Geospatial analysis and mapping of malaria risk using School Malaria Parasiteamia Survey (SMPS) in Tanzania

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Background

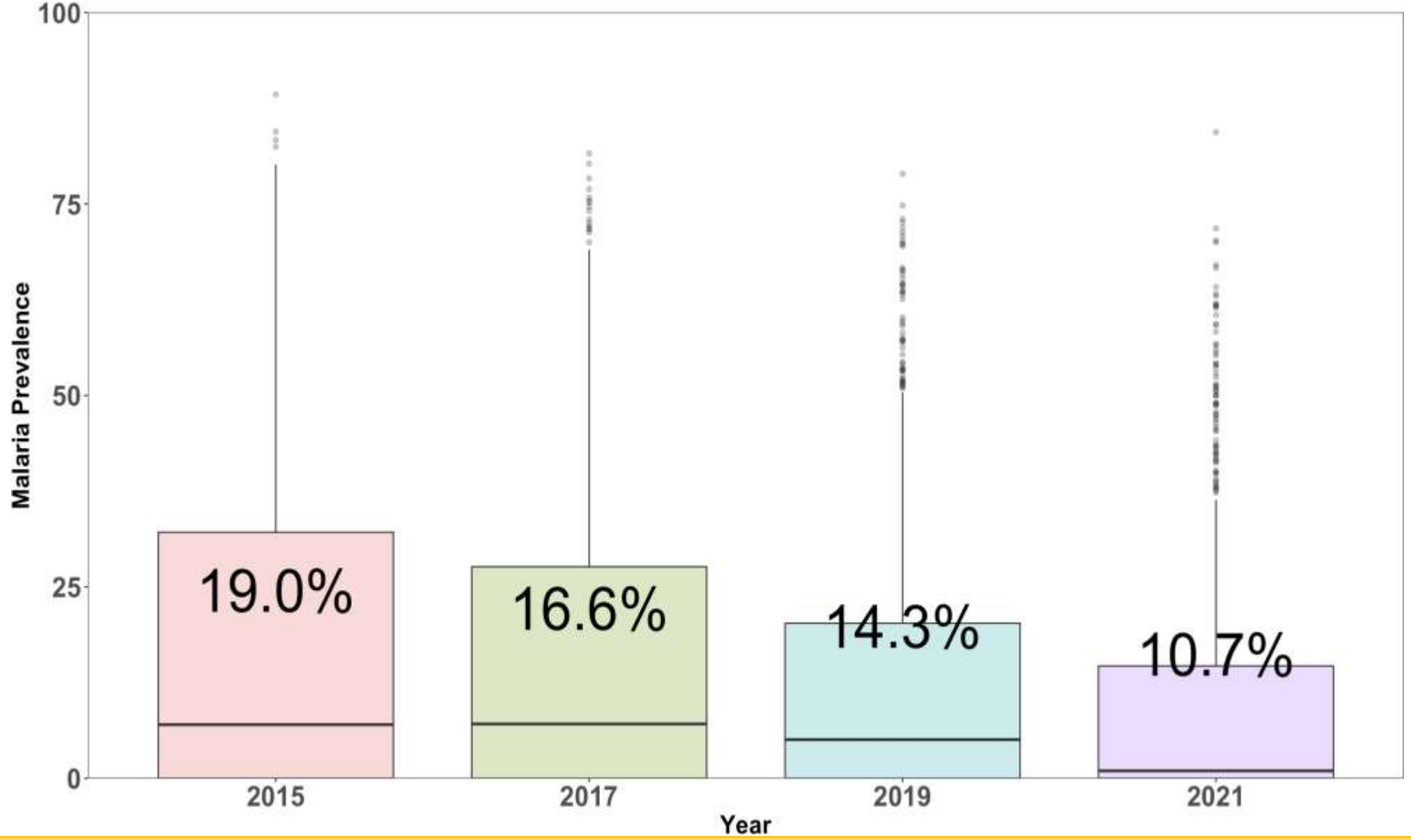

Fig 1. Box plot showing declining burden of malaria prevalence in Tanzania. Data obtained from SMPS survey 2015-2021

