Getting started with MBG

Source: vignettes/mbg.Rmd

This vignette introduces `mbg`, a package for modern Model-Based Geostatistics. This package offers tools for spatial regression analysis:

1. Running Bayesian geostatistical models that relate point-georeferenced outcome data to underlying spatial patterns
2. Fitting machine learning algorithms with point-georeferenced outcome data and raster covariate data
3. Fast aggregation from (gridded, continuous) raster estimates to (discrete) polygon boundaries, allowing for fractional splitting of raster grid cells and population weighting. A common application for aggregation is generating administrative summaries of fine-scale raster data

`mbg` combines functions from several packages:

- `INLA`: for running Bayesian geostatistical models
- `data.table`: for handling tabular data
- `sf` for handling polygons
- `terra` for handling raster data
- `caret` for running ML models with point outcomes and raster predictors

In this tutorial, we will run a simple `mbg` model with prepared data to demonstrate core package functions.

Setting up

Load the `mbg` package, as well as the `data.table`, `sf`, and `terra` packages for data processing, and the `ggplot2` package for plotting.

```
# Load packages
library(data.table)
library(ggplot2)
library(sf)
```

Benin. Load point observations of this outcome from the package data and print the first few rows:

```r
# Outcome: child stunting
outcomes <- data.table::fread(
  system.file('extdata/child_stunting.csv', package = 'mbg')
)
```

cluster_id	indicator	samplesize	x	y
3	5	16	1.762278	6.267199
4	5	14	2.044534	6.335044
5	2	13	2.420548	6.346753
6	1	17	2.371199	6.349460
7	8	20	1.889197	6.351104
8	4	23	2.369804	6.354230

The outcome data has 505 rows, each representing one surveyed location, and five columns:

- **cluster_id**: A unique identifier for each surveyed location
- **samplesize**: The number of children under 5 surveyed at the location
- **indicator**: The outcome of interest—in this case, the number of sampled children who met the definition for stunting
- **x**: The surveyed location's longitude
- **y**: The surveyed location's latitude

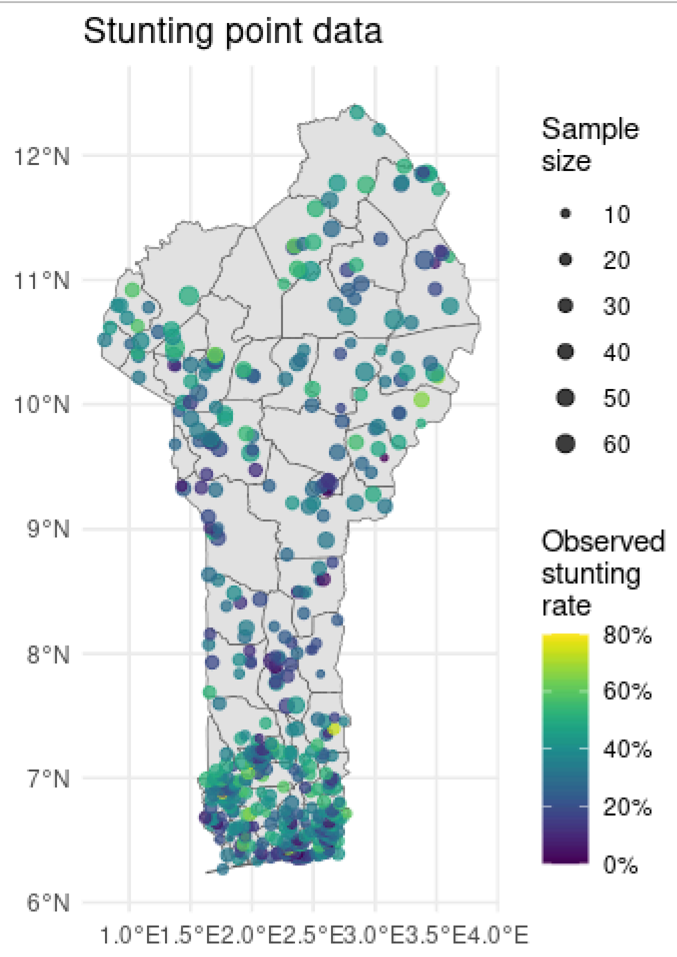
Let's map this survey data over a map of Benin.

```r
# Administrative boundaries
communes <- sf::st_read(
  system.file('extdata/Benin_communes.gpkg', package = 'mbg'),
  quiet = TRUE
)

# Convert point data to sf
```

```
)
outcome_sf$stunting_rate <- outcome_sf$indicator / outcome_sf$samplesize

ggplot2::ggplot() +
  ggplot2::geom_sf(data = communes) +
  ggplot2::geom_sf(
    data = outcome_sf,
    ggplot2::aes(color = stunting_rate, size = samplesize),
    alpha = 0.75
  ) +
  ggplot2::scale_size_continuous(range = c(0.5, 3)) +
  ggplot2::scale_color_gradientn(
    colors = terra::map.pal('viridis'),
    labels = scales::percent
  ) +
  ggplot2::labs(
    title = 'Stunting point data',
    color = 'Observed\nstunting\nrate',
    size = 'Sample\nsize'
  ) +
  ggplot2::theme_minimal()
```



