Simulating the Lake Kariba mass drug administration trial to understand what it takes to eliminate malaria

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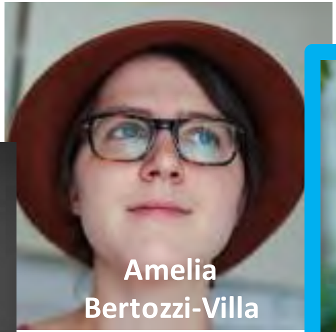
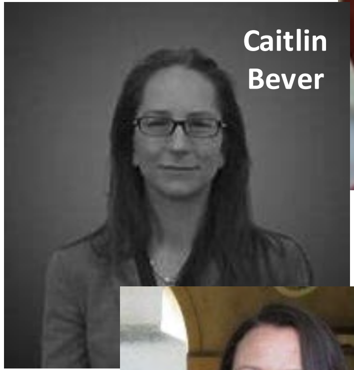
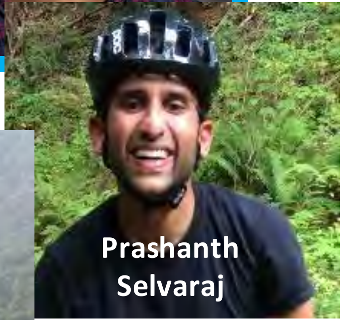
Meet the IDM Malaria Modeling Team

Bed nets
Combined geospatial-dynamical modeling





Elimination settings
Spatial simulations

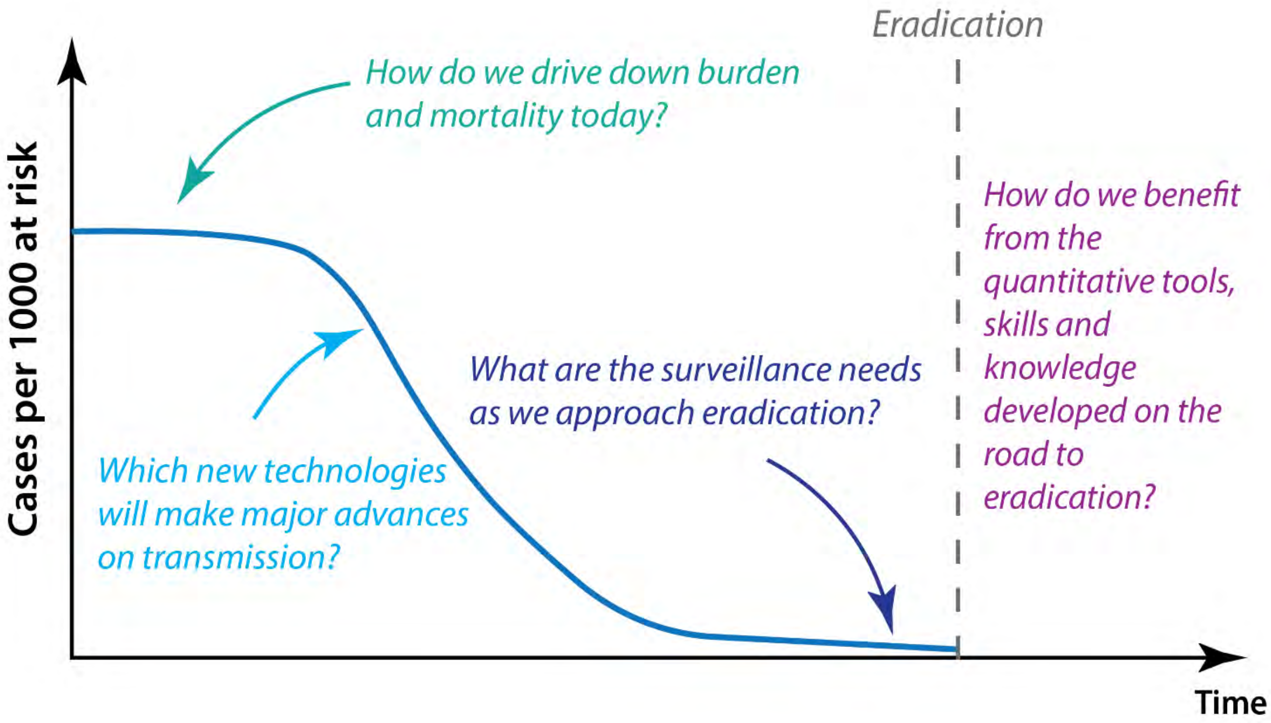


New vector control tools and strategies

Data
Geospatial
Partner Engagement

Subnational tailoring
Model validation
Monoclonals

We use modeling and data analytics to address all the decision-making stages on the way to eradication



Example IDM projects

subnational tailoring (SNT)
HBHI+

attractive targeted sugar baits (ATSBs)
monoclonal antibodies (mAbs)
gene drive

parasite genetics
drug resistance
human mobility

open source modeling tools
knowledge exchange
data and computing infrastructure

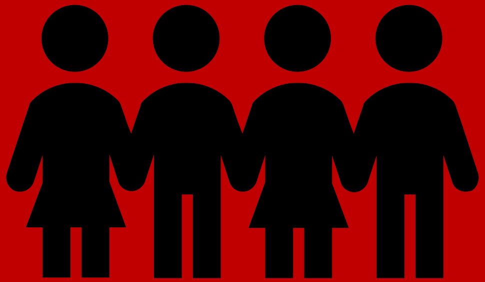
How will we eliminate malaria?

How will we eliminate malaria?


Long-
Lasting
Insecticide-treated
Nets

Indoor Residual Spraying

How will we eliminate malaria?



Good access to healthcare reduces malaria transmission


Mass Drug Administration


Zambia
Google
3D


Kamina
Parc National De l'Upemba
Samakwo
Mbeya
Kasama
Chinsali
Kolwezi
Likasi
Songea
Mansa
Lubumbashi
Mzuzu
Park Parque Nacional da Cameia
Lake Malawi
Kitwe
Ndola
Lichinga
Zambia
Malawi
Kabwe
Lilongwe
Kafue National Park
Kaoma
Cuamba
Mongu
Lusaka
Zomba
Gurue
Mazabuka
Tete
Coutada Pública do Longa Mavinga
Blantyre
Coutada pública do Luiana
Lugela
Choma
Kalomo
Mozambique
Harare
Coutada Pública do Mucusso
Rundu
Victoria Falls
Norton
3D
Google
Tsumeb
Hwange
Zimbabwe
Mutare
Chimoio


Kamina
Parc National
De l'Upemba
Mbeya
Samakwo
Kasama
Chinsali
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Kolwezi
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Mansa
Lubumbashi
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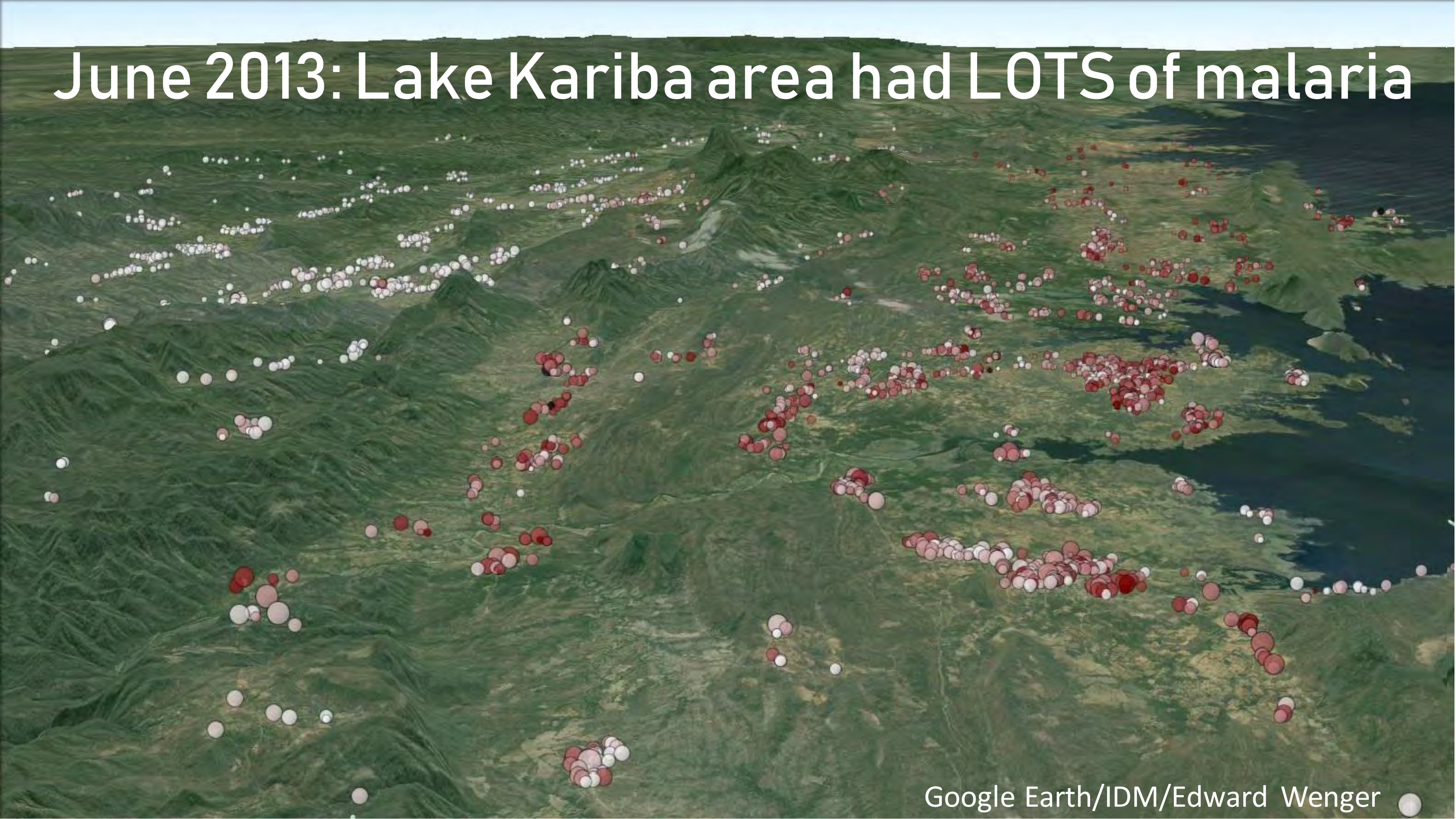
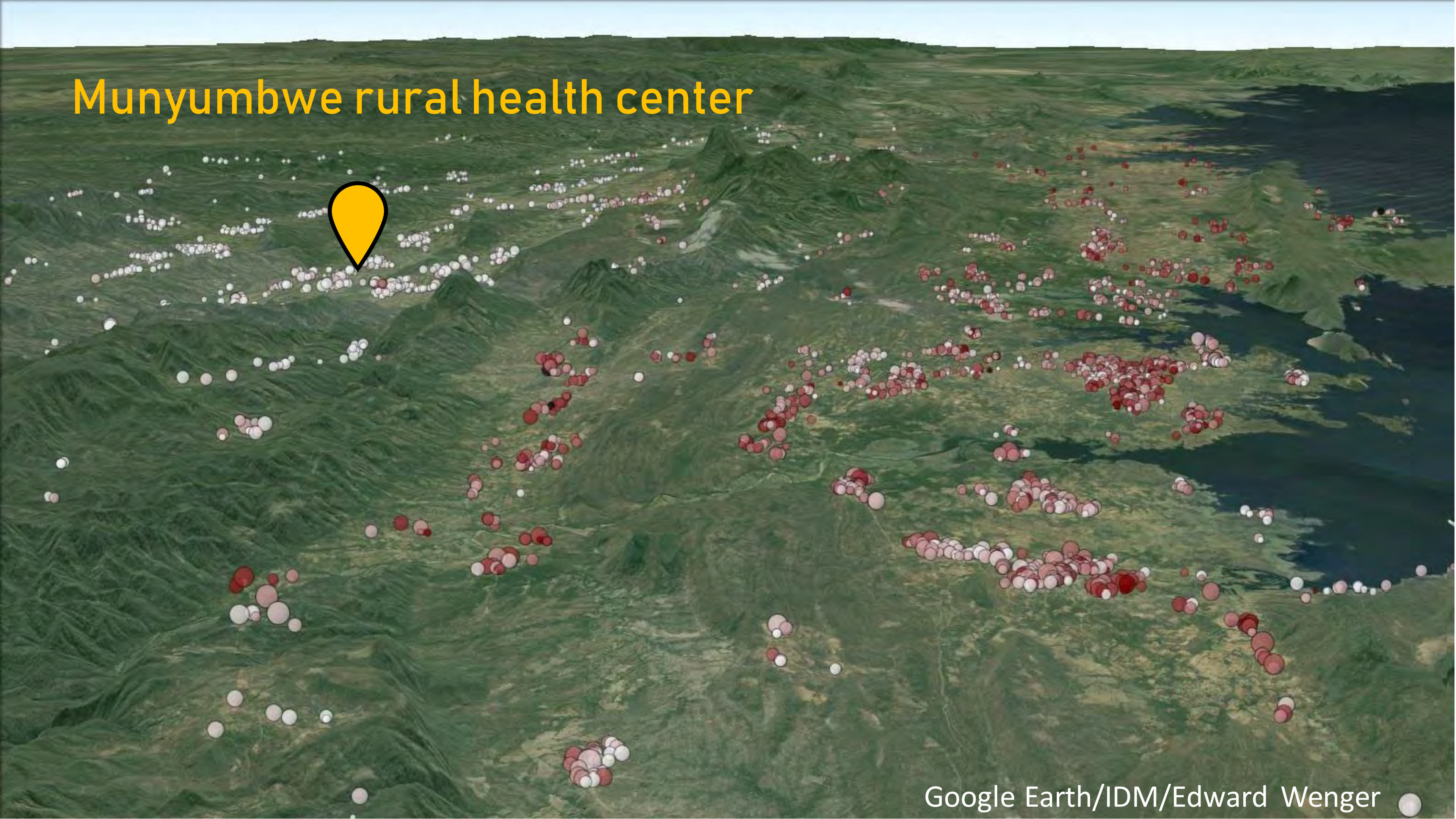
Victoria Falls
Norton
Tsumeb
Google
Hwange
Zimbabwe
Mutare
Chimoio
3D
Lake
KARIBA

