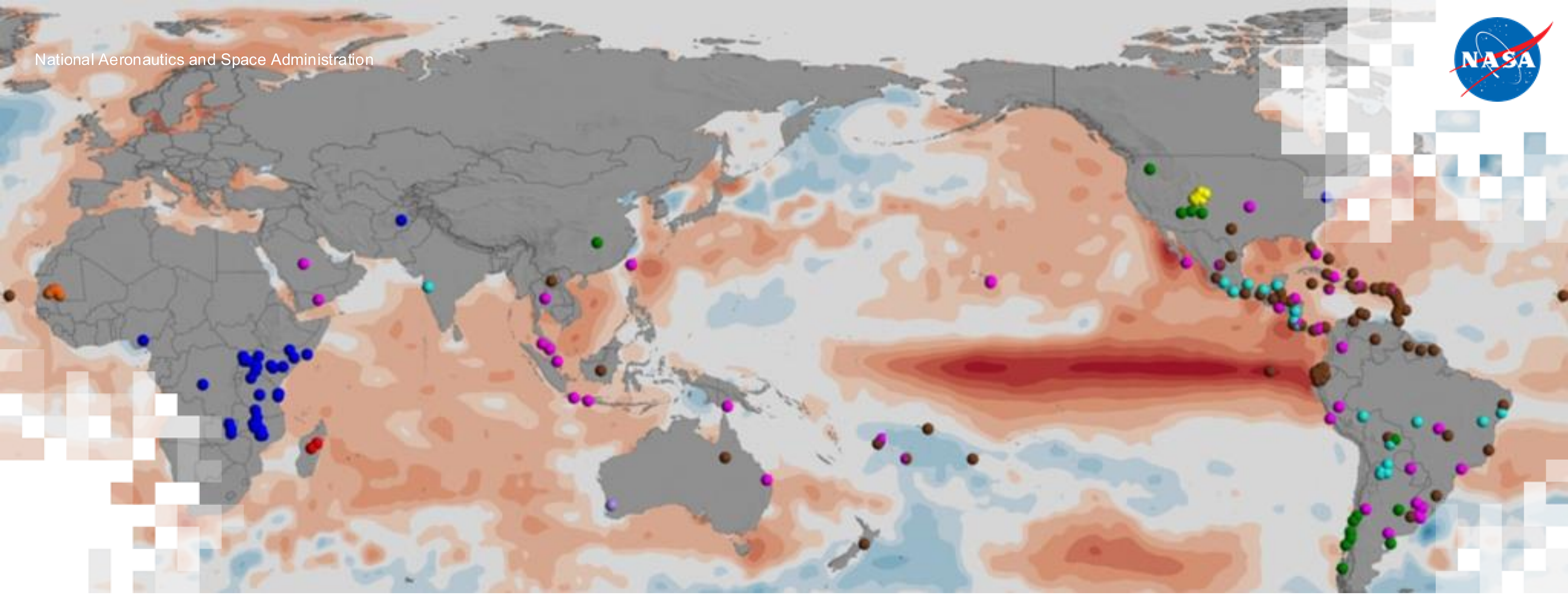
National Aeronautics and Space Administration



Remote Sensing for Climate-Sensitive Infectious Diseases

Part 2: Case Study in the Use of Remote Sensing to Study Climate-Sensitive Infectious Diseases

Assaf Anyamba (UMBC/NASA GSFC), Tatiana Loboda (UMCP), Michael Wimberly (OU)

October 9, 2025

In the Last Part…

- Dr. Tatiana Loboda (University of Maryland) gave an overview of how remote sensing data can be applied to the study of climate-sensitive infectious diseases.
- Remote sensing can tell us about:
  - Hazard: Identify habitats and environmental conditions suitable for disease vectors
  - Exposure: Identify where humans might come into contact with disease vectors
  - Vulnerability: Identify proxies for socio-economic standing and access to care
- Altogether, this allows us to assess the disease risk.
- Different considerations of available parameters, coverage, resolution, and data quality may apply to each aspect of the risk.
- Satellite data preprocessing involves quality filtering, gap-filling, re-gridding, and conversion to a common projection.

Training Outline

Part 1

How Remote Sensing Can be Used to Study Climate-Sensitive Infectious Diseases

October 7, 2025

11:00 - 13:00 EDT

Part 2

Case Study in the Use of Remote Sensing to Study Climate-Sensitive Infectious Diseases

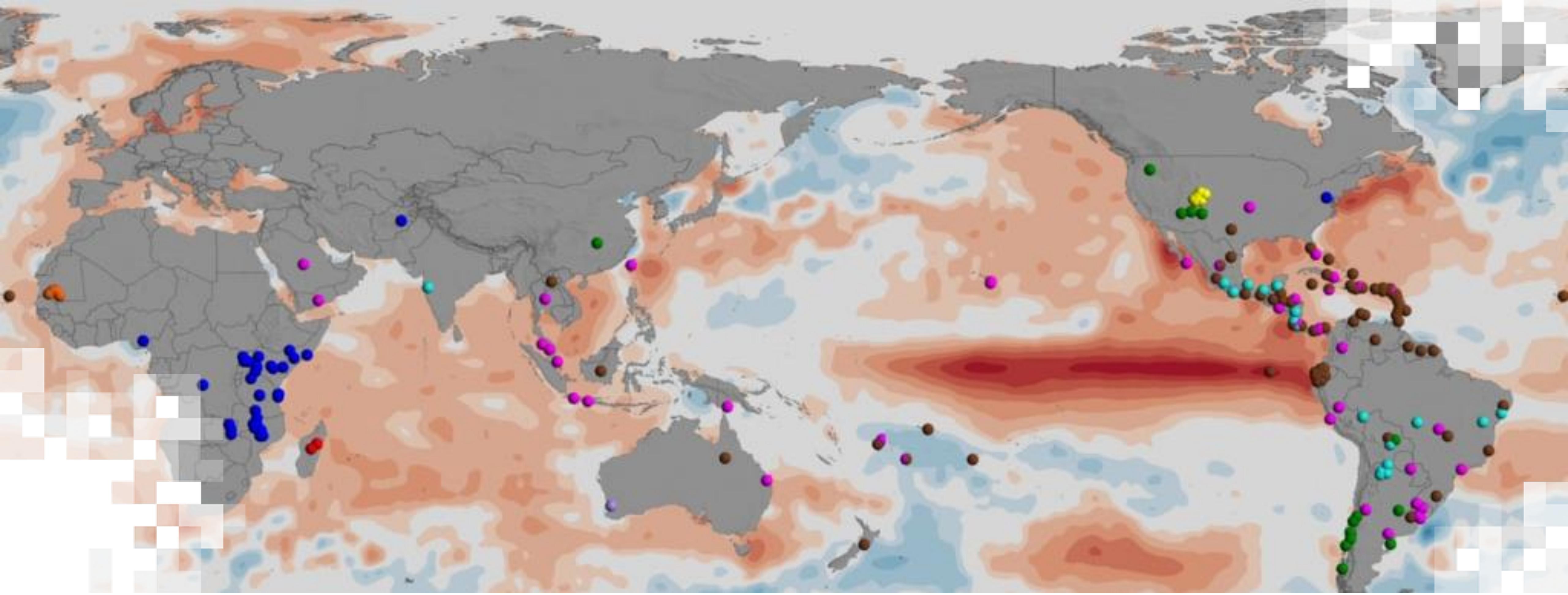
October 9, 2025

11:00 - 13:00 EDT

Homework

Opens October 9 – Due October 23 – Posted on Training Webpage

A certificate of completion will be awarded to those who attend all live sessions and complete the homework assignment(s) before the given due date.



Remote Sensing for Climate-Sensitive Infectious Diseases

Part 2: Case Study in the Use of Remote Sensing to Study Climate-Sensitive Infectious Diseases

Part 2 Objectives

By the end of Part 2, participants will be able to:

- Identify the climatic and non-climatic factors that influence malaria life cycle, transmission, and global malaria burden
- Understand the specific requirements and rationale for malaria forecasting in Ethiopia
- Explain the basic functionality of the Epidemic Prognosis Incorporating Disease and Environmental Monitoring for Integrated Assessment (EPIDEMIA) – Modeling System and the satellite data used in its operation
- List the steps taken by EPIDEMIA to access, preprocess, and harmonize remotely sensed climate and data together with public health information
- Identify common advantages and challenges of working with remotely sensed data for infectious disease forecasting, as encountered in the EPIDEMIA case study

How to Ask Questions

- Please put your questions in the Questions box and we will address them at the end of the webinar.
- Feel free to enter your questions as we go. We will try to get to all of the questions during the Q&A session after the webinar.
- The remainder of the questions will be answered in the Q&A document, which will be posted to the training website about a week after the training.

Part 2 – Trainers

Assaf Anyamba

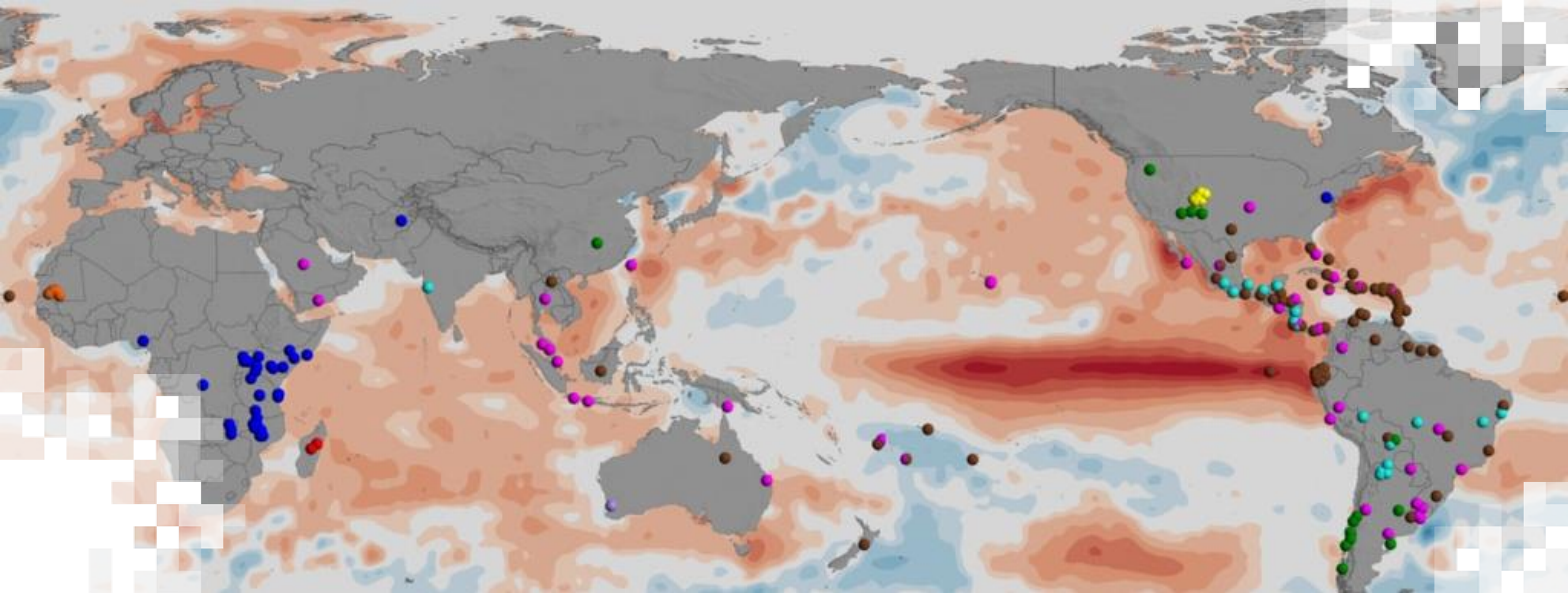
Senior Research Scientist

UMBC & NASA GSFC

Michael Wimberly

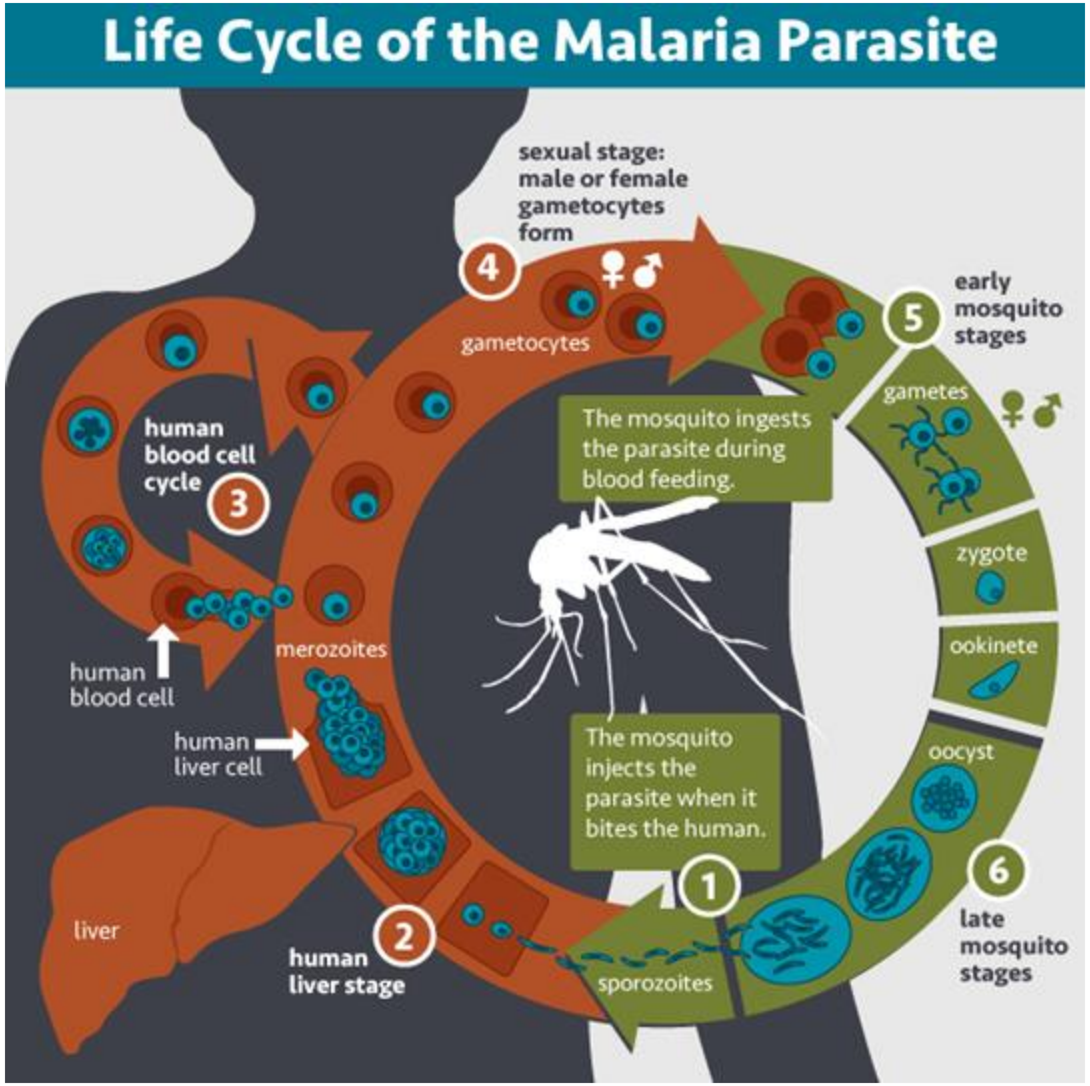
Professor and Interim Director

University of Oklahoma



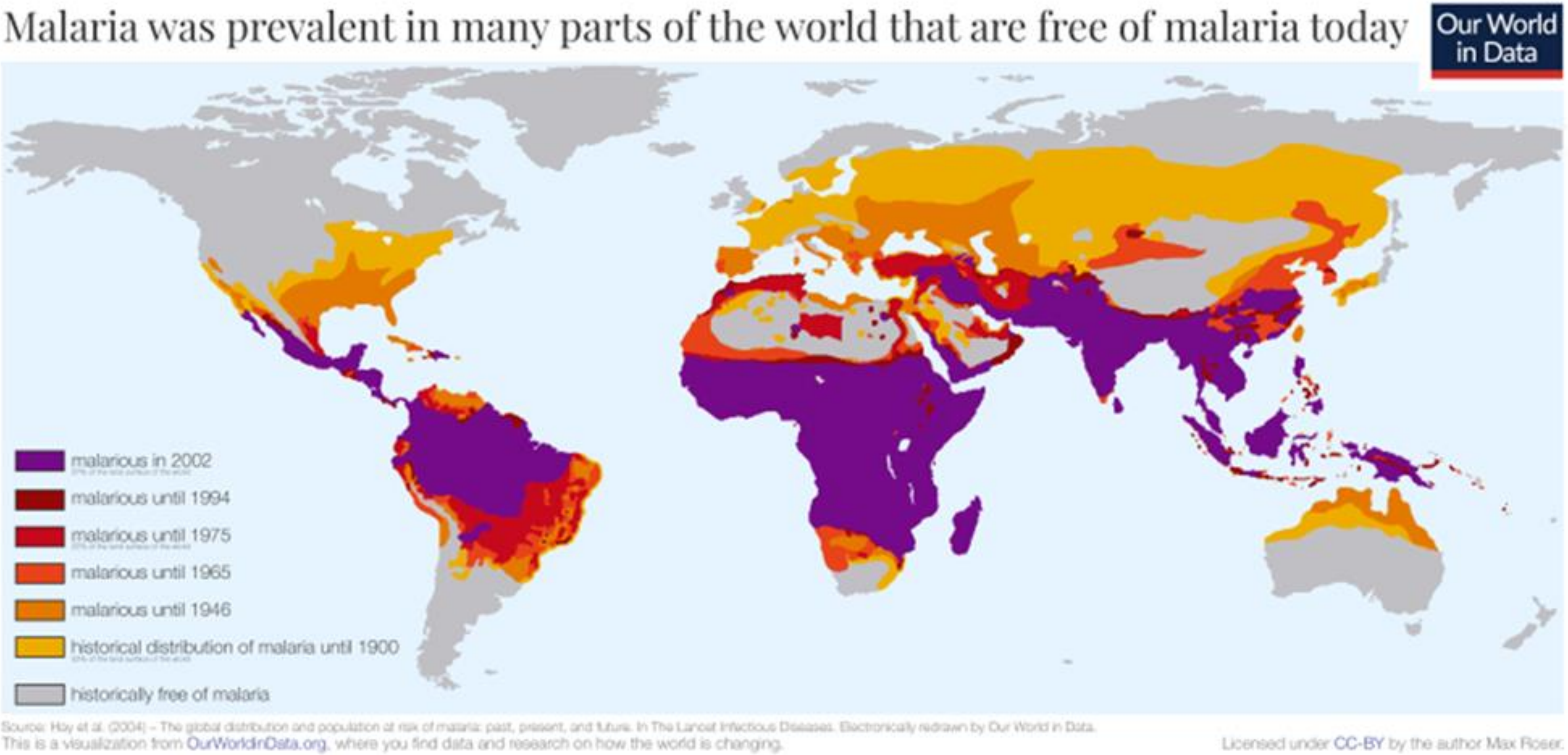
Background: Malaria and Factors that Impact Transmission

Malaria is a disease caused by *Plasmodium* parasites and vectored by mosquitoes in the genus *Anopheles*.

