A flexible framework for the surveillance of *Plasmodium knowlesi* malaria in Indonesia

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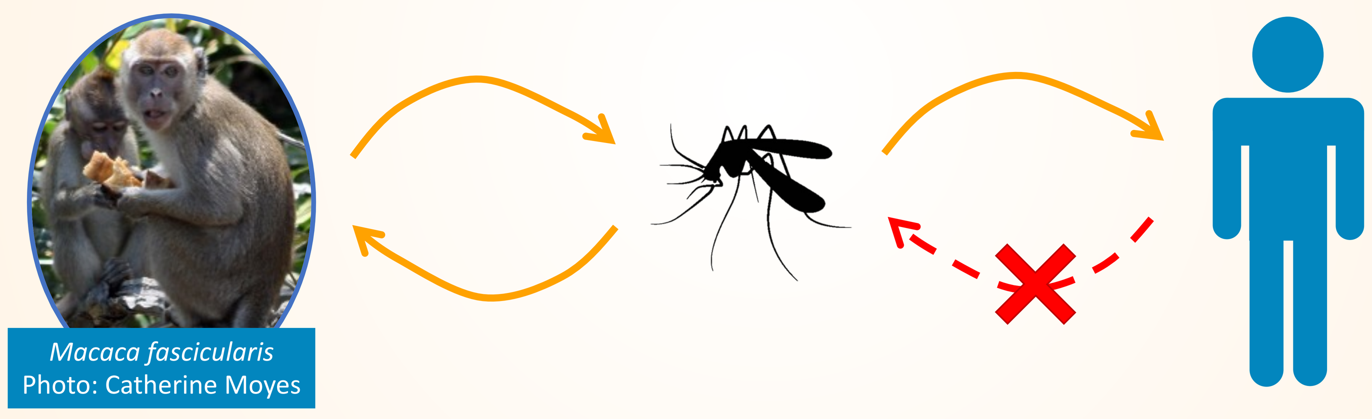
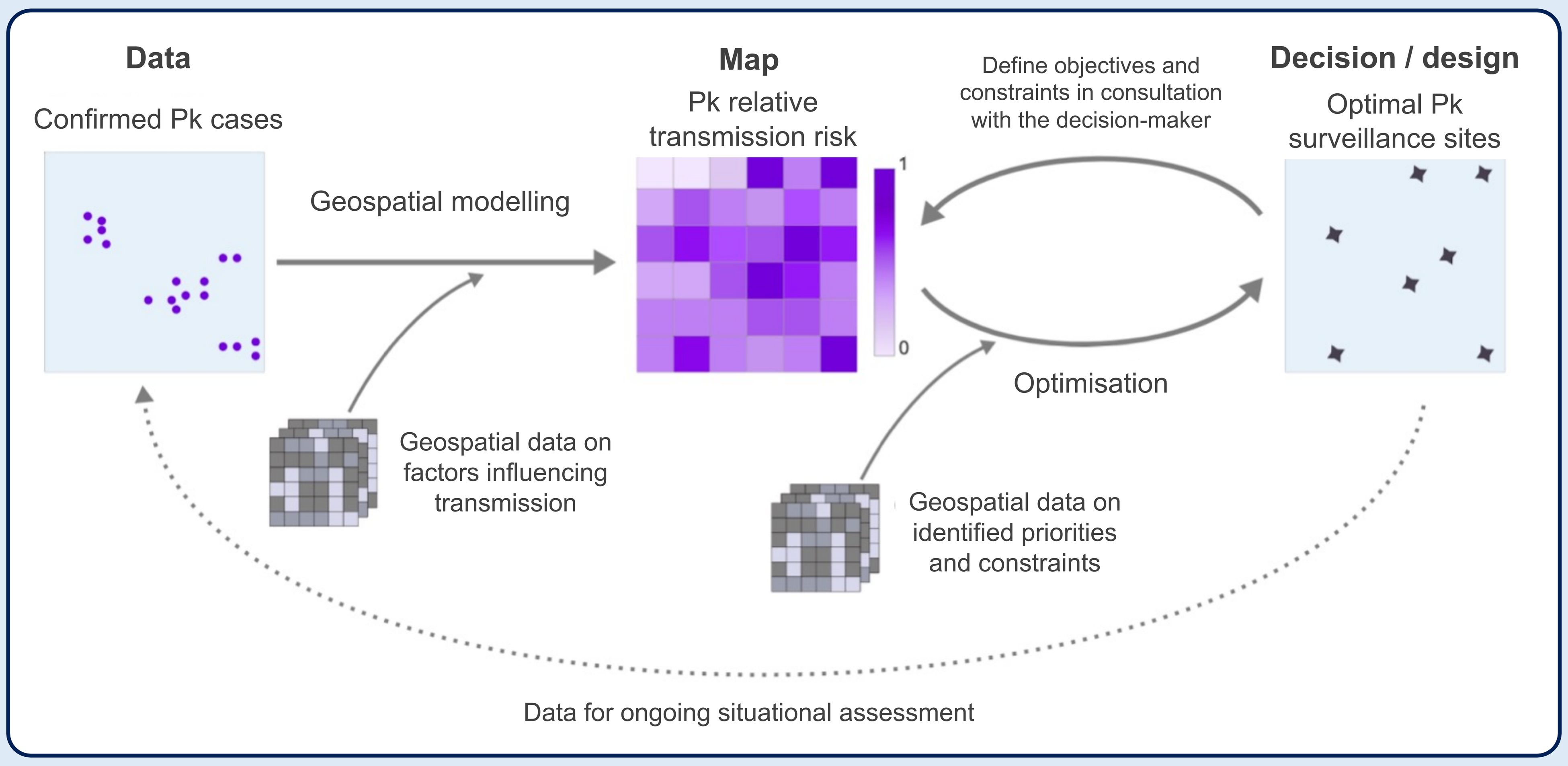
Introduction