June 2013: Lake Kariba area had LOTS of malaria



Google Earth/IDM/Edward Wenger


Munyumbwe rural health center
Google Earth/IDM/Edward Wenger

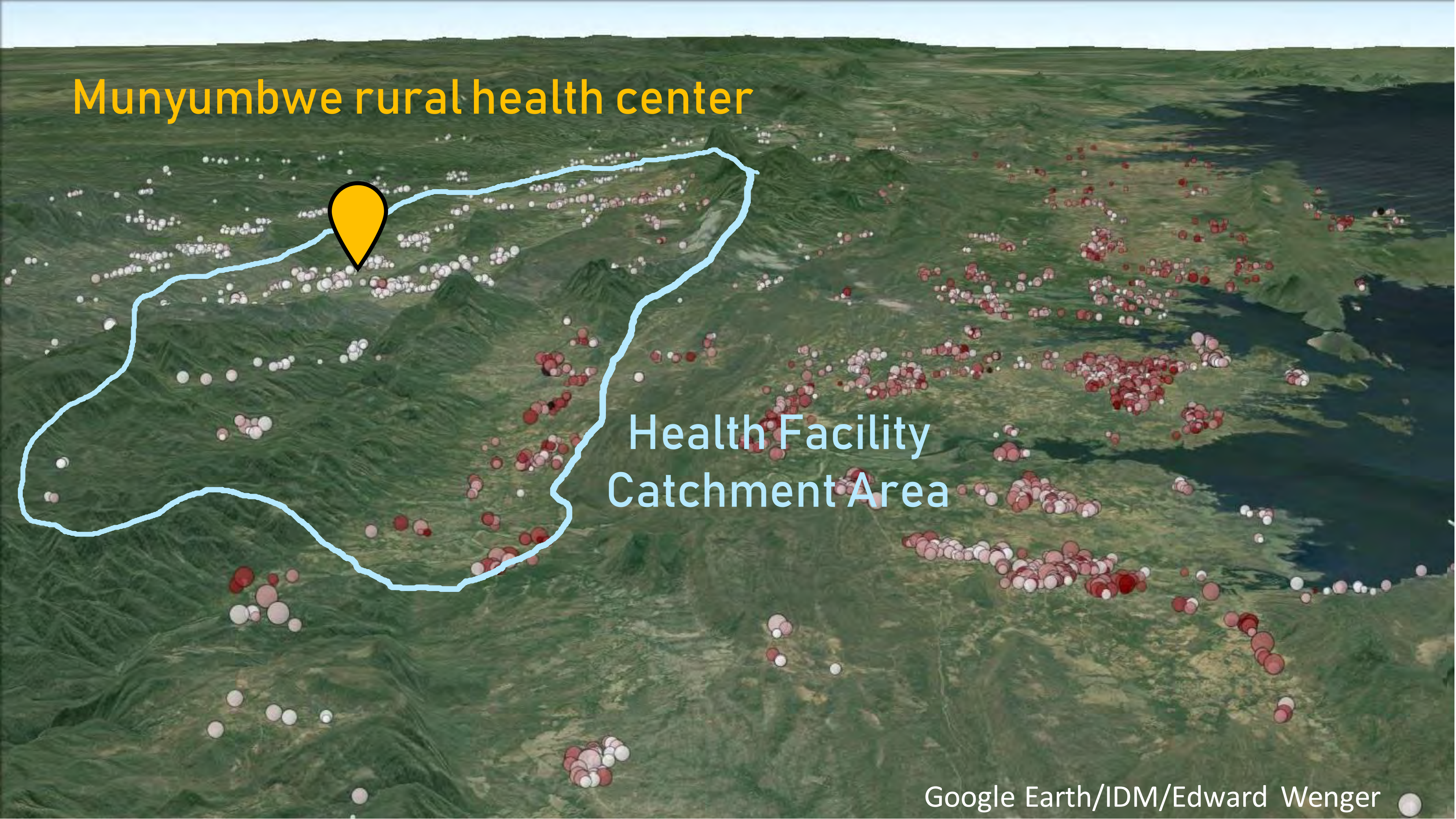

Munyumbwe rural health center
Health Facility
Catchment Area
Google Earth/IDM/Edward Wenger

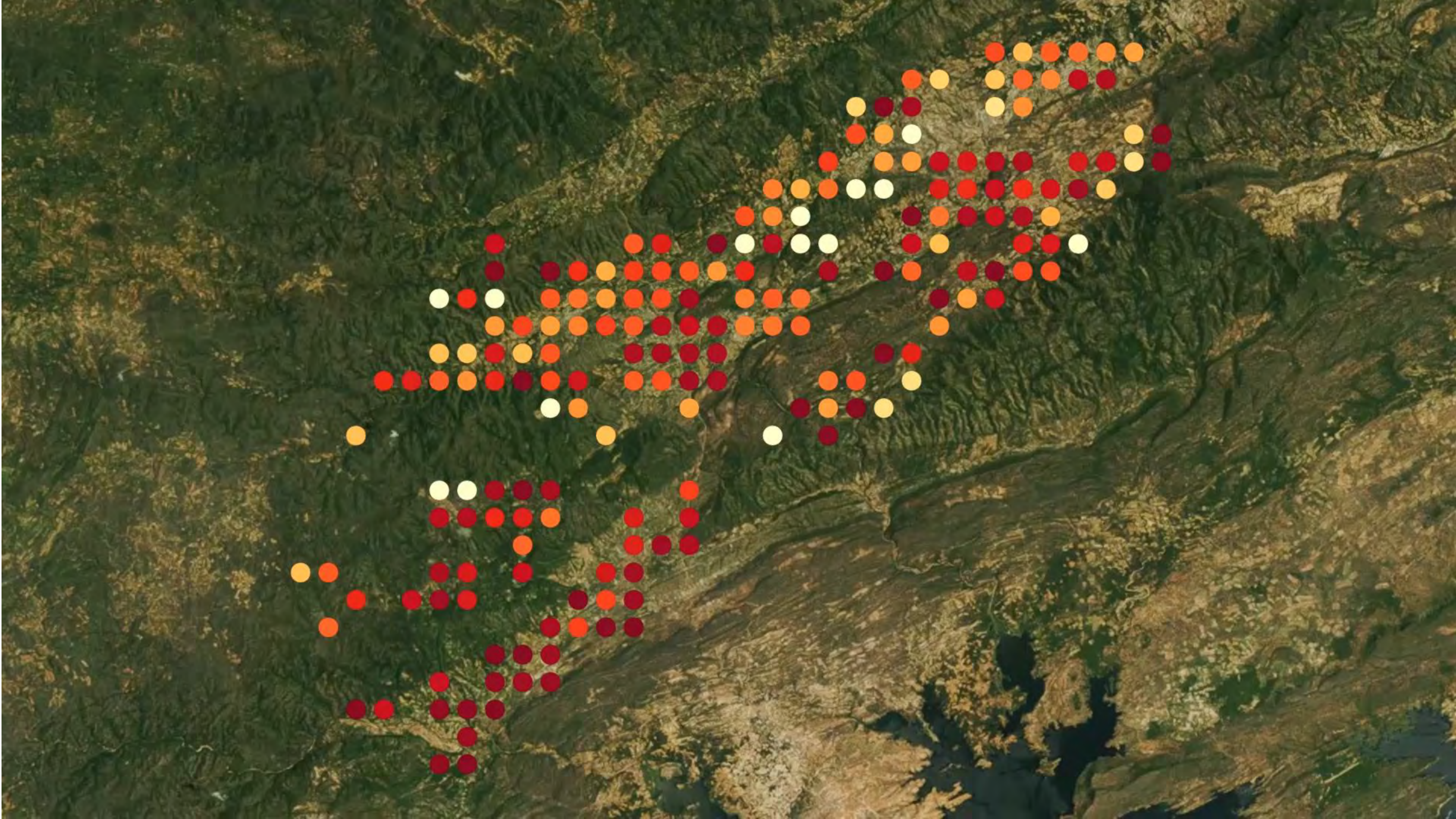
Photo: IDM/Milen Nikolov


Photo: IDM/Milen Nikolov

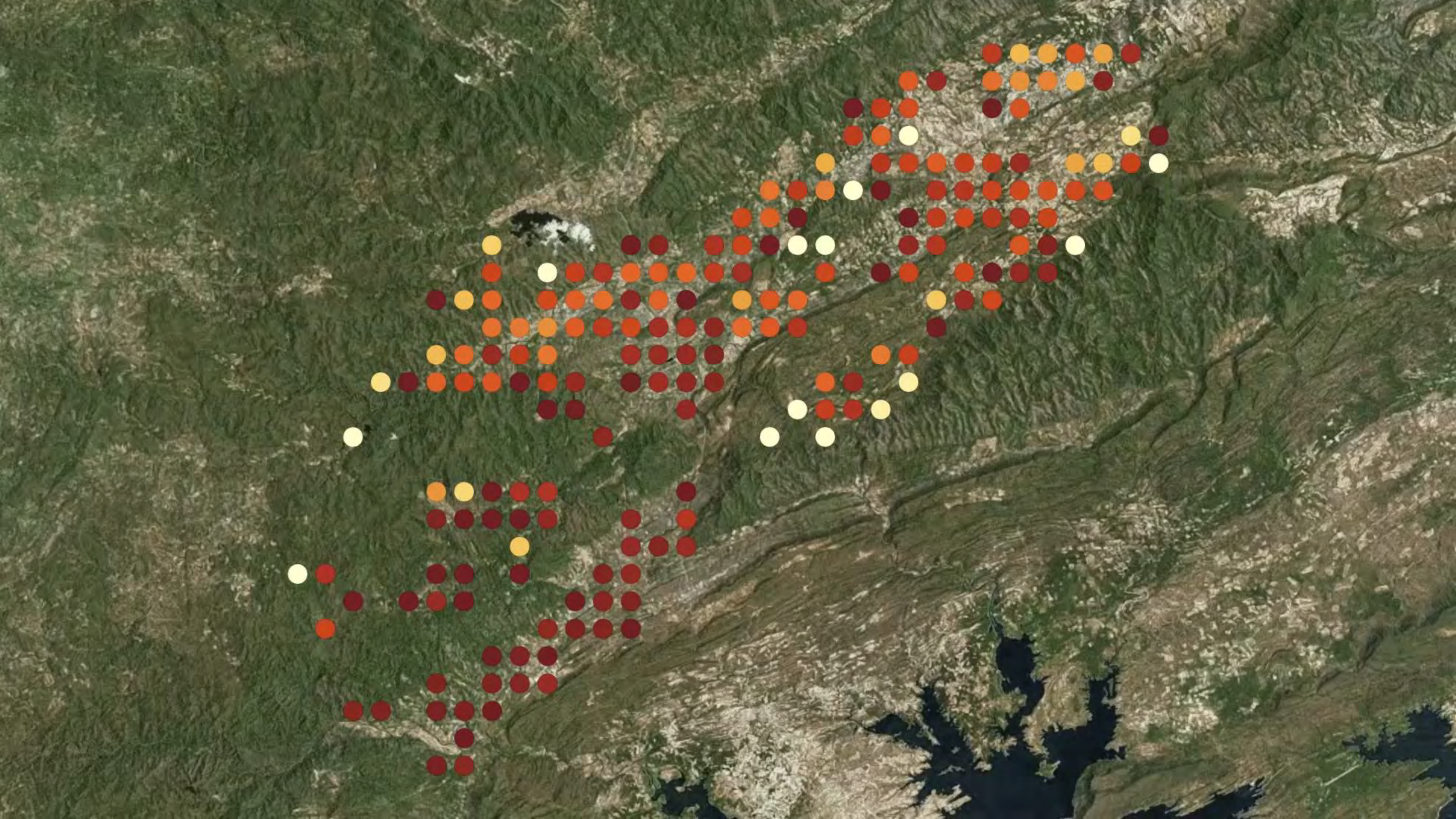
Community health workers are **anti-malaria heroes**

Photo: PATH/Laura Newman

We can simulate malaria in Munyumbwe to assess the potential impact of community health workers.