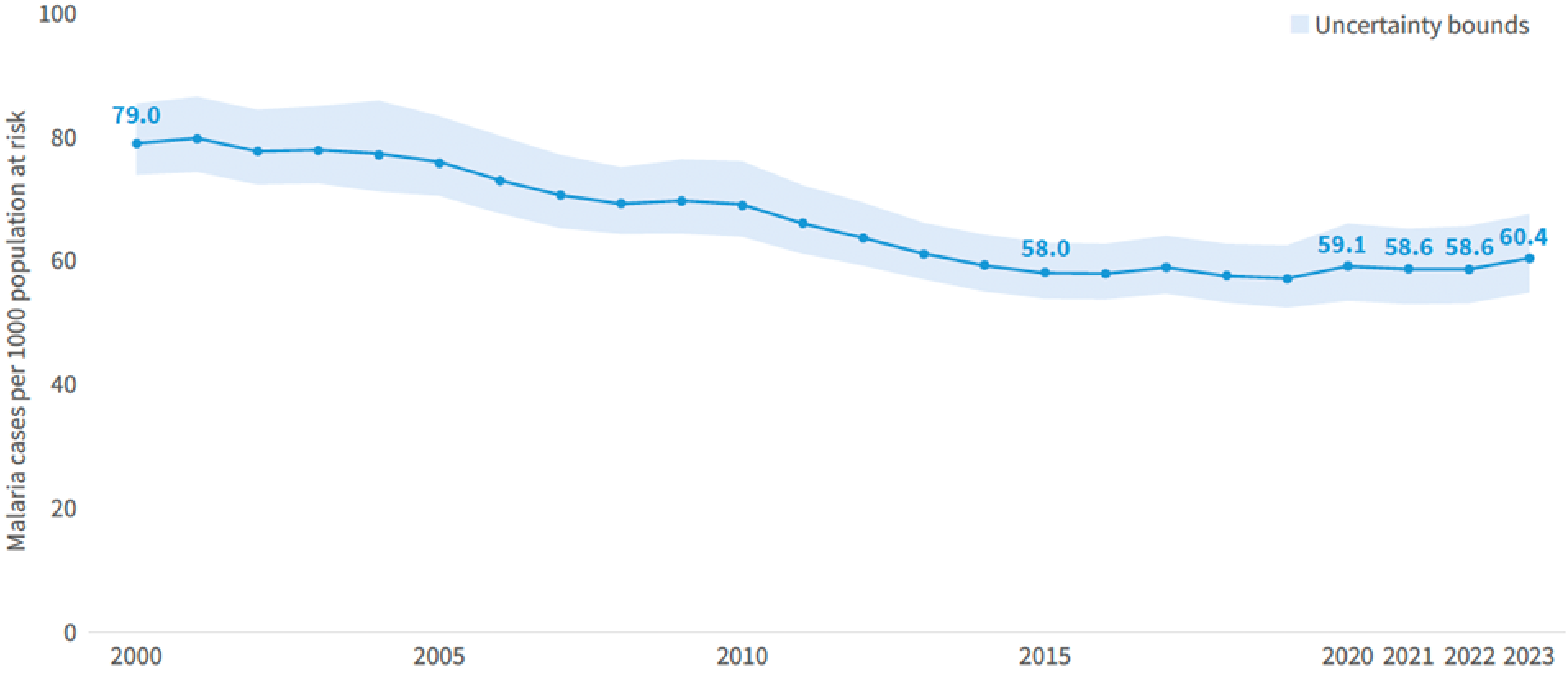


Source: National Institutes of Health

Malaria is a global disease, but its distribution was greatly reduced during the 20th century.

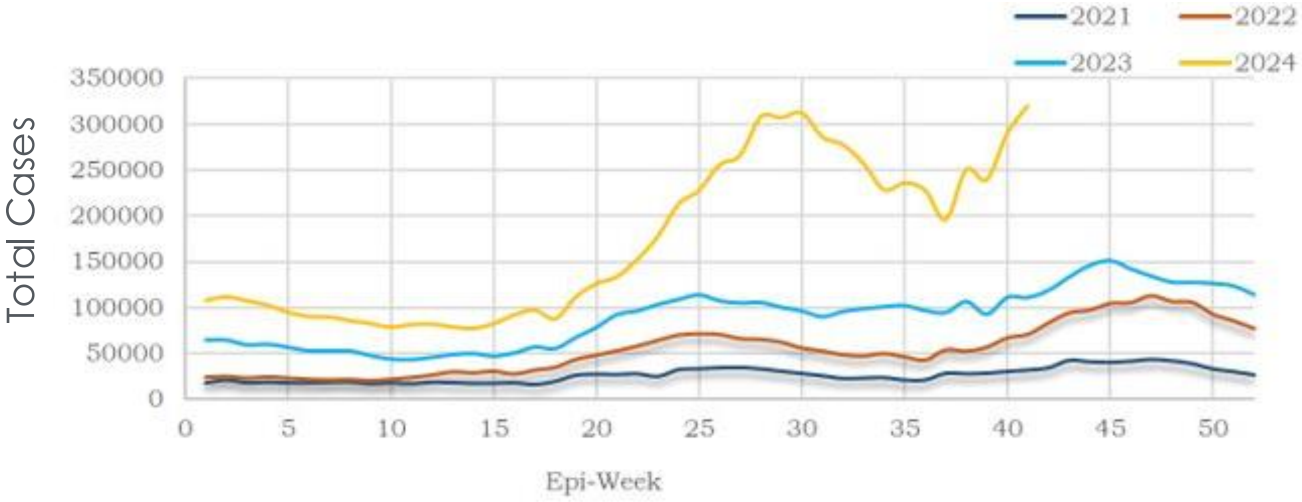


The global malaria burden has continued to decline since 2000, but incidence has resurged since 2015.

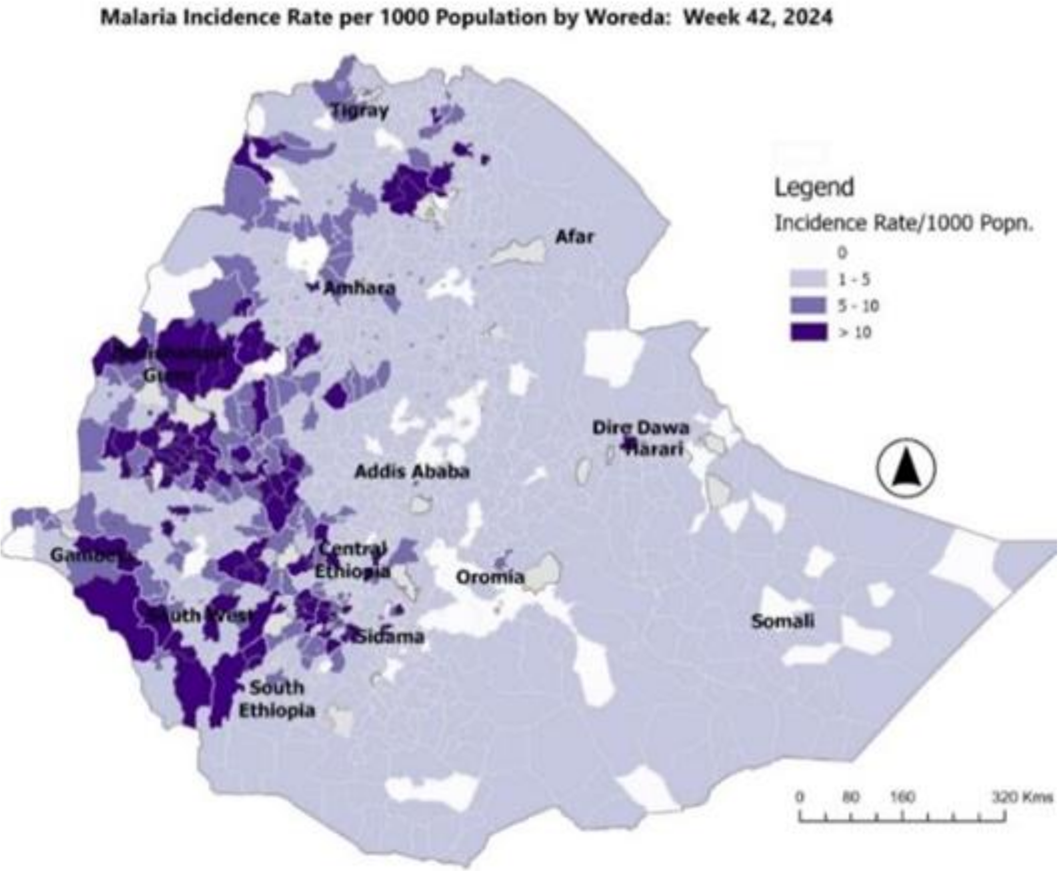


Source: World Malaria Report, 2024

In Ethiopia, there have been substantial increases in malaria incidence since 2020.



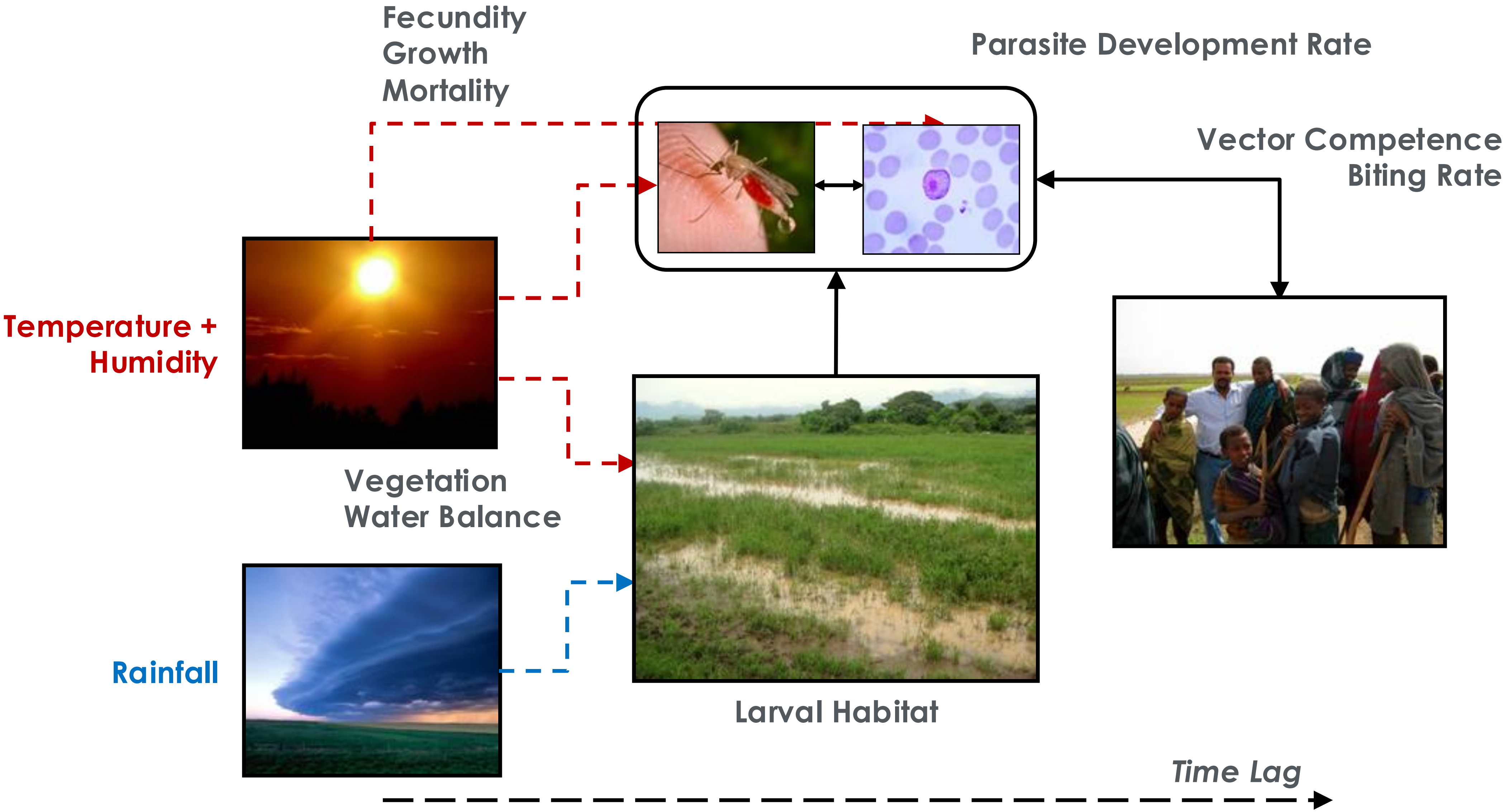
Source: World Health Organization, Disease Outbreak News, October 31, 2024



Background and Rationale for Malaria Forecasting in Ethiopia

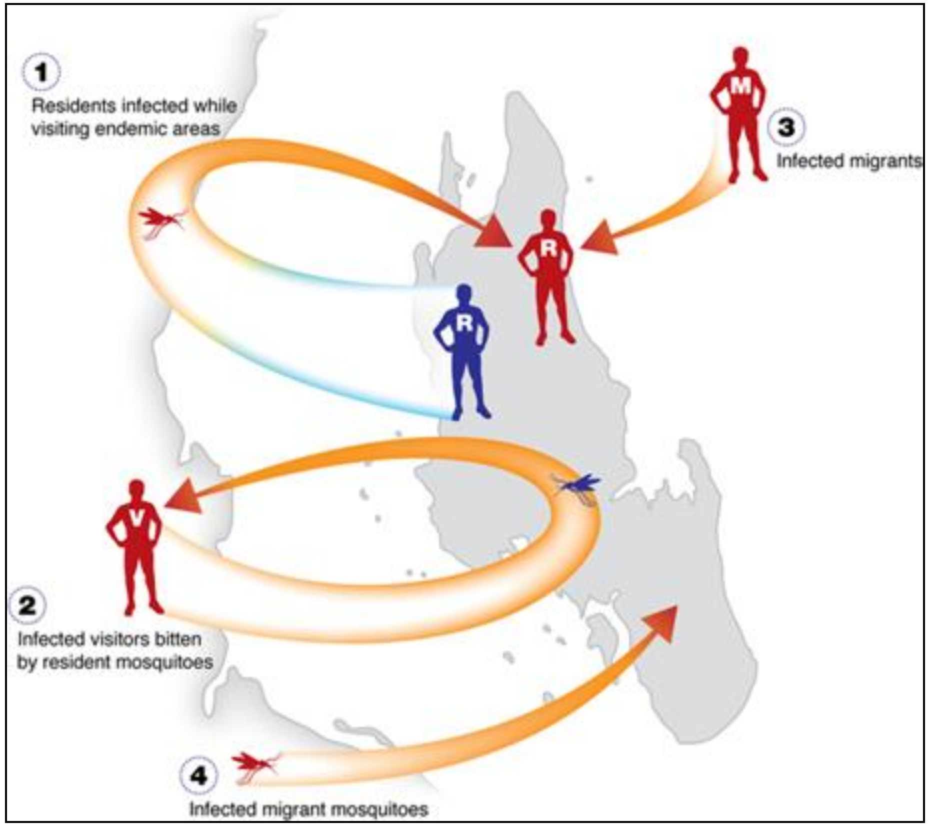
- High morbidity and mortality from epidemics in areas with unstable transmission
- Resurgent outbreaks in areas with declining malaria burdens
- New malaria risks emerging from climate change, drug and insecticide resistance, spread of urban malaria vectors
- Outbreak prediction can facilitate more rapid and targeted interventions that would reduce public health impacts

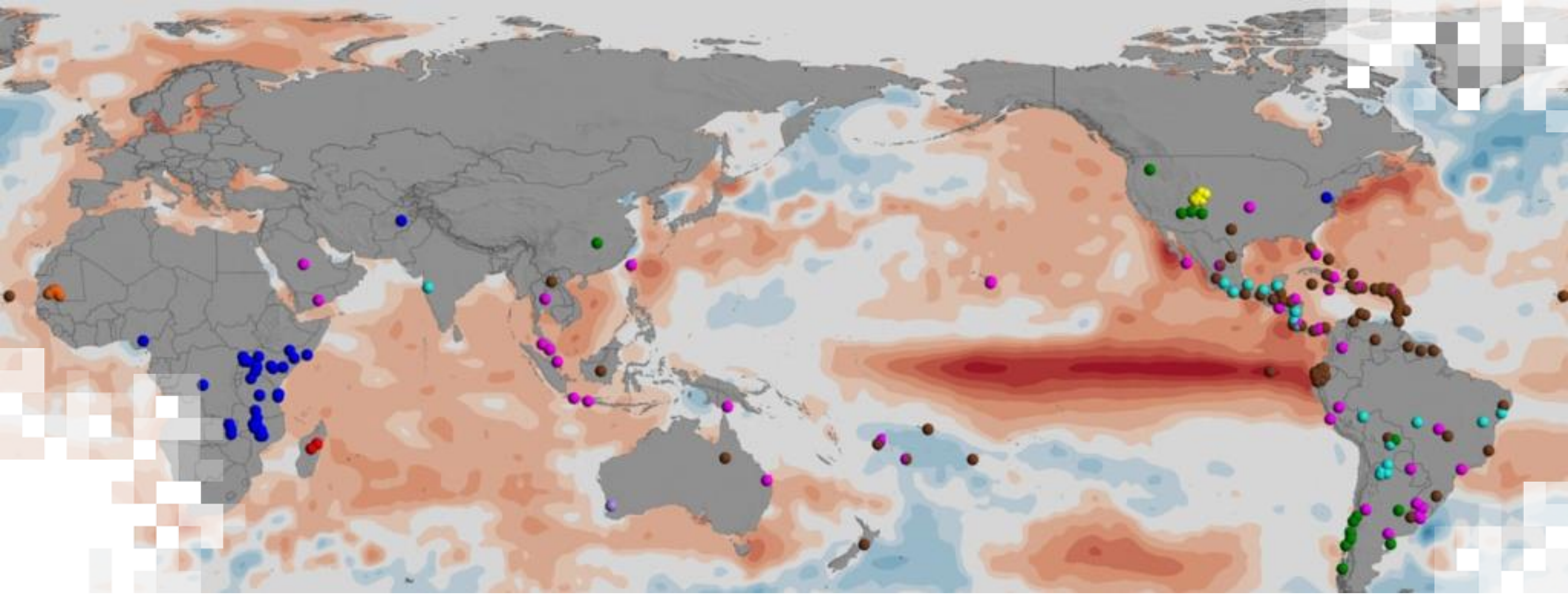
Climate factors, such as temperature and precipitation, affect malaria transmission.



However, non-climatic factors also influence malaria transmission.

