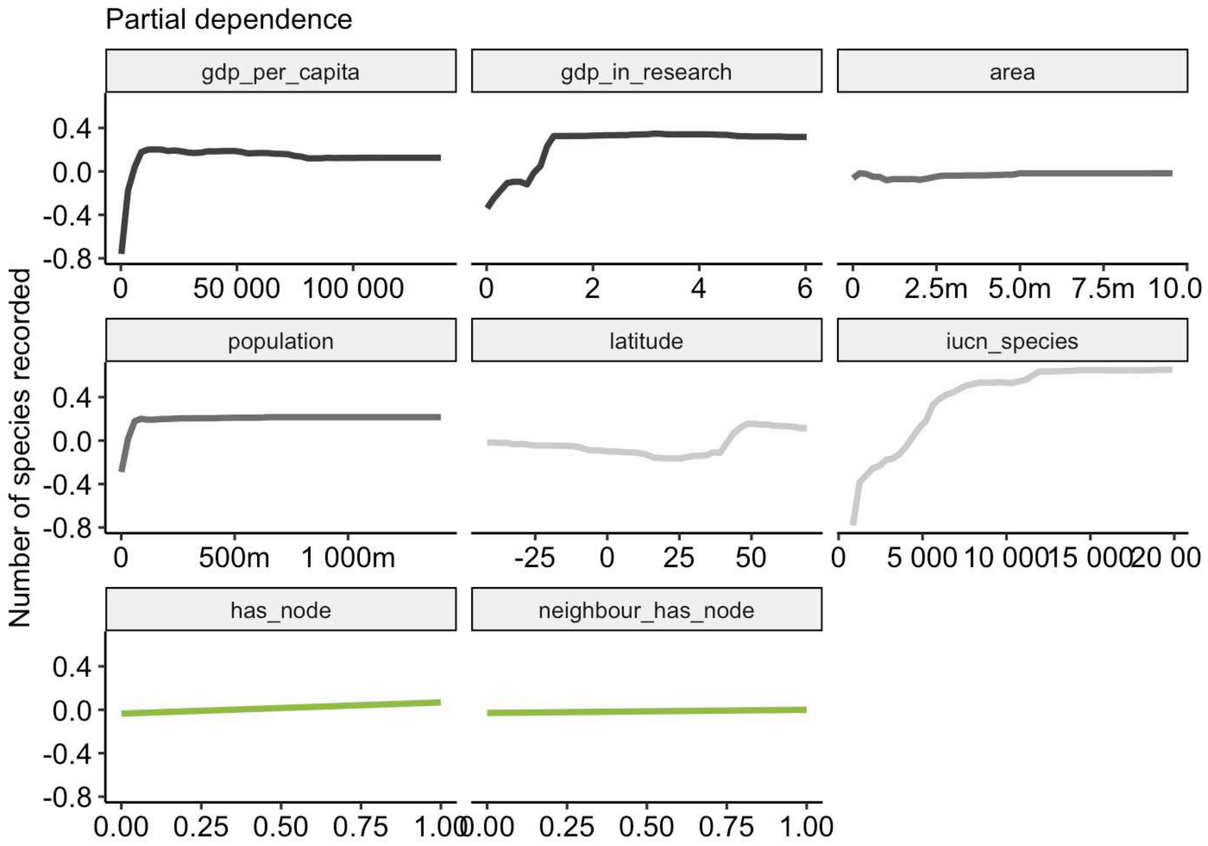


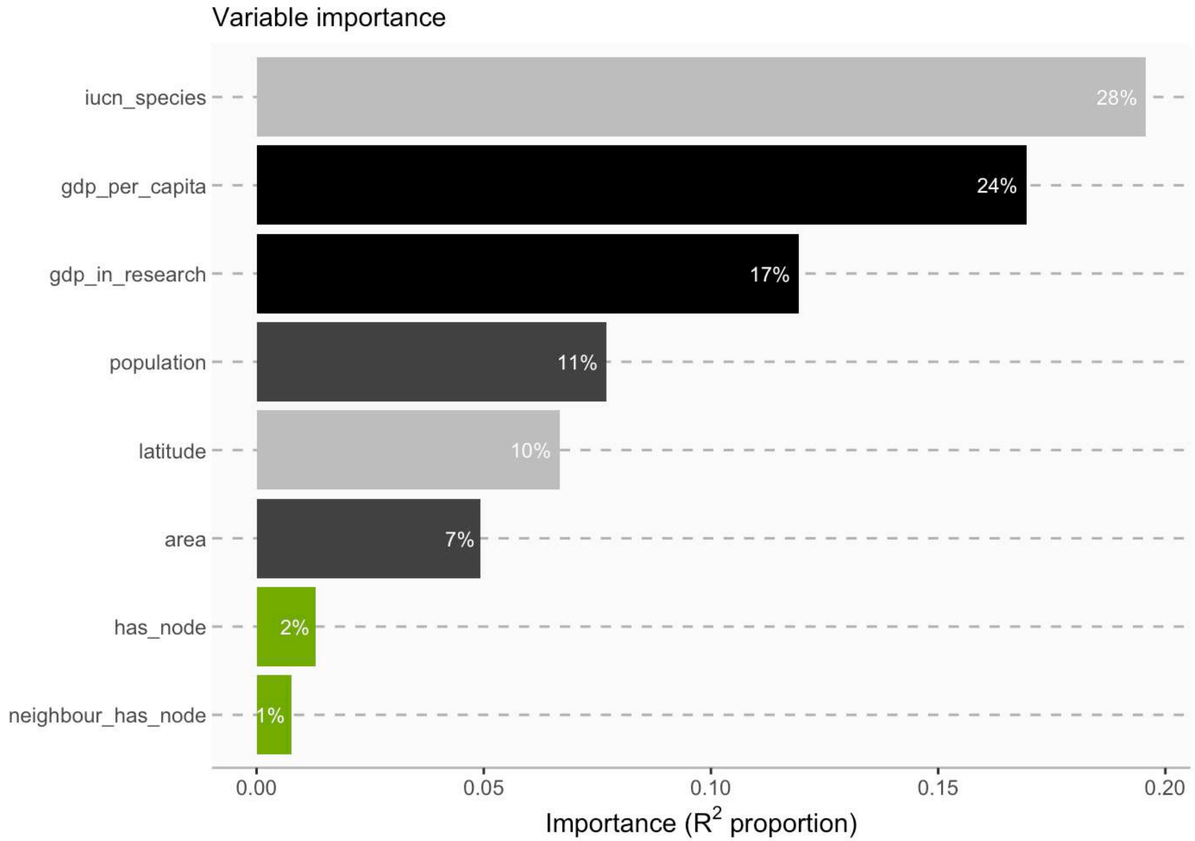


Random forest

model performance	R^2
train	0.968
test	0.698
cross-validation	0.652

number of species

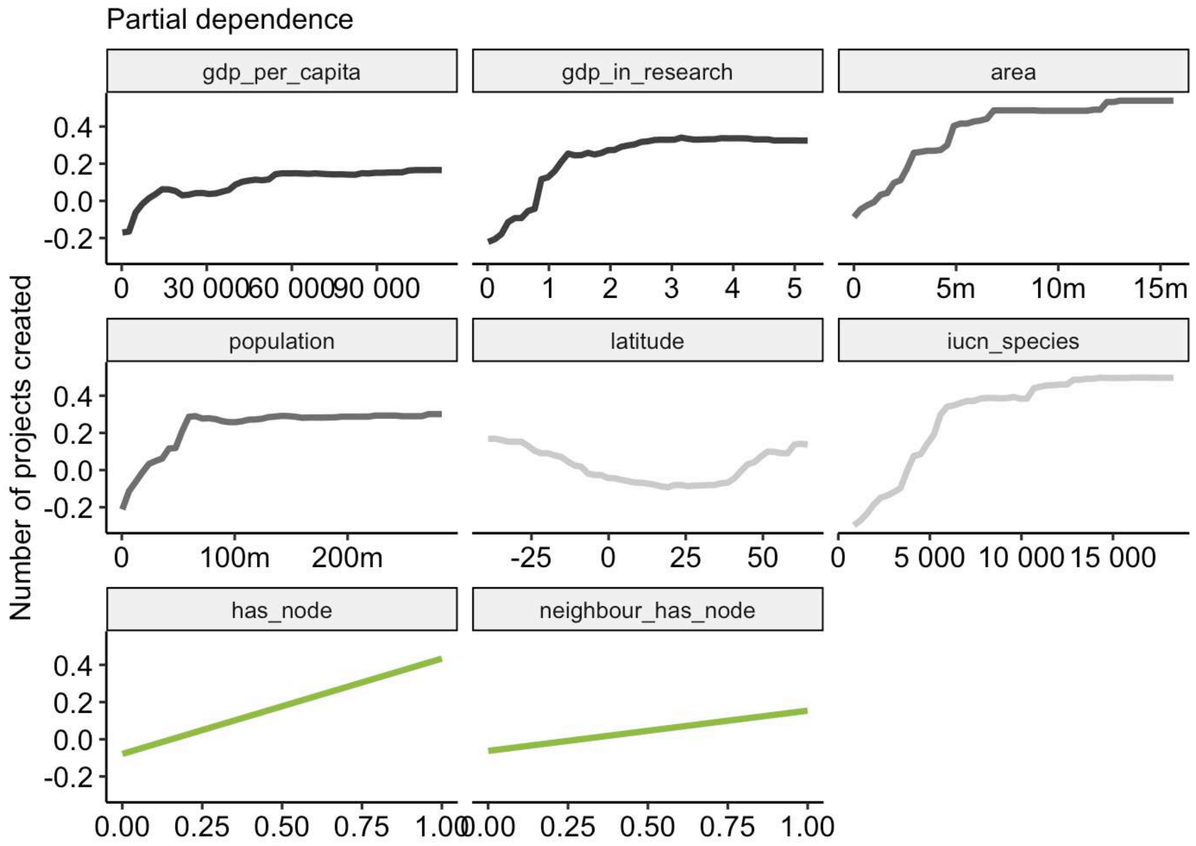


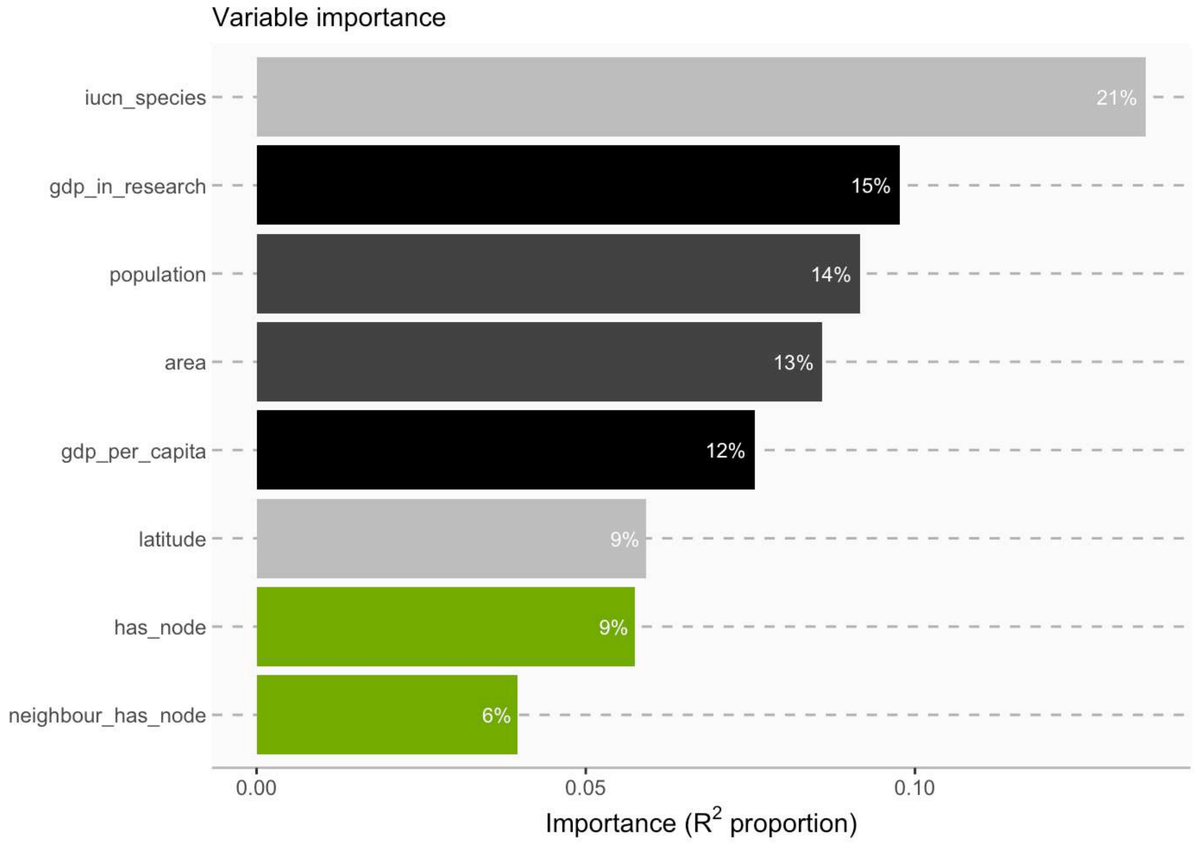


Random forest

model performance	R^2
train	0.975
test	0.642
cross-validation	0.717

number of projects