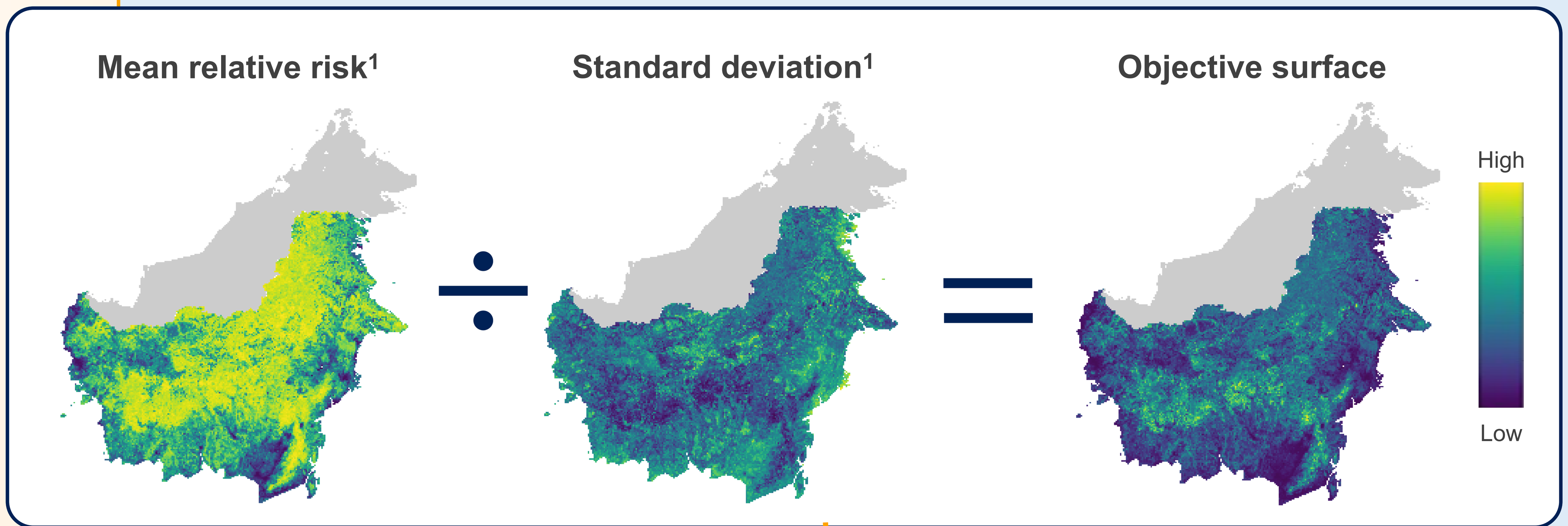
Disease surveillance activities are resource-limited so should be optimised to achieve **specific objectives**. In a spatial context, the allocation of surveillance resources should therefore be based on our knowledge of the spatial distribution of the disease. But how can we account for extreme **uncertainty** in our understanding of the disease's distribution?