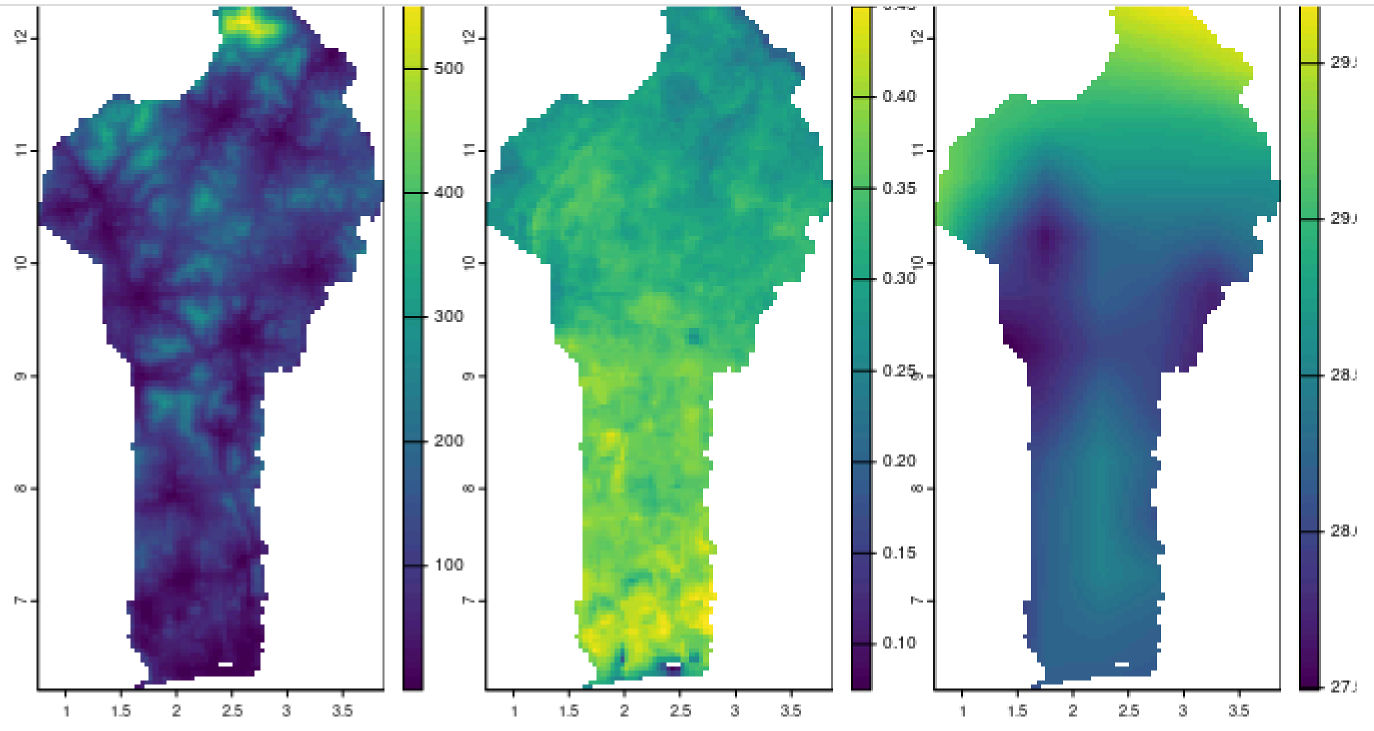
understand the underlying trends in stunting risk across the country, we would ideally like to:

- Adjust for noise in the outcome due to small sample sizes in the point-level survey data;
- Understand likely stunting risk not just at surveyed points, but at locations across the entire country;
- Incorporate data about possible predictors of child stunting and spatial trends to inform our estimates, and;
- Propagate uncertainty due to small sample sizes, uncertain predictor relationships, and distance to data points into our estimates for all locations.

A Bayesian geostatistical model can accomplish all of these goals. We will fit a Bayesian geostatistical model to the outcome data, with three potential predictors formatted as raster surfaces:

1. Travel time to the nearest city, in minutes
2. Enhanced vegetation index (EVI)
3. Mean annual temperature

```
# Spatial covariates
covariates <- list(
  access = terra::rast(system.file('extdata/access.tif', package = 'mbg')),
  evi = terra::rast(system.file('extdata/evi.tif', package = 'mbg')),
  temperature = terra::rast(system.file('extdata/temperature.tif', package = 'mbg'))
)
# Plot the covariates
plot(terra::rast(covariates), nr = 1)
```



Building MBG model inputs

The geostatistical model takes three more arguments:

1. `id_raster` : A `terra::SpatRaster` that lays out the prediction grid. The model will make predictions for all non-NA cells in the `id_raster` .
2. `aggregation_table` (`data.table::data.table` , optional): Used to aggregate model estimates from grid cells to commune polygons, preserving uncertainty
3. `population_raster` (`terra::SpatRaster` , optional): population-based indicators like child stunting should be aggregated using population weighting, which places greater weight on grid cells with higher populations when summarizing those grid cell results by polygon.

```
# Create ID raster
id_raster <- mbg::build_id_raster(
  polygons = communes,
  template_raster = covariates[[1]]
)
# Table to help with aggregation to higher administrative levels
aggregation_table <- mbg::build_aggregation_table(
  polygons = communes,
  id_raster = id_raster,
  polygon_id_field = 'commune_code'
)
```

Fit the geostatistical model

The entire Bayesian geostatistical regression workflow can be run using the `mbg::MbgModelRunner` class. The `MbgModelRunner$new()` method creates a new instance of the class, and the `MbgModelRunner$run_mbg_pipeline()` runs the entire workflow based on the passed inputs.

The following code block runs the `mbg` model using mainly default settings. A typical workflow can take a few minutes to finish, although intermediate steps will be printed to screen. Because we want a regression intercept in this model, the first line in the code block below creates the intercept as one of the covariate rasters.

```
# Add an intercept to the model
covariates$intercept <- covariates[[1]] * 0 + 1
## Run MBG models
model_runner <- MbgModelRunner$new(
  input_data = outcomes,
  id_raster = id_raster,
  covariate_rasters = covariates,
  aggregation_table = aggregation_table,
  aggregation_levels = list(
    commune = c('commune_code', 'commune', 'department_code', 'department'),
    region = c('department_code', 'department')
  ),
  population_raster = population_raster
)
model_runner$run_mbg_pipeline()
#> MBG model fitting
#> MBG model fitting: 13.857 sec elapsed
#> Generating model predictions
#>   Parameter posterior samples
#>   Parameter posterior samples: 6.415 sec elapsed
#>   Cell draws
#>   Cell draws: 2.123 sec elapsed
#>   Summarize draws
#>   Summarize draws: 0.817 sec elapsed
#> Generating model predictions: 9.357 sec elapsed
#> Running population-weighted aggregation from grid cells to polygons
```

