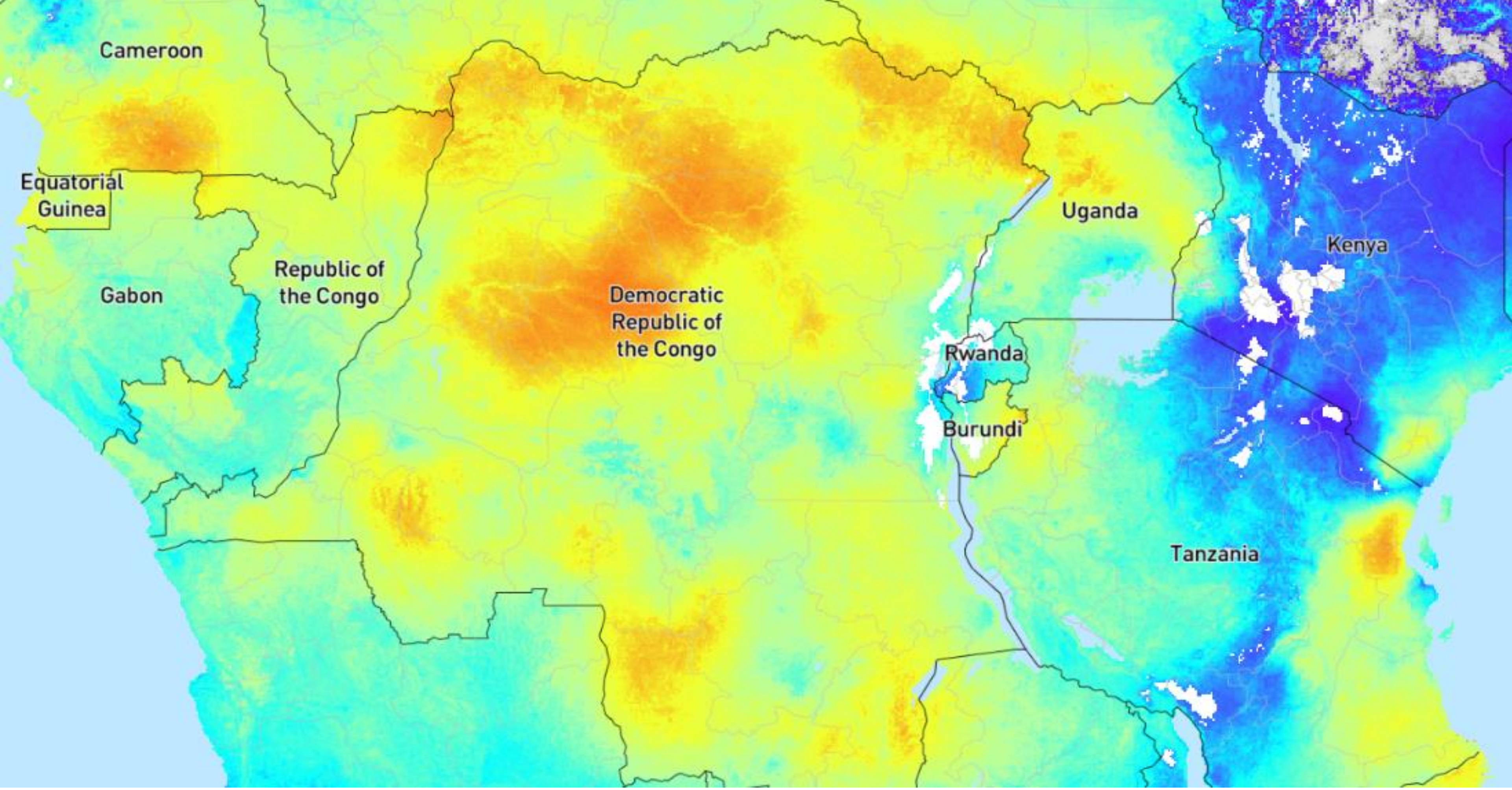


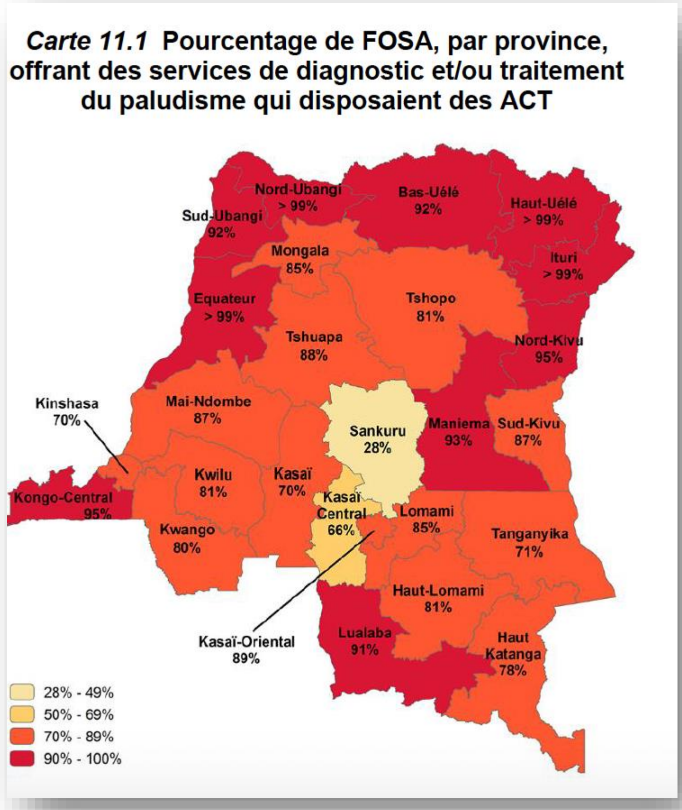
Quantifying Access to Healthcare in the Democratic Republic of the Congo

Alyssa Young
SMERG Meeting
Kigali, Rwanda

USAID FROM THE AMERICAN PEOPLE
CDC
U.S. President's Malaria Initiative
PMI Measure Malaria

Background

- The DRC observes the **2nd highest number of malaria cases and deaths globally** (WHO, 2019)
- Accounts for **> 40%** of all outpatient visits; 19% of deaths among children <5 (PMI, 2020)
- Access to healthcare is **highly variable across DRC**
- The 2017-2018 Service Provision Assessment (SPA) **revealed marked variation at the province level;** variation at finer scales expected but SPA not powered to quantify this



Context

Challenges in accessing healthcare for malaria in the DRC:

- **limited geographic coverage**, i.e., only 30% of the population live within five kilometers of a health facility (USAID/PMI, Malaria National Operational Plan, 2019)
- **low availability of critical drugs**, such as for severe malaria: injectable artesunate (only in 22% health facilities), rectal artesunate (only in less than 5%) (SPA 2017-2018)
- **high economic costs of care** (Kayiba et al., 2021)
- **shortage of trained healthcare providers**, esp. in rural areas (KSPH/MMV, 2018)
- **shortage of diagnostics** (esp. Rapid Diagnostic Tests: SPA 2017-2018)

Project Rationale and Objective

- Use of routine surveillance data in quantifying malaria burden is challenging especially in high-transmission settings such as the DRC
- Data reported by health facilities may not capture all malaria cases due to **variations and in healthcare access and use;** True malaria burden not **accurately represented** in areas with underserved populations

Objective: *Develop a mechanism for quantifying and understanding access to healthcare in order to improve interpretation of surveillance data in the DRC*

Approach: 3 steps

1. Create a modeled spatial layer that helps us understand healthcare accessibility by **fitting catchment models to service populations**