Improving people's ability to get healthcare halved their risk of infection.



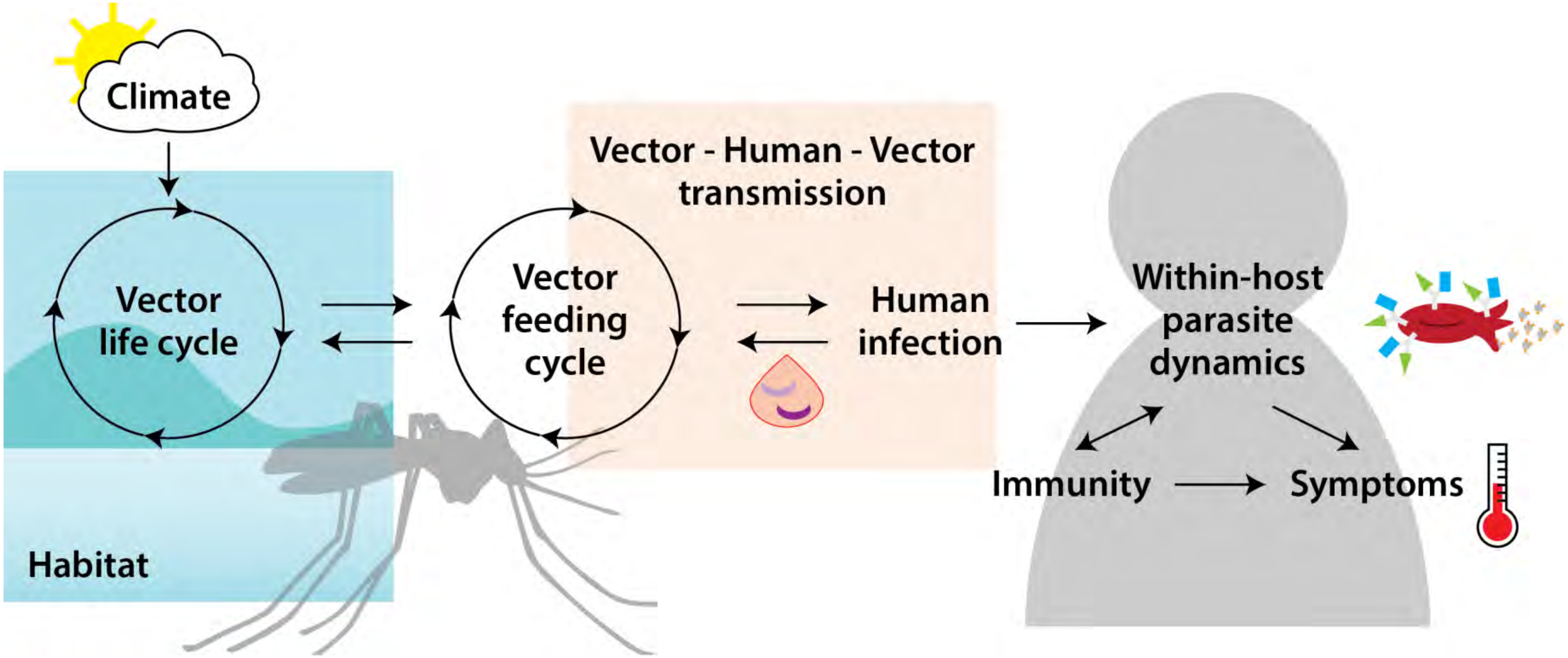
By using a combination of existing tools,

malaria elimination is within reach

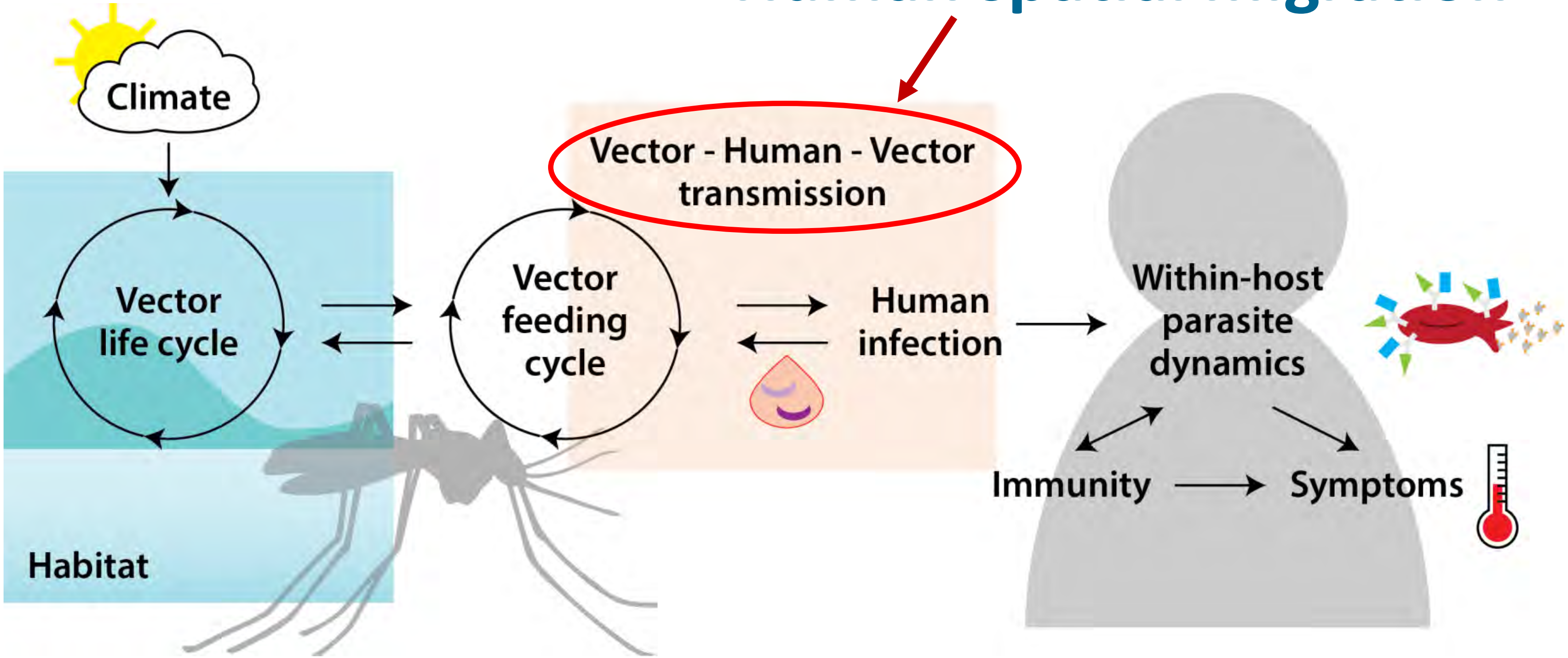
in many places.

Let's talk about

models and data

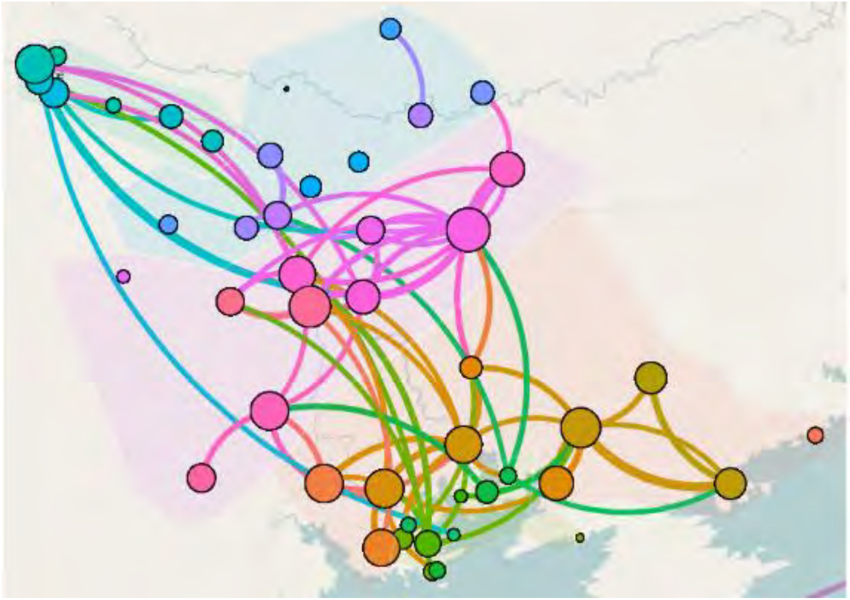

Climate
Vector life cycle
Habitat
Vector feeding cycle
Vector - Human - Vector transmission
Human infection
Within-host parasite dynamics
Immunity
Symptoms

Human spatial migration



Using data to inform importation in the Zambian model

Understanding human movement is essential to understanding malaria transmission.



Humans carry the parasite longer, and sometimes travel much farther than vectors

Movement determines how **well-mixed** a spatially distributed population is

(Human movement) x (Prevalence) = ***Importation pressure***

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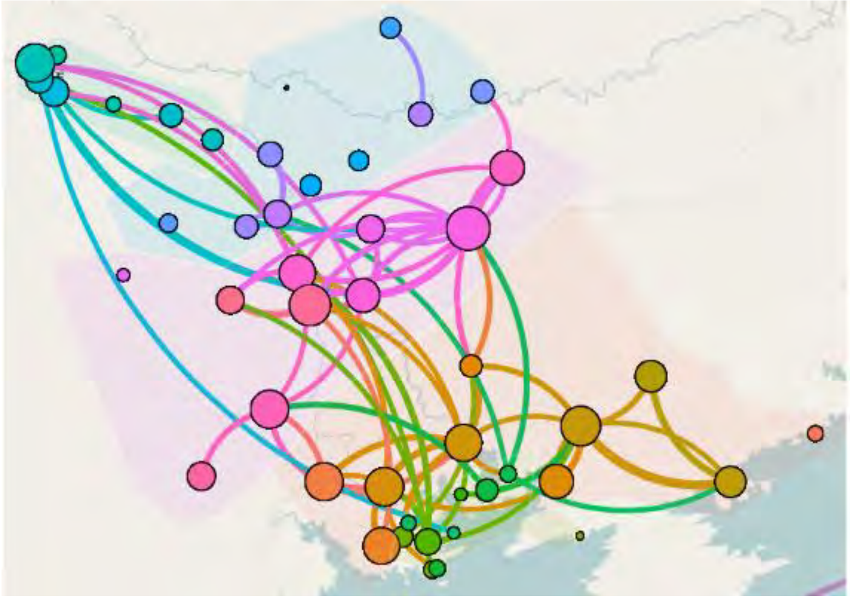

Humans carry the parasite longer, and sometimes travel much farther than vectors

Movement determines how **well-mixed** a spatially distributed population is

(Human movement) x (Prevalence) = ***Importation pressure***

Despite this importance, the amplitude, distribution, seasonality, etc. of human movement is typically unknown.