Malaria heterogeneity

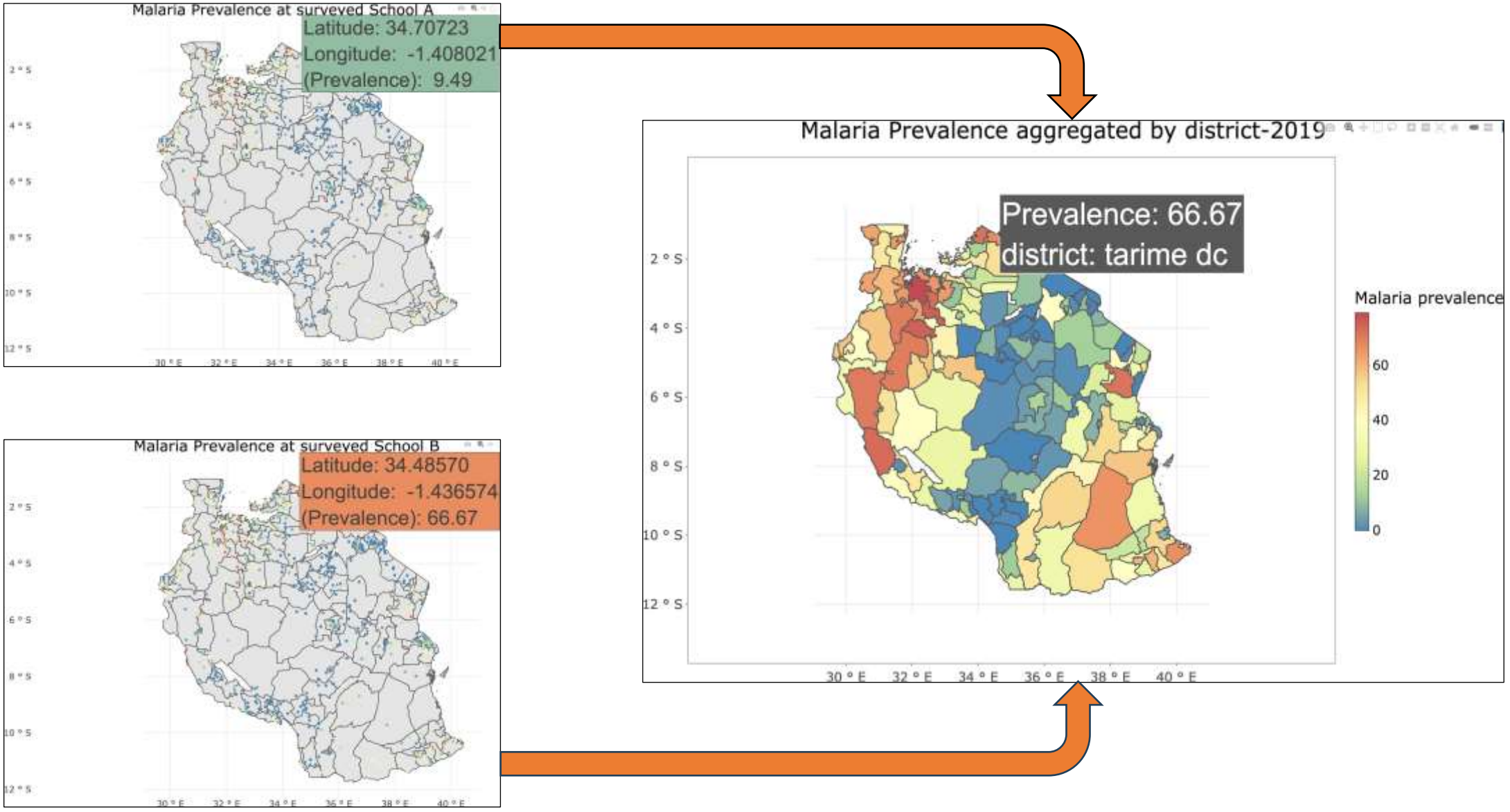

Fig 2. Maps demonstrating heterogeneity of malaria in Tarime district in Tanzania

Study justification

Health Facility	Population-based surveys	School- Malaria Parasiteamia surveys
Pros	**Pros**	**Pros**
Spatially and temporally granular*	Captures disease burden in community.	Spatially granular- make decisions at ward level.
Easily accessible -HMIS	Standardized measurement, unbiased	Rapid & cheaper alternative to population -based surveys
Real time- monitoring of disease trends and timely i nterventions.		Shift in malaria-burden towards older children.
Cons	**Cons**	**Cons**
Catchment HS disease burden only	Limited in spatial and temporal granularity	Incompleteness-sick children may miss school, underestimating risk.
Not representative of the population	Cost, labour and time intensive	Cross-sectional
Aggregated reporting in HMIS loses spatial granularity	Restricted to pregnant women & under 5's	