- Movement of people and parasites
- Accessibility and quality of health care
- Interventions for malaria prevention and control





Remote Sensing Datasets, Tools, & Processing

Epidemic Prognosis Incorporating Disease and Environmental Monitoring for Integrated Assessment (EPIDEMIA)

- Computer software co-developed by the University of Oklahoma (formerly South Dakota State University); Health, Development, and Anti-Malaria Association, Amhara Public Health Institute, and Bahir Dar University
- Piloted in the Amhara region
- Data driven approach combines malaria surveillance data with environmental data from Earth-observing satellites
- Multiple techniques for outbreak prediction
  - Early warning forecasts based on environmental models
  - Early detection based on recent malaria observations

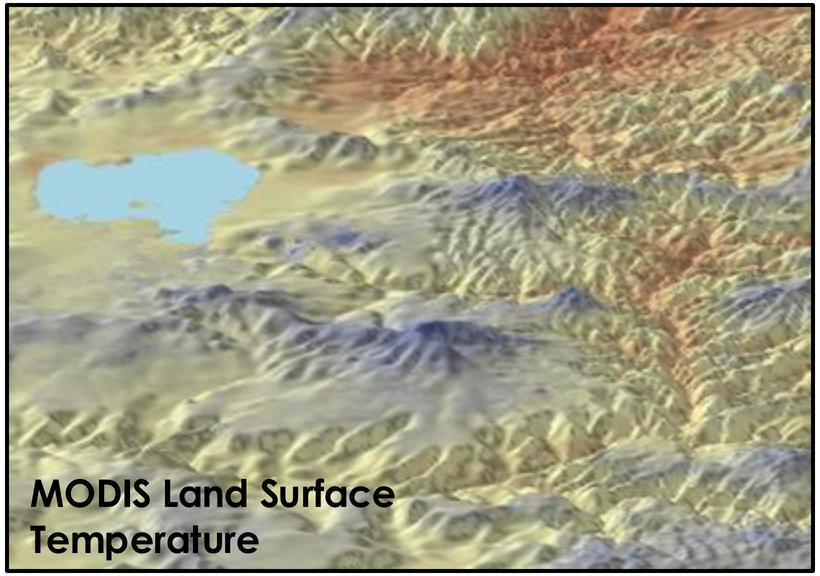
EPIDEMIA has features that make it particularly well-suited for scaling up malaria early warning.

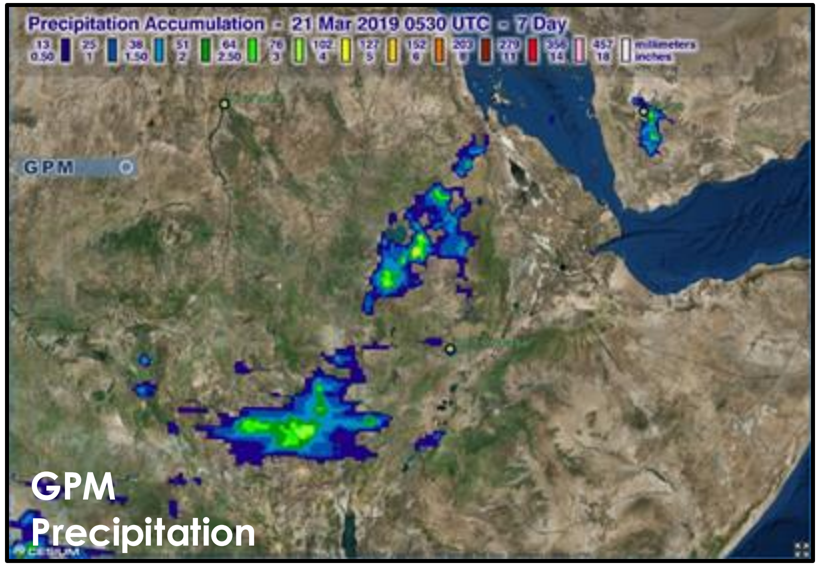
- Free and open-source software using freely available data
  - R language and environment for statistical computing
  - NASA remote sensing data products accessed through Google Earth Engine
- Automates time-consuming steps in the forecasting workflow
  - Acquires, processes, and formats data
  - Fits predictive models and generates forecasts
  - Produces detailed formatted reports with maps and charts
- Can be applied in any locations where the appropriate malaria and environmental data are available
- Requires trained analysts to operate software and interpret outputs

We use environmental data collected by NASA Earth-observing satellites.

- Requirements:
  - Global availability
  - Spatially continuous observations
  - Frequent measurement intervals
  - Rapid availability (within days)

- Datasets Used:
  - Land Surface Temperature (MODIS LST)
  - Vegetation Greenness and Moisture Indices (MODIS/VIIRS Optical-IR Reflectance)
  - Precipitation (Global Precipitation Measurement [GPM] Mission)


MODIS Land Surface Temperature



GPM Precipitation

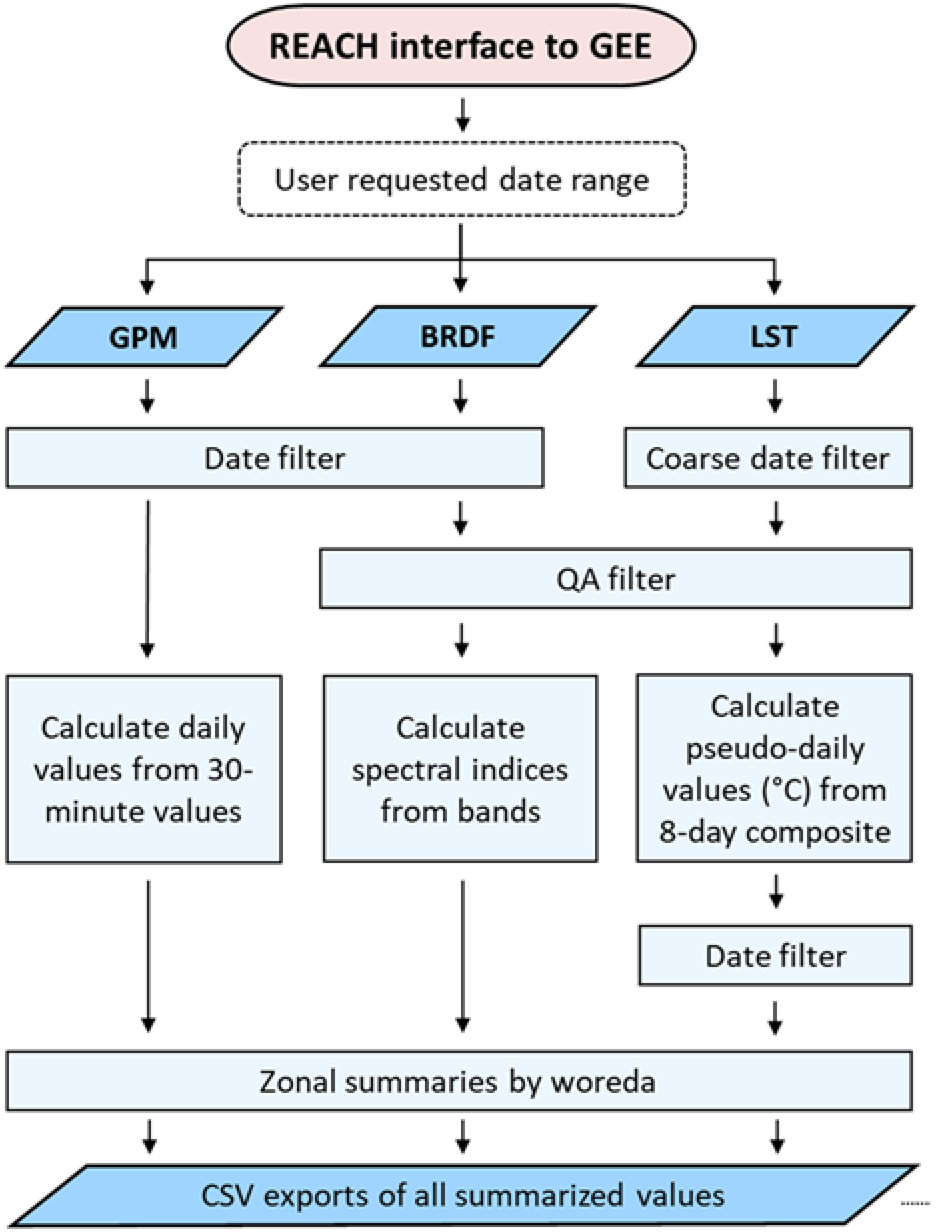
NASA Earth science data products are processed to generate environmental indices.

Data Source	Indices
MODIS Terra 8-day land surface temperature and emissivity product (MOD11A2)	Daytime land surface temperature (LST), Nighttime LST, Mean LST
MODIS bidirectional reflectance distribution function (BRDF) adjusted surface reflectance product (MCD43B3)	Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), Normalized difference water indices (NDWI5 and NDWI6)
Integrated Multi-SatellitE Retrievals for GPM (IMERG) product version 6	Total precipitation

Wimberly et al. (2022) *Scientific Data* 9: 208

Multiple data processing steps are…

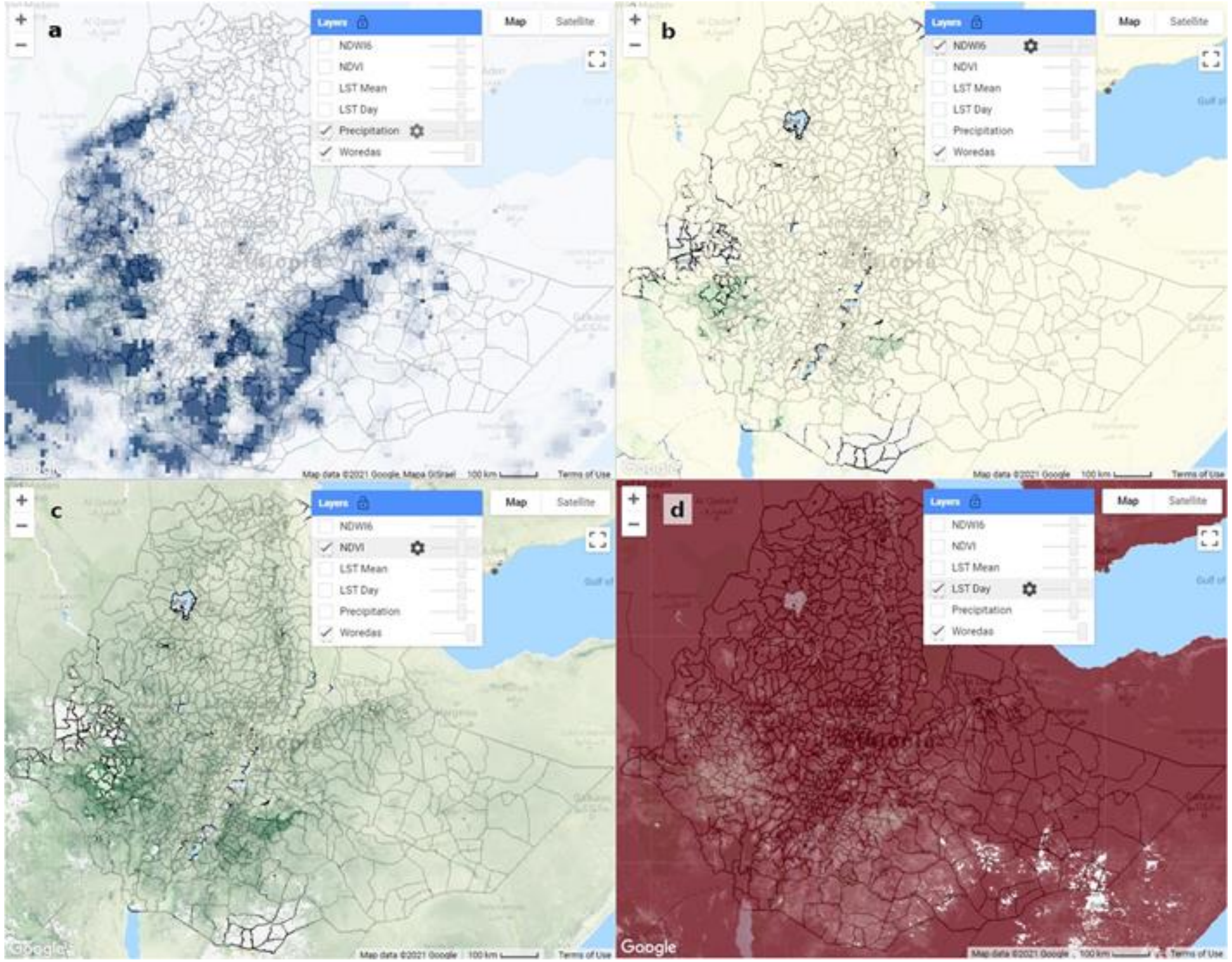
- Select desired date range
- Filter out low-quality observations
- Calculate spectral indices
- Temporal summarization (daily)
- Spatial summarization by zone (woreda)
- Export data summarized data table
- Additional quality-control steps are carried out on the woreda-level time series
  - Screening anomalous values
  - Imputation of missing data



Wimberly et al. (2022) *Scientific Data* 9: 208

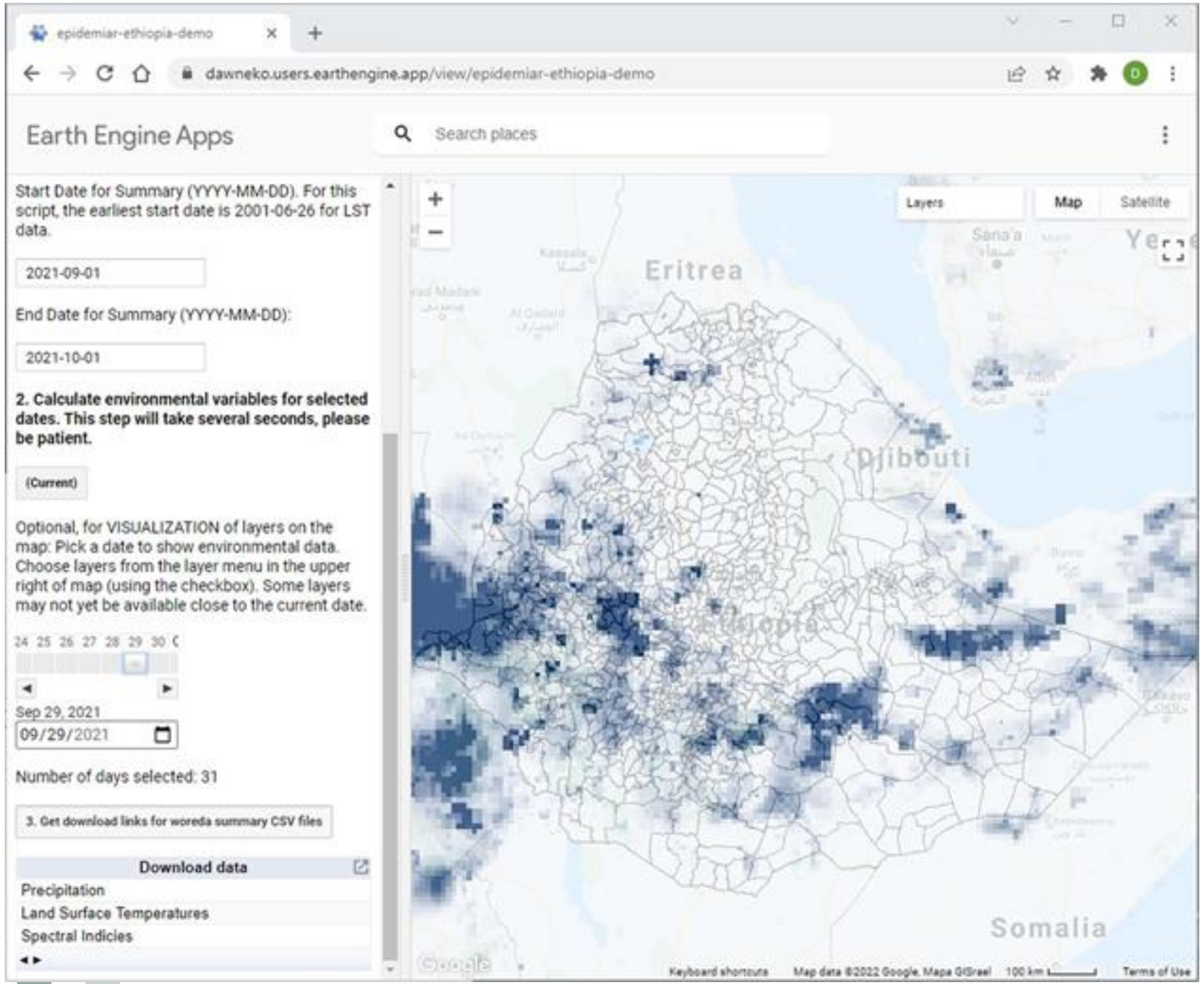
Geographic Patterns of Environmental Indices and Woreda Boundaries

a) Precipitation
b) Normalized Difference Water Index (Near-Infrared/Shortwave Infrared)
c) Normalized Difference Vegetation Index (Near-Infrared/Red)
d) Land Surface Temperature

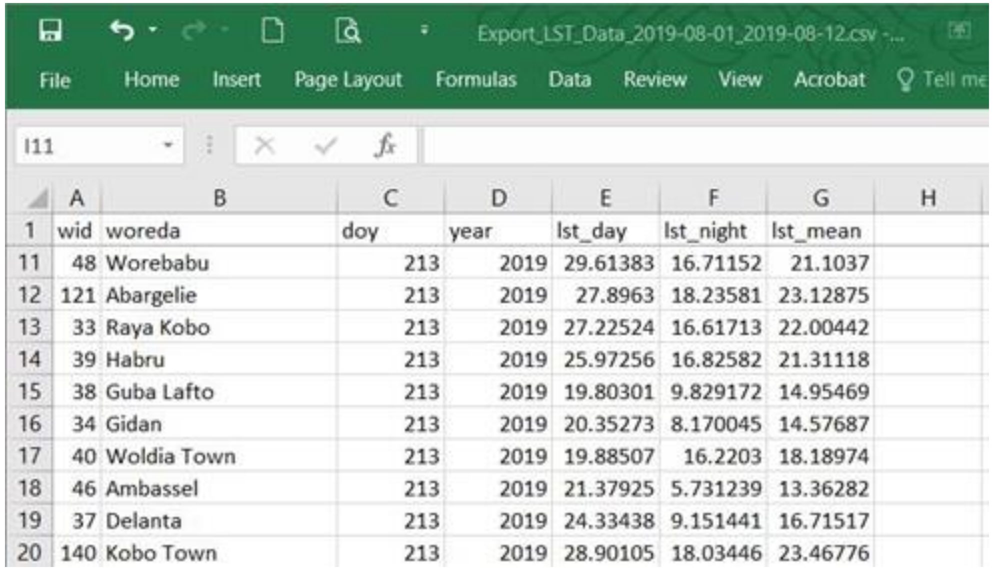


Wimberly et al. (2022) *Scientific Data* 9: 208

These environmental data are accessed and processed in the cloud using Google Earth Engine (GEE).