We can use an unusually rich dataset to estimate human movement patterns.

Up to 10 rounds of MDA/MTAT data over ~5 years, with attached surveys

We can use an unusually rich dataset to estimate human movement patterns.

Up to 10 rounds of MDA/MTAT data over ~5 years, with attached surveys

Essentially a population census repeated multiple times in quick succession

PersonID	Round	(Lat, Lon)	Name	Age	Gender
73FF8BCC-1136-489B-976F-902E203D58F4	1	-16.93, 27.59	Owen Mweene	2	1
FC16DEAB-62F4-47B2-BCE5-ED8FA5286CE8	1	-16.92, 27.58	Abraham Mutinda	14	1
...	...	...	...	...	...

Identifying unique individuals

PersonID	Round	(Lat, Lon)	Name	Age	Gender
73FF8BCC-1136-489B-976F-902E203D58F4	1	-16.93, 27.59	Owen Mweene	2	1
FC16DEAB-62F4-47B2-BCE5-ED8FA5286CE8	1	-16.92, 27.58	Abraham Mutinda	14	1
B4148EE4-508A-49F8-82F4-C1F658D1D8F5	1	-16.94, 27.60	Grace Siambata	9	2
…	…	…	…	…	…
86F2F810-70A0-4197-B42D-F61C8E9FA635	2	-16.93, 27.58	Syambwata Grace	9	2
D9B40515-41A7-492A-A447-439D05F1CD32	2	-16.94, 27.60	Elenora M Dobola	3	2
55CC5FFA-1A71-4C93-8AEA-BB263A91BDCF	2	-16.93, 27.59	Tommy Moonga	35	1
…	…	…	…	…	…
AFA77A28-D30D-42D0-B653-F92A11431E7B	3	-16.94, 27.60	Elin Dobola	5	2

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…	…	…	…	…	…
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…	…	…	…	…	…
AFA77A28-D30D-42D0-B653-F92A11431E7B	3	-16.94, 27.60	Elin Dobola	5	2

Find linkages based on

Levenshtein distance between first & last names

Age difference

Perfect gender match

PersonID	Round	(Lat, Lon)	Name	Age	Gender
73FF8BCC-1136-489B-976F-902E203D58F4	1	-16.93, 27.59	Owen Mweene	2	1
FC16DEAB-62F4-47B2-BCE5-ED8FA5286CE8	1	-16.92, 27.58	Abraham Mutinda	14	1
B4148EE4-508A-49F8-82F4-C1F658D1D8F5	1	-16.94, 27.60	Grace Siambata	9	2
…	…	…	…	…	…
86F2F810-70A0-4197-B42D-F61C8E9FA635	2	-16.93, 27.58	Syambwata Grace	9	2
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55CC5FFA-1A71-4C93-8AEA-BB263A91BDCF	2	-16.93, 27.59	Tommy Moonga	35	1
…	…	…	…	…	…
AFA77A28-D30D-42D0-B653-F92A11431E7B	3	-16.94, 27.60	Elin Dobola	5	2

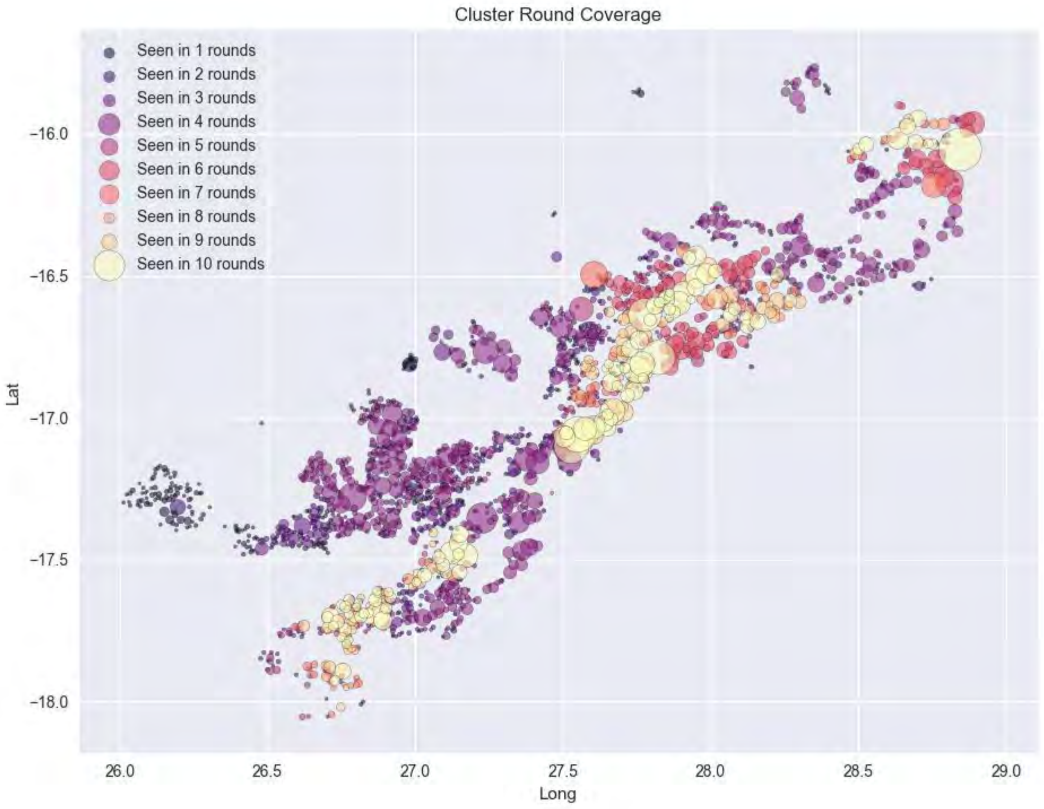
Linkage generates a master list of unique individuals

UniqueID	Round 1	Round 2	Round 3	...	Round 10
B4148EE4-508A-49F8-82F4-C1F658D1D8F5	Grace Siambata, 2	Syambwata Grace, 2	N/A	...	N/A
D9B40515-41A7-492A-A447-439D05F1CD32	N/A	Elenora M Dobola, 5	Elin Dobola, 3	...	N/A
55CC5FFA-1A71-4C93-8AEA-BB263A91BDCF	N/A	N/A	Tommy Moonga, 35	...	N/A
73FF8BCC-1136-489B-976F-902E203D58F4	Owen Mweene, 1	N/A	N/A	...	Oren Mweene, 2
FC16DEAB-62F4-47B2-BCE5-ED8FA5286CE8	Abraham Mutinda, 14	N/A	N/A	...	N/A
4EAC21FC-E181-40D7-BD91-51DF55B11A24	N/A	N/A	N/A	...	Felix Chembo, 44
264F9889-D463-43BF-A446-A0D2D7B31E18	N/A	N/A	N/A	...	Janet Nyambe, 2

Linkage gives a longitudinal picture of how people move

UniqueID	Round 1 Location	Round 2 Location	Round 3 Location	...	Round 10 Location
B4148EE4-508A-49F8-82F4-C1F658D1D8F5	(-16.93, 27.59)	(-16.94, 27.63)	N/A	...	N/A
D9B40515-41A7-492A-A447-439D05F1CD32	N/A	(-16.88, 27.61)	(-16.91, 27.40)	...	N/A
55CC5FFA-1A71-4C93-8AEA-BB263A91BDCF	N/A	N/A	(-16.93, 27.59)	...	N/A
73FF8BCC-1136-489B-976F-902E203D58F4	(-16.91, 27.40)	N/A	N/A	...	(-16.31, 27.08)
FC16DEAB-62F4-47B2-BCE5-ED8FA5286CE8	(-16.88, 27.61)	N/A	N/A	...	N/A
4EAC21FC-E181-40D7-BD91-51DF55B11A24	N/A	N/A	N/A	...	(-16.88, 27.61)
264F9889-D463-43BF-A446-A0D2D7B31E18	N/A	N/A	N/A	...	(-16.83, 27.65)

Next, we identify population clusters



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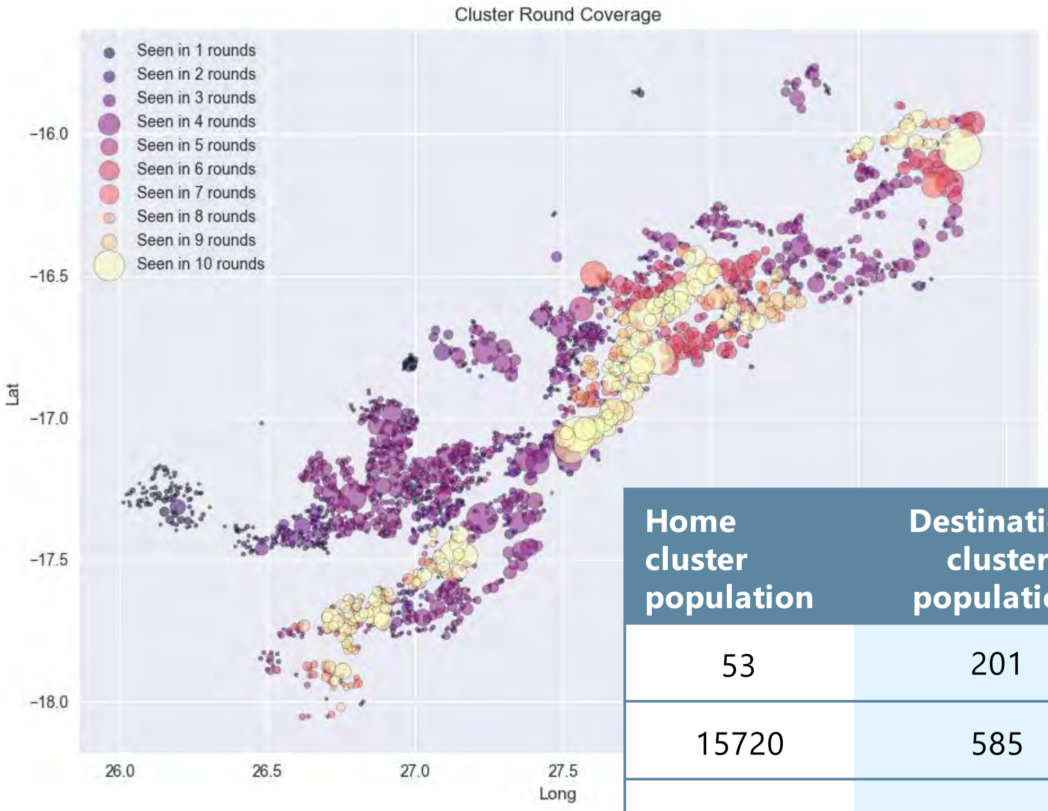
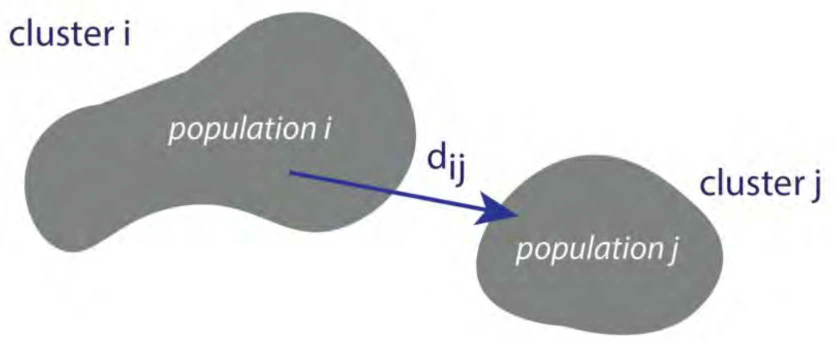


Home cluster population	Destination cluster population	Distance between clusters (km)	# of observed trips
53	201	2.1	5
15720	585	5.8	58
…	…	…	…