Study design

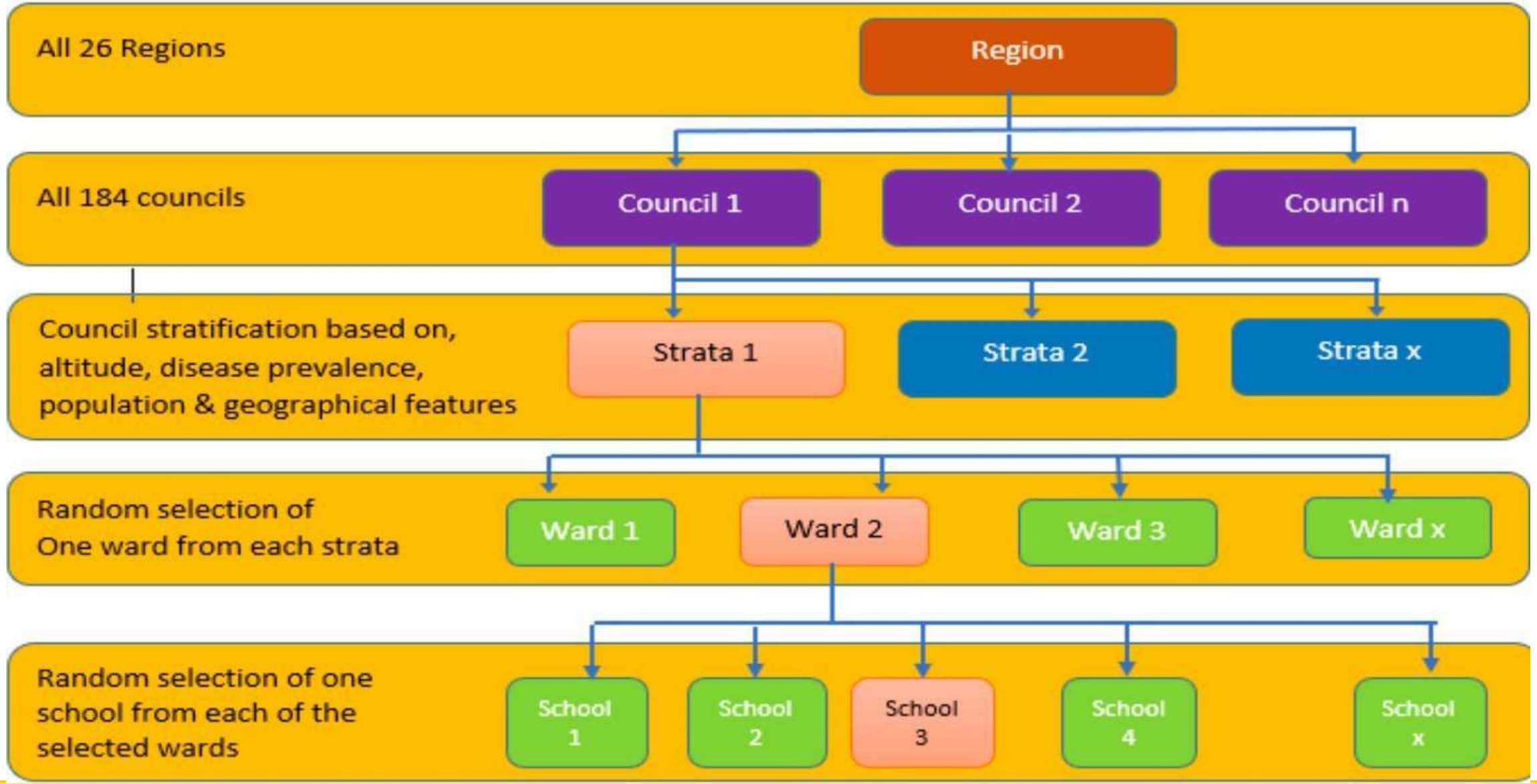

Fig 3. Study design flow chart; *Chacky et al 2019; Nationwide school malaria parasitaemia survey in public primary schools in Tanzania*

