LMU LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN

Identification of Health Risk Factors in Developing Countries using Intrinsic Model Selection Approaches

Daniel Seussler
Master‘s Thesis

supervised by Dr. Cornelius Fritz
Department of Statistics

Introduction

Introduction

Objective:

- Identification of risk factors of two common disease burdens in sub-Saharan Africa.
- Statistically, how to approach moderate dimensional regression where effect selection is necessary, and how to approach predictive modelling with binomial data where inference on the underlying risk is desired.

Methodology:

- Component-wise (model-based) boosting with intrinsic variable selection and model choice.

Data Source: Demographic and Health Surveys (DHS)

- Large N household surveys in low- and middle income countries collect data on important population health and socio-economic characteristics.
- Often used in the epidemiological literature due to it’s temporal compatibility and representative samples, e.g., in the research of determinants of disease burdens.

- I use the Madagascar 2021 Standard DHS and the Mali 2021 Malaria Indicator Survey (MIS).

Component-wise boosting for variable selection and model choice

Component-wise boosting

Functional gradient boosting: estimate function by numerical optimisation in function space (Friedmann 2001).

Very popular in the literature given it’s superiority in many tasks (XGBoost). Generally boosted trees but a model based approach is also possible (Bühlmann and Yu 2003, Bühlmann and Hothorn 2007).

Boosting additive models (component-wise). In a generalised additive regression:

$$E(y|\mathbf{x}) = h(\eta(\mathbf{x}))$$

$$\eta(\mathbf{x}) = \beta_0 + \sum_{j=1}^{J} f_j(\mathbf{x}).$$

We define the following optimisation problem

$$\arg\min_{\eta} = E(\rho(y, \eta))$$

where ρ is the negative log-likelihood (i.e., loss) and replace the expectation with the empirical risk

$$R = n^{-1} \sum_{i=1}^{n} \rho(y_i, \eta).$$

Component-wise boosting

Init $\hat{\eta}^{[0]}$ and define a set of base-learners $b_l, l = 1, \dots, L$. In each iteration m refit each to the negative gradient

$$u_i = -\frac{\partial}{\partial \eta} \rho(y_i, \eta) \Big|_{\eta = \eta^{[m-1]}(\mathbf{x}_i)}$$

and select the best-fitting learner b_{l*} by residual-sum-of-squares.

Update $\hat{\eta}^{[m]}$

$$\hat{\eta}^{[m]} = \hat{\eta}^{[m-1]} + \nu \hat{b}_{l*}$$

where the parameter ν is $0 < \nu \ll 1$.

Early stopping (to avoid overfitting and improve generalisation error) can be achieved through holdout sets and resampling methods (k-fold cv, bootstrap etc.).

- Intrinsic selection of learners as in each iteration exactly *one* learner is added to the additive predictor.
- Effect selection by decomposition of smooth effects (Kneib et al. 2009). Allows to choose none, linear, non-linear effects.
- Many statistical tasks covered: survival analysis, quantile regression (Fenske et al. 2011), multivariate distributions (Strömer et al. 2021) and copulas (Hans et al. 2022).

Component-wise boosting

Distributional regression (or GAMLSS: Generalised Additive Models for Location, Scale and Shape)

➔ Allows modelling of each distribution parameter with a seperate additive predictor.

➔ Algorithm: non-cyclical boosting. In each iteration both the learner *and* the parameter are selected jointly for an update. (see Thomas et al. 2018)

Uncertainty quantification

➔ Subsampling replications or bootstrap replications of the model, but: no theoretical guarantees of coverage.

➔ Use it to assess stability of estimated coefficients.

➔ Stability selection (Meinshausen and Bühlmann 2010) allows for finite sample control of Type 1 error for variable selection, but: very conservative.

Case Studies

Case Study 1: Childhood malnutrition in Madagascar

Objective: Identification of risk factors (or determinants).

Outcome: child is stunted yes / no
(height-for-age score is more than 2σ below the reference)

Explanatory Covariates:

- Individual-level risk factors (age, gender, mother’s bmi, if twin, etc.) ,
- household- (no. of household members, DHS wealth index, etc.),
- and community-level (urbanicity, distance to healthcare facilities etc.).

Additional Specifications:

- Decomposition of smooth effects for continuous covariates to allow for effect selection.
- Markov random field for administrative regions (first-order neighbourhood structure).

Case Study 2: Geographic malaria risk in Mali

Objective: Identification of environmental correlates of malaria prevalence and inference of risk.

Outcome: *k* children out of *n* tested positive in cluster *c*, i.e., binomial.

- Following Dong and Wakefield 2021, I model the outcome with a beta-binomial distribution that accounts for cluster overdispersion due to within-cluster variability.

Explanatory Covariates:

- Elevation, land surface temperature (day/night), rainfall - aggregated annually (mean / sum).
- Vegetation indices, NDVI and EVI.
- Population (Global Human Settlement Layer Data).
- Urbanicity variable to account for survey design.

Additional Specifications:

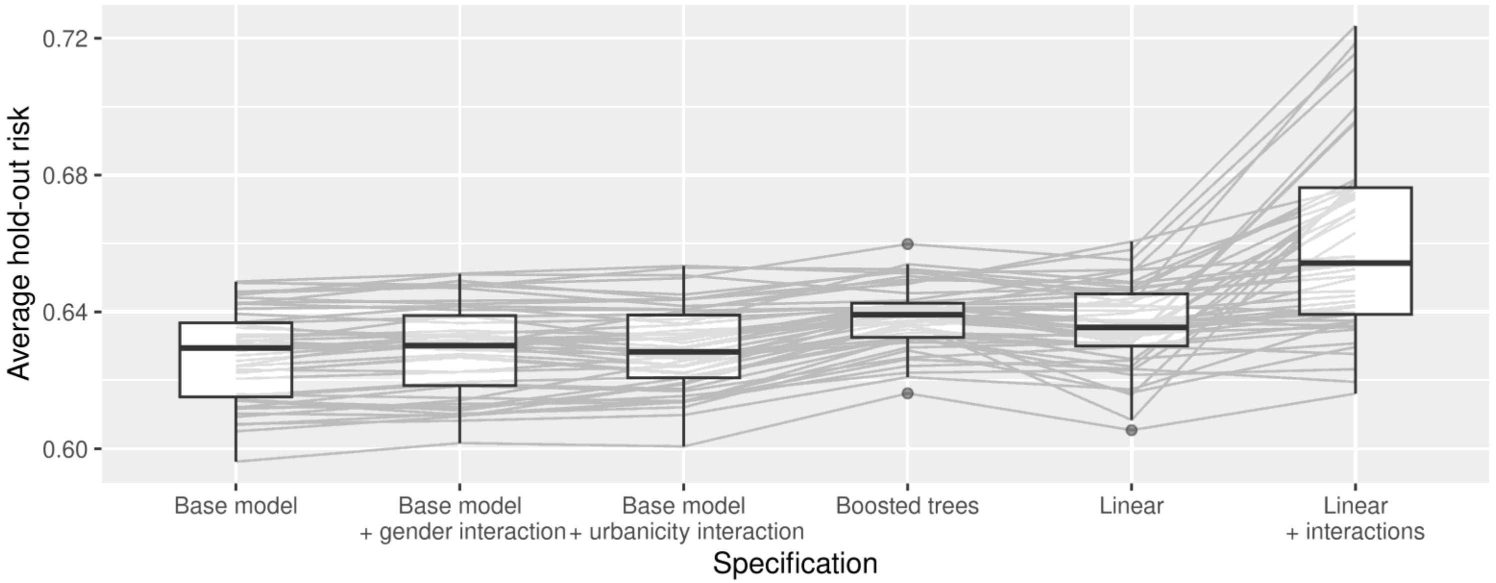
- Decomposition of smooth effects for continuous covariates to allow for effect selection.
- Bivariate tensor P-spline to model spatial effects.

Results

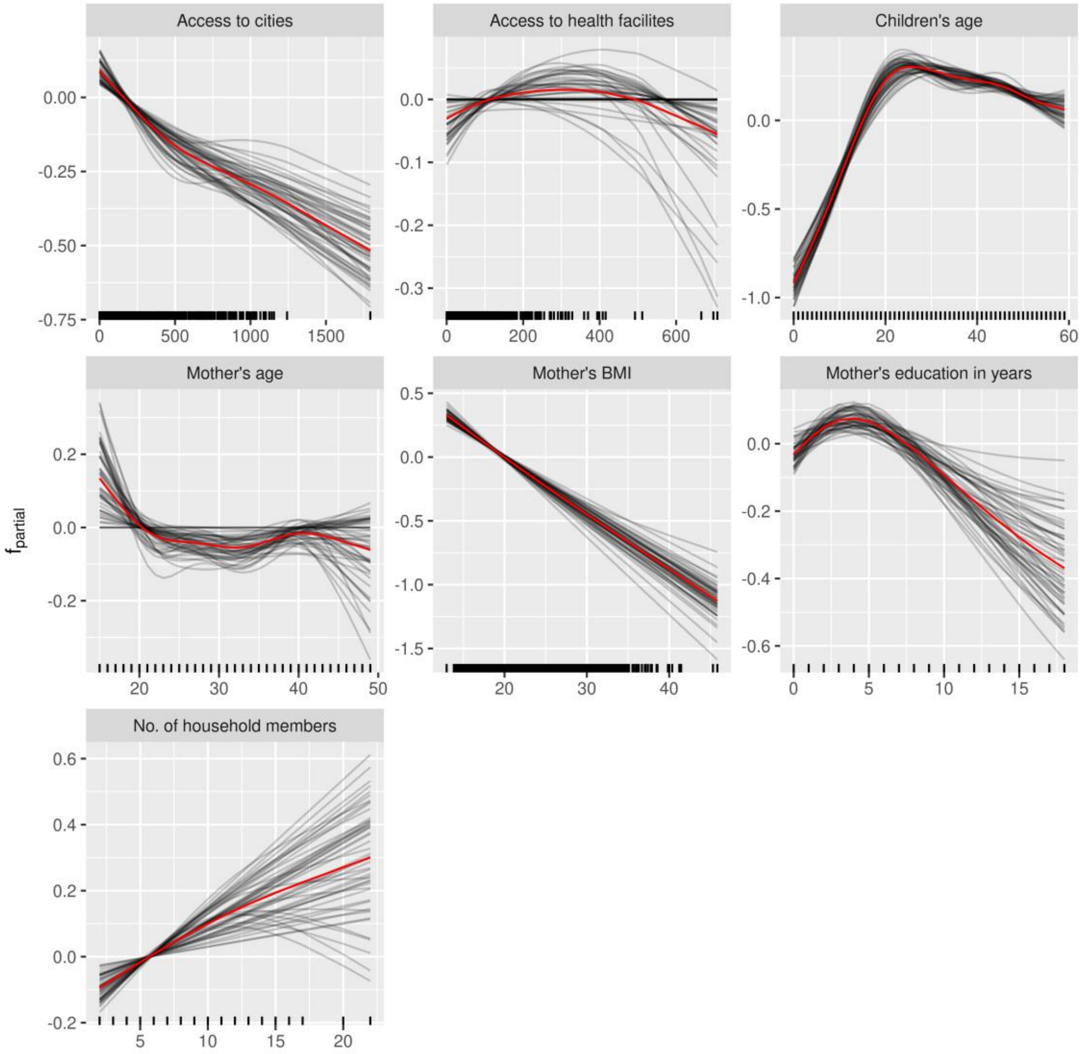
Childhood malnutrition in Madagascar

Model selection

- by three-way holdout method (70/20/10), no. of boosting iterations selected optimal performance on validation set.
- Following results based on 50 subsampling replications. Red line indicates pointwise average.