Finally, we fit a gravity migration model

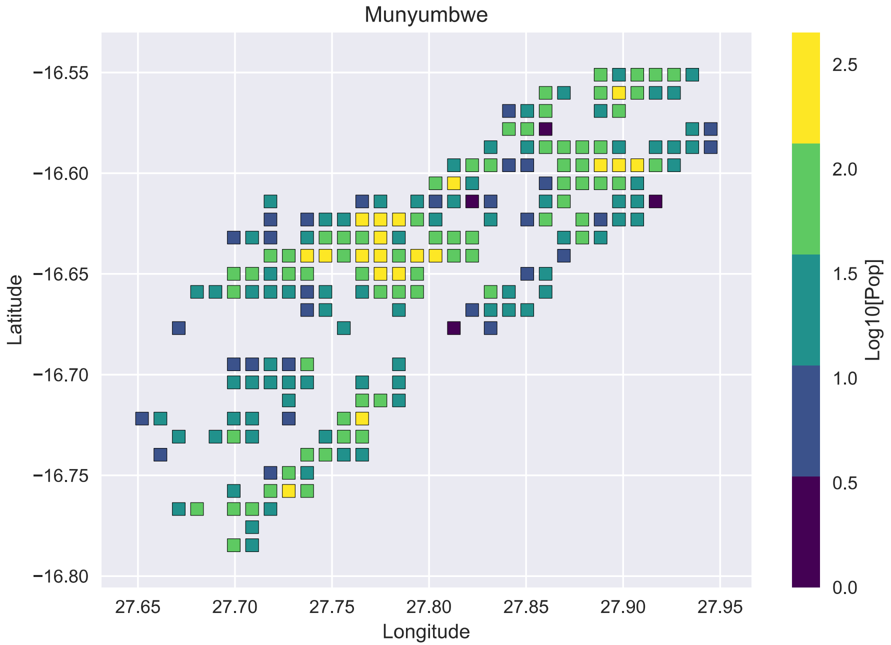


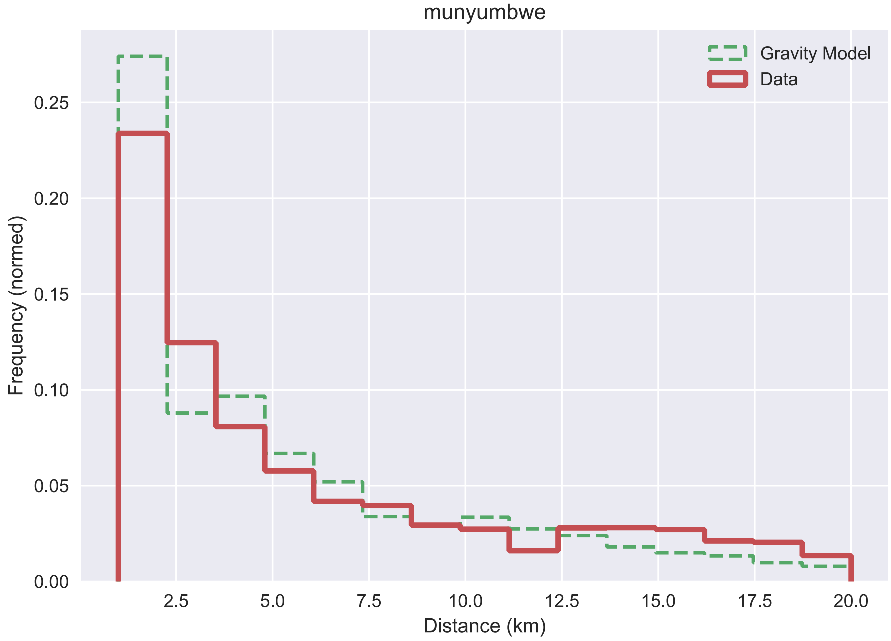
Rate of travel between clusters $\propto \frac{p_i^{0.95} p_j^{0.95}}{d^{1.1}}$

Home cluster population	Destination cluster population	Distance between clusters (km)	# of observed trips	# of predicted trips
53	201	2.1	5	7
1572	585	15.8	72	68
…	…	…	…	…

The gravity model fits longitudinal linkage quite well

$$\text{Rate of travel between clusters} \propto \frac{p_i^{0.95} p_j^{0.95}}{d^{1.1}}$$

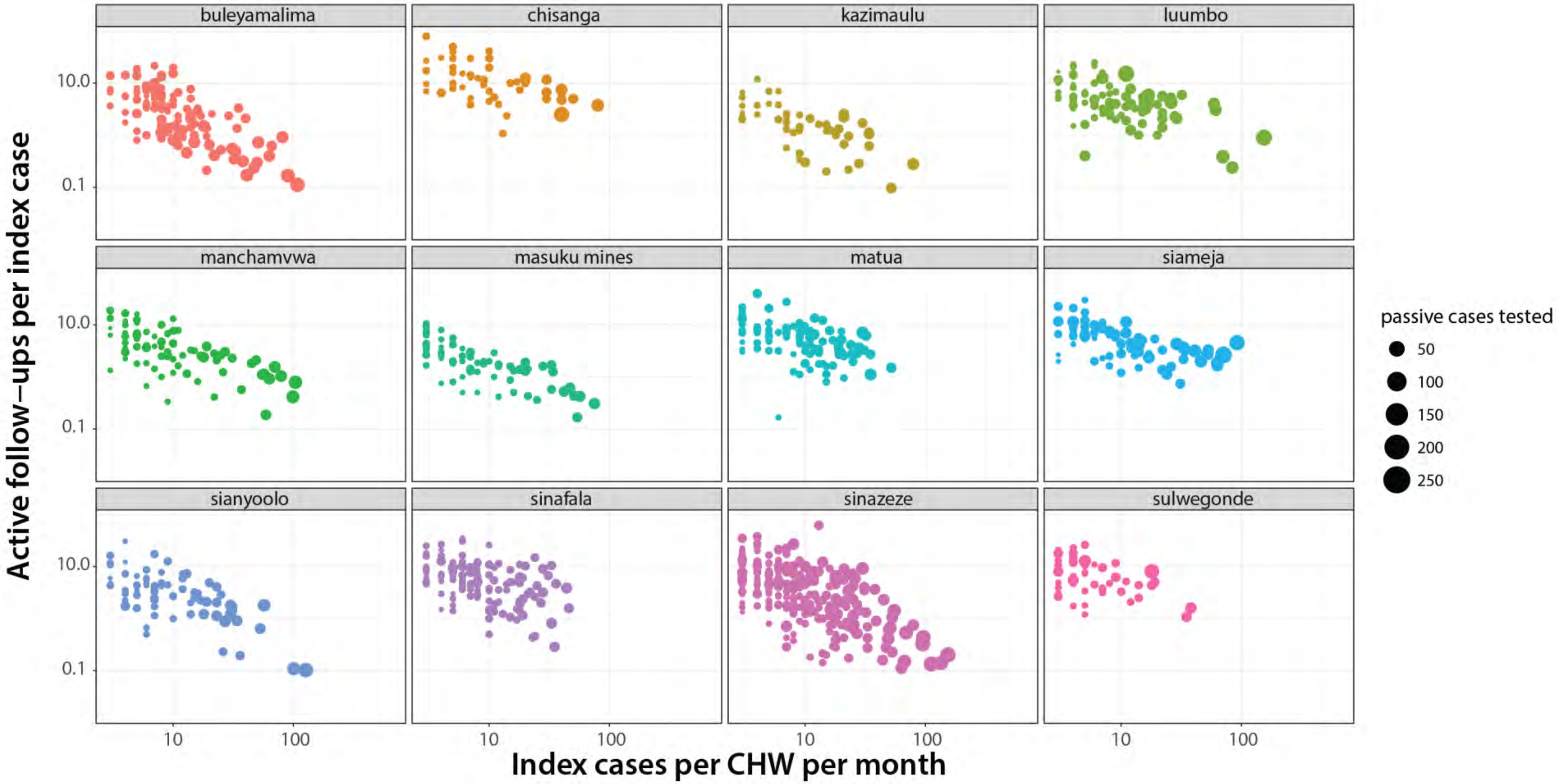




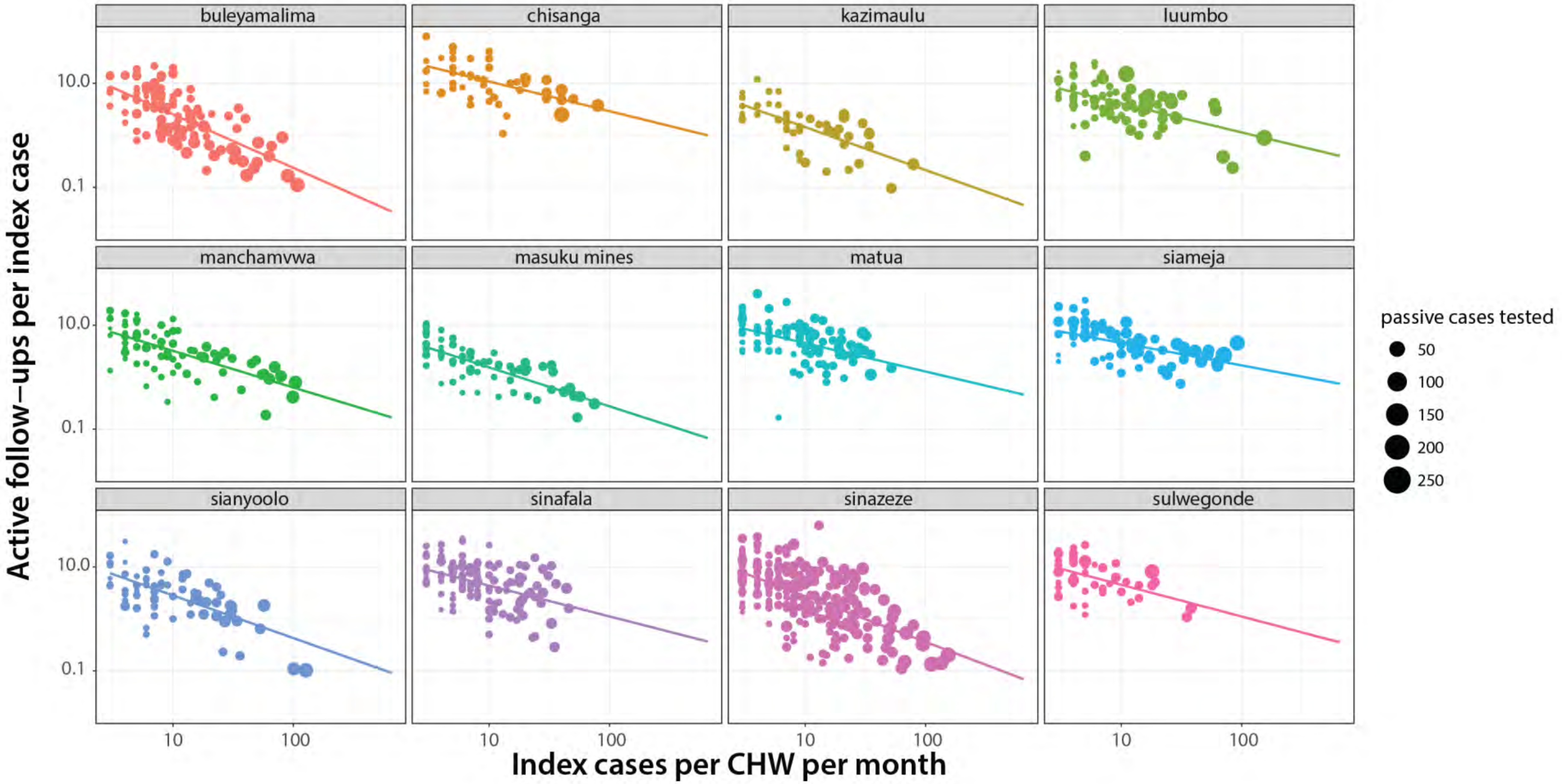
Helping the health system help

community health workers (CHWs).