Study objective

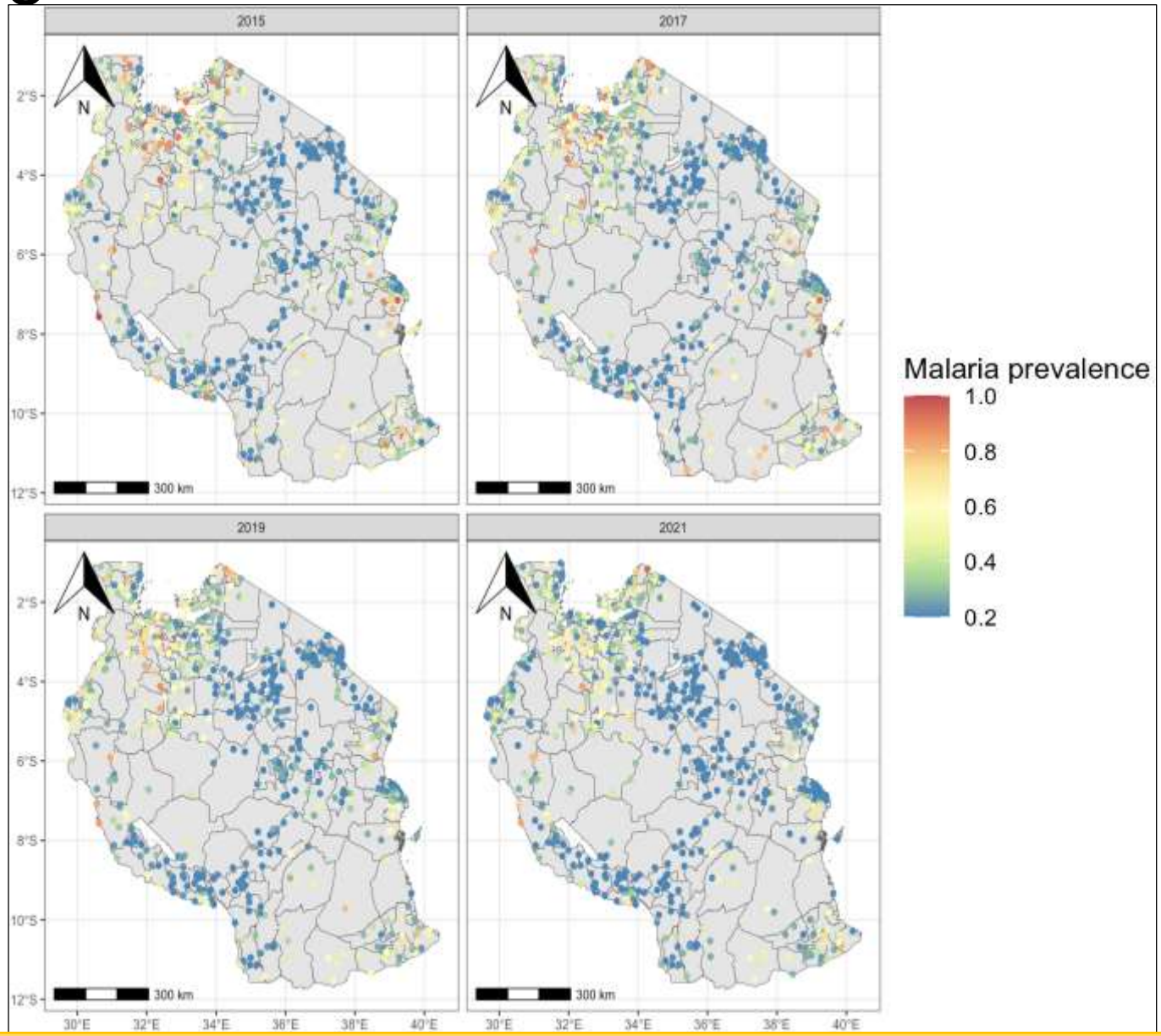

Fig 4. Observed malaria prevalence at surveyed locations grouped by year.