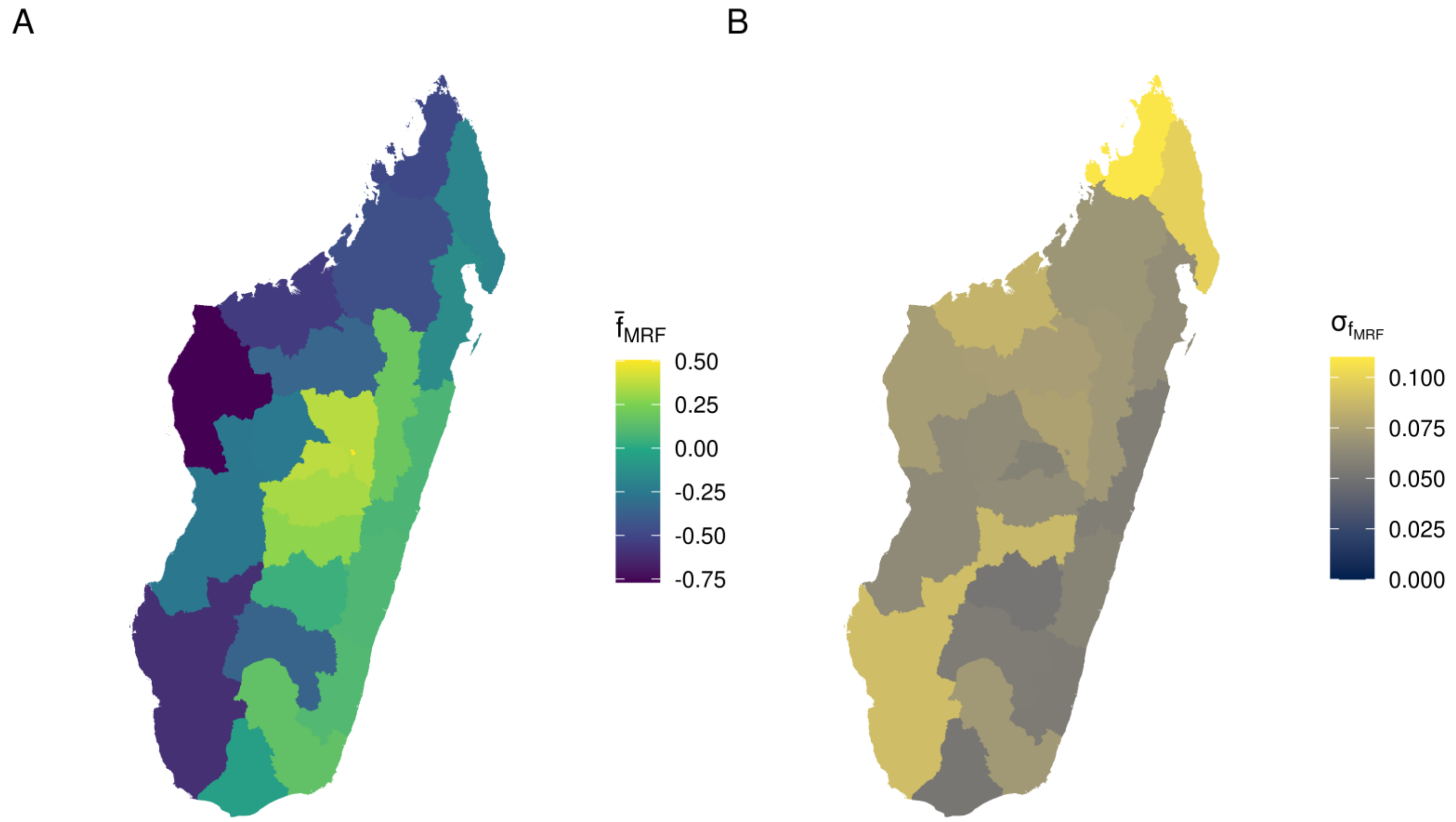


Childhood malnutrition in Madagascar



- Estimated effects of the continuous covariates.

Childhood malnutrition in Madagascar



- Markov random field effect for admin 1 regions, mean (A) and standard deviation (B) of the subsampling replications.

Geographic malaria risk in Mali

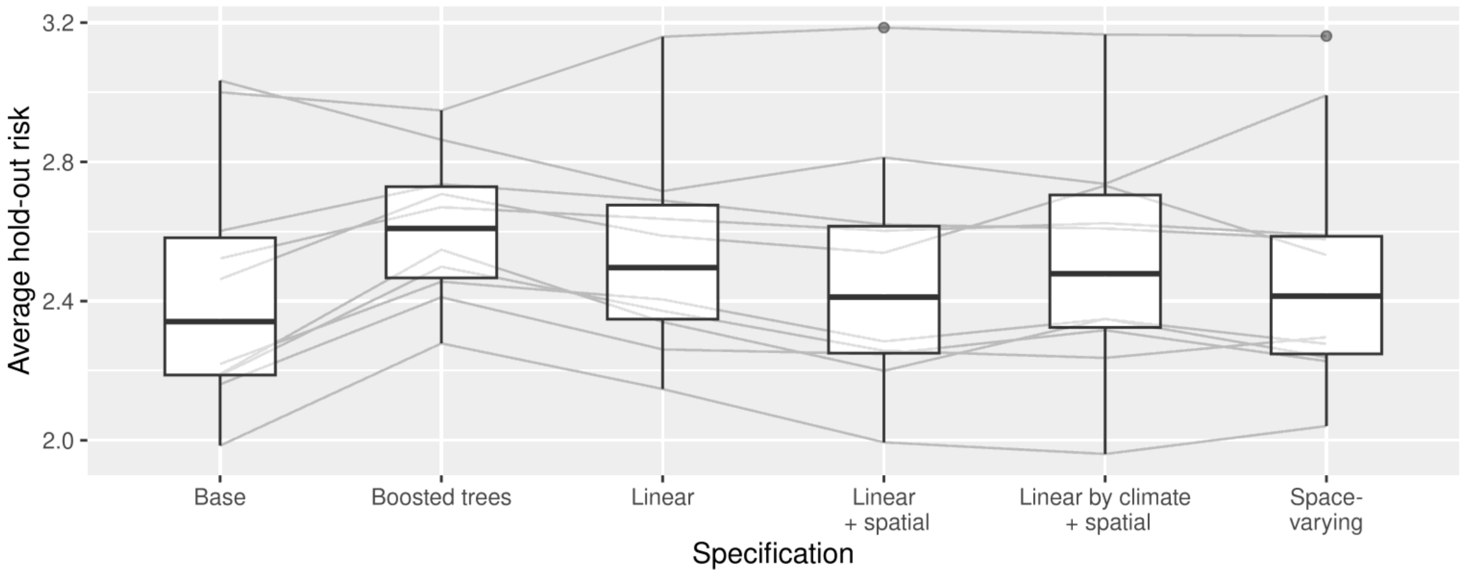
Model validation and selection

- by nested cross-validation (10-fold, stratified by region)
- comparison of base specification to boosted trees and
  - Linear
  - Linear + bivariate tensor P-spline
  - Linear + climate interactions + bivariate tensor P-spline
  - Linear + spatially-varying coefficient

Early stopping by 10-fold cross-validation. Uncertainty quantification with bootstrap samples.