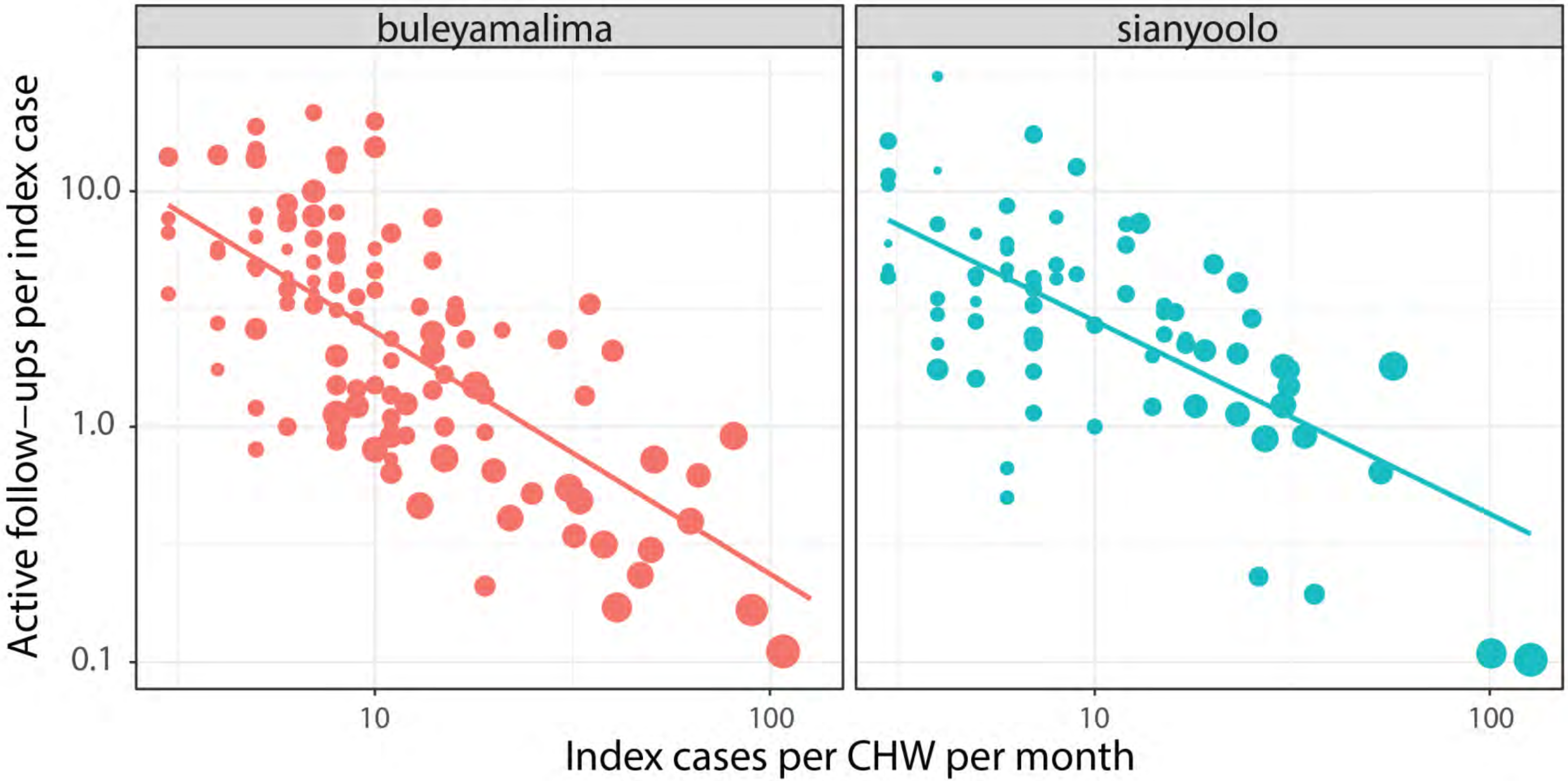
Reactive case detection follow-ups per index case



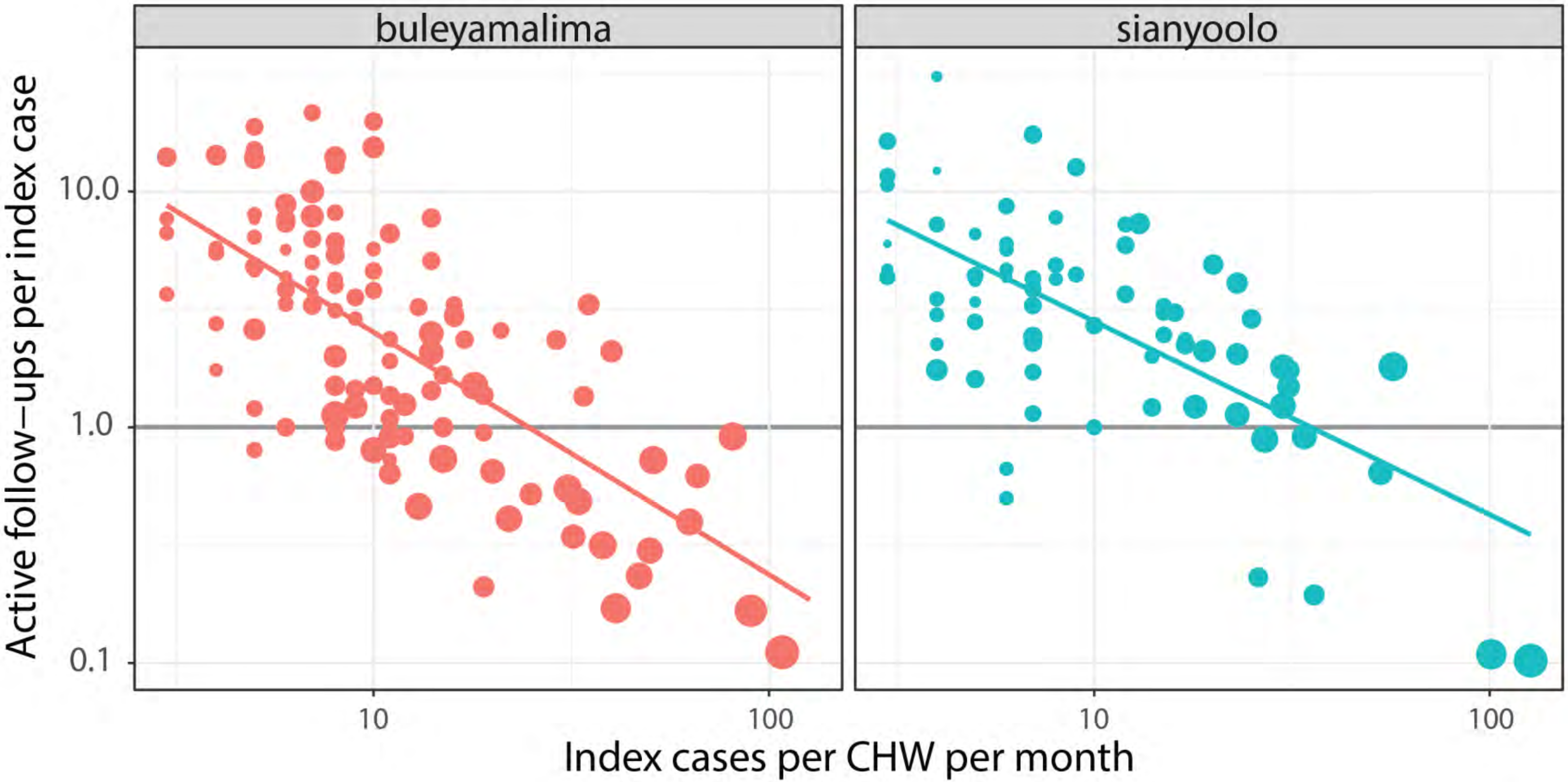
It’s a power law!



Closer look with Buleyamalima and Sianyoolo as examples



At what point do the CHWs stop doing follow-ups because they have too many index cases?



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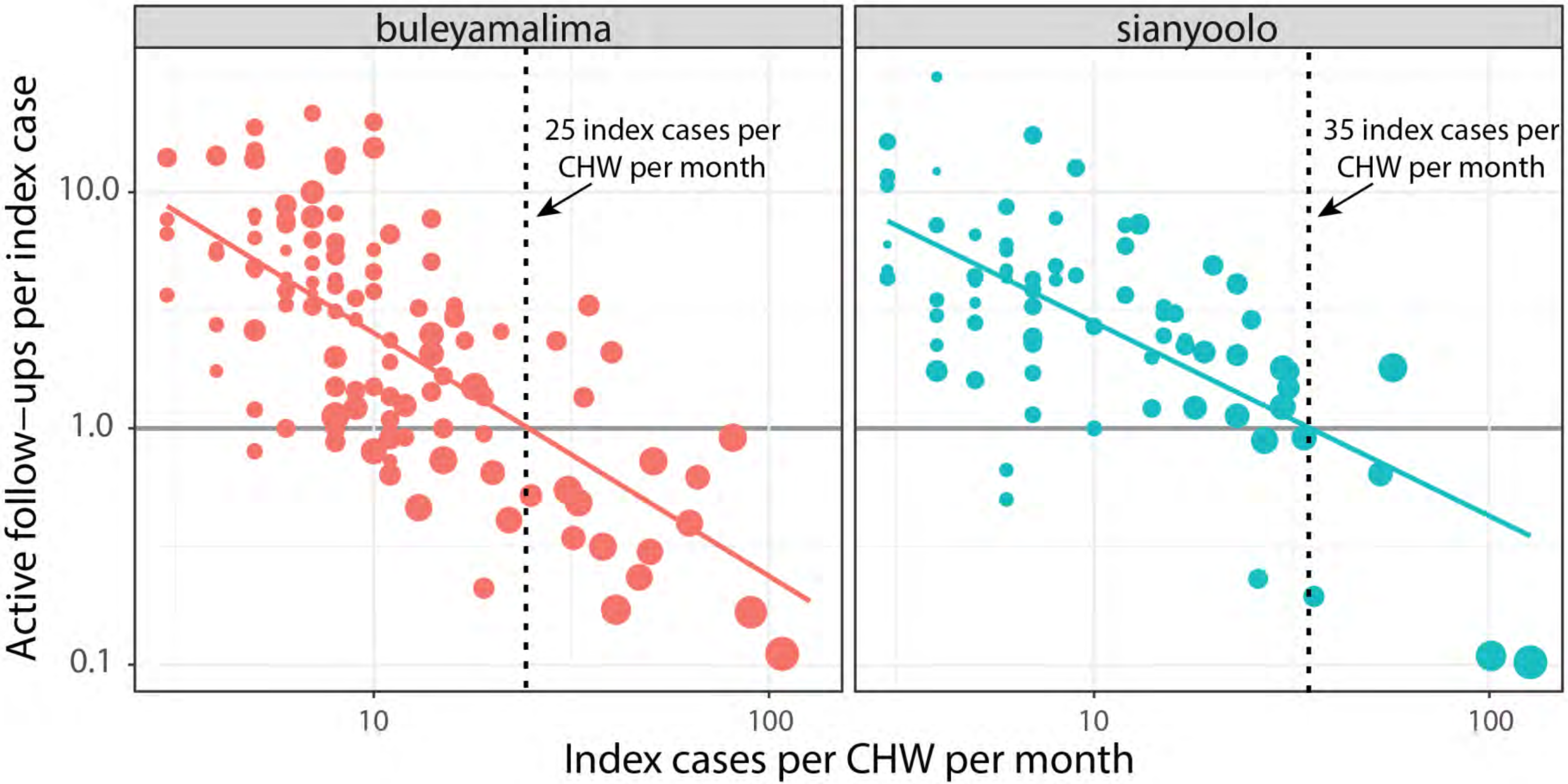