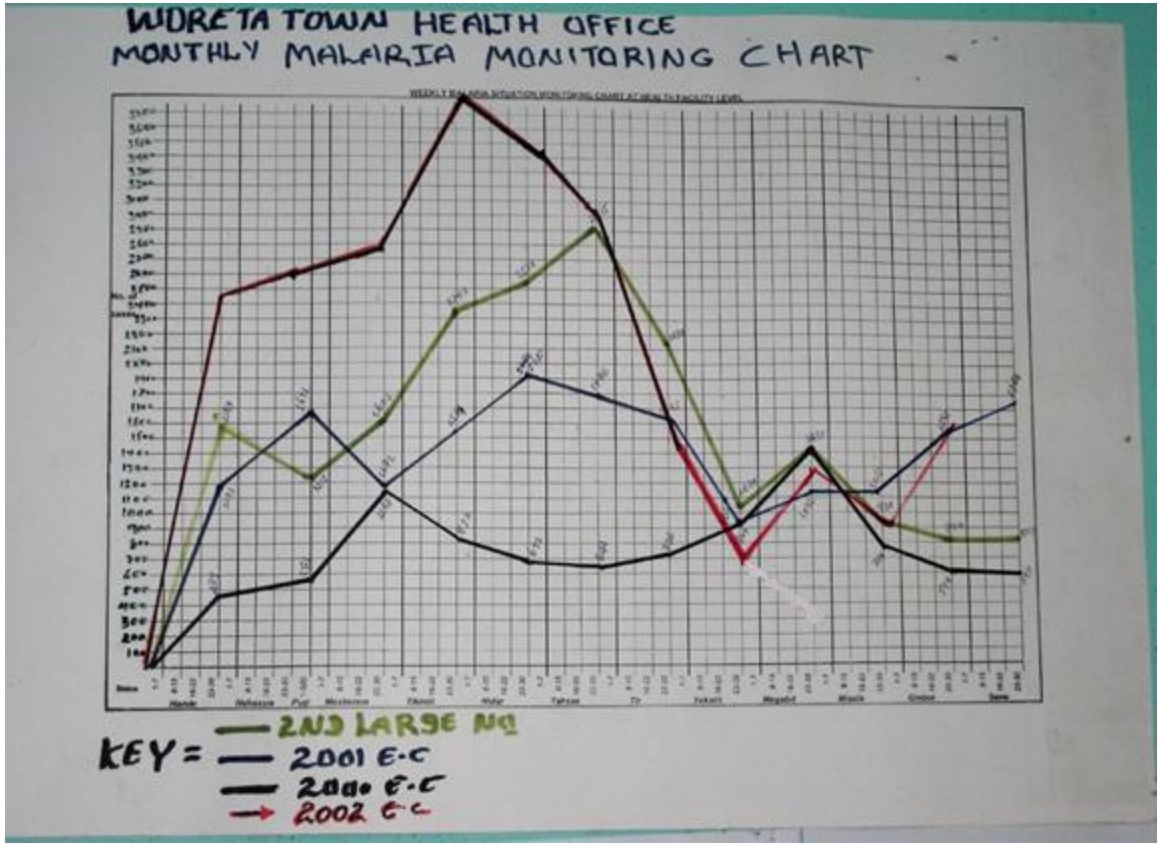
- Retrieving Environmental Analytics for Climate and Health (REACH)
- Web-based GEE tool for data access



	A	B	C	D	E	F	G
1	wid	woreda	doy	year	lst_day	lst_night	lst_mean
11	48	Worebabu	213	2019	29.61383	16.71152	21.1037
12	121	Abargelie	213	2019	27.8963	18.23581	23.12875
13	33	Raya Kobo	213	2019	27.22524	16.61713	22.00442
14	39	Habru	213	2019	25.97256	16.82582	21.31118
15	38	Guba Lafto	213	2019	19.80301	9.829172	14.95469
16	34	Gidan	213	2019	20.35273	8.170045	14.57687
17	40	Woldia Town	213	2019	19.88507	16.2203	18.18974
18	46	Ambassel	213	2019	21.37925	5.731239	13.36282
19	37	Delanta	213	2019	24.33438	9.151441	16.71517
20	140	Kobo Town	213	2019	28.90105	18.03446	23.46776

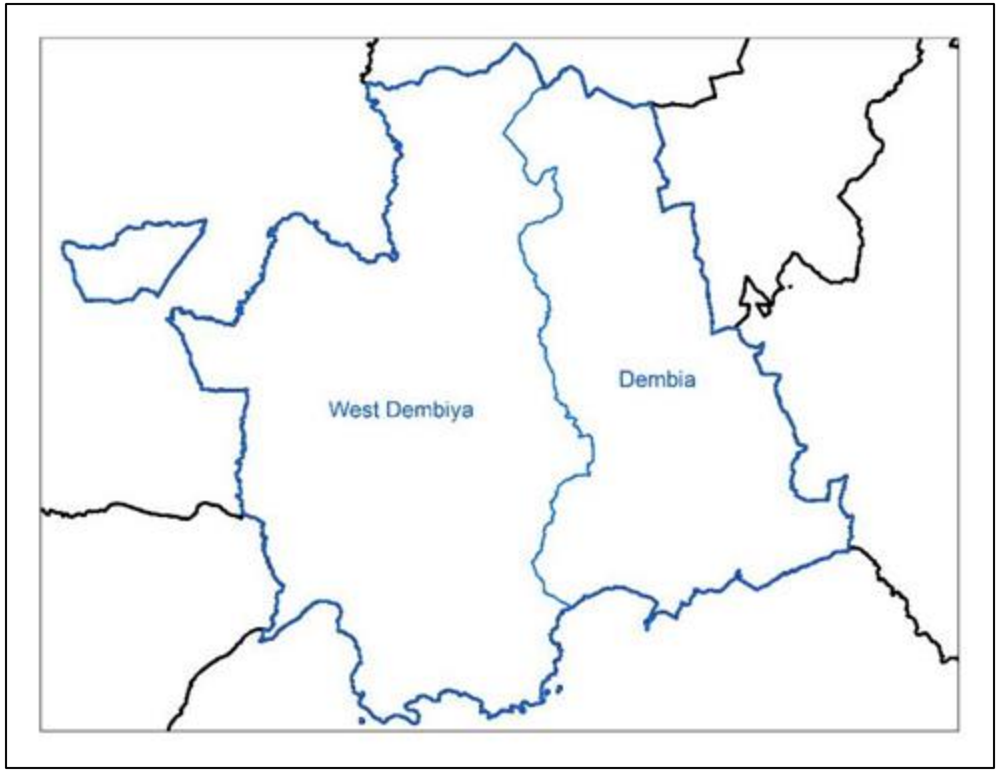
Weekly malaria data are obtained from Ethiopia's Public Health Emergency Management (PHEM) system.

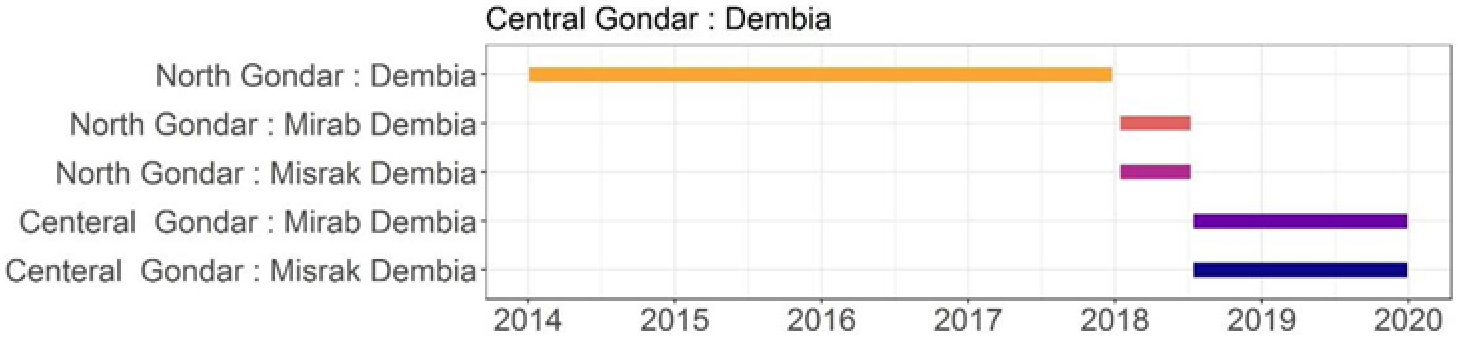
- Weekly woreda-level counts of confirmed malaria cases by species from 2014-2019
  - *Plasmodium falciparum*/mixed
  - *Plasmodium vivax*
- Require multiple levels of processing
  - Harmonization with other data sources
  - Screening for suspect values
  - Imputation of missing and suspect data



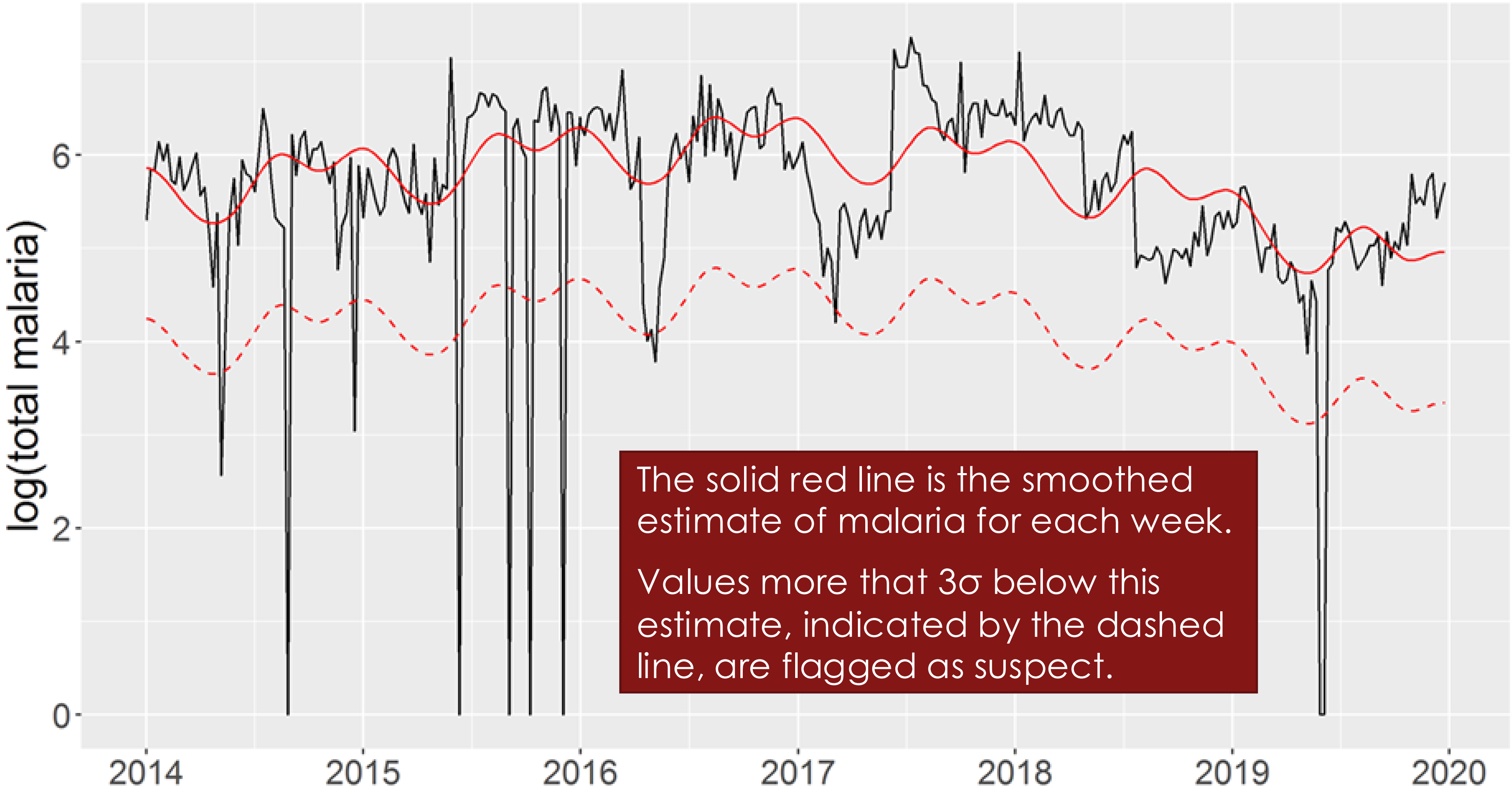
Geographic data are harmonized to resolve inconsistencies.

- Geographic Changes
  - Split from “Dembia” into “Misrak Dembia” & “Mirab Dembia”
  - Change of zone from “North Gondar” to “Centeral Gondar”
- Spelling Differences
  - “West Dembiya” vs. “West Dembia” vs. “Mirab Dembia”
  - “Central Gondar” vs. “Centeral Gondar”
- All merged into “Dembia” to create a standardized time series for modeling





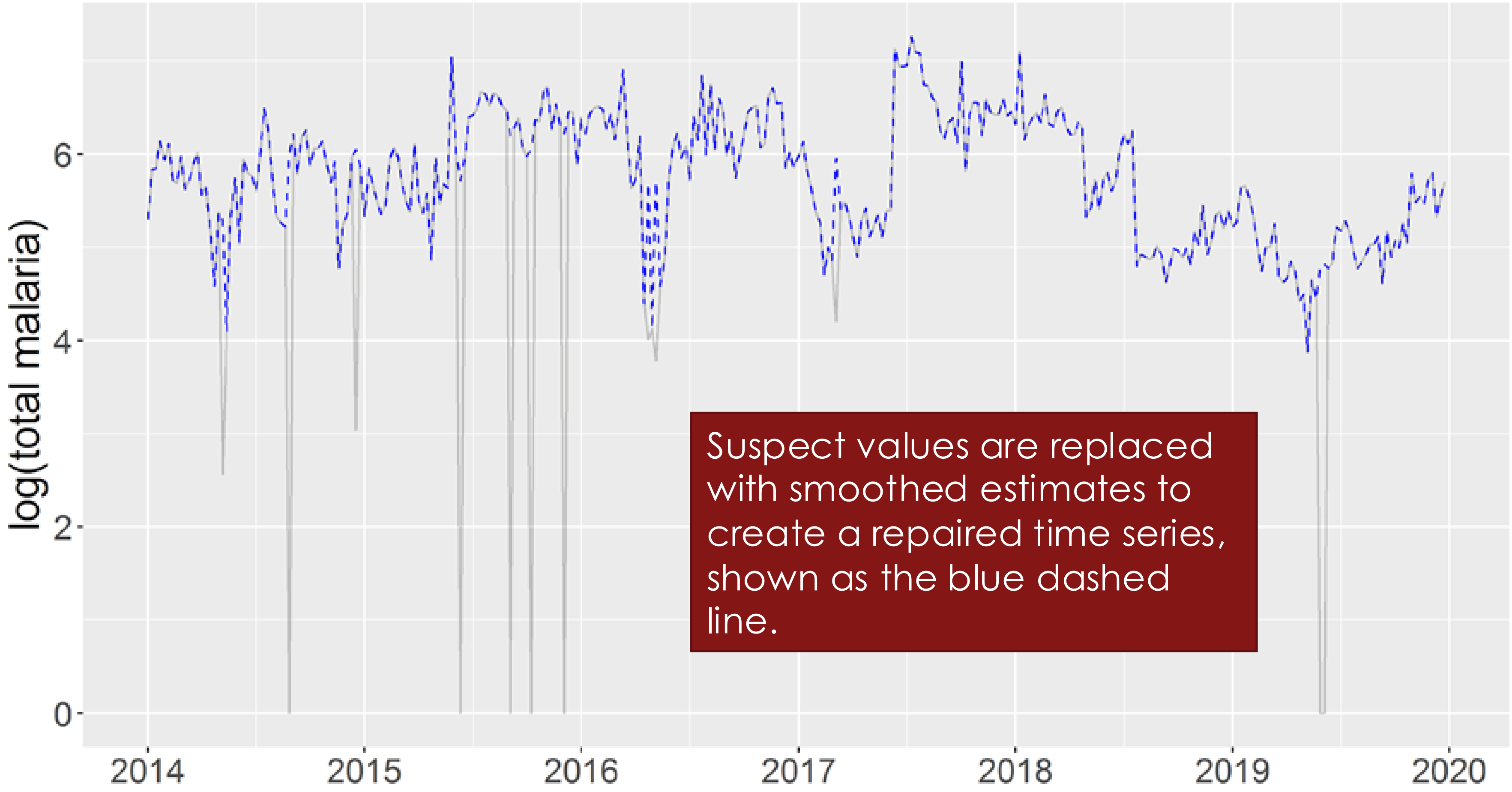
We used a robust linear model to screen out weeks where there were unusually low case counts.



The solid red line is the smoothed estimate of malaria for each week.

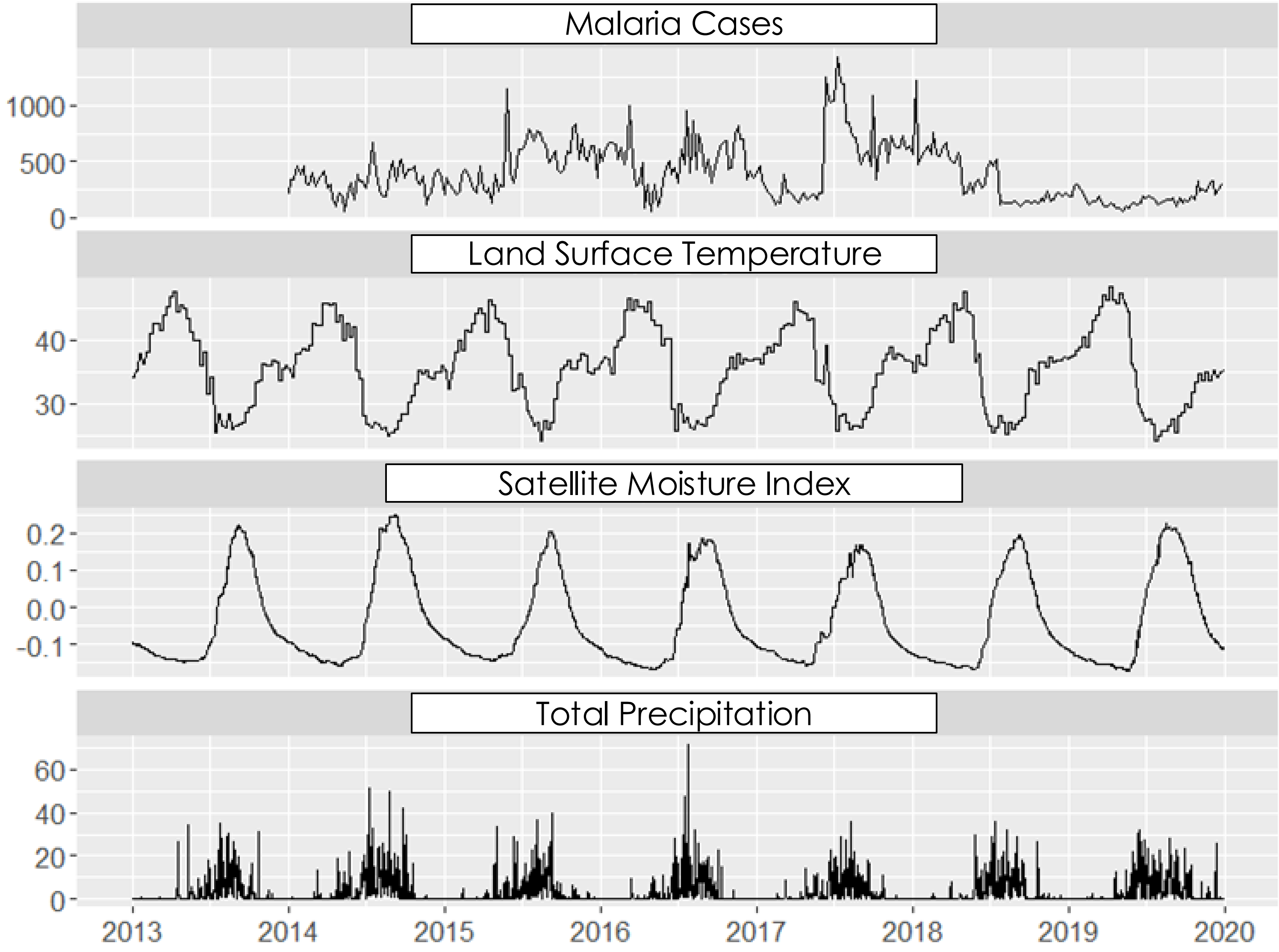
Values more that 3σ below this estimate, indicated by the dashed line, are flagged as suspect.