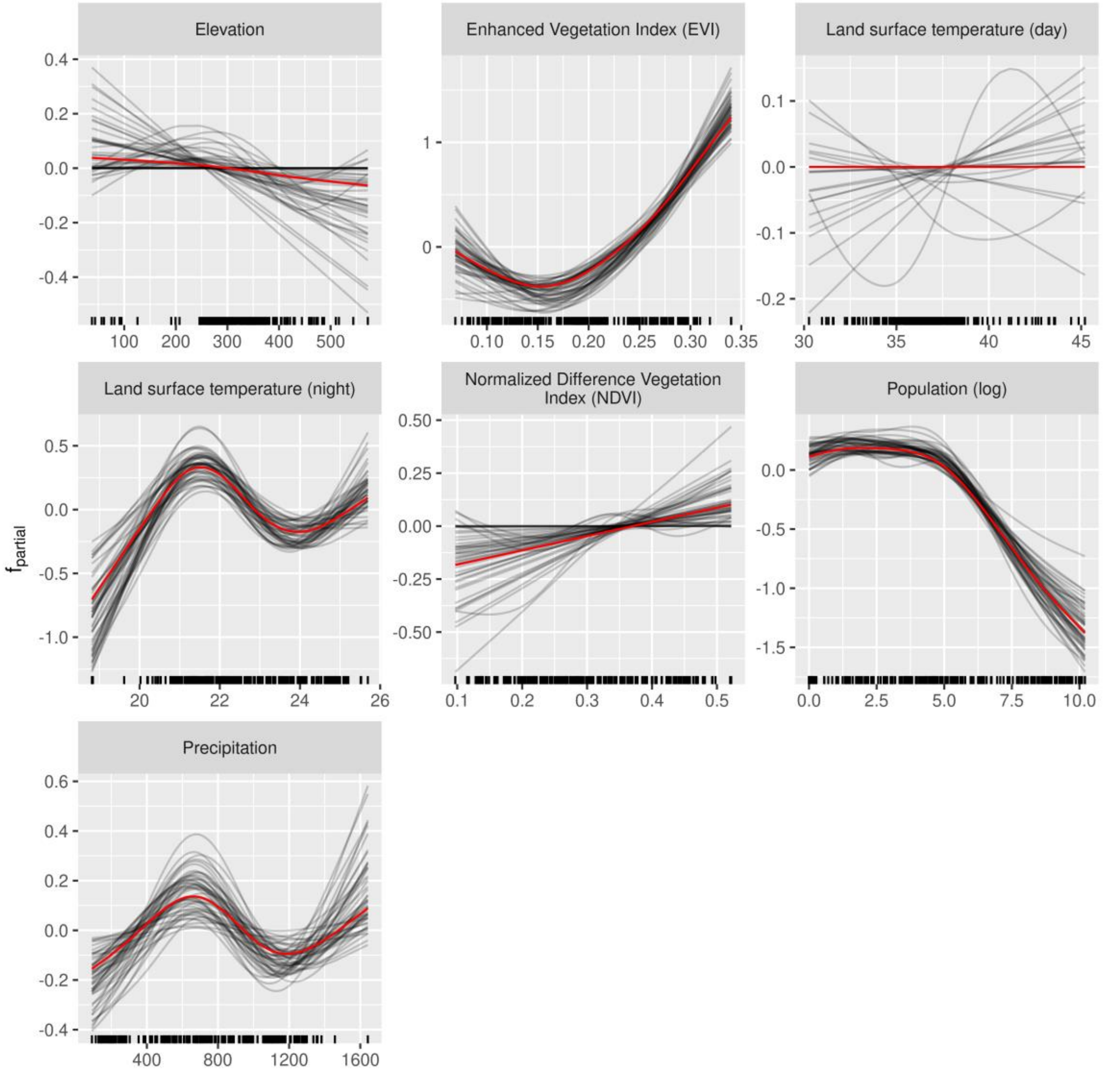
Geographic malaria risk in Mali

Model	Bias	MAE	RMSE	80% PI	90% PI	95% PI
Beta binomial	-0.005	0.093	0.131	0.861	0.944	0.963
Binomial	-0.007	0.091	0.131	0.597	0.708	0.759

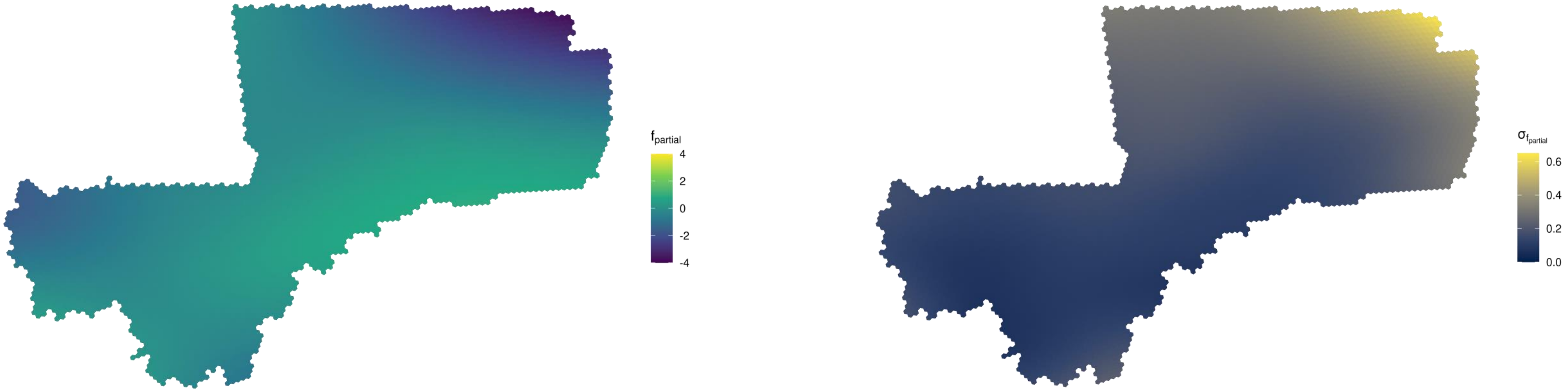


Geographic malaria risk in Mali

- Red line / dot indicates estimate of the principal model.
- Uncertainty quantification based on 50 bootstrap samples.