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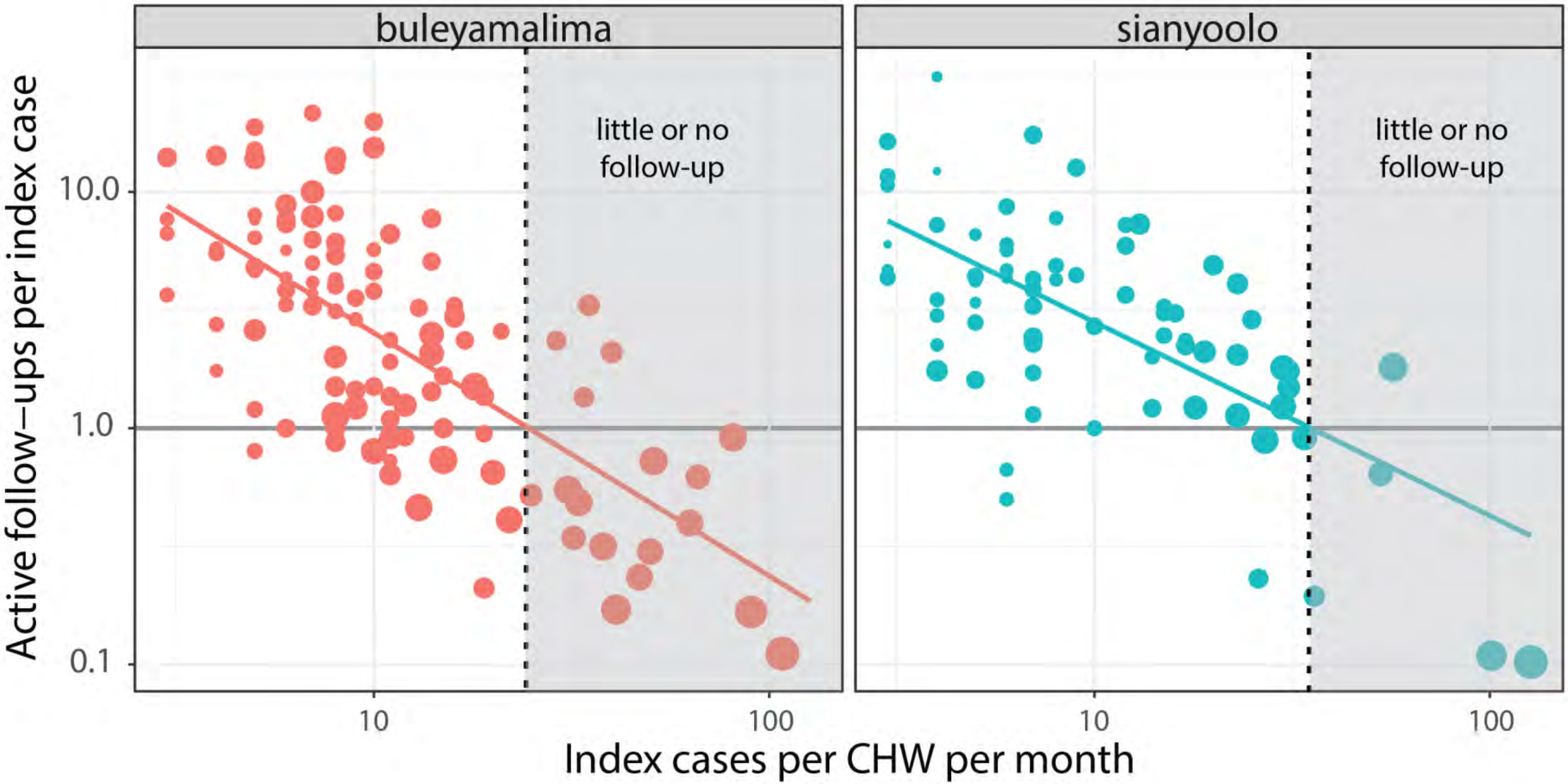
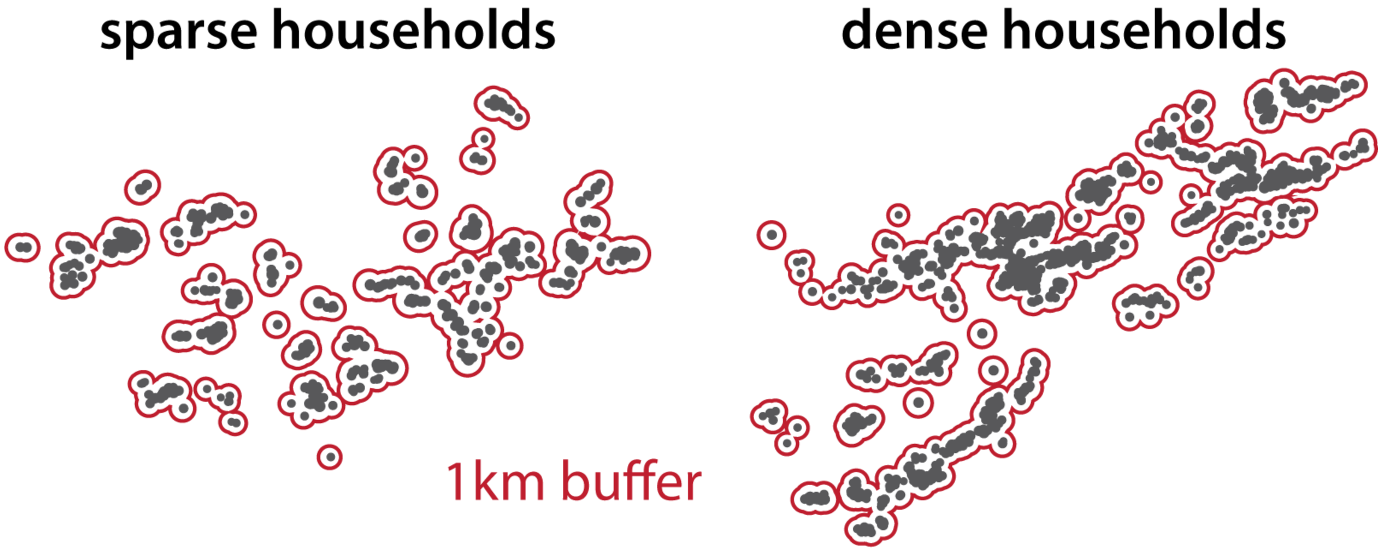
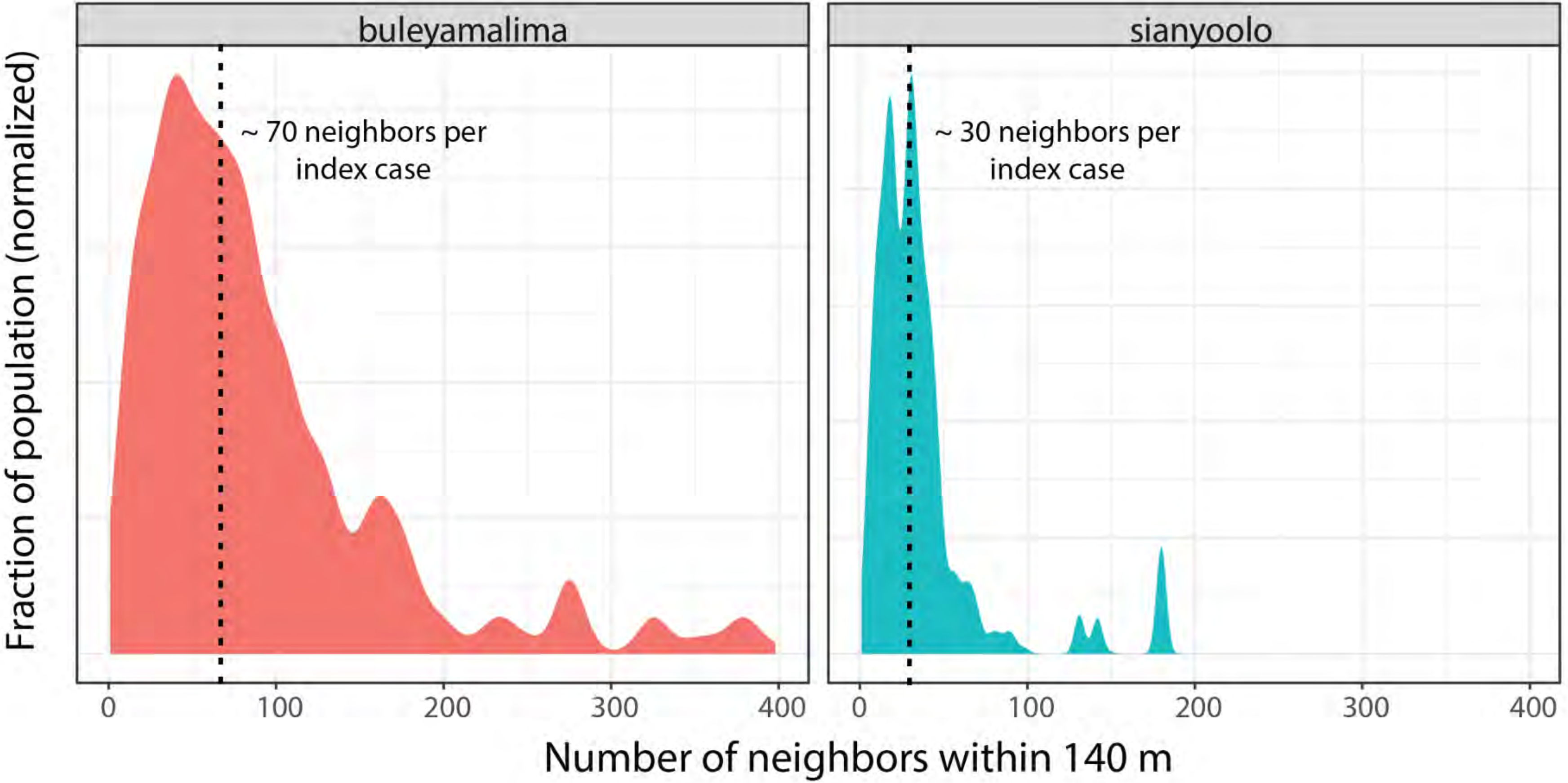


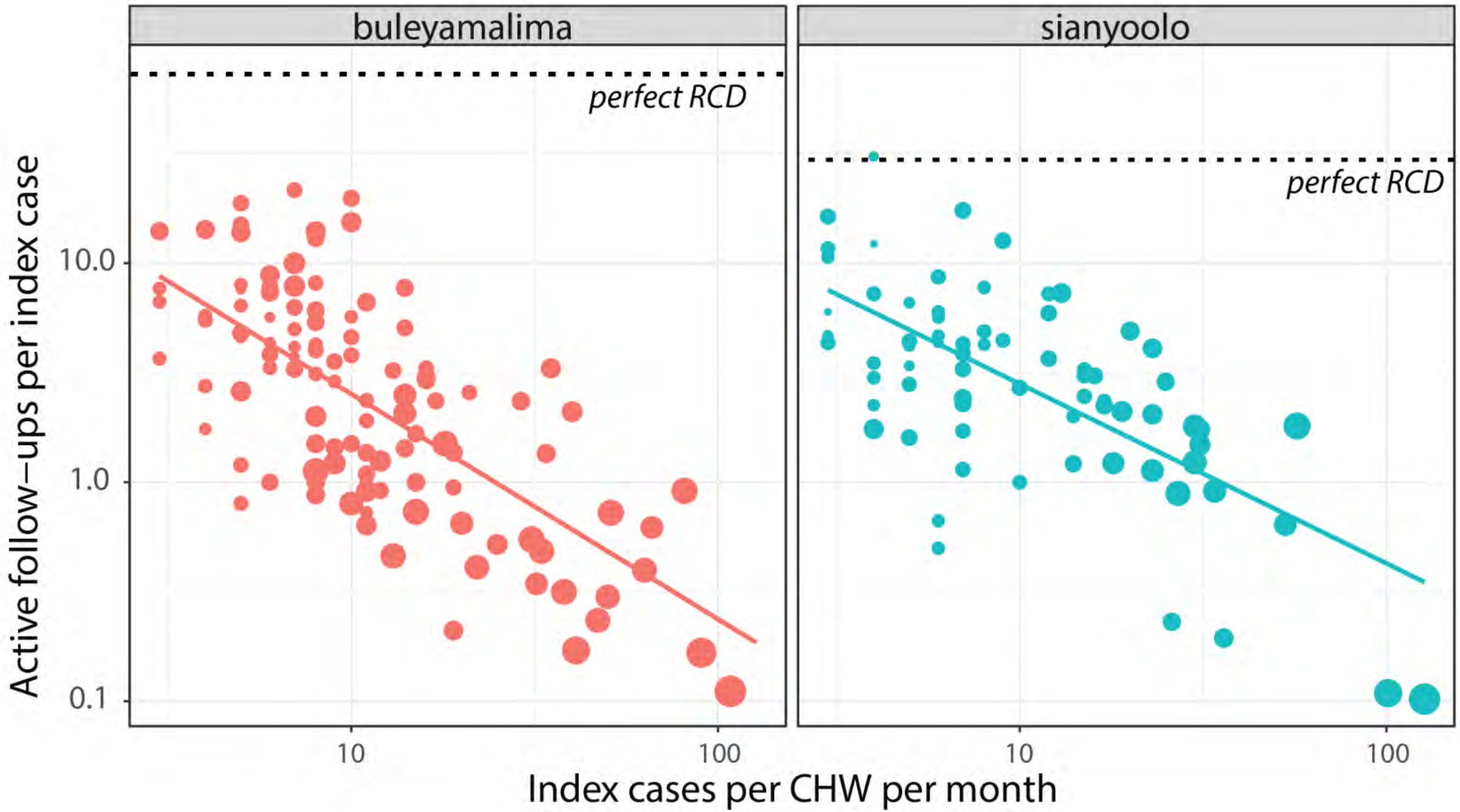
The demands of reactive case detection depend strongly on population density.