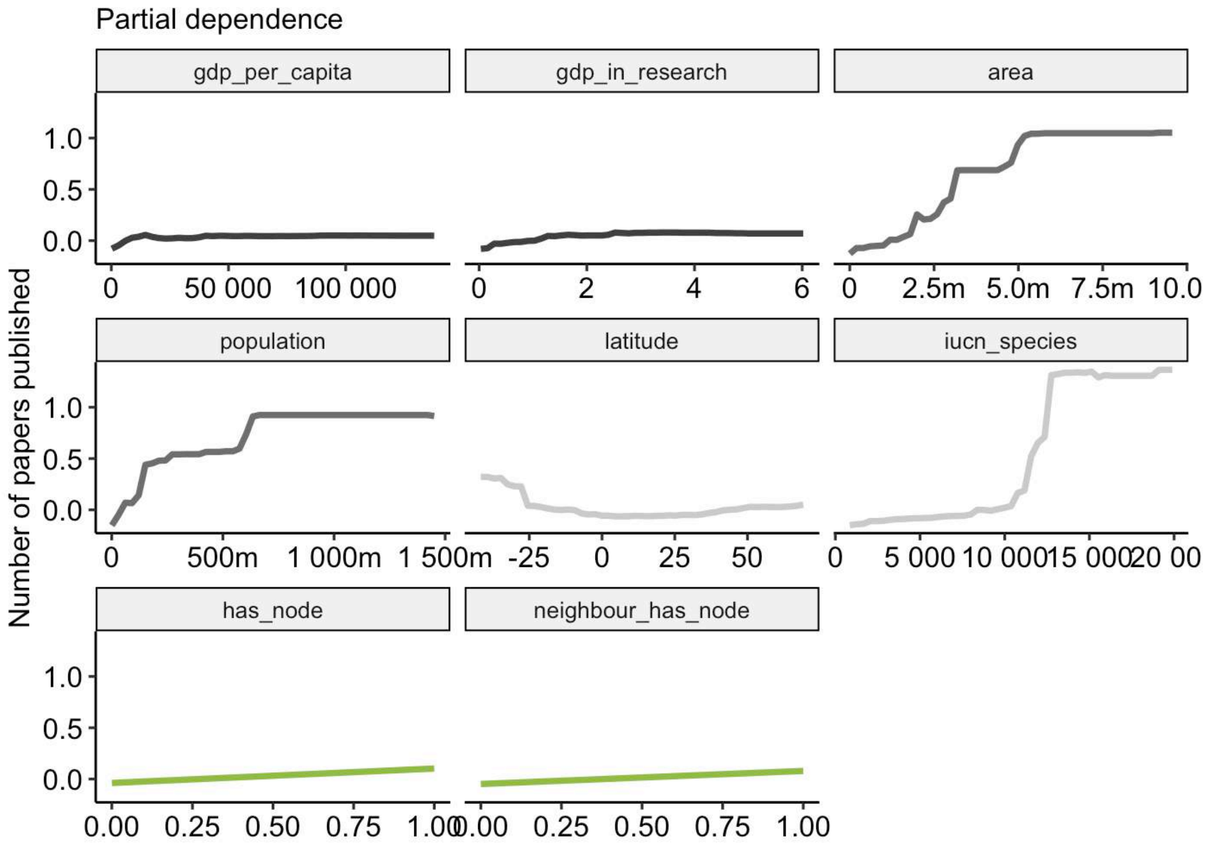


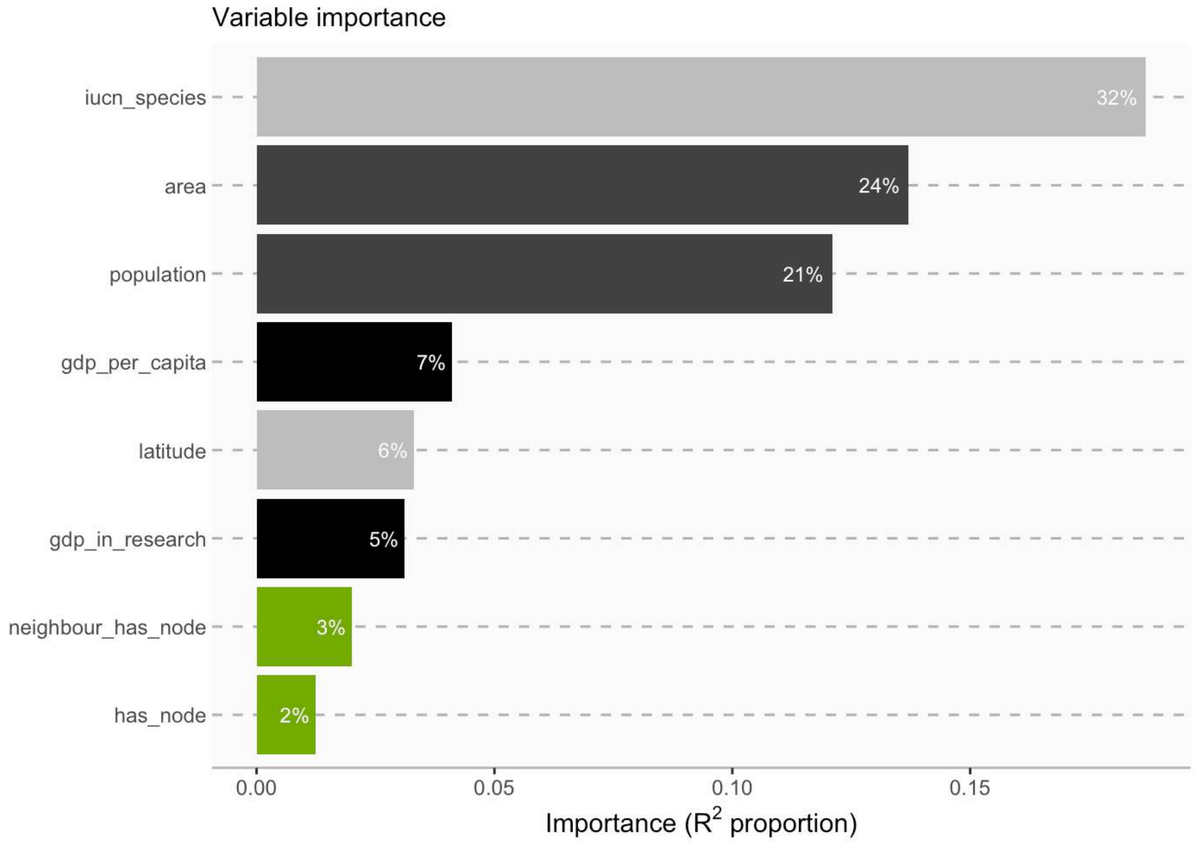


Random forest

model performance	R^2
train	0.965
test	0.583
cross-validation	0.484

number of publications

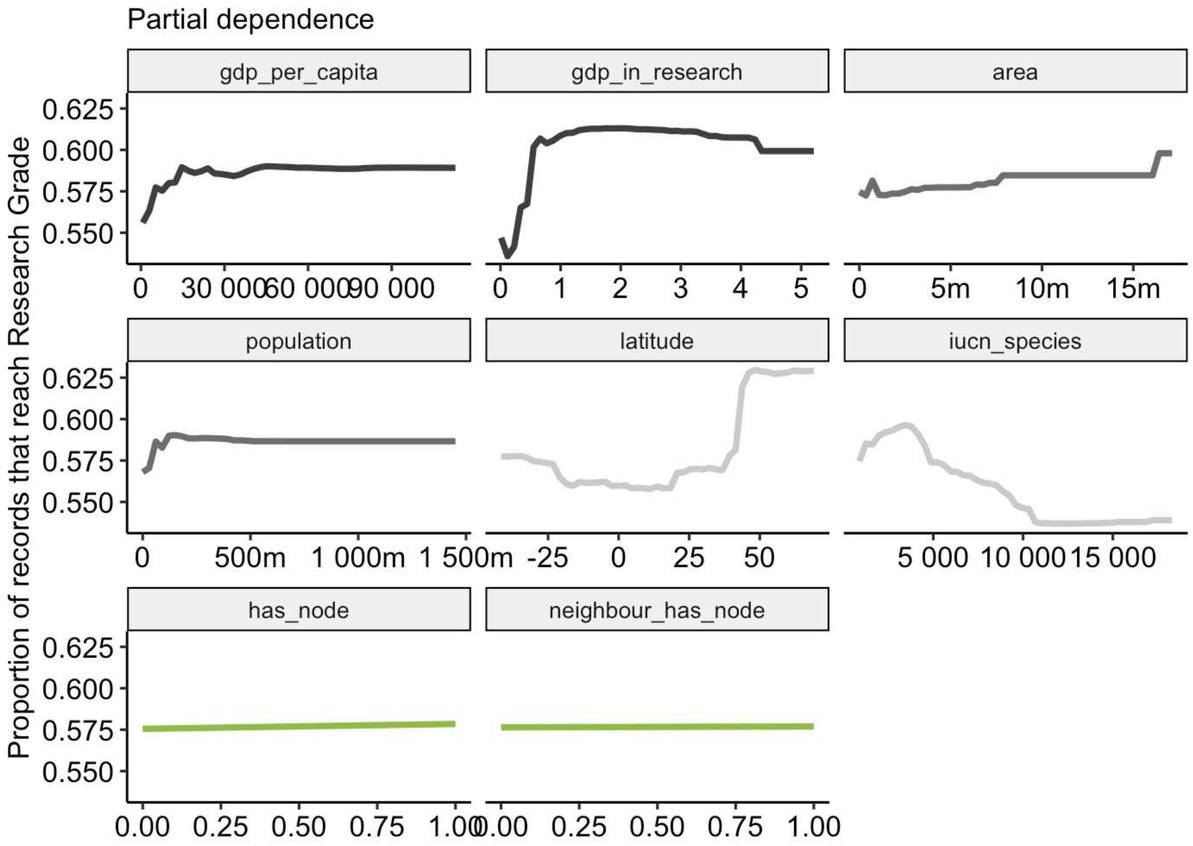


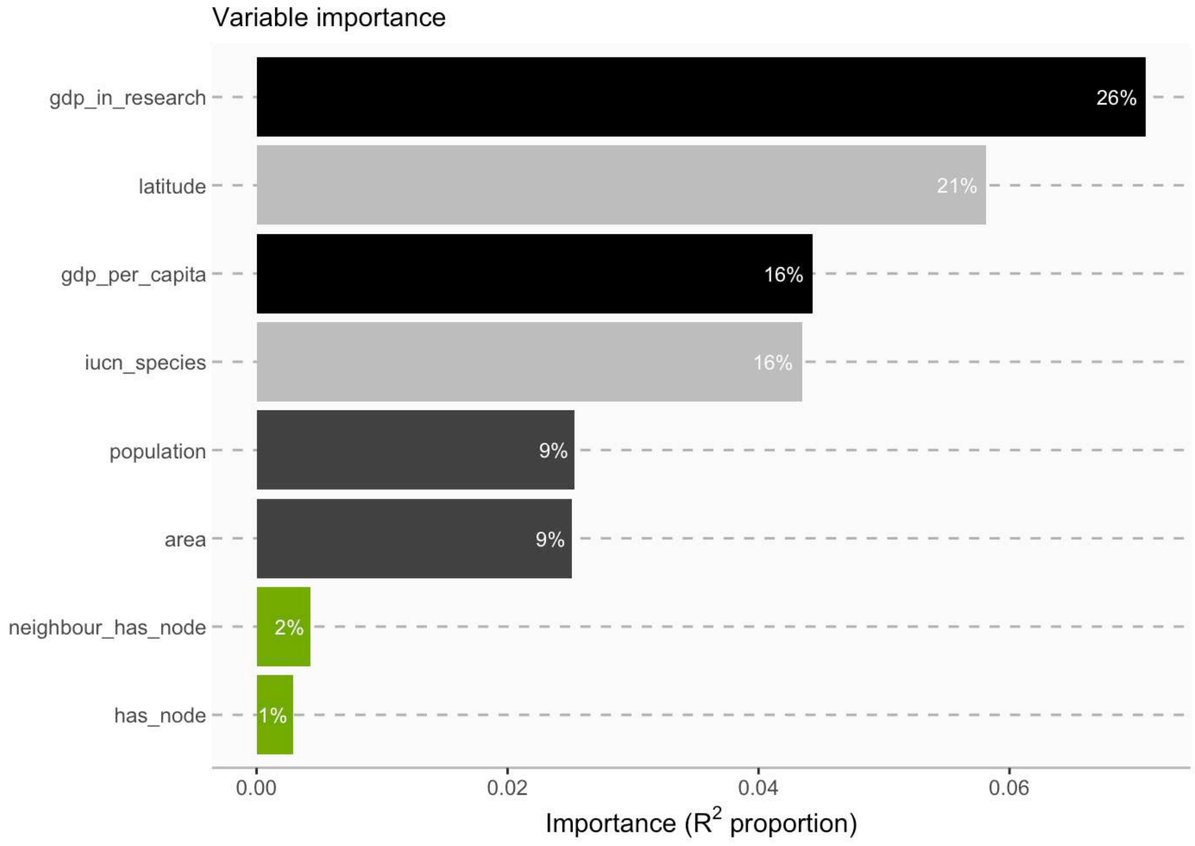


Random forest

model performance	R^2
train	0.951
test	0.274
cross-validation	0.430