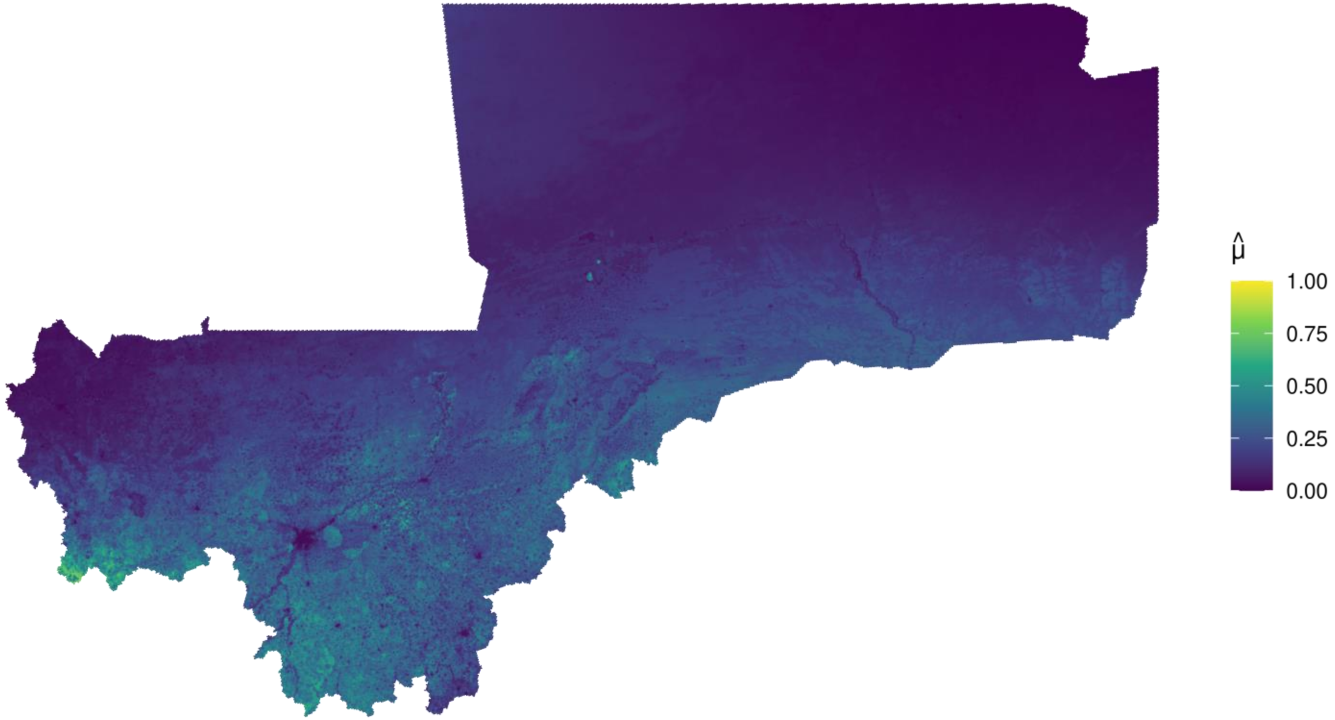


Geographic malaria risk in Mali



- Spatial effect (left) and standard error of bootstrap samples (right).

Geographic malaria risk in Mali



- Predicted malaria risk.

Discussion

Discussion

Component-wise boosting for risk identification?

➔ Yes, can allow for interesting insights in moderate dimensional datasets where a priori the functional form of an effect is not known, but difficult if rigorous notion of statistical inference is required.

Case Study 1 (Malnutrition)

➔ If effect *type* selection of interest – great. But difficult to achieve controls for variable selection: stability selection is very conservative in low dimensional settings.

➔ Probably more useful: hierarchical modelling of main factors to distinguish regional differences and deviations from country-level relationship.

Case Study 2 (Malaria)

➔ Likely competitive and interpretable approach compared to Bhatt et al. 2017 and Weiss et al. 2015 with respect to variable selection and predictive accuracy (and: appropriate response distribution).

➔ High accuracy masks large uncertainties in predicted risk, if admin 2 estimates are the objective probably not the right approach (since uncertainty is central).

Q&A

References

References

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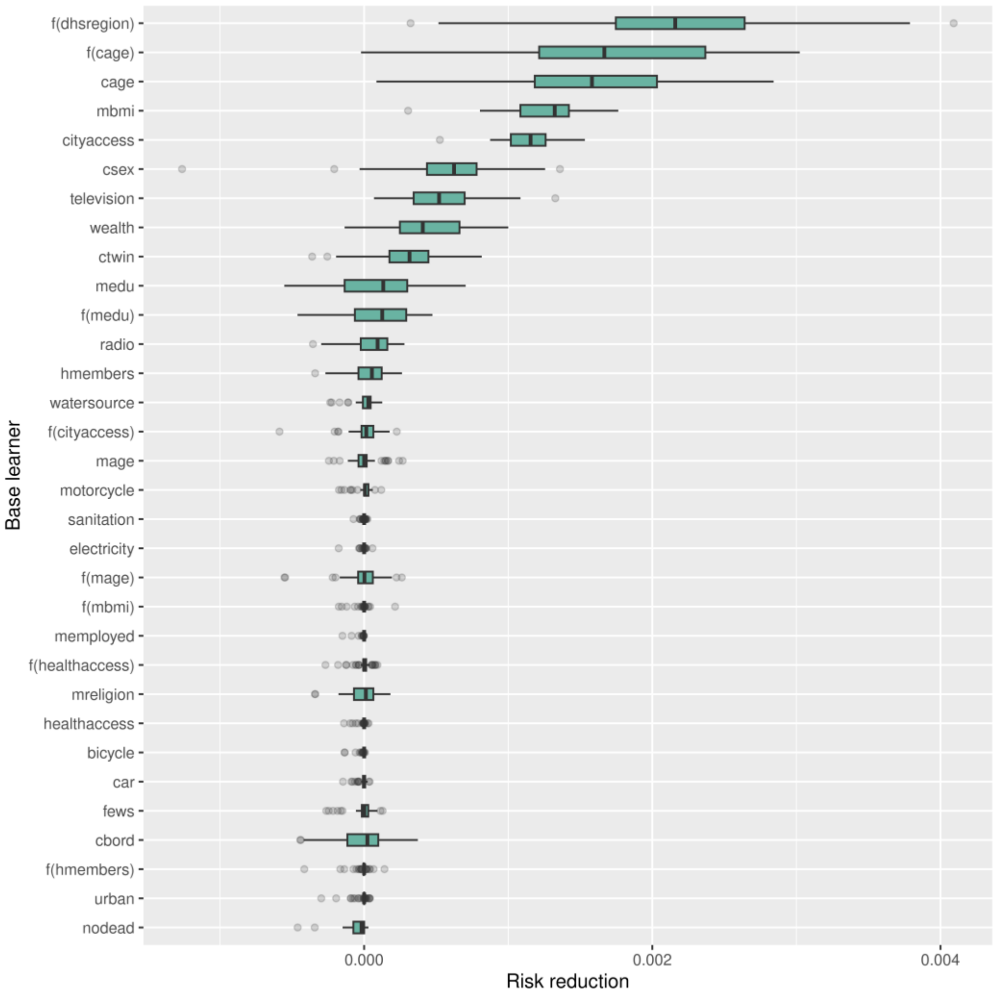
Additional Figures