We then replaced suspect and missing data with smoothed estimates from the robust model.

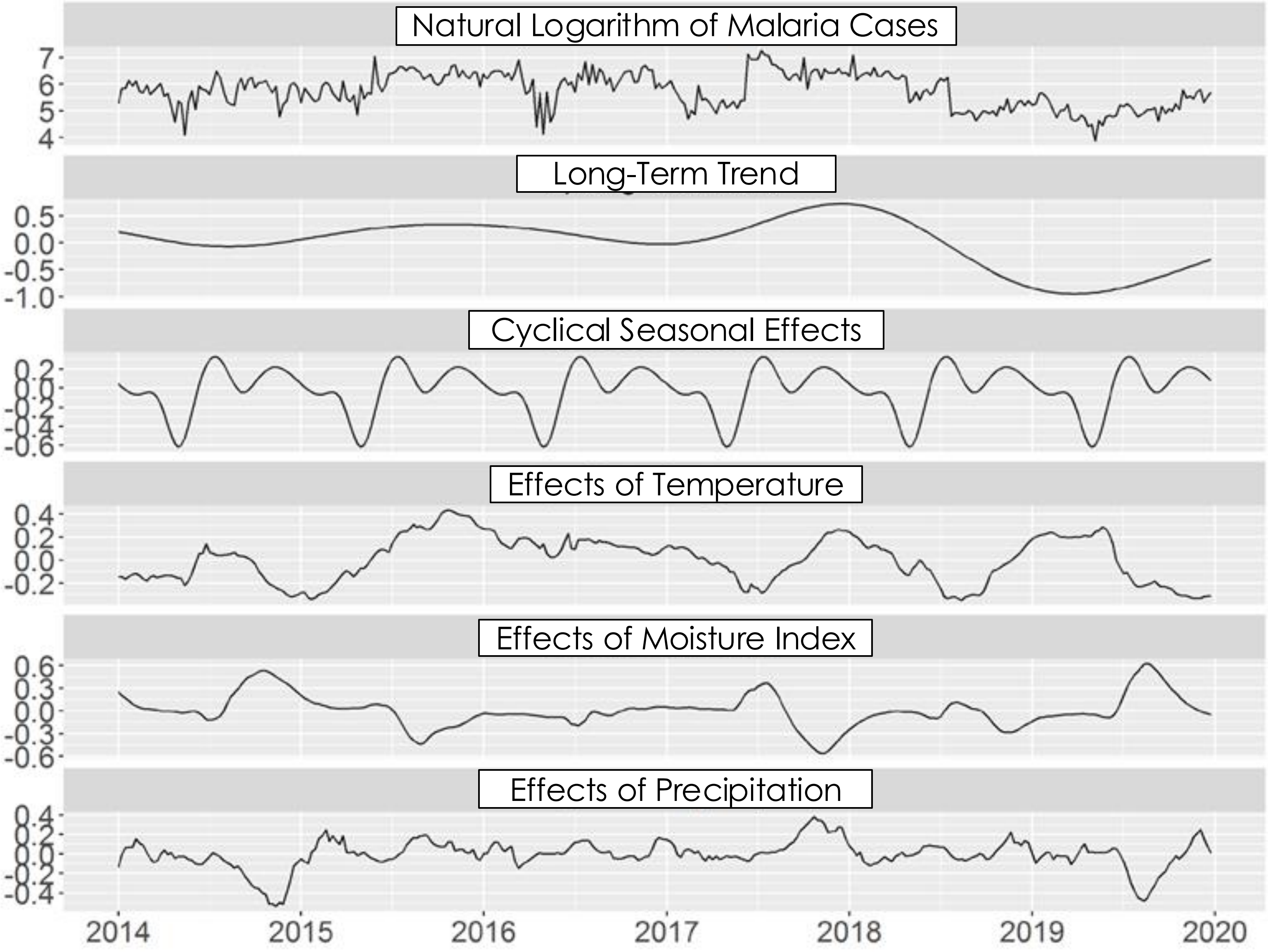


Suspect values are replaced with smoothed estimates to create a repaired time series, shown as the blue dashed line.

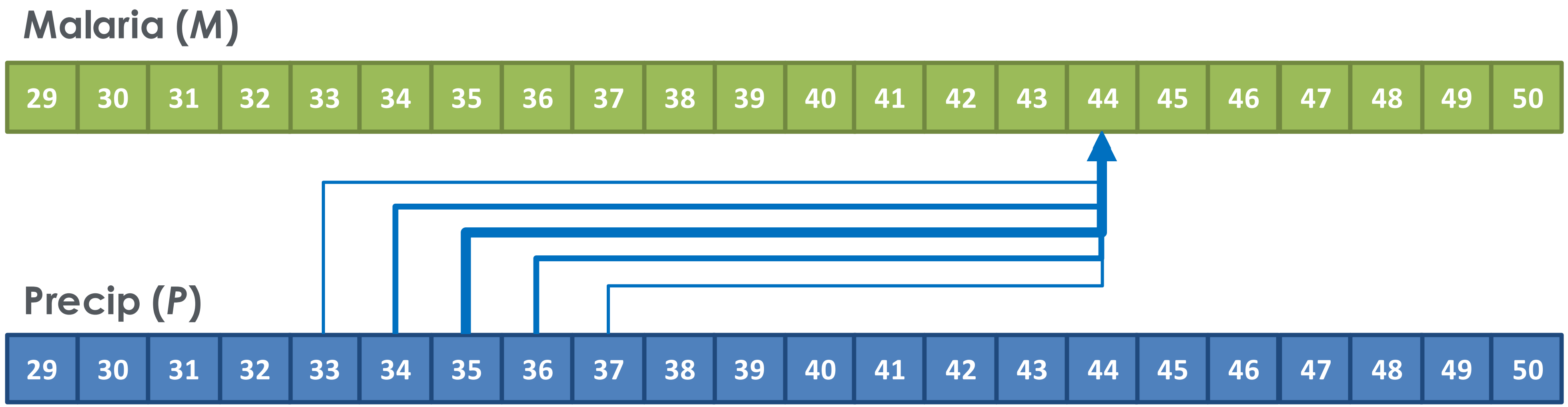
Data for modeling include time series of malaria cases and remote-sensed environmental variables for each district.



Time series models are used to decompose the malaria data into a set of predictable components.

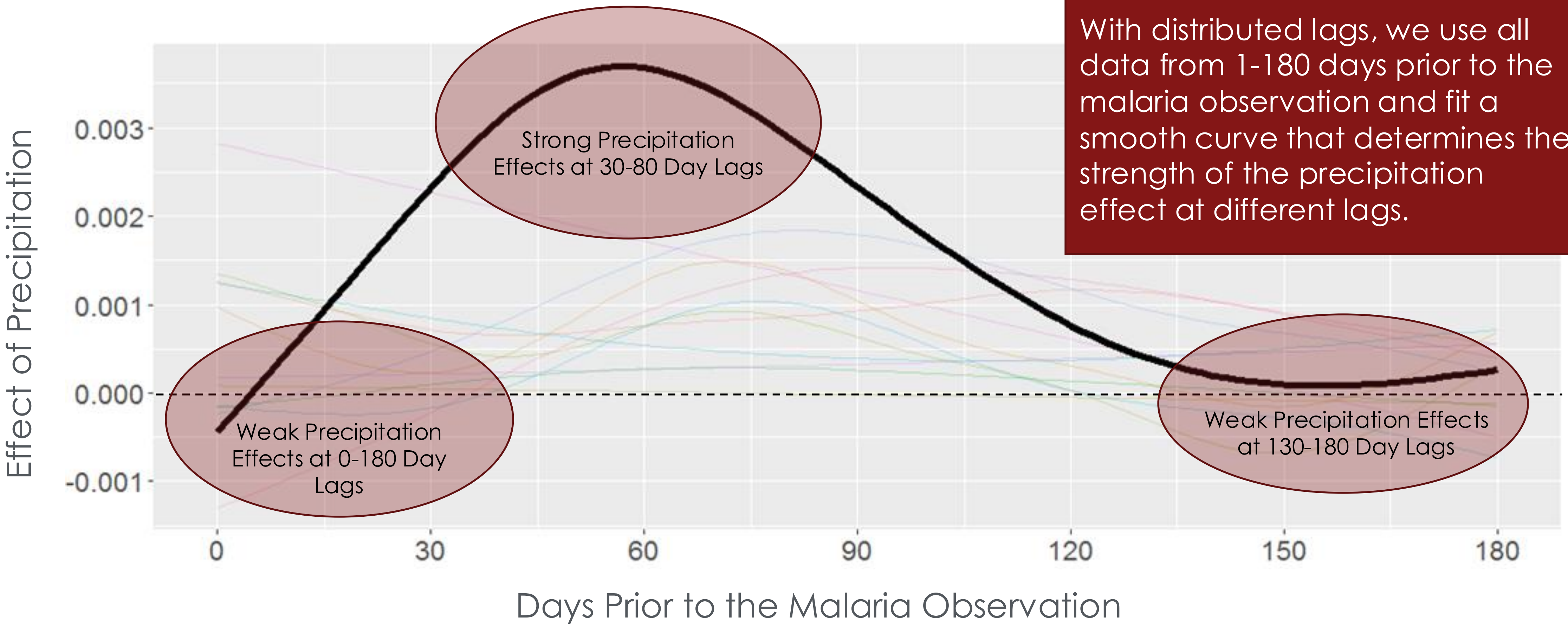


The influences of climate variation on malaria are modeled as *lagged environmental effects*.



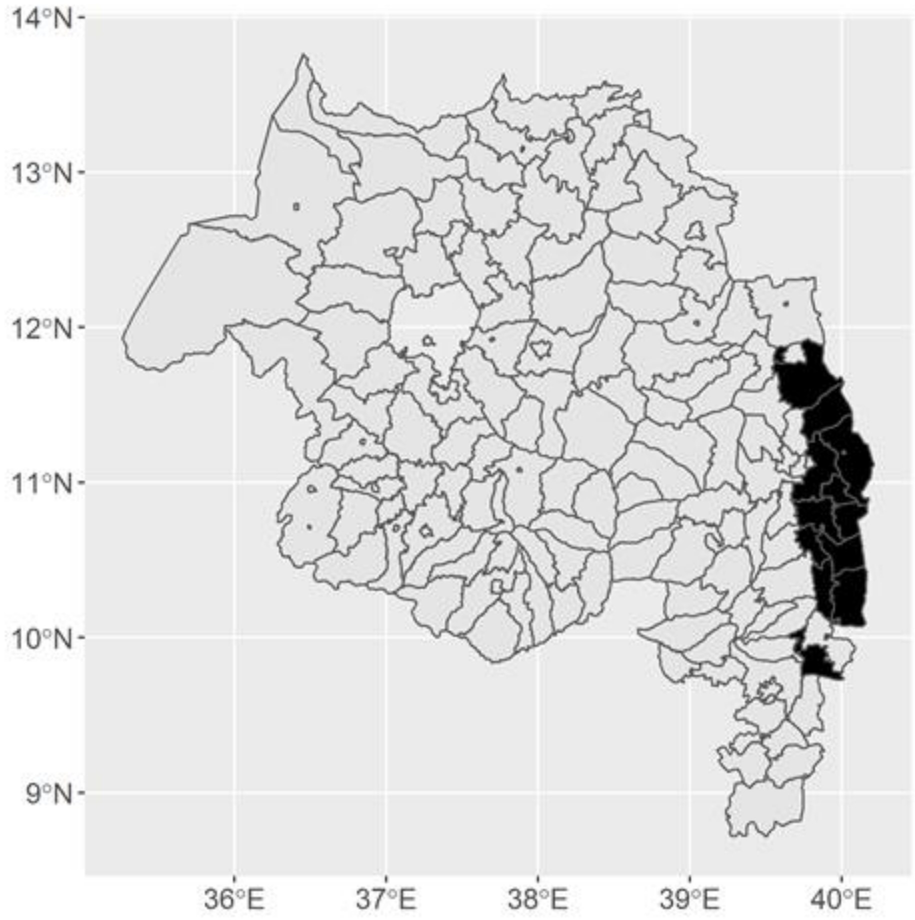
- How do we determine the correct lag between precipitation and malaria case occurrence?
- What if there are multiple lags, with a different effect for each lag?

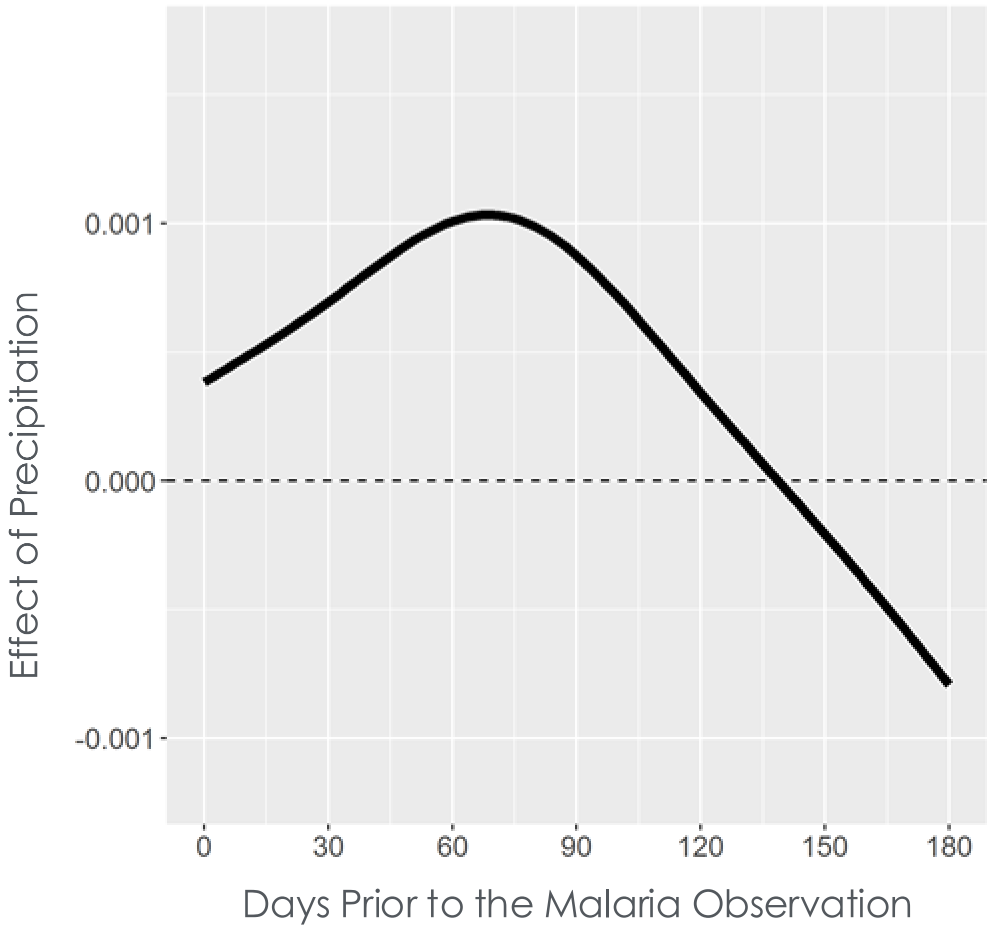
We use *distributed lags* to model these effects as a smooth functions, estimating the shapes of these functions from the data using machine learning techniques.



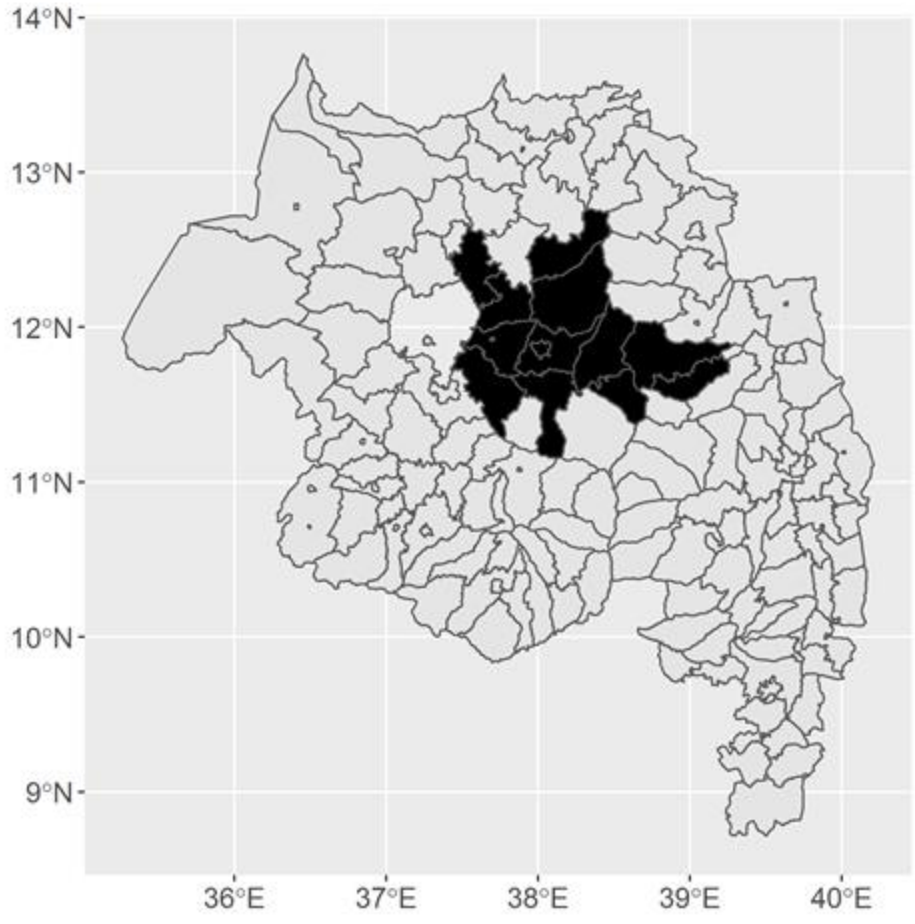
With distributed lags, we use all data from 1-180 days prior to the malaria observation and fit a smooth curve that determines the strength of the precipitation effect at different lags.