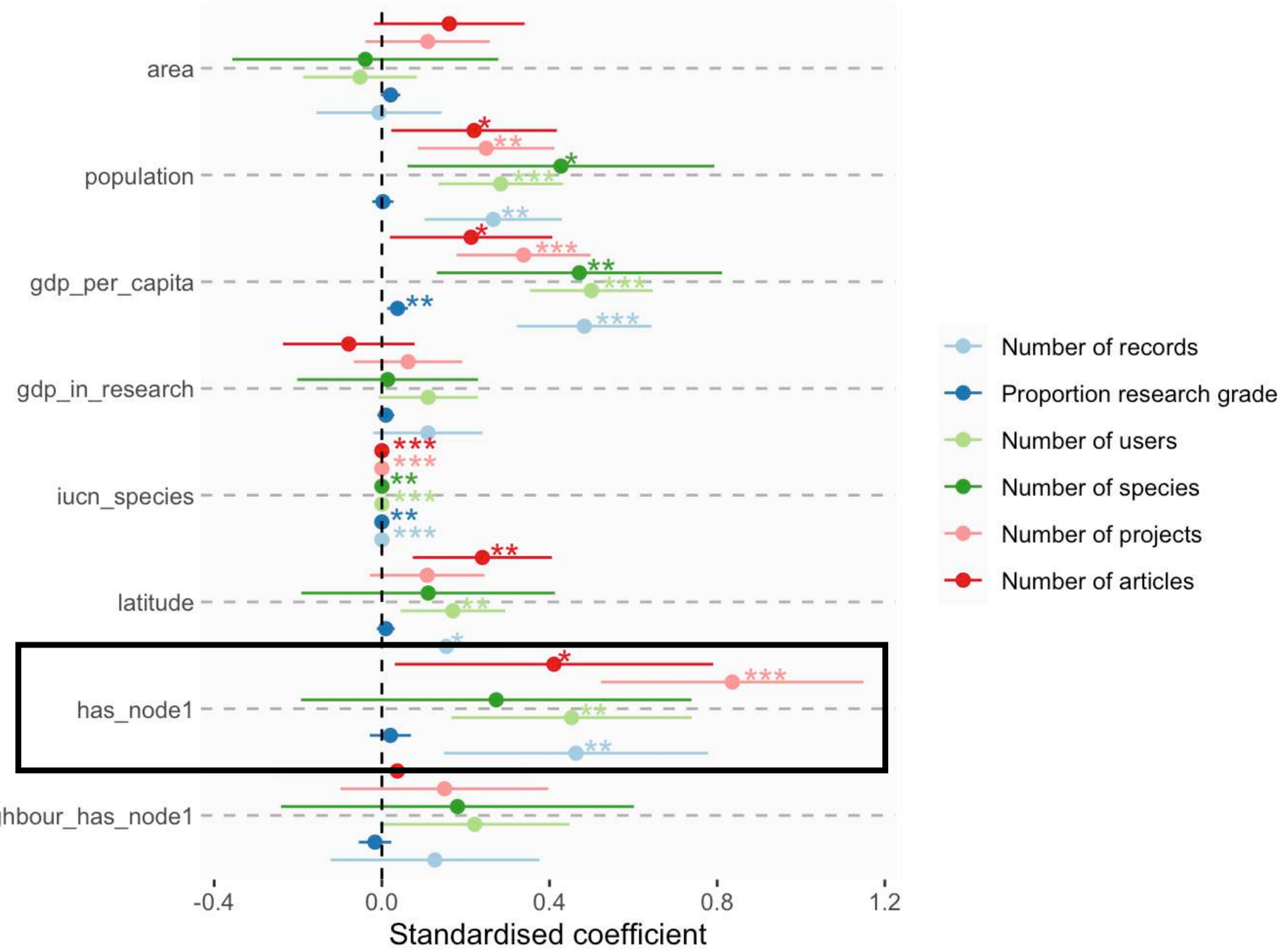
proportion of RG

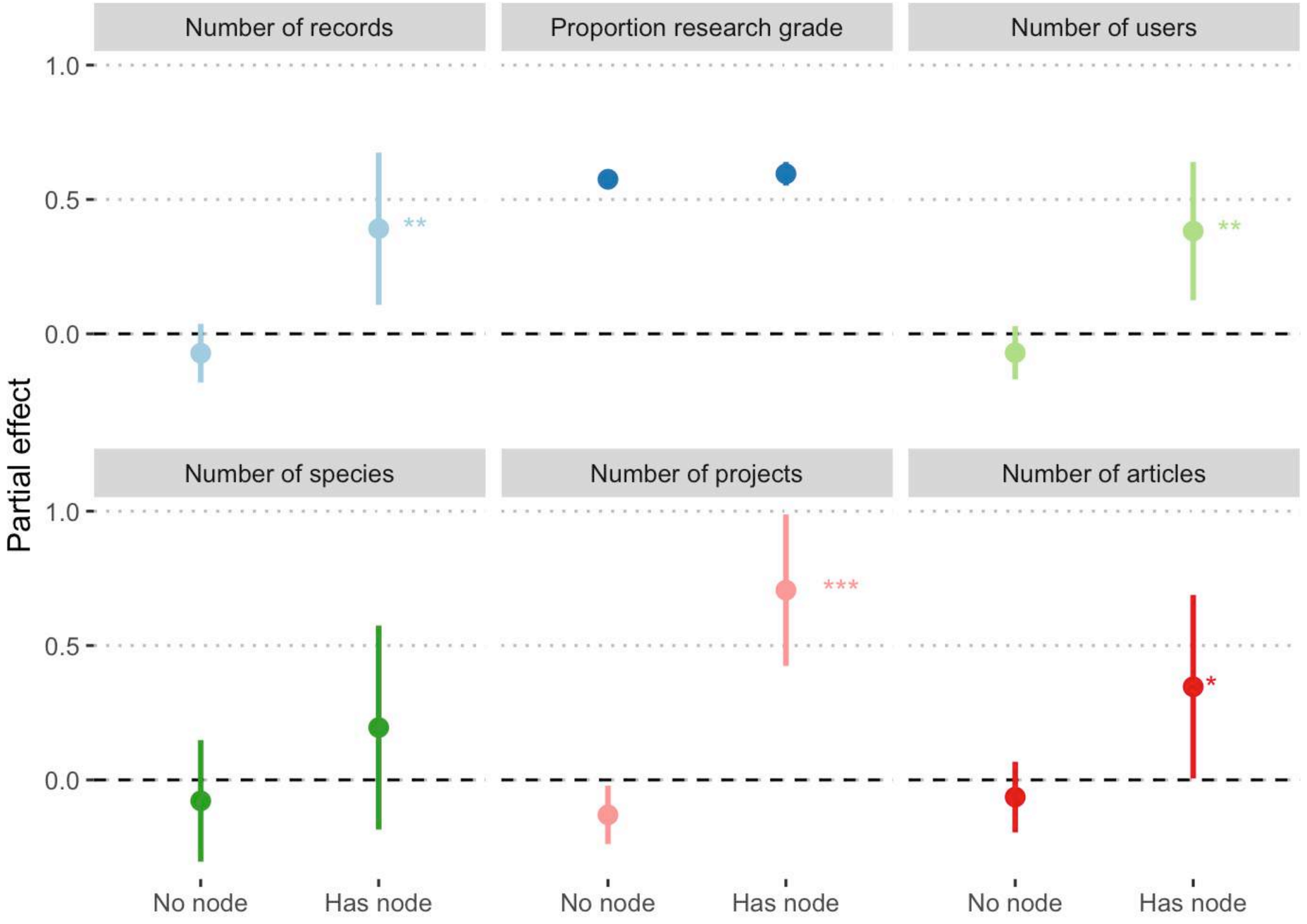




Linear model

response	has_node estimate	adj. model R^2
n_records	0.463**	0.672
n_users	0.453**	0.729
n_species	0.273 **NS**	0.413
n_projects	0.836***	0.675
proportion RG	0.02 **NS**	0.308
n_literature	0.411*	0.523




Number of records
Proportion research grade
Number of users
Number of species