f(dhsregion)
f(cage)
cage
mbmi
cityaccess
csex
television
wealth
ctwin
medu
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radio
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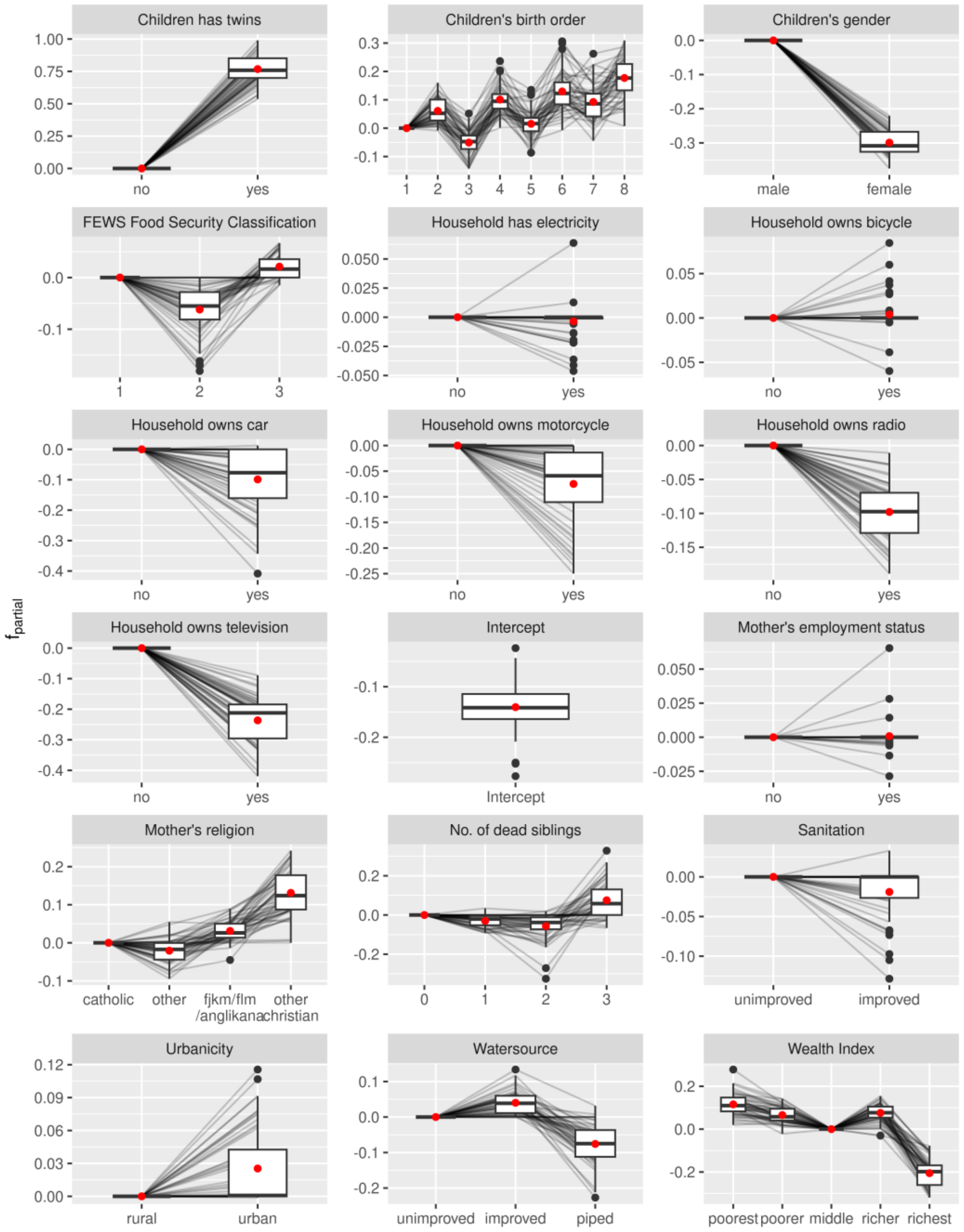
f(cityaccess)
mage
motorcycle
sanitation
electricity
f(mage)
f(mbmi)
memployed
f(healthaccess)
mreligion
healthaccess
bicycle
car
fews
cbord
f(hmembers)
urban
nodead
Base learner
0.000
0.002
0.004
Risk reduction