2. Apply a statistical model to identify **latent processes behind healthcare seeking behavior and malaria risk**

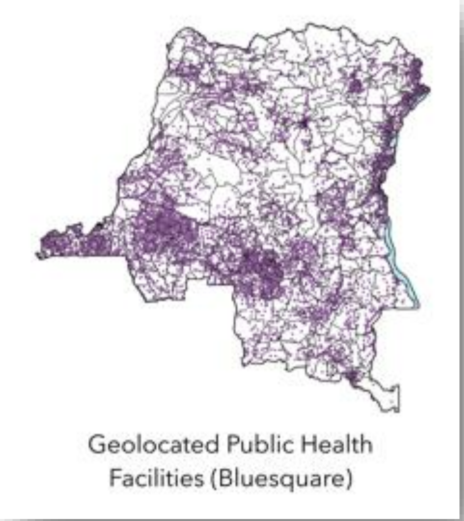
3. Translate these outputs into indicator(s) that can be **integrated into DHIS2 dashboards**

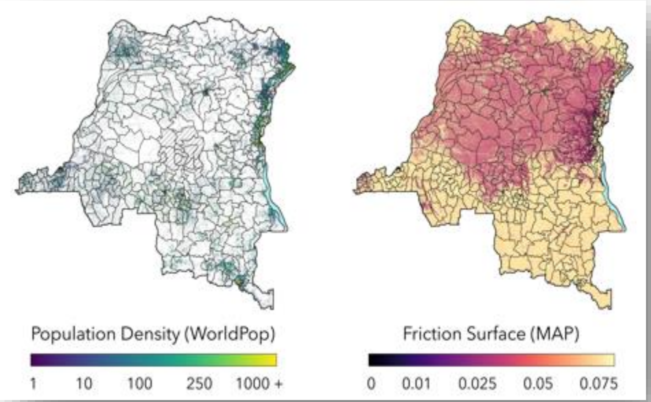
Methodology: *Fitting catchment models to service populations*

- The first step focuses on **fitting catchment models to service populations using a gravity model**, as opposed to quantifying ‘access’ strictly as number of facilities per population
- Catchment modelling for service provision is estimated at the lowest possible administrative unit (health zone)
- Incorporates overlapping catchment boundaries in which the attractiveness of facilities is **based on their size and services available**
- Model accounts for **bypassing of facilities** and assumes (for the moment) that no individual will travel beyond their 5th closest health facility to access care
- <u>*Summary:*</u> Create model-based synthesis of **health facility spatial density and travel time accessibility, guided by the service population statistic**

Data inputs: *Fitting catchment models to service populations*

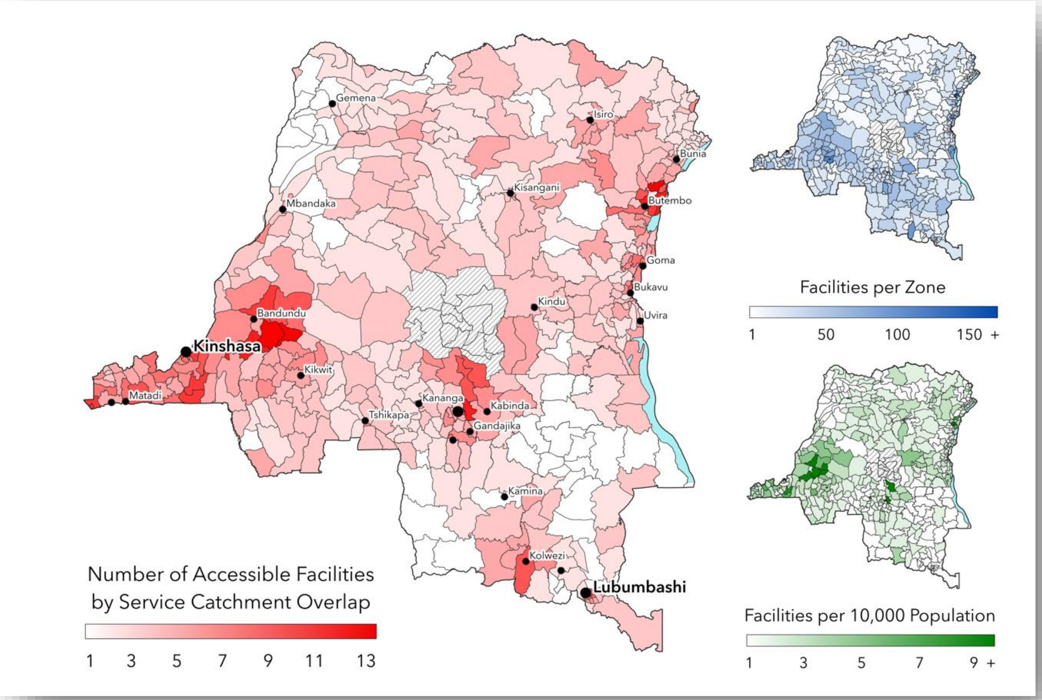
Input	Source	Description
Geolocated public health facility master list	*Bluesquare*	Master list of predicted and validated public health facility locations in the DRC
Travel-time friction surface layer	Malaria Atlas Project (MAP)	Created using data from OSM and Google Maps, measures land-based travel/walking time to nearest HF, accounting for movement by vehicles along main roads and walking across terrain/tracks
Population density estimates	WorldPop	UN-adjusted population density surface
Service population estimates	DRC Health Information System (HIS)	Total population in area from which patients are regularly observed as attendees of a given HF