Meaning of “perfect follow-up” differs by catchment due to the population distribution



Identify categories of RCD quality based on local population distribution



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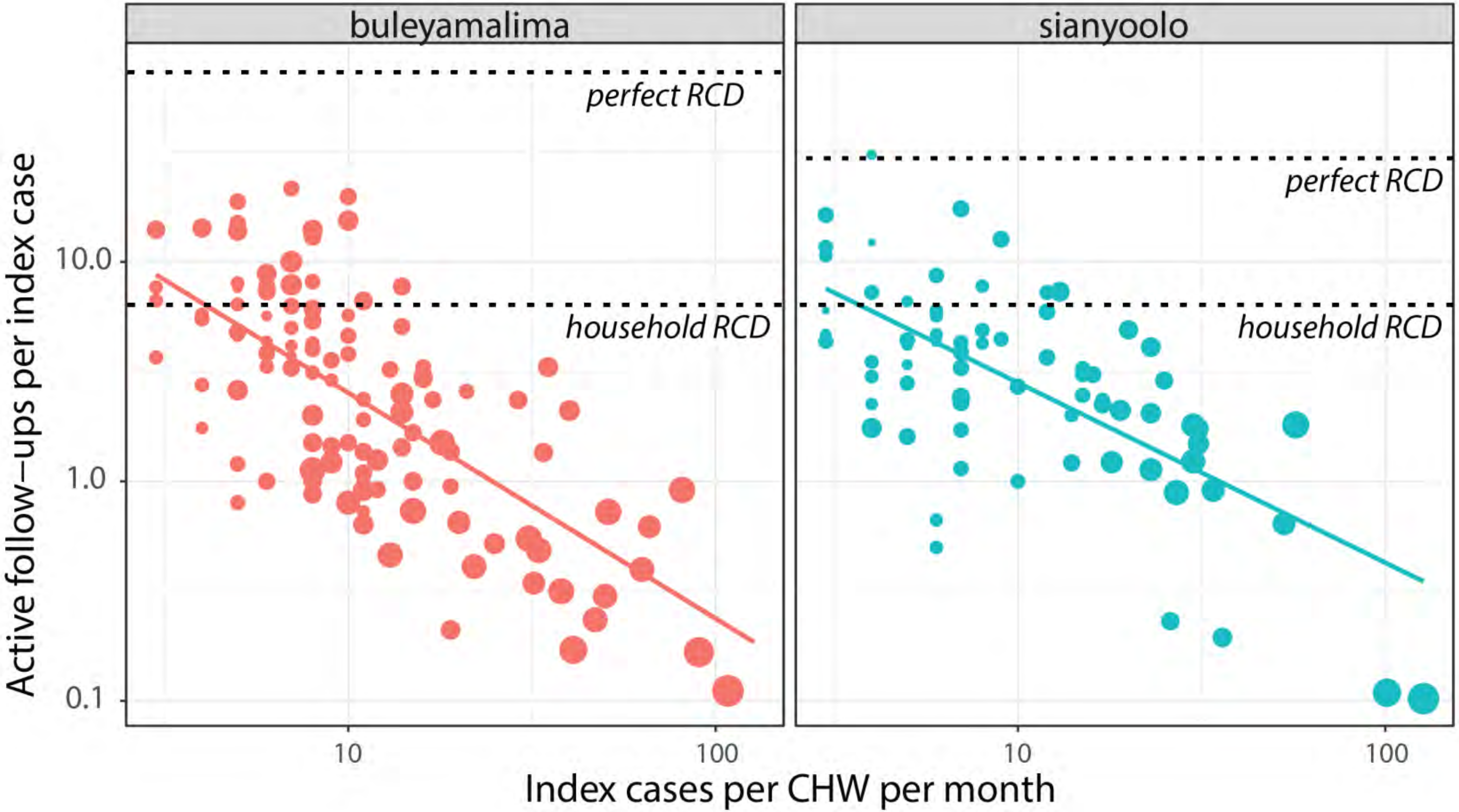

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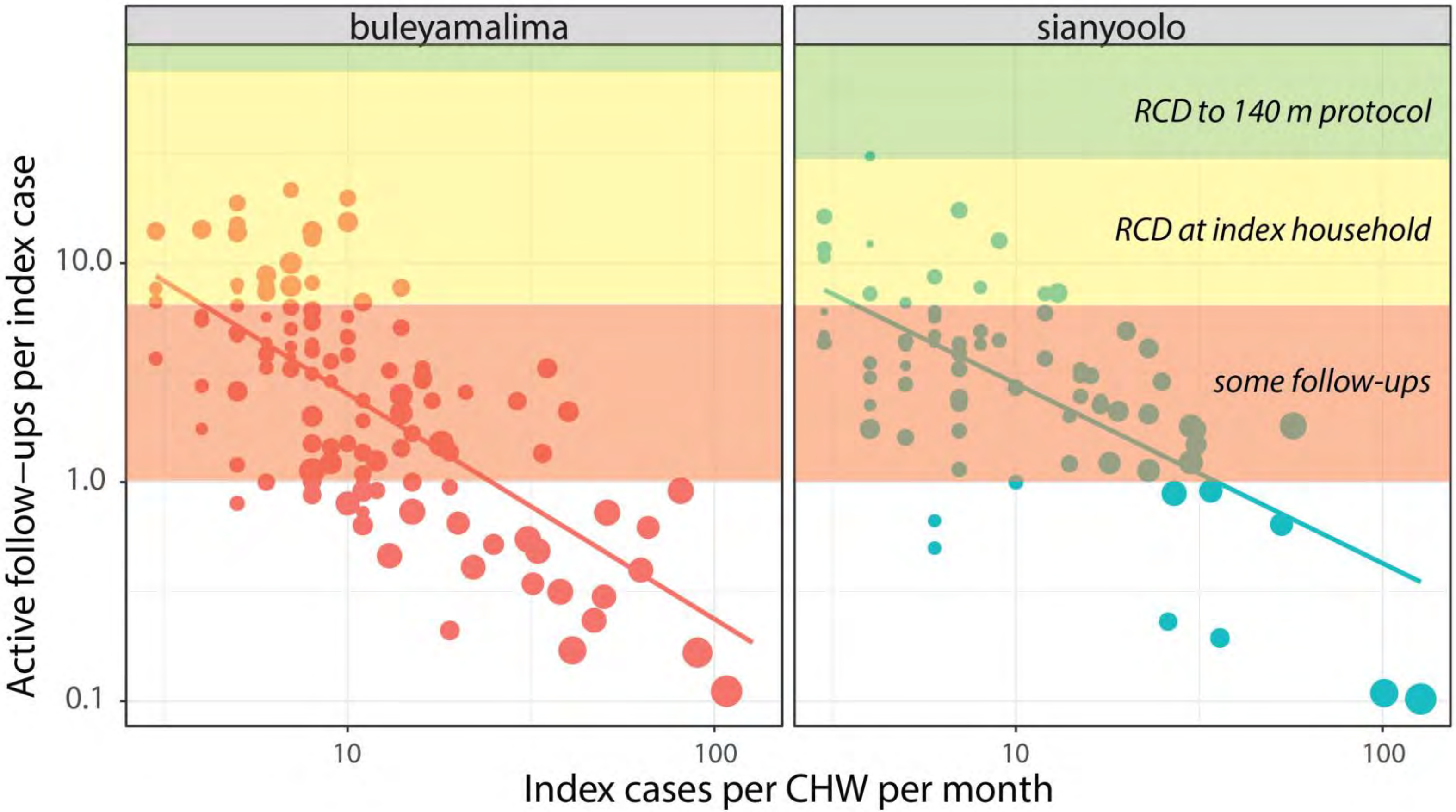
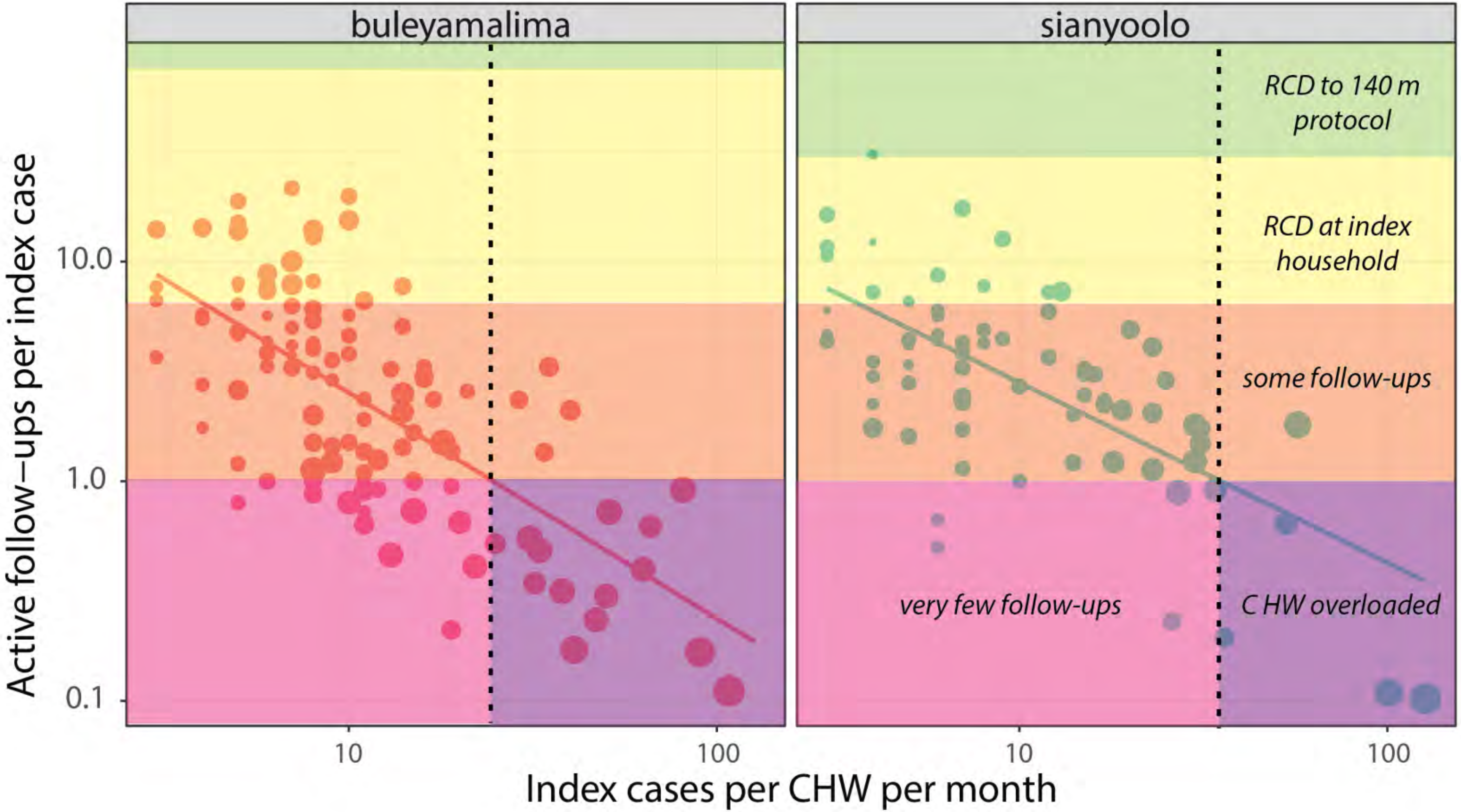


Flag CHWs when the lack of RCD is likely due to overload



Many thanks to

- **MDA study participants**
- **Zambia NMEC:** Busiku Hamainza
- **PATH-MACEPA:** John Miller, Kamm Schneider, Reine Rutagwera, Kafula Silumbe, Rick Steketee, Javan Chanda, Duncan Earle
- **Tulane University:** Thom Eisele
- **USCF:** Adam Bennett
- **Past IDMers**: Jaline Gerardin, Milen Nikolov