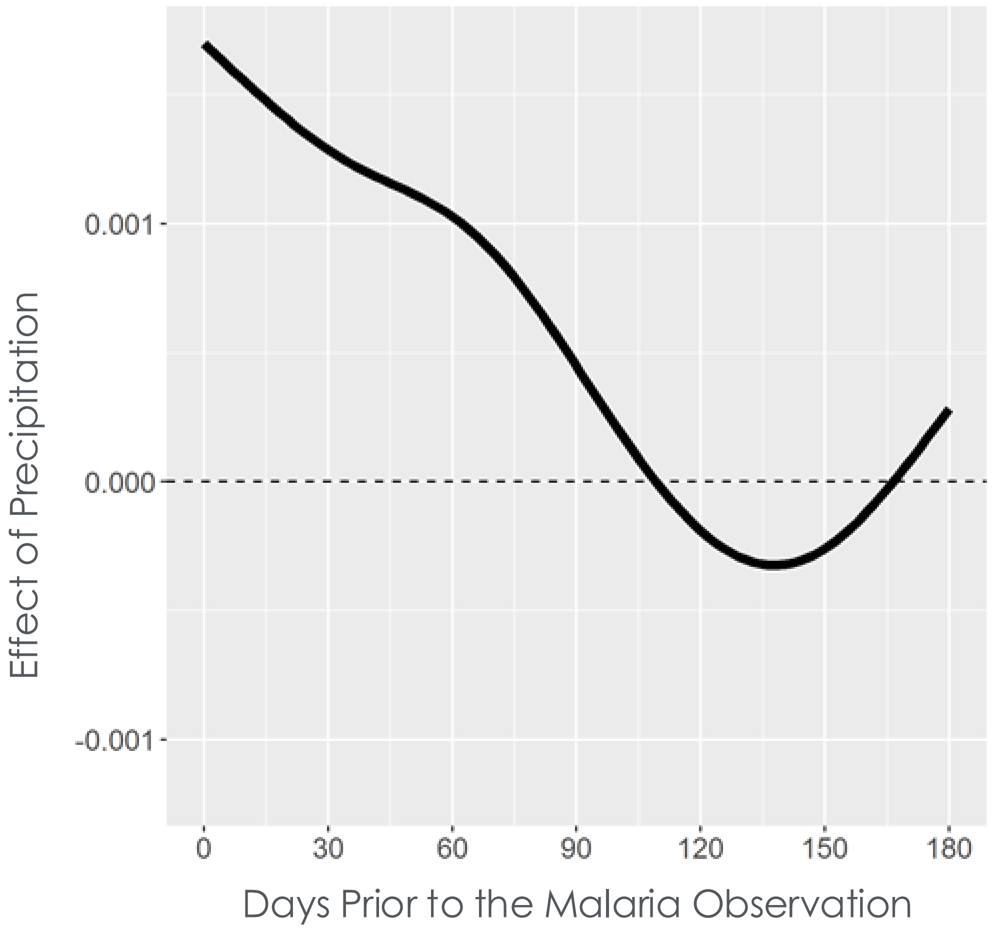
We do not expect lagged effects to be the same everywhere. This cluster in a drier location with a dual rainfall peak has the strongest precipitation effect on malaria at a 10-week lag.



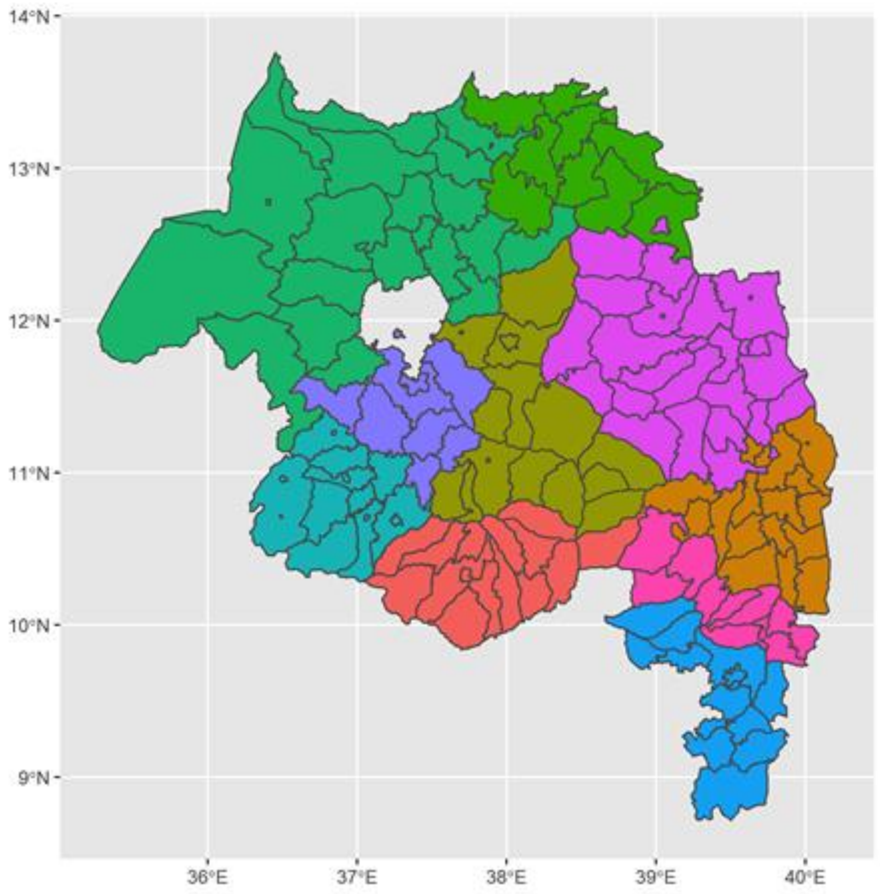


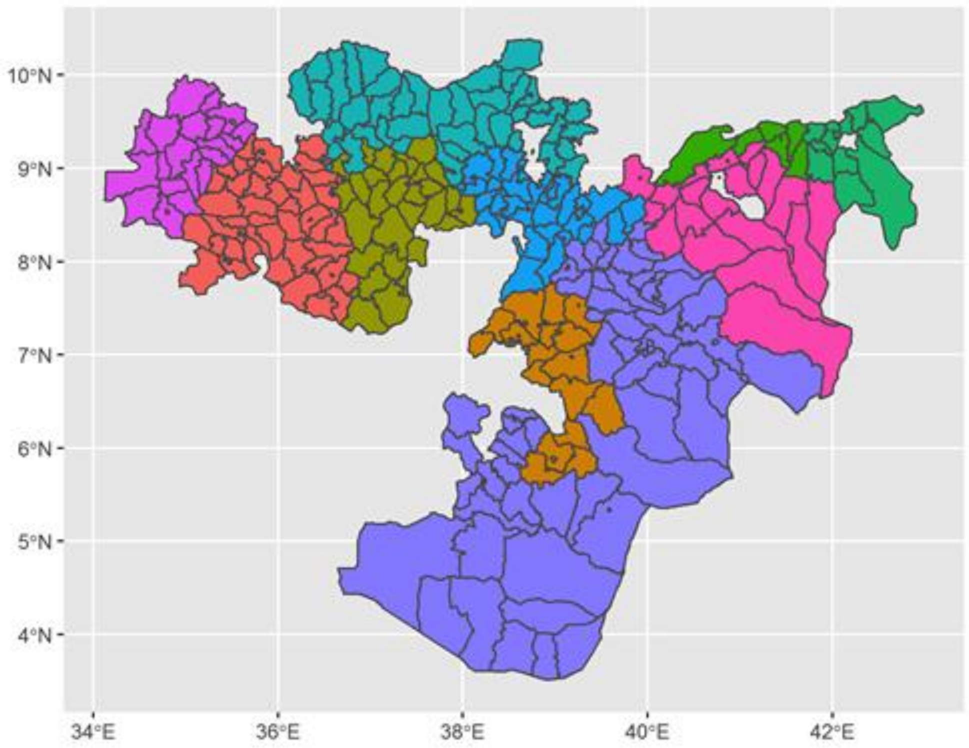
In contrast, this cluster in a wetter region with a single rainfall peak has the strongest precipitation effect on malaria at lags of 1-4 weeks.



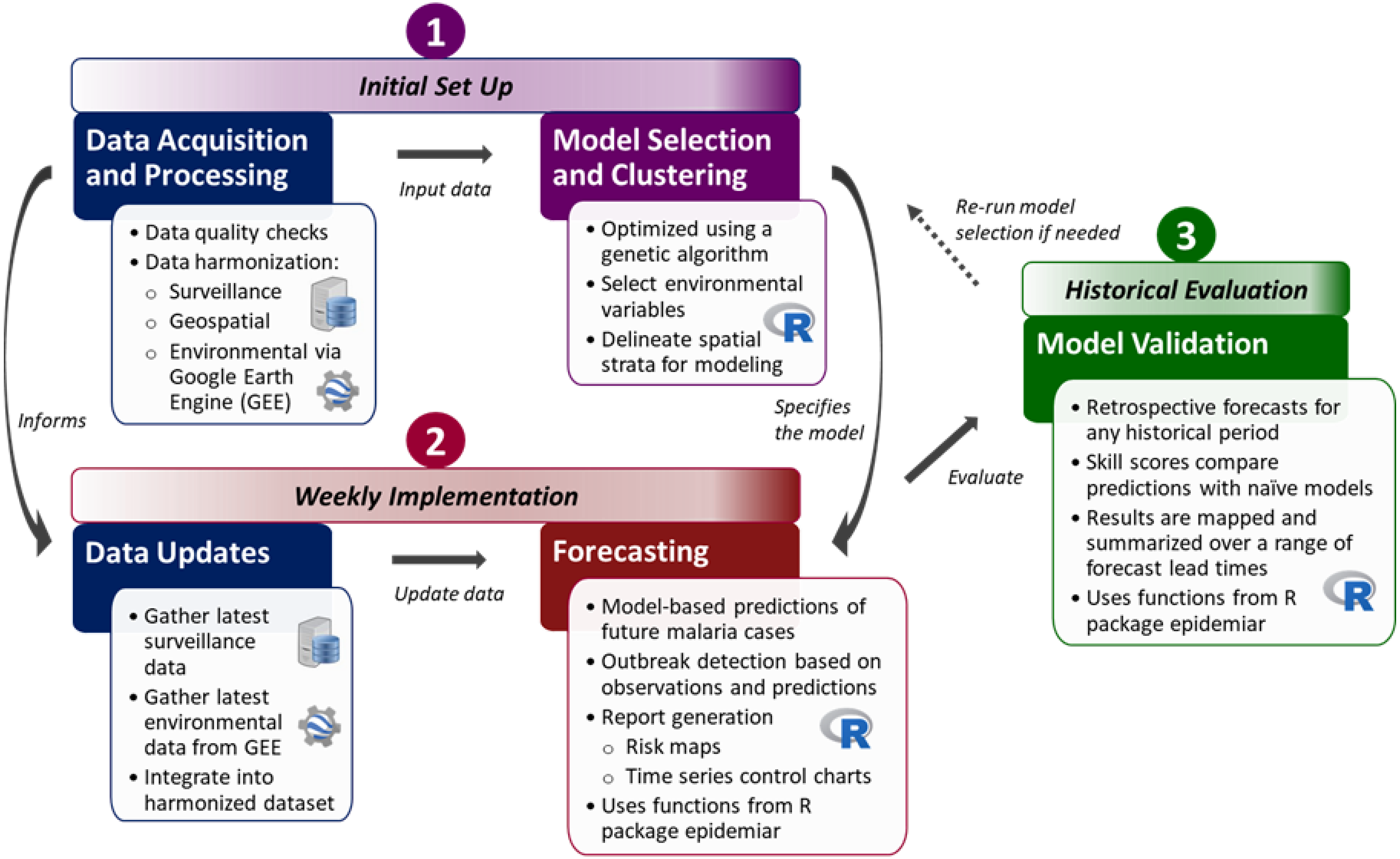


Optimization methods are used to assign woredas to clusters with similar environmental sensitivities.

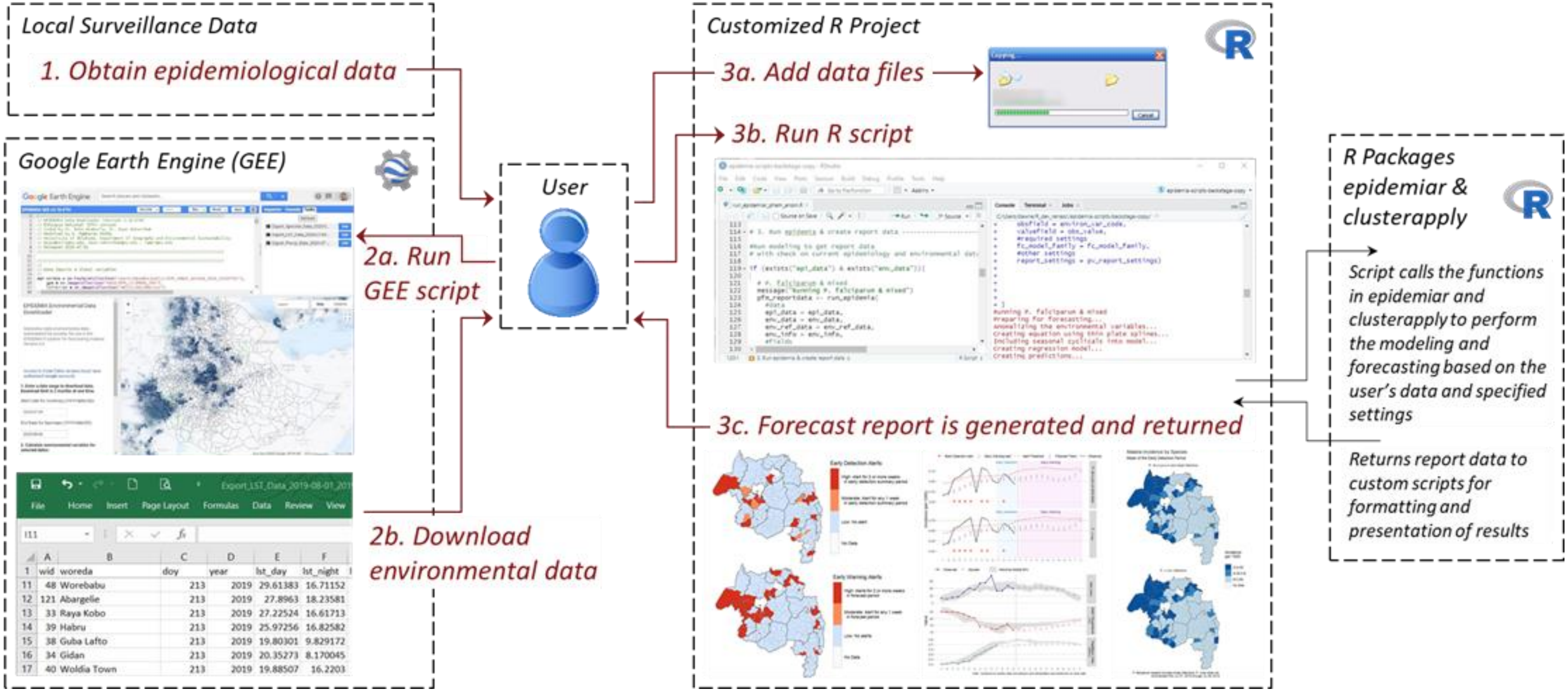




The basic workflow for implementing malaria forecasting in EPIDEMIA involves three steps.



Running EPIDEMIA operationally requires several steps to generate a weekly forecast.

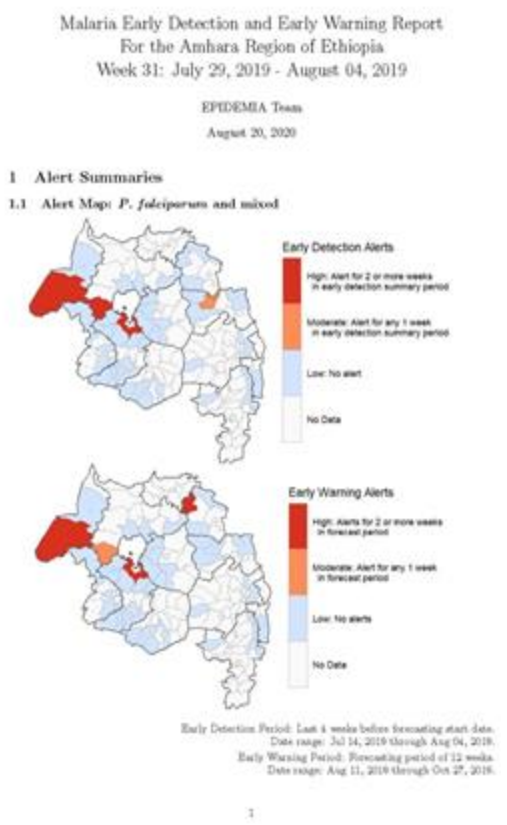


We implemented EPIDEMIA as a semi-automated system running on local workstations.

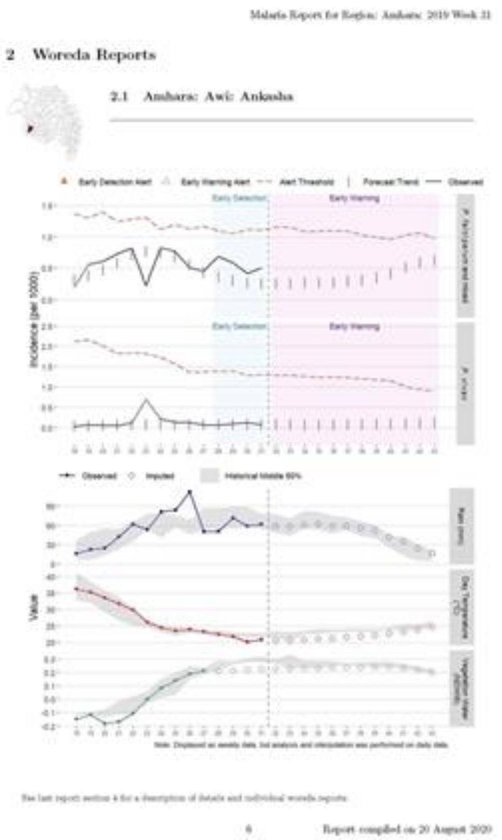
Completely Manual using Software on Local Workstations	Semi-Automated System Running on Local Workstations (EPIDEMIA)	Completely Automated, Menu-Driven, Web-Based System
• Minimal development costs • Leverages existing computer resources	• Considerably faster than a fully manual approach • Implementable on a variety of computers • Highly customizable	• Easiest and quickest to use • Centralized maintenance
• Time and cost of data analysis • Lack of consistency • Difficult to replicate	• Troubleshooting on diverse systems • Requires some manual steps • R and RStudio can be challenging for some users	• High cost for development and maintenance • Data sharing limitations • System integration challenges

EPIDEMIA automatically generates a formatted report with several types of graphical output.