f_partial
Children has twins
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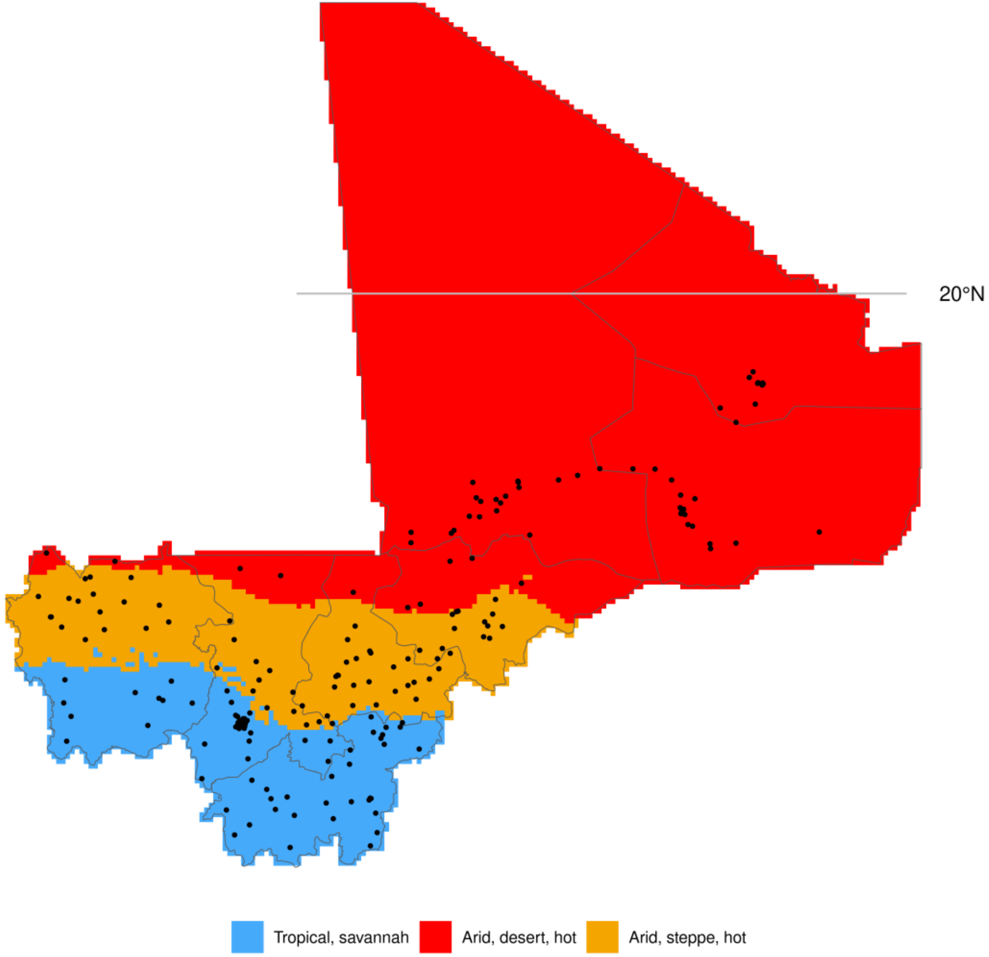
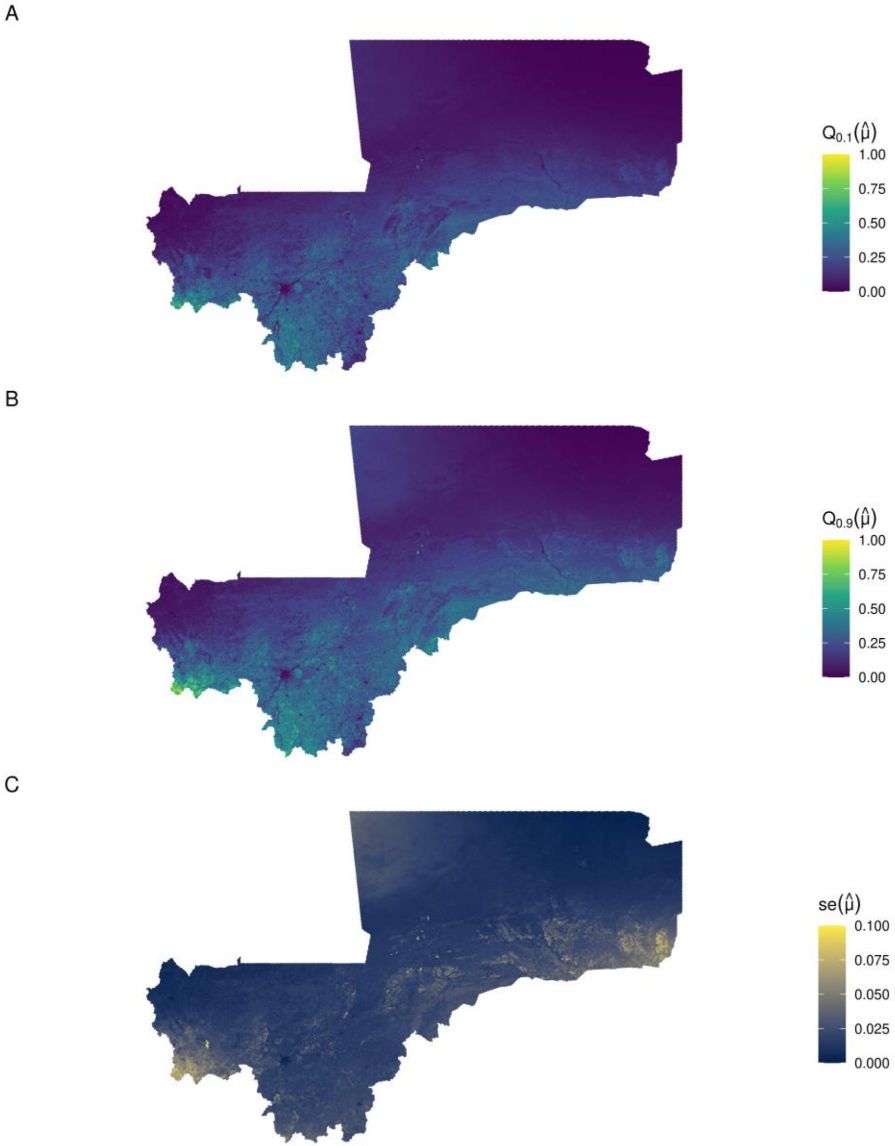
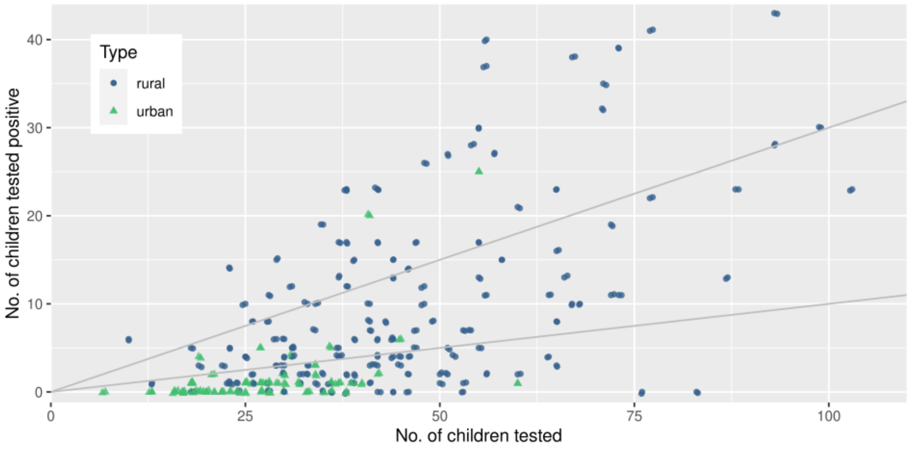
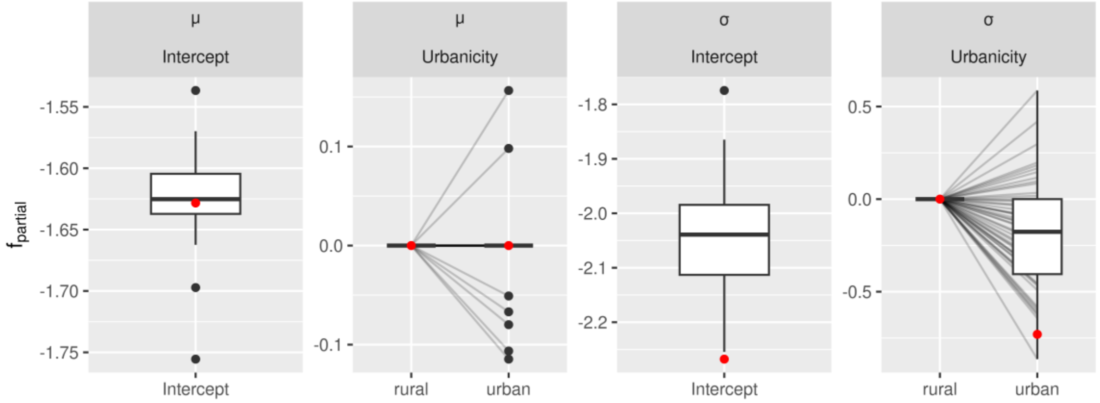
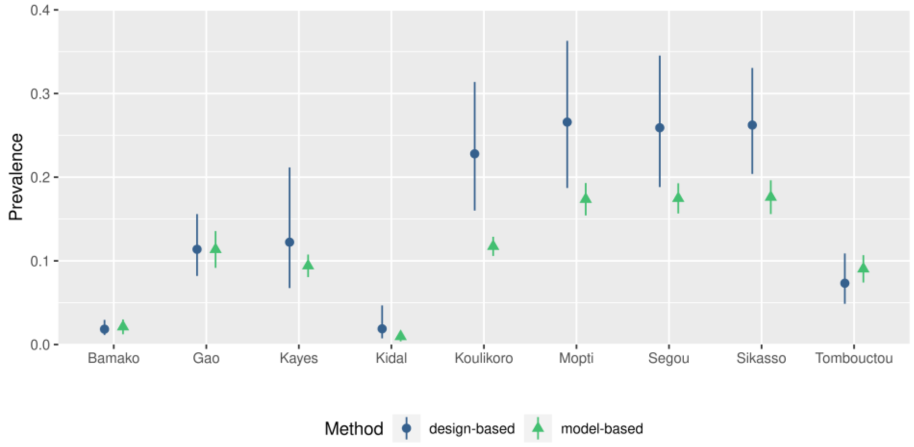
0.75
0.50
0.25
0.00
no
yes
Children's birth order
0.3
0.2
0.1
0.0
-0.1
1
2
3
4
5
6
7
8
Children's gender
0.0
-0.1
-0.2
-0.3
male
female
FEWS Food Security Classification
0.0
-0.1
1
2
3
Household has electricity
0.050
0.025
0.000
-0.025
-0.050
no
yes
Household owns bicycle
0.05
0.00
-0.05
no
yes
Household owns car
0.0
-0.1
-0.2
-0.3
-0.4
no
yes
Household owns motorcycle
0.00
-0.05
-0.10
-0.15
-0.20
-0.25
no
yes
Household owns radio
0.00
-0.05
-0.10
-0.15
no
yes
Household owns television
0.0
-0.1
-0.2
-0.3
-0.4
no
yes
Intercept
-0.1
-0.2
Intercept
Mother's employment status
0.050
0.025
0.000
-0.025
no
yes
Mother's religion
0.2
0.1
0.0
-0.1
catholic
other
fjkm/flm /anglikana
other christian
No. of dead siblings
0.2
0.0
-0.2
0
1
2
3
Sanitation
0.00
-0.05
-0.10
unimproved
improved
Urbanicity
0.12
0.09
0.06
0.03
0.00
rural
urban
Watersource
0.1
0.0
-0.1
-0.2
unimproved
improved
piped
Wealth Index
0.2
0.0
-0.2
poorest
poorer
middle
richer
richest


