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Integrating remote sensing and spatially explicit epidemiological modeling

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Spatially explicit epidemiological models are a crucial tool for the prediction of epidemiological patterns in time and space as well as for the allocation of health care resources. In addition they can provide valuable information about epidemiological processes and allow for the identification of environmental drivers of the disease spread.

Most epidemiological models rely on environmental data as inputs. They can either be measured in the field by the means of conventional instruments or using remote sensing techniques to measure suitable proxies of the variables of interest. The later benefit from several advantages over conventional methods, including data availability, which can be an issue especially in developing, and spatial as well as temporal resolution of the data, which is particularly crucial for spatially explicit models.

Here we present the case study of a spatially explicit, semi-mechanistic model applied to recurring cholera outbreaks in the Lake Kivu area (Democratic Republic of the Congo). The model describes the cholera incidence in eight health zones on the shore of the lake. Remotely sensed datasets of chlorophyll *a* concentration in the lake, precipitation and indices of global climate anomalies are used as environmental drivers. Human mobility and its effect on the disease spread is also taken into account. Several model configurations are tested on a data set of reported cases. The best models, accounting for different environmental drivers, and selected using the Akaike information criterion, are formally compared via cross validation. The best performing model accounts for seasonality, El Niño Southern Oscillation, precipitation and human mobility.