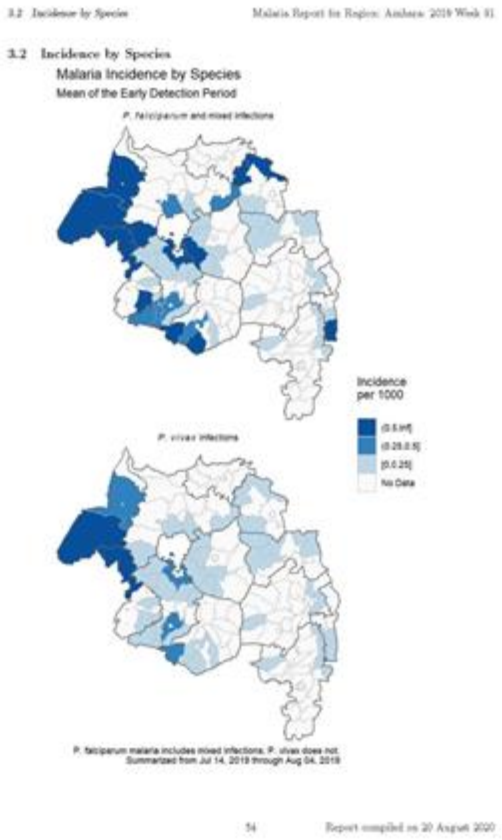
Summary **Alert Maps**



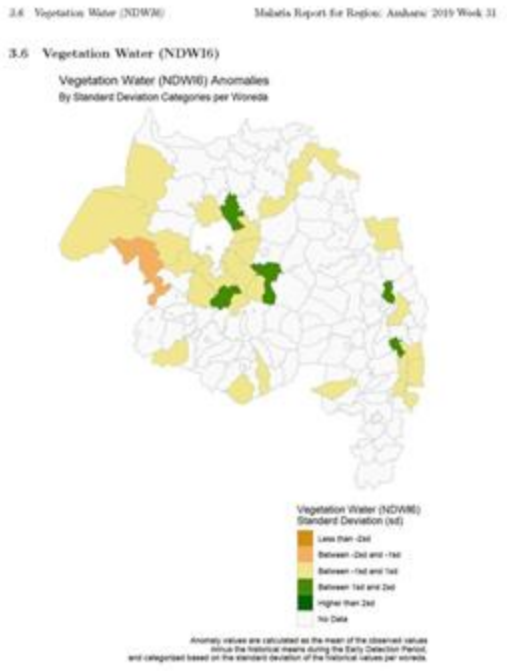
Time Series Charts for Each Woreda



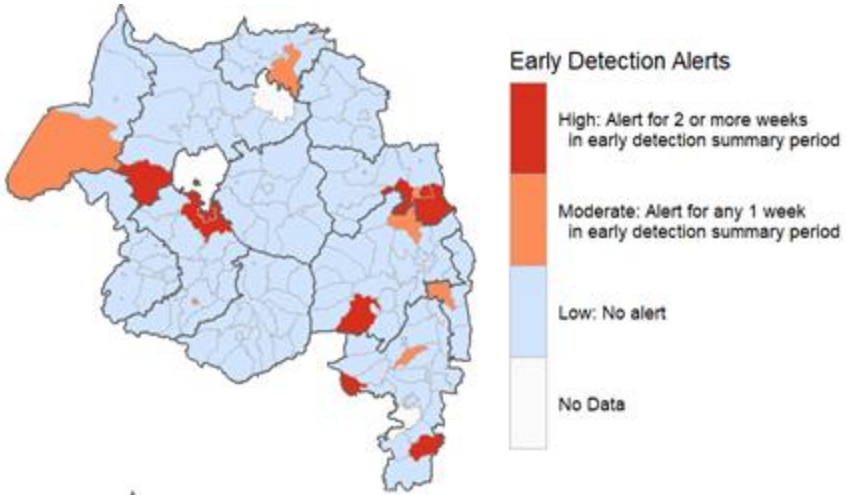
Maps of Recent Malaria Incidence

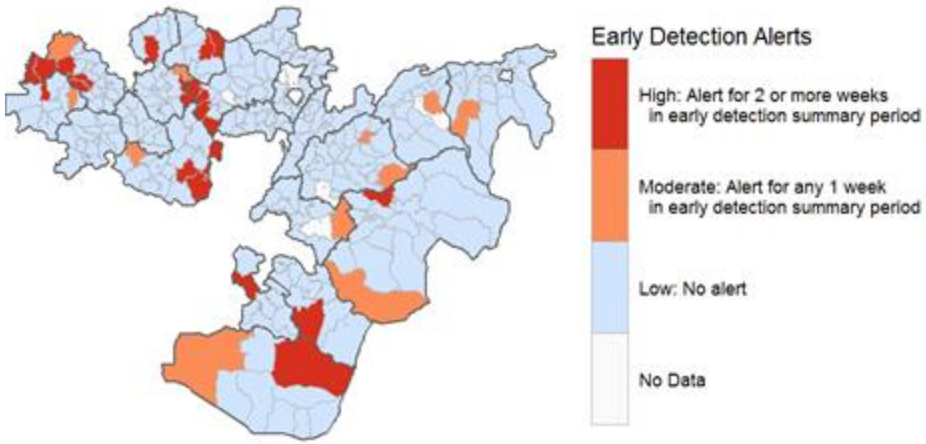


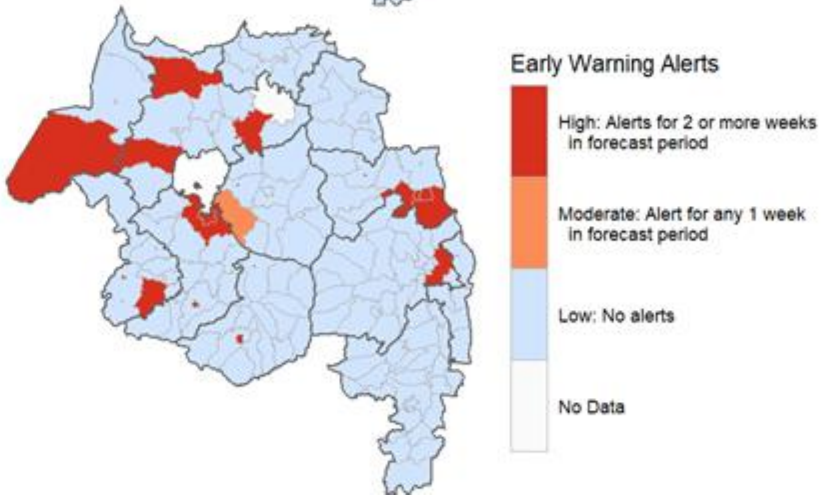
Maps of Recent Climate Anomalies

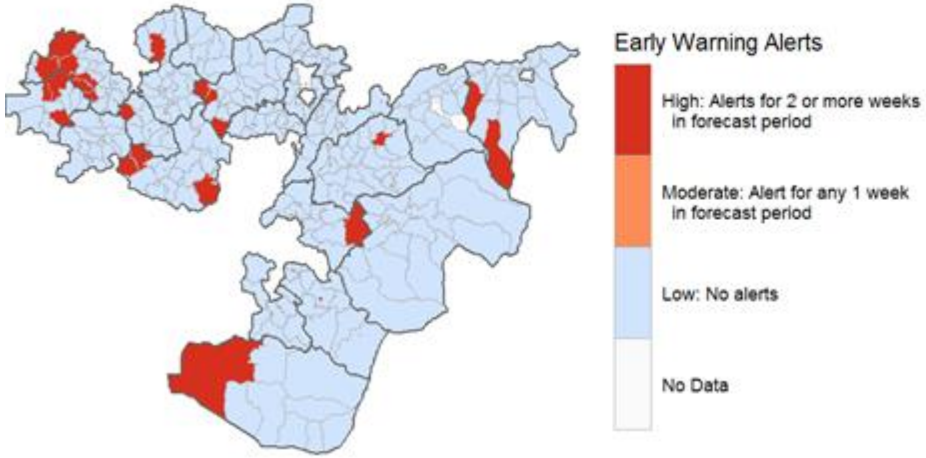


Summary alert maps provide a regional overview, identifying woredas where outbreaks have been detected or predicted.

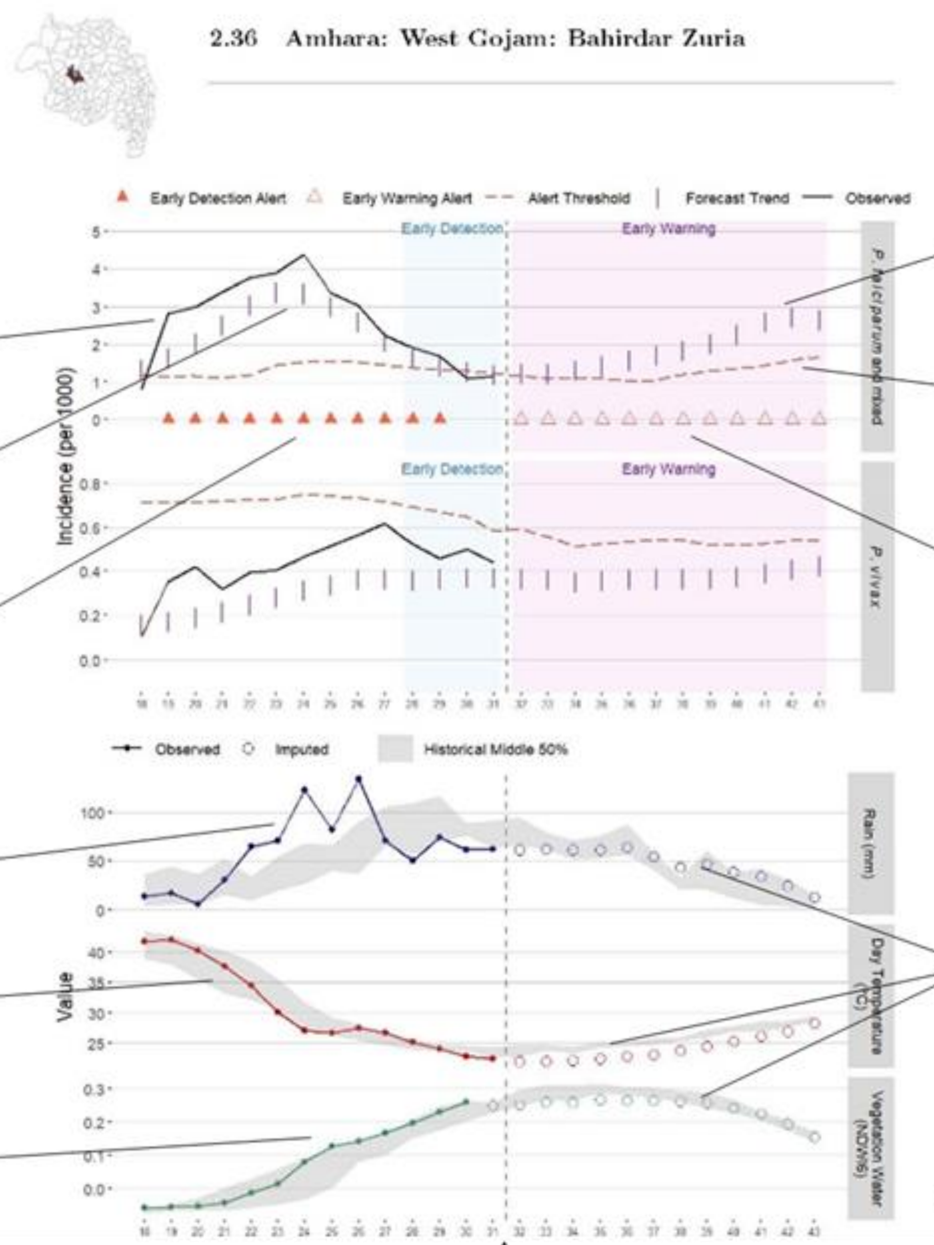








Time series reports provide details about each Woreda.



Observed malaria incidence (solid lines)

Previous 1-week ahead forecasts (vertical bars)

Early detection alerts (solid triangles)

Precipitation (blue line)

Temperature (red line)

Satellite moisture index (green line)

Future malaria forecasts (vertical bars)

Outbreak threshold (dashed line)

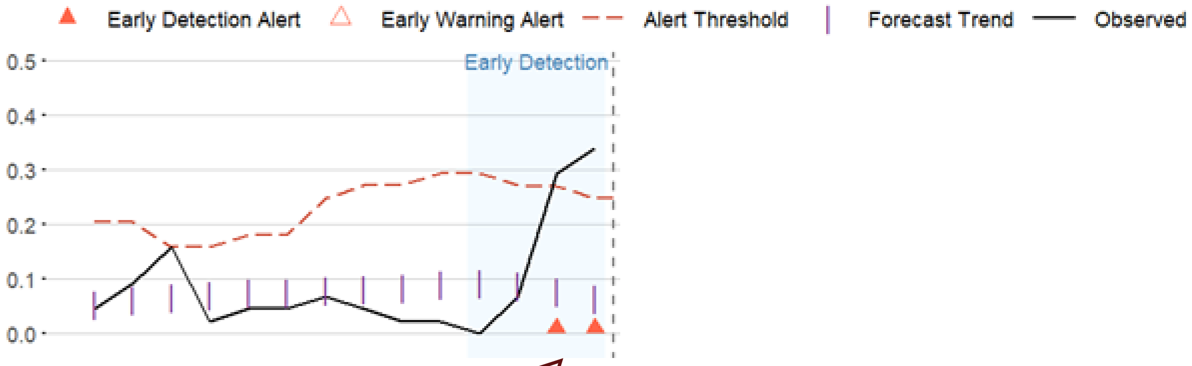
Early warning alerts (hollow triangles)

Extrapolations of recent climate trends

Date of forecast

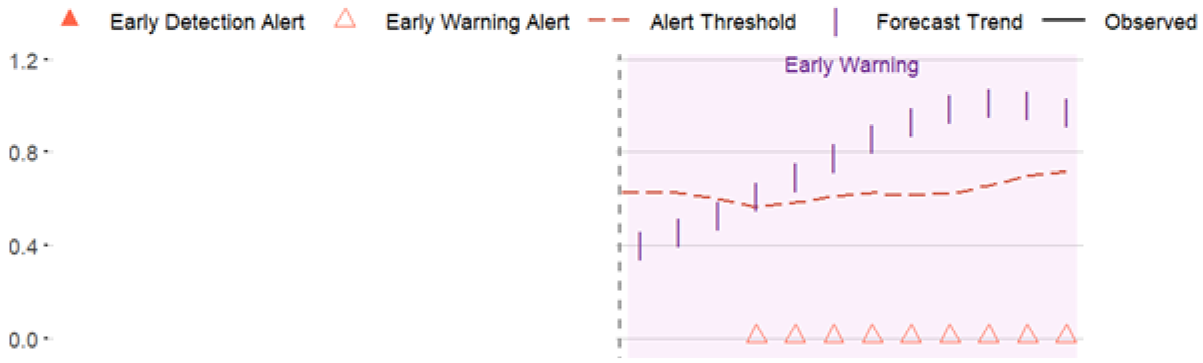
The time series charts provide early detection of emerging epidemics as well as early warning of future epidemics.

Early Detection



Early **Detection** Alerts triggered when the **observed value** is higher than the threshold

Early Warning



Early **Warning** Alerts triggered when the **forecasted values** are higher than the threshold

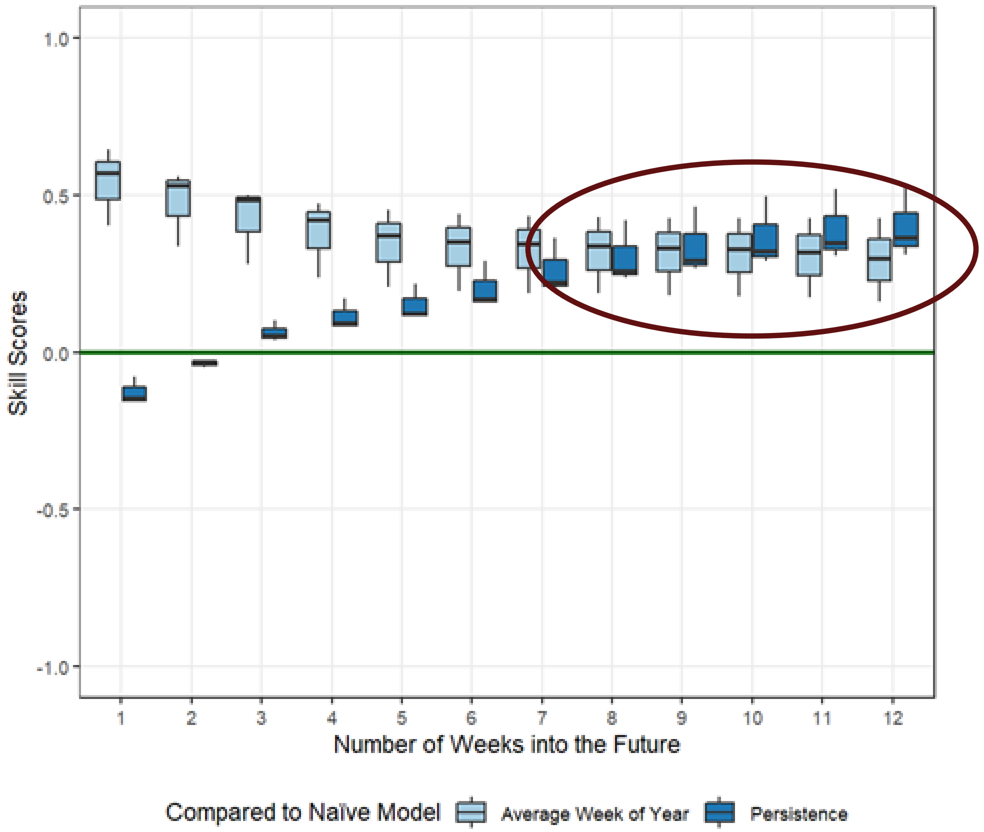
Thresholds are calculated using Farrington Improved algorithm:

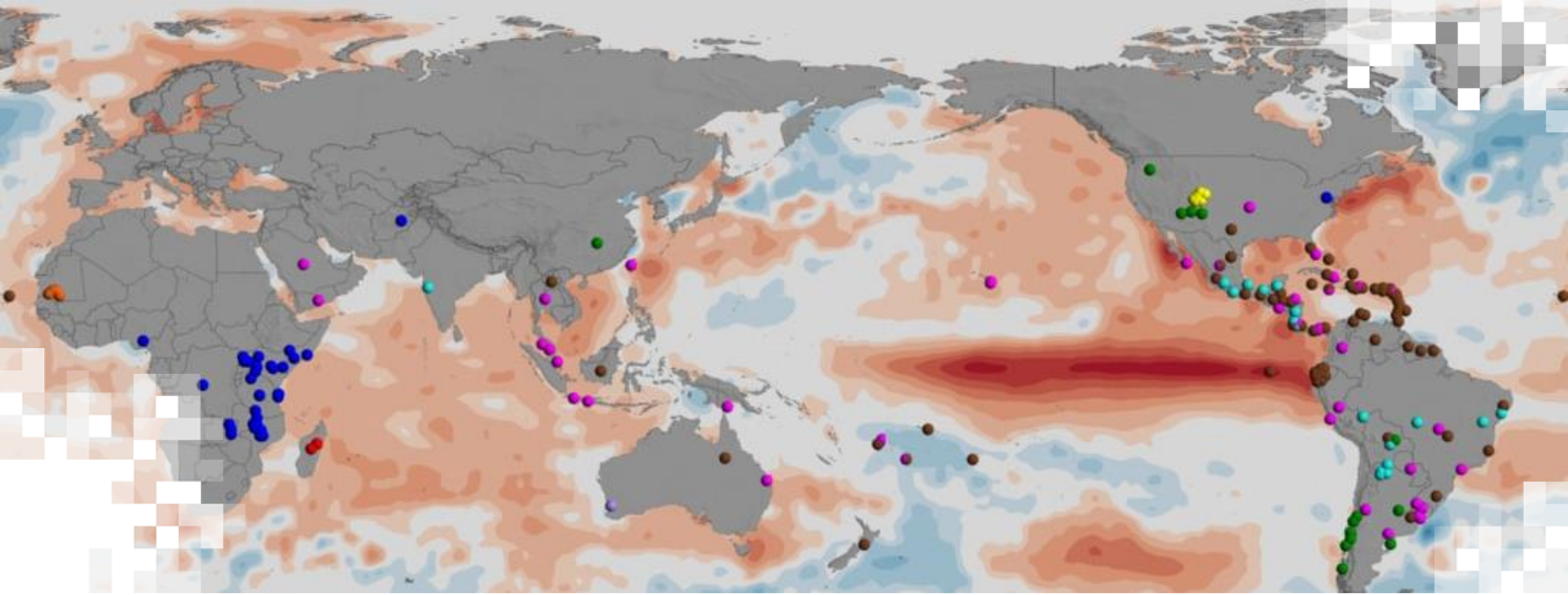
- Based on historical case counts and patterns
- Allows adjustments for trend, seasonality, prior outbreaks, and more

EPIDEMIA automatically produces validation reports of historical forecast accuracy.