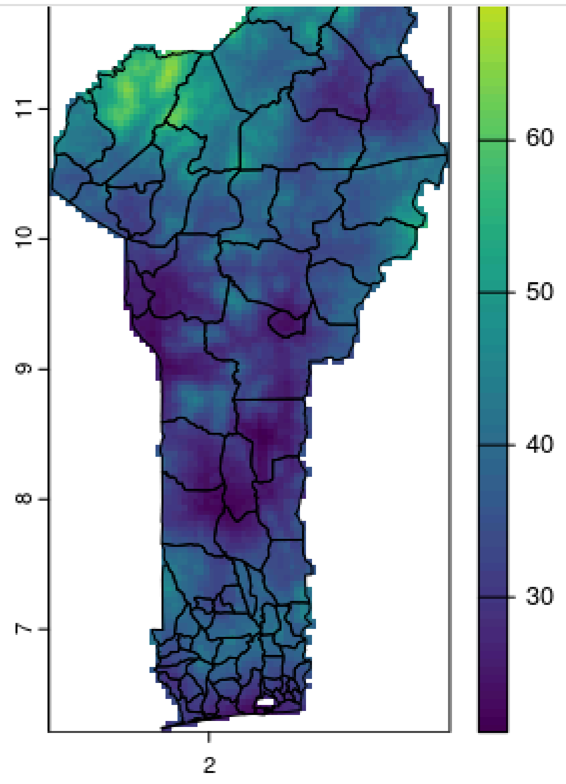
Plot gridded estimates

Once the geostatistical workflow has finished, we can pull the gridded raster model predictions from the `MbgModelRunner$grid_cell_predictions` attribute. This attribute is a list with the following items:

- `'parameter_draws'` (`matrix`): Samples of the underlying model parameters
- `'cell_draws'` (`matrix`): Samples of model estimates at each grid cell location from the `id_raster`
- `'cell_pred_mean'` (`terra::SpatRaster`): The mean estimates across all sampled `cell_draws` , represented as a raster.
- `'cell_pred_lower'` (`terra::SpatRaster`): Lower bounds of an uncertainty interval, summarized across the sampled `cell_draws` and represented as a raster. By default, we use a 95% uncertainty interval, so this raster shows the 2.5th percentile across the samples for each grid cell.
- `'cell_pred_upper'` (`terra::SpatRaster`): Upper bounds of the uncertainty interval, represented as a raster. By default, shows the 97.5th percentile of samples for each grid cell.

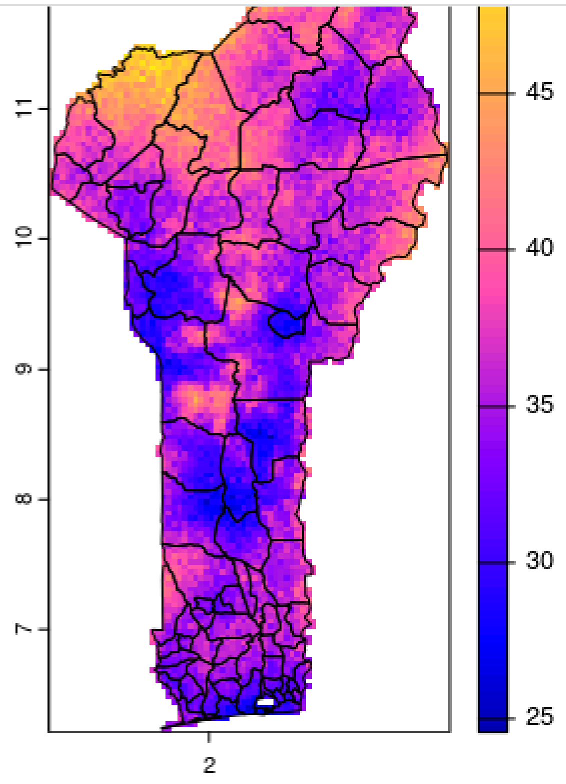
We can plot the mean estimates from the geostatistical model:

```r
# Get predictions by pixel
grid_cell_predictions <- model_runner$grid_cell_predictions
# Plot mean estimates
plot(
  grid_cell_predictions$cell_pred_mean * 100,
  main = 'MBG mean estimates (%)'
)
lines(communes)
```