20°N
Tropical, savannah
Arid, desert, hot
Arid, steppe, hot


A
Q0.1(μ̂)
1.00
0.75
0.50
0.25
0.00
B
Q0.9(μ̂)
1.00
0.75
0.50
0.25
0.00
C
se(μ̂)
0.100
0.075
0.050
0.025
0.000


Type
rural
urban
No. of children tested positive
0
10
20
30
40
0
25
50
75
100
No. of children tested


μ
Intercept
μ
Urbanicity
σ
Intercept
σ
Urbanicity
$f_{partial}$
-1.55
-1.60
-1.65
-1.70
-1.75
Intercept
0.1
0.0
-0.1
rural
urban
-1.8
-1.9
-2.0
-2.1
-2.2
Intercept
0.5
0.0
-0.5
rural
urban


Prevalence
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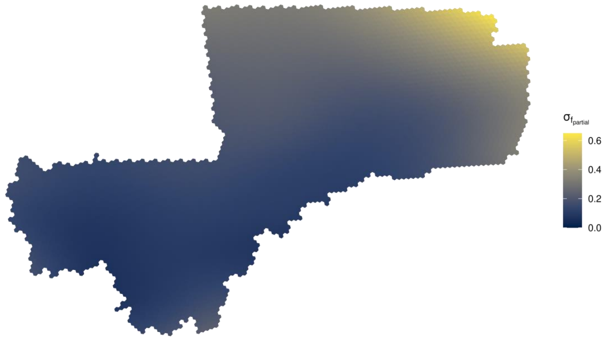
0.1
0.2
0.3
0.4
Bamako
Gao
Kayes
Kidal
Koulikoro
Mopti
Segou
Sikasso
Tombouctou
Method
design-based
model-based


$\sigma_{f_{partial}}$
0.6
0.4
0.2
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