Plasmodium knowlesi is a zoonotic strain of malaria that is increasingly found across Southeast Asia and is now the most common cause of malaria in Malaysia. Previous surveillance of *P. knowlesi* malaria has been limited by diagnostic accuracy and available resources. As a result, *P. knowlesi* malaria case data is **sparse** and **highly spatially biased**.



Human surveillance at **primary healthcare centres** is planned. Given an **existing geospatial statistical model** of relative *P. knowlesi* malaria risk and specific stakeholder sampling objectives, we develop a **flexible decision workflow** to support the selection of sites for human surveillance of *P. knowlesi* malaria. This workflow quantifies study aims into an objective surface and considers a meaningful definition of healthcare centre catchment area.



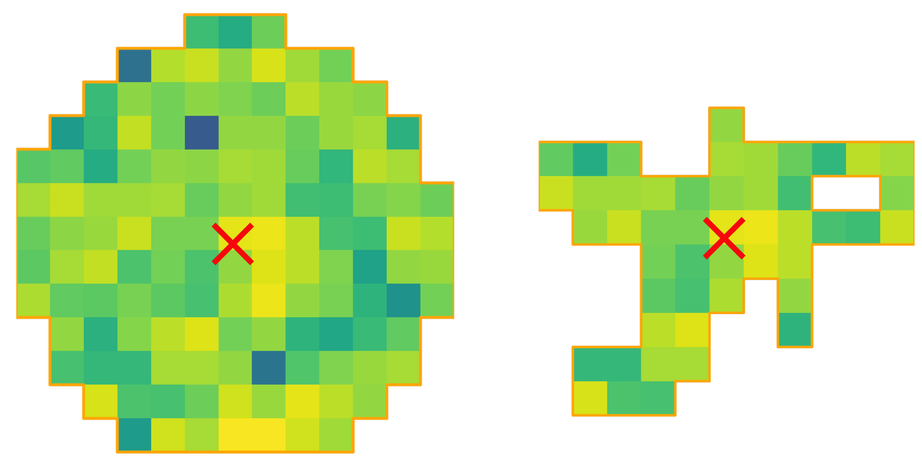


Workflow

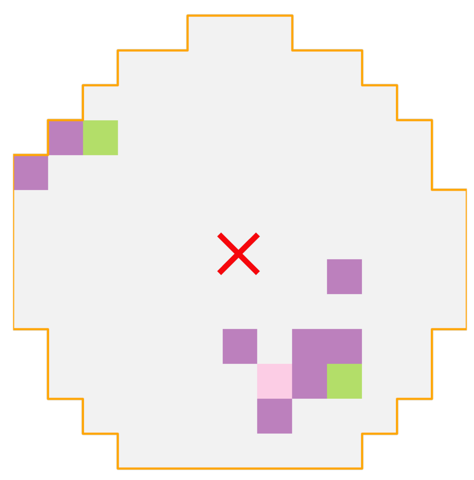
1. Characterise healthcare centre catchment area: area within which *P. knowlesi* malaria transmission is expected to have occurred
2. Calculate objective value for catchment: aim to identify positive cases of *P. knowlesi* malaria
   ↳ Select sites where **mean relative risk is high** and **model uncertainty is low**
3. Determine presence of target landscape types
4. Compare alternative healthcare centres for prospective human surveillance

Primary healthcare centre catchment area

Distance (e.g. 30 km) Travel time[2] (e.g. 100 min)