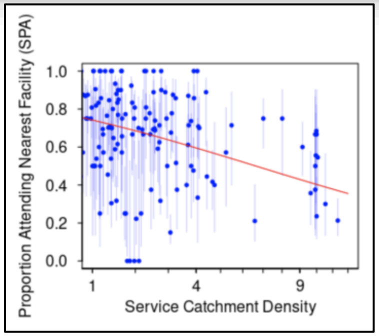


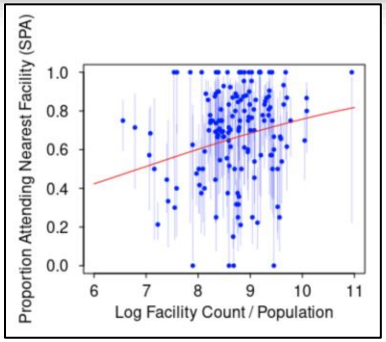


Results: *Fitting catchment models to service populations*

- Modeled output (far left) broadly reflects crude density of facilities per population (bottom right) but refines the ‘picture’ by using service population data and travel time surface to estimate **number of accessible facilities per population/service catchment overlap**
- Whereas the crude number of facilities per health zone may be high (top right), **there are many zones where health facility access is highly vulnerable** (far left) → i.e., some individuals reside within the catchment area of only one health facility!







Approach: 3 steps

1. Create a modeled spatial layer that helps us understand healthcare accessibility by **fitting catchment models to service populations**

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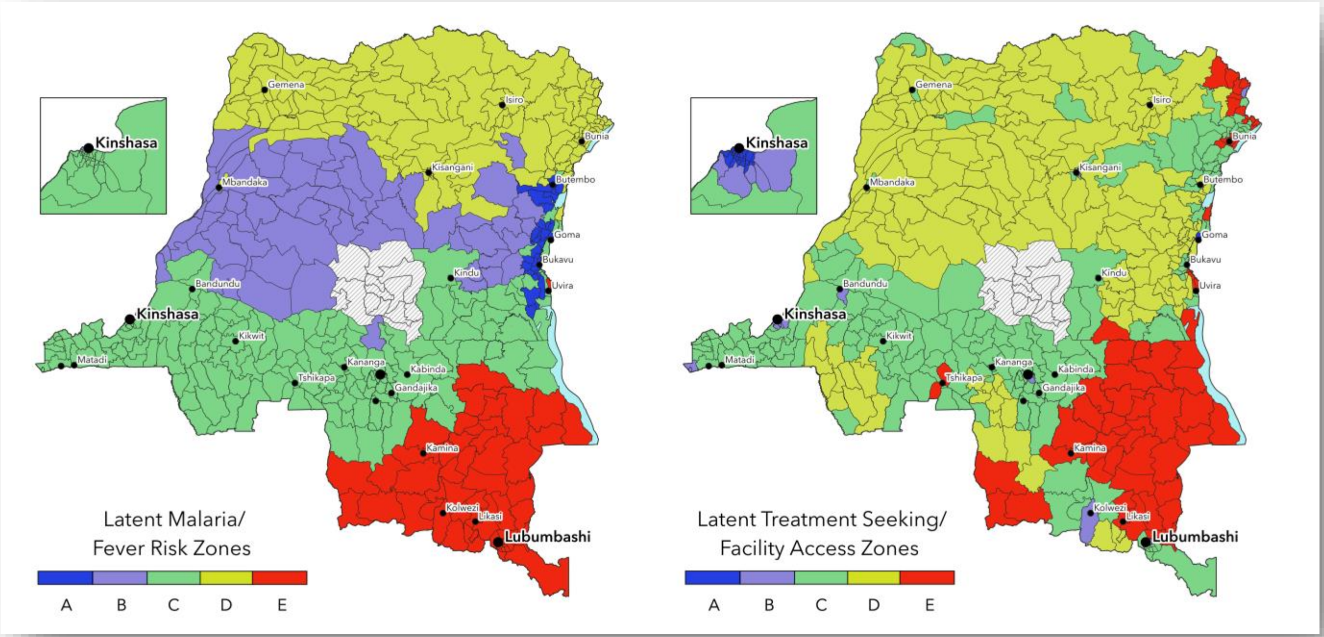
Methodology: *Identifying latent processes behind malaria risk and treatment-seeking behavior*