- Summary charts display skill scores for forecasts made over a range of lead times.
- Positive skill scores mean that environmental data are improving the predictions of malaria compared to a null model.
  - Historical weekly averages
  - Most recent weekly observation
- EPIDEMIA forecasts generally have high predictive skill out to 12 weeks in the future.

Skill Score Summary Chart for Amhara (47 Pilot Woredas) from Jan. 1 2018-Dec. 31 2019





Advantages and Challenges of Using Remote Sensing Data for the Case Study

Benefits and Drawbacks to Using Remote Sensing Data in the Case Study

- **Benefits:**
  - Freely available
  - Consistent measurements and continuous spatial coverage
  - Only feasible source of environmental data
  - Provides information about important environmental determinants of malaria (temperature and precipitation)
- **Drawbacks:**
  - High volume of data to process
  - Data gaps and anomalies related to clouds
  - Lack of data on some key environmental determinants (humidity)

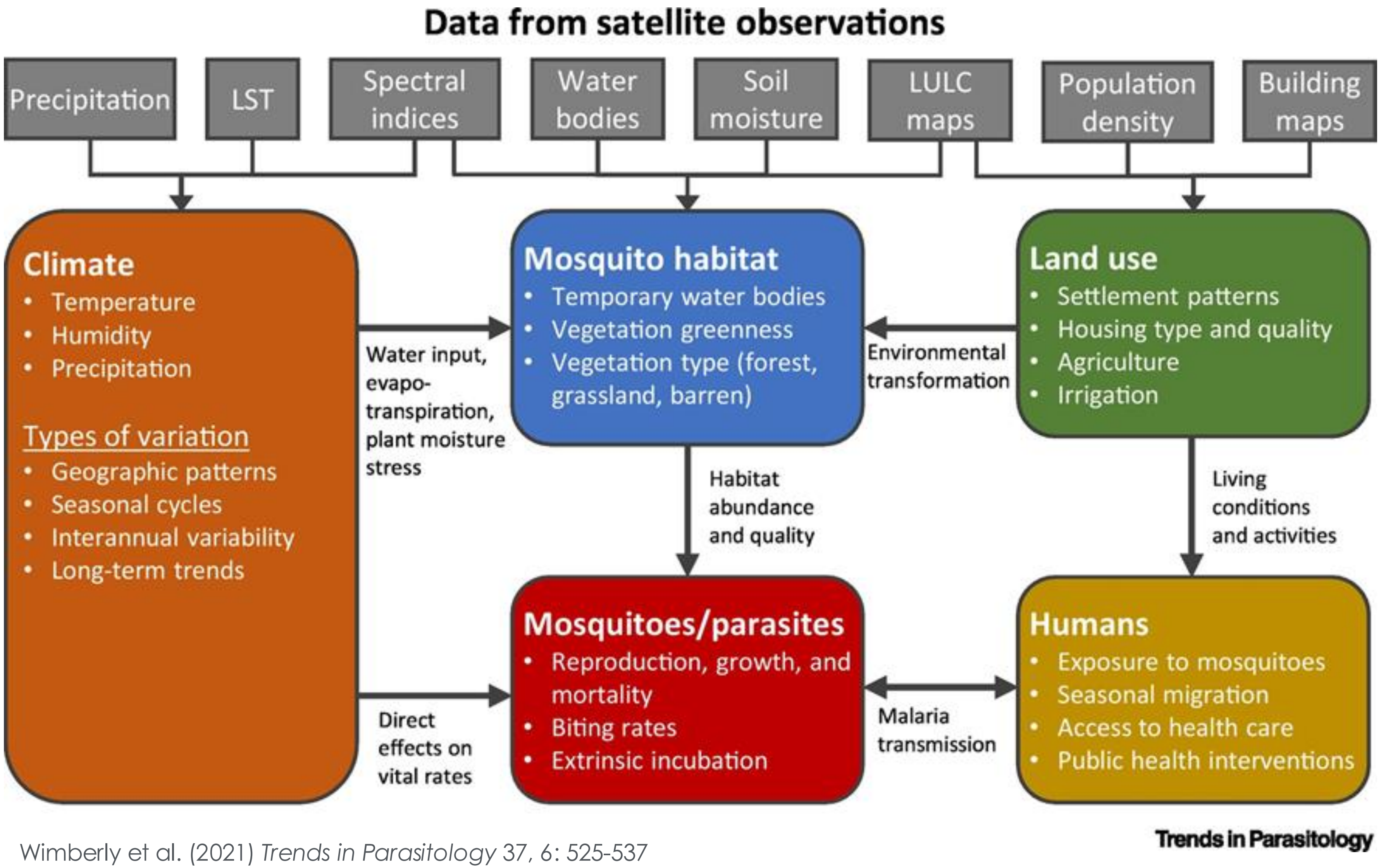
Barriers to Integration and how These were Overcome

- Large volumes of remote sensing data to process
  - Automated systems
  - Cloud-based implementation in GEE
- Access to malaria surveillance data
  - Design for location implementation to bring the tool to the users
- Limited understanding of satellite data
  - Training and capacity building

Challenges with Long-Term Sustainability and Implementation

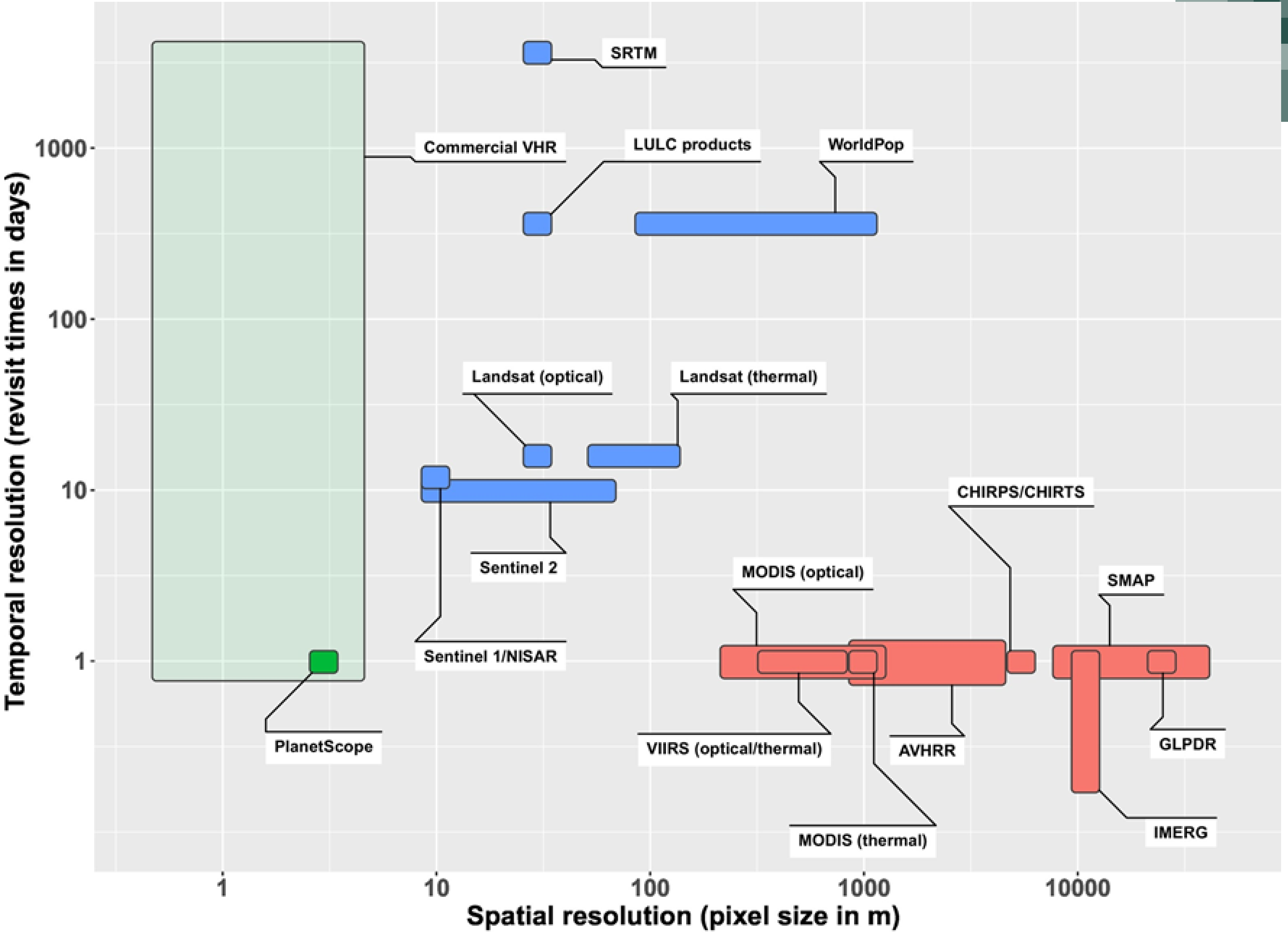
- Limited resources in public health agencies for implementing early warning systems
- Need to maintain and update software
- Disruptions to malaria surveillance programs
- Changes in satellite missions
  - TRMM to GPM transition
  - MODIS to VIIRS transition
- Overarching need for more expertise in satellite remote sensing, epidemiological modeling, and software engineering
  - Long-term efforts to build expertise and develop communities of practice
  - Substantial growth over the past 15 years

Alternative Datasets and Approaches



Wimberly et al. (2021) *Trends in Parasitology* 37, 6: 525-537

Alternative Datasets and Approaches



Applications:

- Climate Variability
- Individual Landscape Features
- Land Use and Habitat Types

Wimberly et al. (2021) *Trends in Parasitology* 37, 6: 525-537

Resources

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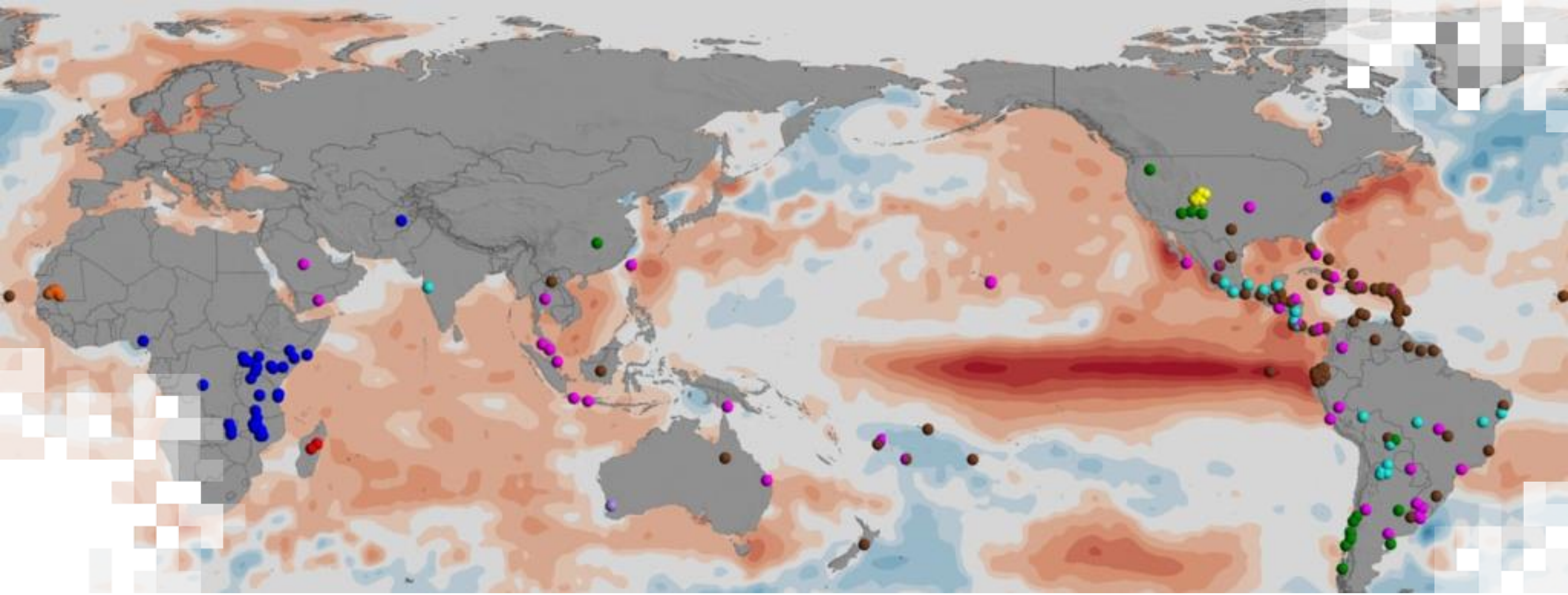
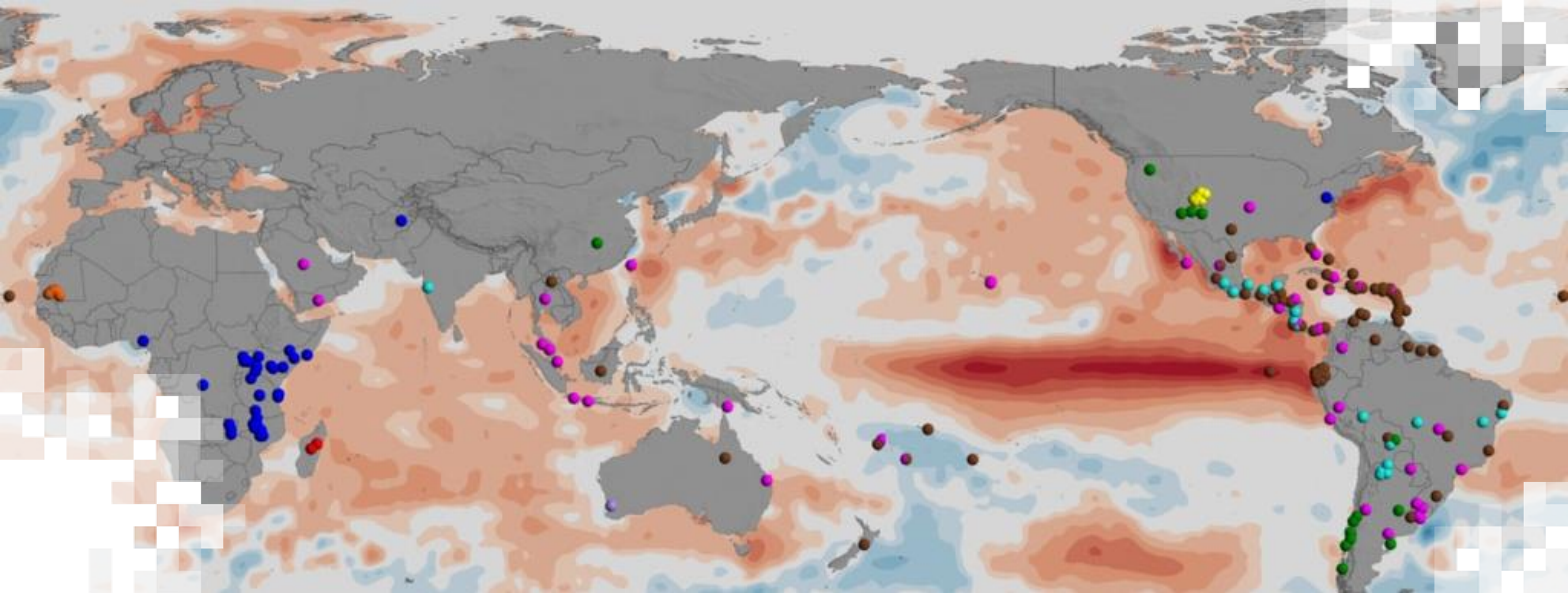


Part 2:
Summary

ARSET Summary

- In Ethiopia, new malaria risks are emerging, which requires accurate forecasting to support rapid, targeted interventions to reduce public health impacts.
- The Epidemic Prognosis Incorporating Disease and Environmental Monitoring for Integrated Assessment (EPIDEMIA) – Modeling System uses satellite remote sensing data:
  - MODIS: Land Surface Temperature
  - MODIS, VIIRS: Vegetation Greenness (NDVI) and Moisture (NDWI) Indices
  - GPM/IMERG: Precipitation
- The EPIDEMIA process involves:
  - Access and preprocess remote sensing data on the cloud (Google Earth Engine)
  - Gather recent case data from Ethiopia's Public Health Emergency Management system
  - Harmonize & integrate the data, accounting for missing data and changing boundaries
  - Run a forecasting model and produce a report of early detections and early warnings
- Remote sensing provides the only feasible source of the required environmental data in Ethiopia.
- High data volumes, transition to new missions, need for local training on the use of satellite data, and limited resources to sustain long-term implementation are continuing challenges.



Remote Sensing for Climate-Sensitive Infectious Diseases

Summary

Training Summary

- Remote sensing datasets commonly used to study climate sensitive infectious diseases include:
  - MODIS, VIIRS: land surface temperature, vegetation (e.g., NDVI)
  - Landsat, Sentinel 2: land use/land cover, perennial/ephemeral water
  - GPM/IMERG: precipitation
- Common **benefits** of using remote sensing data include:
  - Diverse measured parameters
  - Broad availability
  - Consistent & repeated coverage
  - Free accessibility
- Common **challenges** of using remote sensing data include:
  - Data discovery
  - Quality assessment
  - Gap-filling
  - Large data volumes

Homework and Certificates

- **Homework:**
  - One homework assignment
  - Opens on 10/09/2025
  - Access from the training webpage
  - Answers must be submitted via Google Forms
  - **Due by 10/23/2025**

- **Certificate of Completion:**
  - Attend all live webinars (attendance is recorded automatically)
  - Complete the homework assignment by the deadline
  - You will receive a certificate via email approximately two months after completion of the course.

Contact Information

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- ARSET YouTube

Thank You!