Target landscape types



Aim to target several landscapes:

- Oil palm plantation[3]
- Forest fringe / disturbed forest[4]
- Croplands[5]
- Village[6]

Malinau district: travel time catchments (100 min)

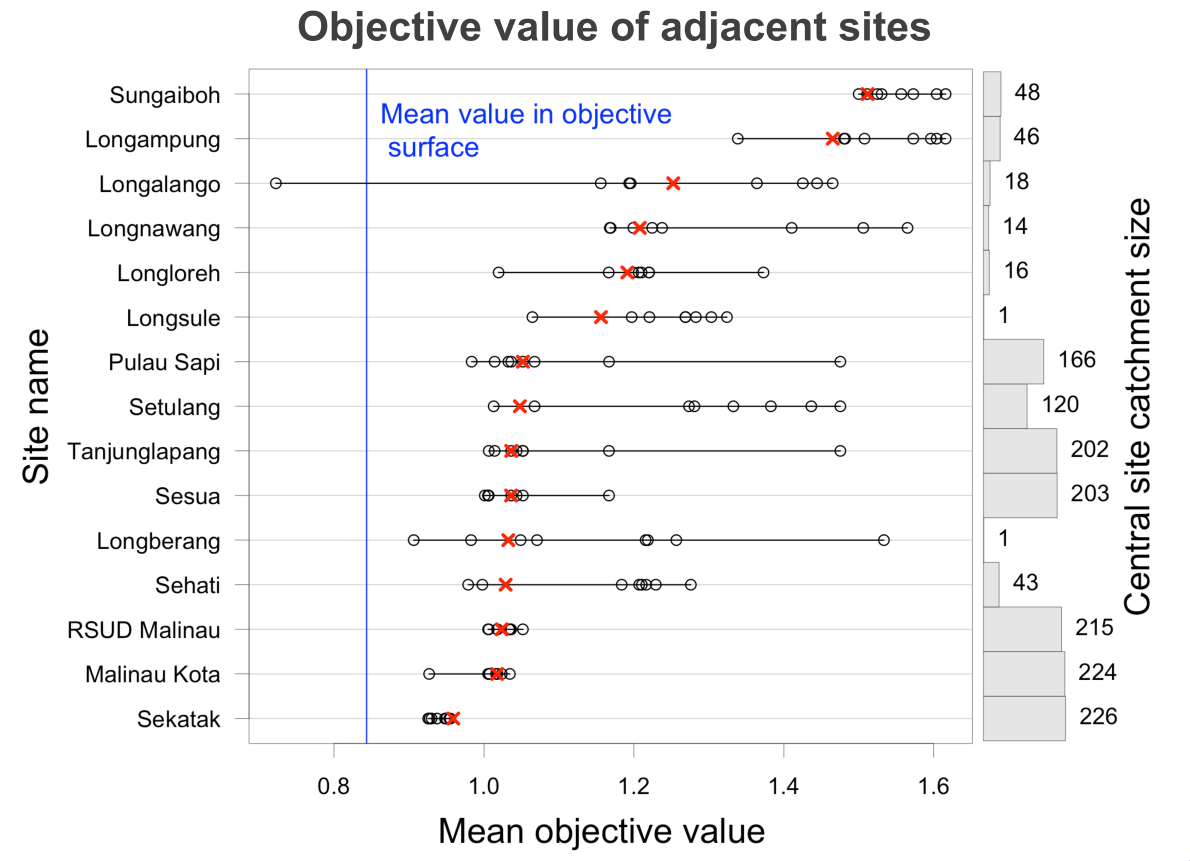
Rank	Name	No' Pixels	Objective Mean	Objective Std Dev	Eco-constraints Present	Total Human Pop	Maximum Single Value Croplands	Maximum Single Value Oil Palm	Maximum Single Value Forest Loss
1	Sungaiboh	48	1.51	0.27	1	****	0	0.00	0.01
2	Longampung	46	1.47	0.31	2	****	0	20.68	0.05
3	Longalango	18	1.25	0.39	2	****	0	26.82	0.01
4	Longnawang	14	1.21	0.20	2	****	0	21.80	0.09
5	Longloreh	16	1.19	0.24	2	****	0	26.57	0.14
6	Longsule	1	1.16	NA	0	**	0	0.00	0.00
7	Pulau Sapi	166	1.05	0.32	3	*****	0	37.00	0.19
8	Setulang	120	1.05	0.31	3	*****	0	37.00	0.19
9	Tanjunglapang	202	1.04	0.35	3	*****	0	37.00	0.19
10	Sesua	203	1.04	0.35	3	*****	0	37.00	0.19