- Second step in our process is to examine the explanatory value of our modeled access layer through **application of a statistical model that synthesizes SPA and DHS data related to malaria risk and access/treatment-seeking behavior**
- Fit covariate data (including modeled access layer) to SPA/DHS survey data to create machine learning style model which tries to explain the covariance between the different SPA/DHS indicators in terms of **1) Malaria risk and 2) treatment-seeking behavior**
- Objective is to generate **latent classes that identify areas sharing similar characteristics in terms of the factors behind observed malaria risk and treatment-seeking behavior,** as well as determine how important our modeled catchment layer is in explaining observed treatment-seeking patterns

Data inputs: *Identifying latent processes behind malaria risk and treatment-seeking behavior*

Variable/input	Source	Description/use
Modeled catchment area/access layer	Tulane/MAP	Output layer created in Step 1; features the number of HFs claiming the residents of that pixel in their catchment areas; used to smooth and interpolate noisy DHS/SPA data before fitting
Mean number of days since fever began prior to seeking care; Proportion of children <5: (1) Seeking care with fever (2) Seeking care with severe malaria symptoms (3) Seeking care at their nearest facility	DRC SPA 2017-2018	Combined with modeled access layer and satellite imaging covariates to identify primary contributors to malaria risk/febrile illness and healthcare access within a given region
Proportion of children <5: (1) that had an inpatient stay at a health facility for fever/malaria in the past six months; (2) that received outpatient care for fever/malaria in past 4 weeks (3) exhibiting severe malaria symptoms (4) testing positive for malaria via RDT	DRC DHS 2013-2014	Combined with modeled access layer and satellite imaging covariates to identify primary contributors to malaria risk/febrile illness and healthcare access within a given region
Elevation; annual rainfall; stable lights; enhanced vegetation index (EVI); Predicted P. falciparum prevalence; P.f. temperature suitability index	SRTM, CHIRPS, MODIS, MAP	High resolution (1-5km) satellite imaging covariates characterizing local environments; allows for modulation when investigating relationships between catchment/access layer, access indicators, and malaria risk; used to smooth and interpolate noisy DHS/SPA data before fitting

Results: *Identifying latent processes behind malaria risk and treatment-seeking behavior*