Static and dynamic covariates

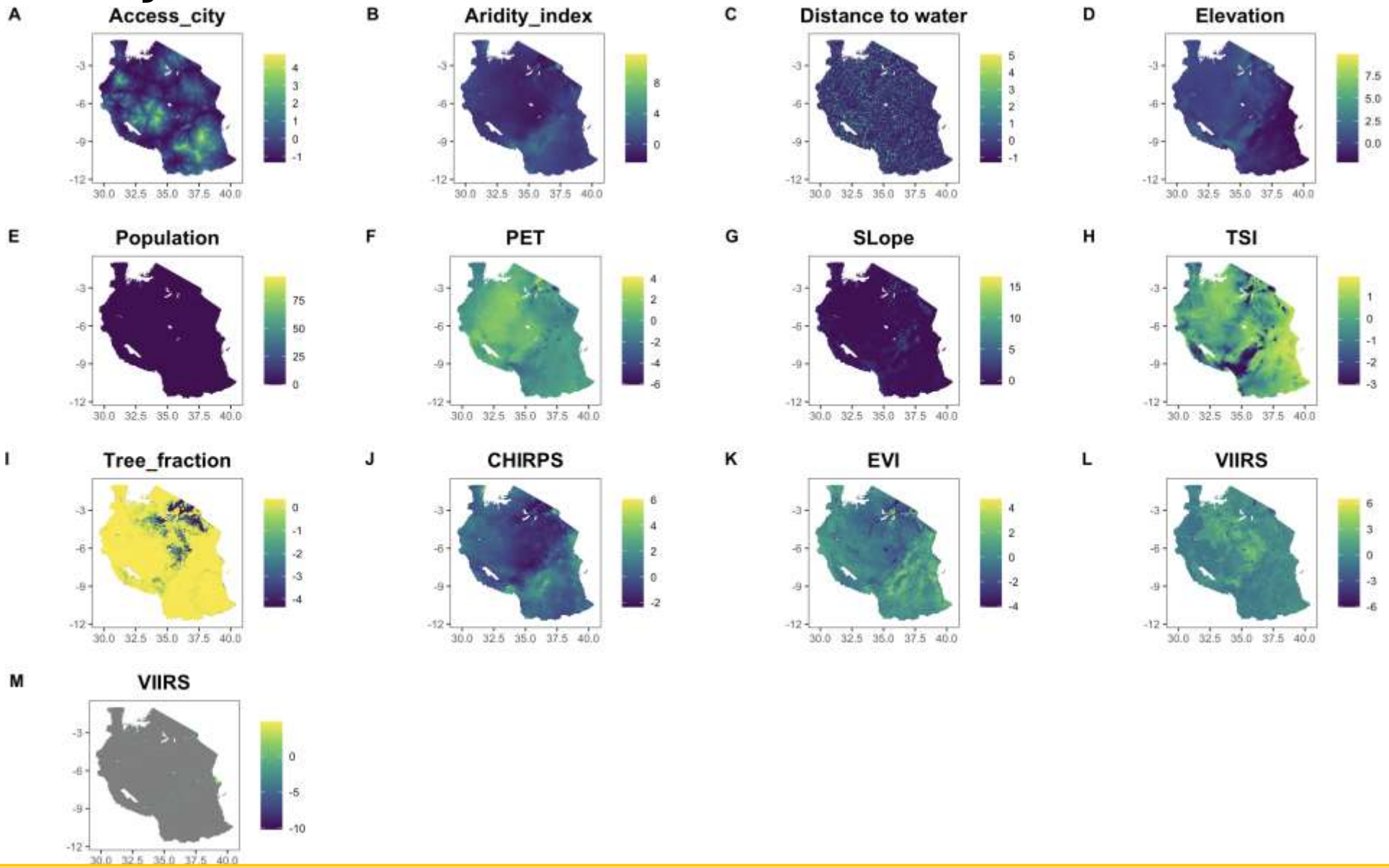

Fig 5. Suite of dynamic and static covariates

Spatiotemporal model

A Bayesian framework was used to model the spatial and temporal distribution of malaria prevalence at the ward level. Malaria prevalence, P at the surveyed ward j (j =1…n), in year k (k = 1…m) and the number of positive pupils, N_{jk} in ward j and year k was assumed to follow a binomial distribution

$$Y_{jk} \sim Binomial(P_{jk}, N_{jk}).$$

Malaria prevalence was then linked to linear predictors through a logit linear regression model:

$$logit\,(P_{jk}) = \beta_0 + X_{jk}\beta + u_j + v_j + \gamma_k$$

Where β_0 - intercept

X - matrix of covariates

β - regression parameters

u_j - spatial random parameter

γ_k - temporal random effect

v_j - independent and identically distributed random effect (i.i.d).