Number of projects
Number of articles
Partial effect
1.0
0.5
0.0
**
**
***
*
No node
Has node
No node
Has node
No node
Has node

So...

How important is having a node?

Variable	Description	Random forest	Linear model
n_records	Number of records on iNaturalist in the country	5% of R^2	0.463**
n_users	Number of users that uploaded at least one observation in the country (regardless of their country of residency)	6% of R^2	0.453**
n_species	Number of species recorded in the country	2% of R^2	NS
n_projects	Number of projects registered by country	9% of R^2	0.836***
n_literature	Number of peer-reviewed publications indexed by GBIF that use iNaturalist data with a documented geographic focus on the country	3% of R^2	0.411*
p_research_grade	Proportion of records on iNaturalist in the country that are “Research Grade” (as a proxy for data quality)	2% of R^2	NS

GDP per capita and biodiversity

GDP per capita and biodiversity

Conclusions

- Having a node on the iNaturalist Network is **important** (local efforts matter!) — mostly for having more records, users, projects and derived publications.
- Nationally organised efforts have thus played a significant role in driving iNaturalist's worldwide growth, extending its reach well beyond its US origins.

Conclusions

- Our work suggests that institutional support and local organisational structures can strongly influence the long-term effectiveness and sustainability of citizen-science initiatives.

- While much citizen science research focuses on individual motivations or local project design, our findings show that large-scale institutional design, in the form of national coordinated nodes, plays a critical role in mediating between global platforms and local engagement.

That's all!

The impact of nationally organised efforts on global citizen-science platforms

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