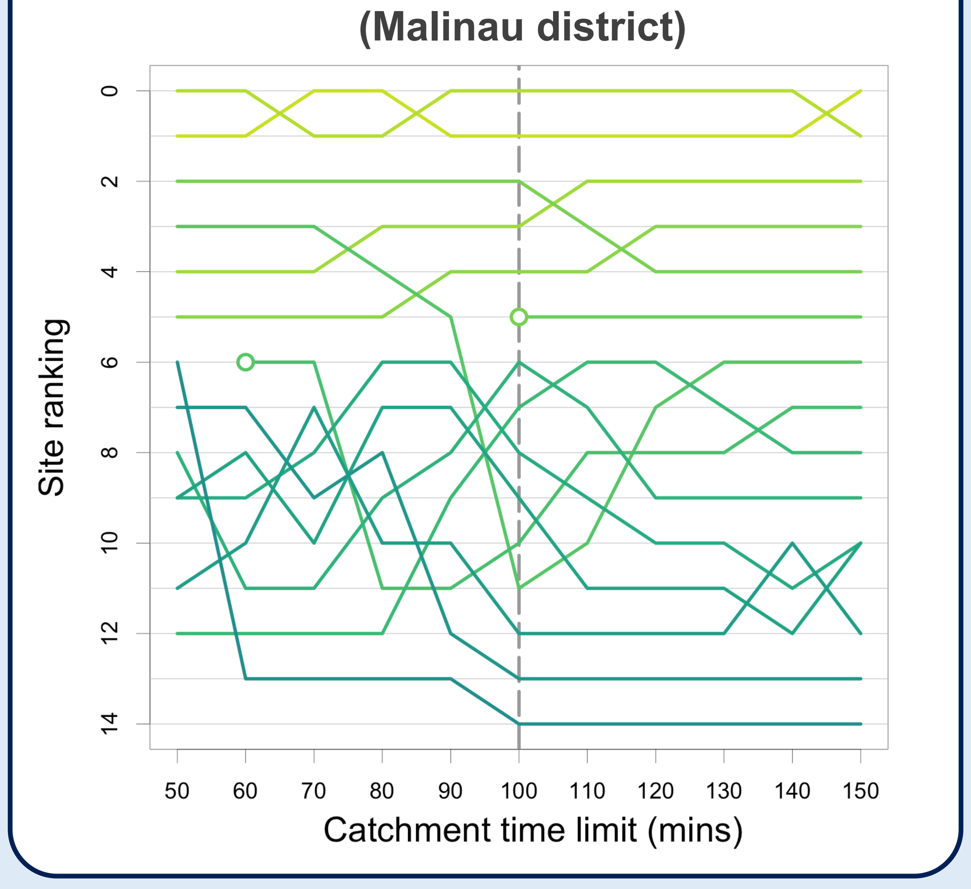
Site suggested by stakeholders

Target landscape present
Target landscape absent

Key outcomes

- A **statistical prediction of relative disease risk** based on environmental data is incorporated into public health decisions, together with logistical factors
- Clinical stakeholders inform objective and constraint selection and maintain **ownership** of decision-making process
- Surveillance sites' utility to surveillance can be **quantitatively compared**





Future work

- Multi-objective site selection (e.g. to balance mean objective values and catchment size)
- Selection of multiple sites simultaneously (e.g. by selection of site network or multi-objective method)
- Incorporation of other health infrastructure (e.g. aim to select sites not over-shadowed by regional hospital)
- Selection of mosquito and macaque surveillance sites within healthcare centre catchments

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