We can also show the width of the 95% uncertainty interval by subtracting the “lower” from the “upper” summary raster:

```
# Plot estimate uncertainty
plot(
  (grid_cell_predictions$cell_pred_upper - grid_cell_predictions$cell_pred_lower) * 100,
  col = sf::sf.colors(n = 100),
  main = 'MBG estimates: 95% uncertainty interval width (%)'
)
lines(communes)
```



Compare these gridded estimates to the underlying point data. The results seem to meet our goals for estimating stunting risk across Benin:

1. Gridded estimates are available for every region in Benin, not just at survey points
2. The mean estimates for stunting risk show a similar spatial pattern to the underlying point data
3. Some extreme values from the point data, which may have been noisy due to small sample sizes, have been smoothed out in these estimates
4. Model uncertainty, as shown by the width of the 95% uncertainty interval, is higher in areas that were far from any surveyed points.
5. Underlying relationships between the raster predictors and the point outcomes seem to have influenced estimates: for example, locations with a higher travel time to cities generally also have higher estimated stunting risk.

Many of these observations can be quantified and tested, as demonstrated in later vignettes.

Plot aggregated estimates

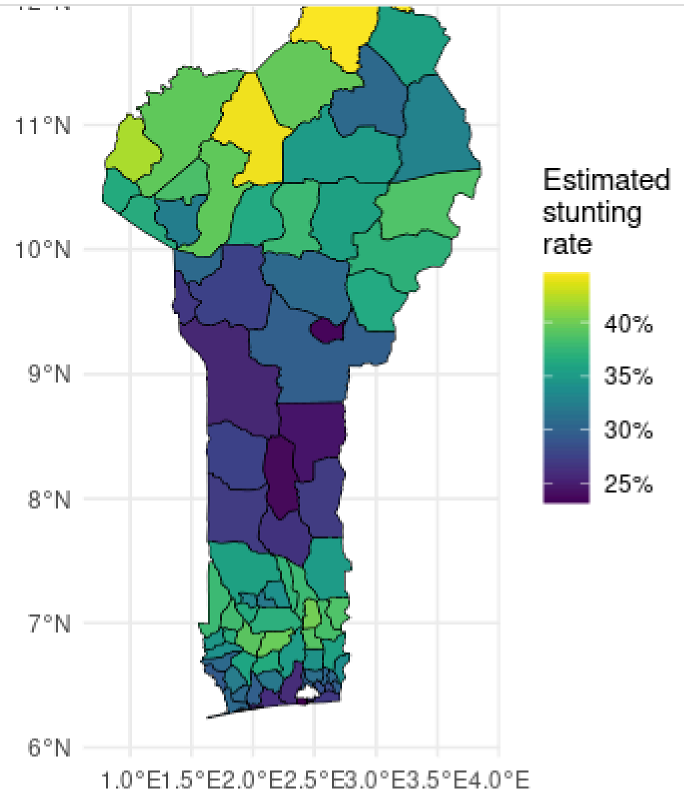
Each sample from the geostatistical model yields a *candidate map*, a single realization of the outcome across each pixel in the study area that is consistent with the fitted model parameters

Aggregated samples and summaries are available from the `MbgModelRunner$aggregated_predictions` attribute. This attribute is a named list, where each item contains polygon estimates for each of the passed `aggregation_levels`. Each of those levels has two items:

- `'draws'` (`data.table::data.table`): Predictive model samples by aggregated polygon unit
- `'summary'` (`data.table::data.table`): Summaries of `draws` for each aggregated polygon unit, including the mean and the bounds of the 95% uncertainty interval across samples

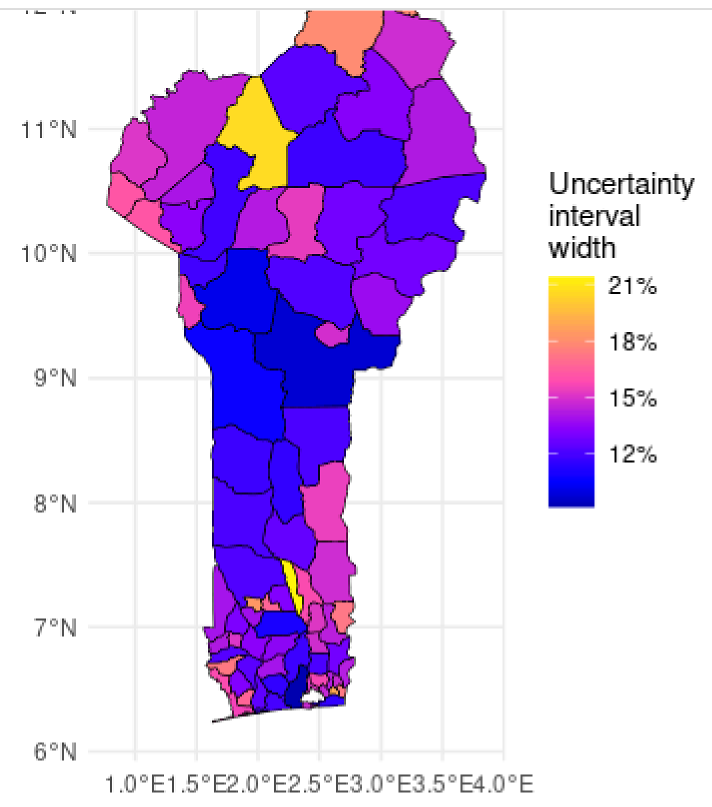
We can merge the commune estimate summaries back onto the `communes` sf object to plot the results.

```r
# Get predictions by commune
aggregated_predictions <- model_runner$aggregated_predictions
commune_summary <- aggregated_predictions$commune$summary
summary_sf <- merge(
  x = communes,
  y = commune_summary,
  by = c('commune_code', 'commune', 'department_code', 'department')
)
# Plot aggregated estimates by commune
ggplot2::ggplot() +
  ggplot2::geom_sf(data = summary_sf, ggplot2::aes(fill = mean), color = 'black') +
  ggplot2::scale_fill_gradientn(
    colors = terra::map.pal('viridis'),
    breaks = seq(0.15, 0.45, by = .05),
    labels = scales::percent
  ) +
  ggplot2::labs(
    title = 'MBG mean estimates by commune',
    fill = "Estimated\nstunting\nrate"
  ) +
  ggplot2::theme_minimal()
```



We can also plot the width of the 95% uncertainty interval by commune.

```
# Plot aggregated uncertainty interval widths by commune
summary_sf$ui <- summary_sf$upper - summary_sf$lower
ggplot2::ggplot() +
  ggplot2::geom_sf(data = summary_sf, ggplot2::aes(fill = ui), color = 'black') +
  ggplot2::scale_fill_gradientn(
    colors = sf::sf.colors(n = 100),
    labels = scales::percent
  ) +
  ggplot2::labs(
    title = 'MBG 95% uncertainty interval width by commune',
    fill = 'Uncertainty\ninterval\nwidth'
  ) +
  ggplot2::theme_minimal()
```



Note that in general, uncertainty intervals tend to be wider at the pixel level than for aggregated polygons. This is because some sources of uncertainty are uncorrelated between pixels, and this uncorrelated uncertainty shrinks when estimates are aggregated across pixels.

Developed by Nathaniel Henry, Benjamin Mayala. Site built with pkgdown 2.1.3.