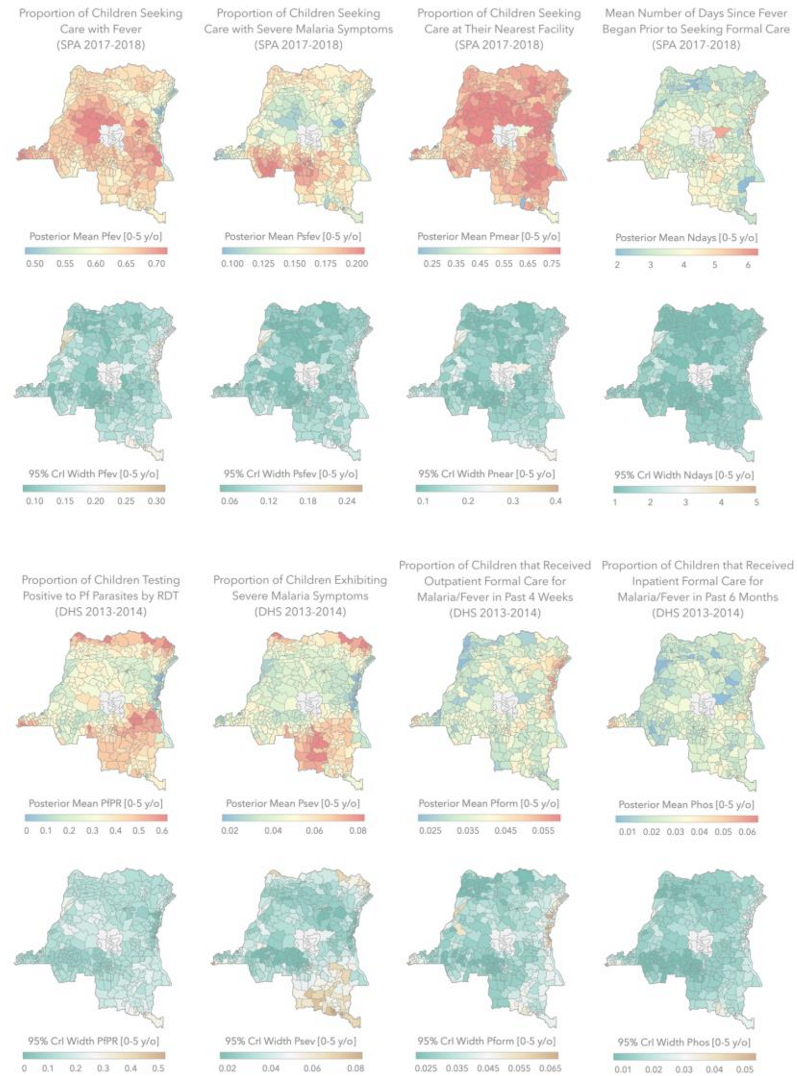
- The latent malaria risk and treatment-seeking covariance matrices describe the degree of connectedness of each region (i.e. how similar the model says each region is) in terms of the factors that characterize their malaria risk and healthcare access

- Health zones are grouped according to how similar they are in this respect

Next steps: Model updates

- Model does not currently account for other factors that may influence treatment-seeking behavior or healthcare access
    - Density/spatial distribution of disruptive events (ex. armed conflict) may also influence an individual's ability or desire to access health care in a setting like the DRC

- Recent Facebook user data indicates that people in urban areas in the DRC are willing to travel to the 20th closest facility to seek care
    - Model currently uses standard threshold of closest 5 health facilities, regardless of rural/urban designation



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Use Cases

Refine population denominators used in calculation of key malaria indicators: **Incidence rates, Population At Risk (PAR), Annual Blood Examination Rate (ABER), Curative Service Utilization Rates**

Identify facilities that may not be servicing all malaria cases in specific regions due to inaccessibility

Rank health zones by mean access to healthcare values for targeting of specific interventions