Geostatistical analysis of malaria prevalence was run using the R-INLA package.

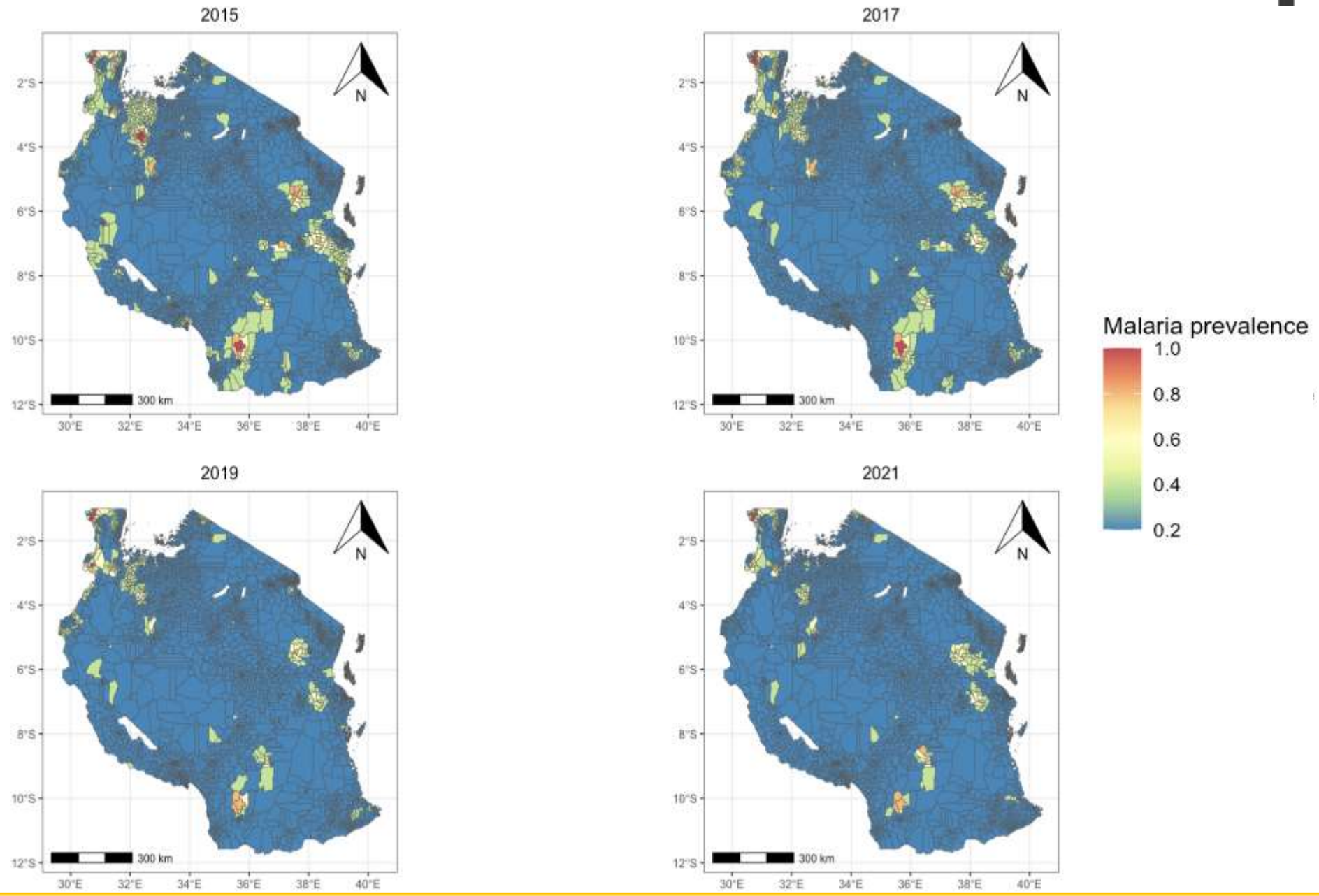

Fig 6. Predicted malaria prevalence by ward grouped by year

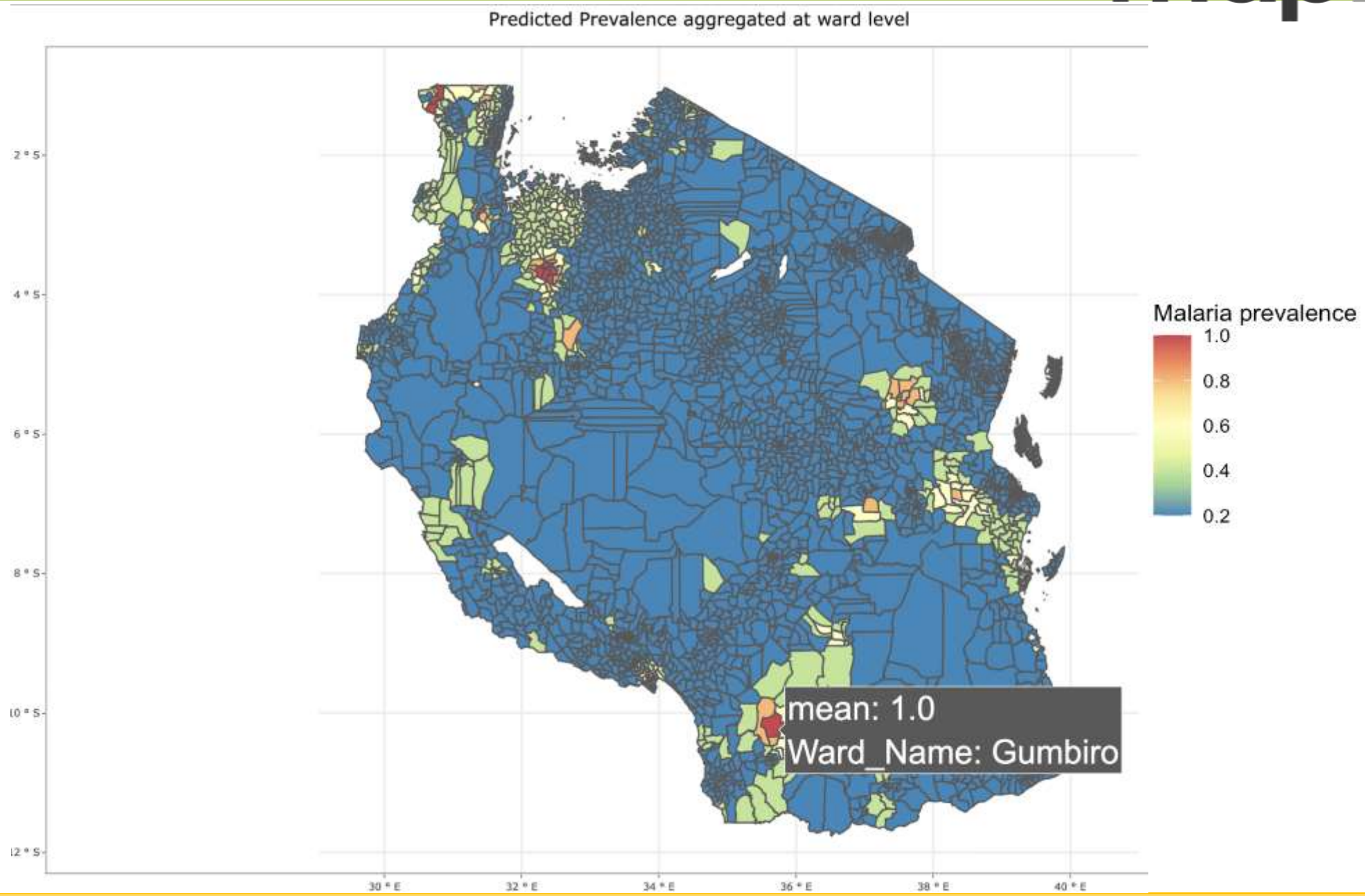

Fig 7. Predicted malaria prevalence at Gumbiro ward

Model validation

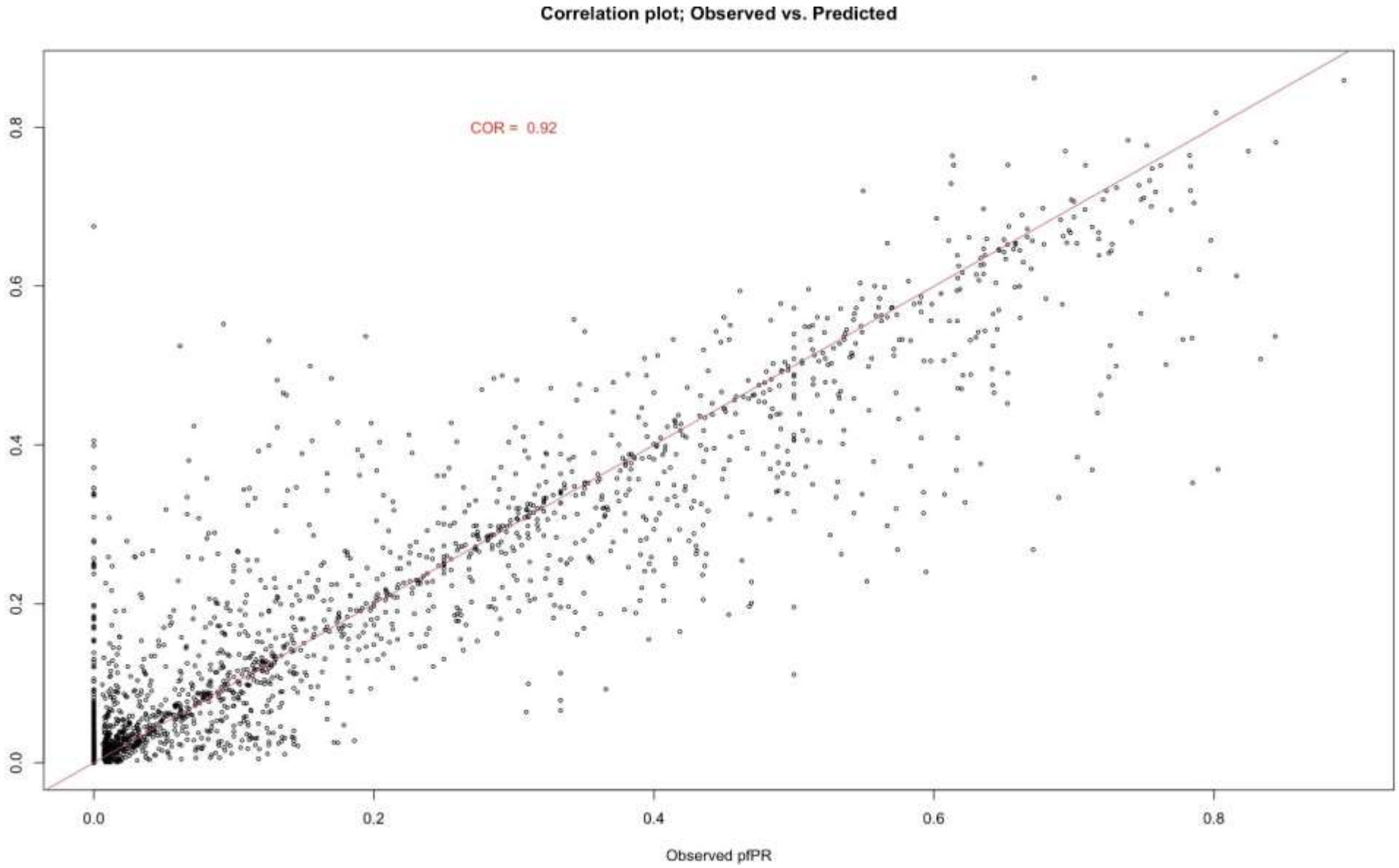

Fig 8. Scatter plot of predicted and observed malaria prevalences

Conclusion

- The observed prevalence among school children showed marked variation (heterogeneity) at regional and sub-regional levels across the country.

- This work demonstrated the potential of SMPS data to identify different epidemiological strata and potentially provide the malaria program with evidence guide malaria interventions at micro-planning units in Tanzania.

Limitations

- This model did not integrate intervention data as a covariate and may have biased the estimations of our model.

- School absenteeism- Children may have missed school during the sampling day due to malaria, dropouts and some regions may have had lower enrolment rates. This would have led to an under estimation of malaria risk in that region.

- The SMPS, is a cross-sectional surveys and therefore captures malaria infection prevalence only at a certain time point and seasonal variations of malaria will inevitably be missed which may lead to under/over-estimating malaria risk.

Future work

- There's need to explore other geospatial modeling techniques to compare predictive performance with the current model.

- We did not test the goodness of fit between different models, this process is underway.

- Representativeness of SMPS data – It is not known how well school prevalence reflects population prevalence and therefore using SMPS data provides an opportunity to explore this relationship.

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