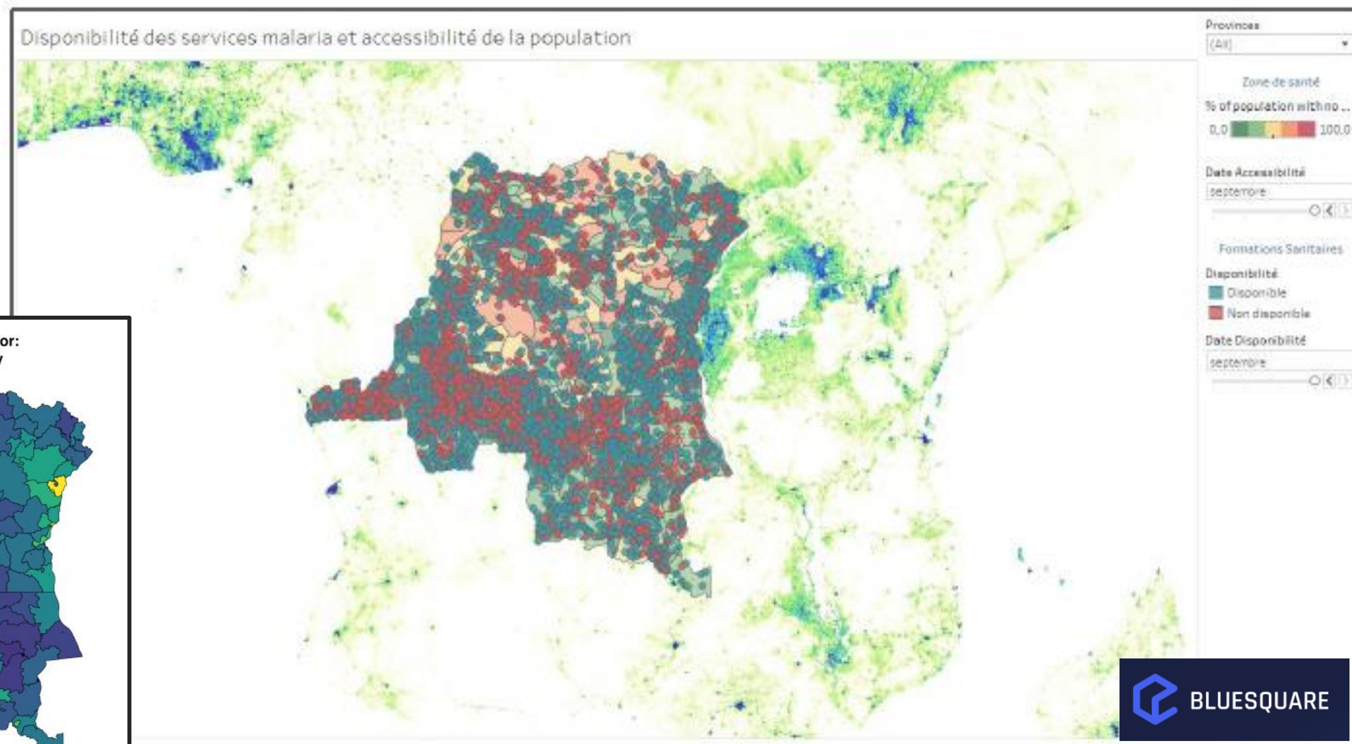
Identify regions sharing similar characteristics that drive lower access to care/treatment-seeking behavior

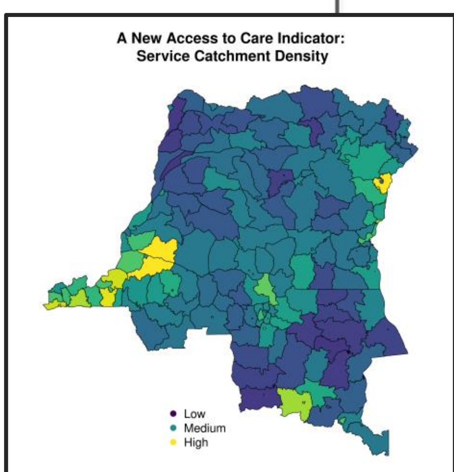
Enumerate high-risk populations which fall within a single HF service catchment area

Next steps: Automation and integration

- Translate outputs into indicator(s) that can be used to better understand healthcare access in the DRC

- Will require an automated platform (ex. OpenHexa) for updating and linking the service readiness layer and latent malaria risk/treatment-seeking zones into DHIS2 to calculate KPIs as monthly malaria case count data is reported





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