



THE UNIVERSITY *of* EDINBURGH
School of GeoSciences

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BETTER DATA FOR GEOGRAPHIC TARGETING OF RESOURCES: THE ROLE OF EARTH OBSERVATION DATA FOR MAPPING SOCIAL AND ECONOMIC CONDITIONS.

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How to achieve the SDGs?

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A grid of 17 icons representing the Sustainable Development Goals, arranged in three rows. The icons are numbered 1 through 17 and include titles and symbols for each goal. The grid is partially obscured by text overlays.

Goal Number	Goal Title
1	NO POVERTY
2	ZERO HUNGER
3	GOOD HEALTH AND WELL-BEING
4	QUALITY EDUCATION
5	GENDER EQUALITY
6	CLEAN WATER AND SANITATION
7	AFFORDABLE AND CLEAN ENERGY
8	DECENT WORK AND ECONOMIC GROWTH
9	INDUSTRY, INNOVATION AND INFRASTRUCTURE
10	REDUCED INEQUALITIES
11	SUSTAINABLE CITIES AND COMMUNITIES
12	RESPONSIBLE CONSUMPTION AND PRODUCTION
13	CLIMATE ACTION
14	LIFE BELOW WATER
15	LIFE ON LAND
16	PEACE, JUSTICE AND STRONG INSTITUTIONS
17	PARTNERSHIPS FOR THE GOALS

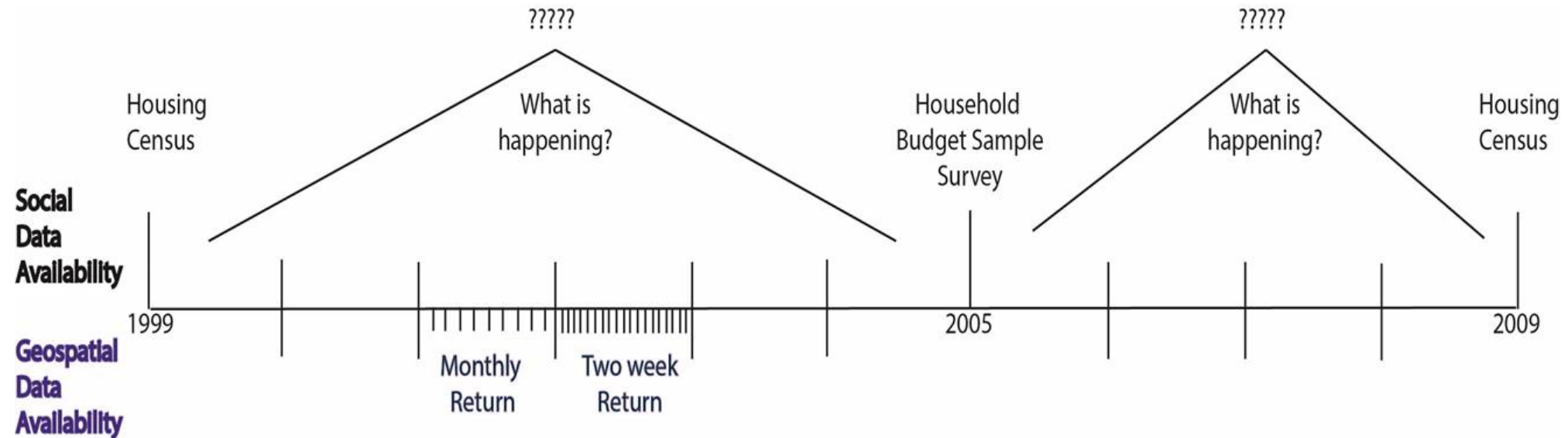
- Examining the role of Remote Sensing of land use and ecosystem services in mapping and monitoring deprivation
- Building evidence for socioeconomic indicators
- Monitoring socioeconomic aspects of SDGs:
 - Census – 10 years
 - Demographic and Health Survey - 5 years
 - Living Standards Survey – 5 Years
 - Consumption Survey - Annual

\$253 Billion

Jerven (2014)

Missing Data: Monitoring socioeconomic conditions

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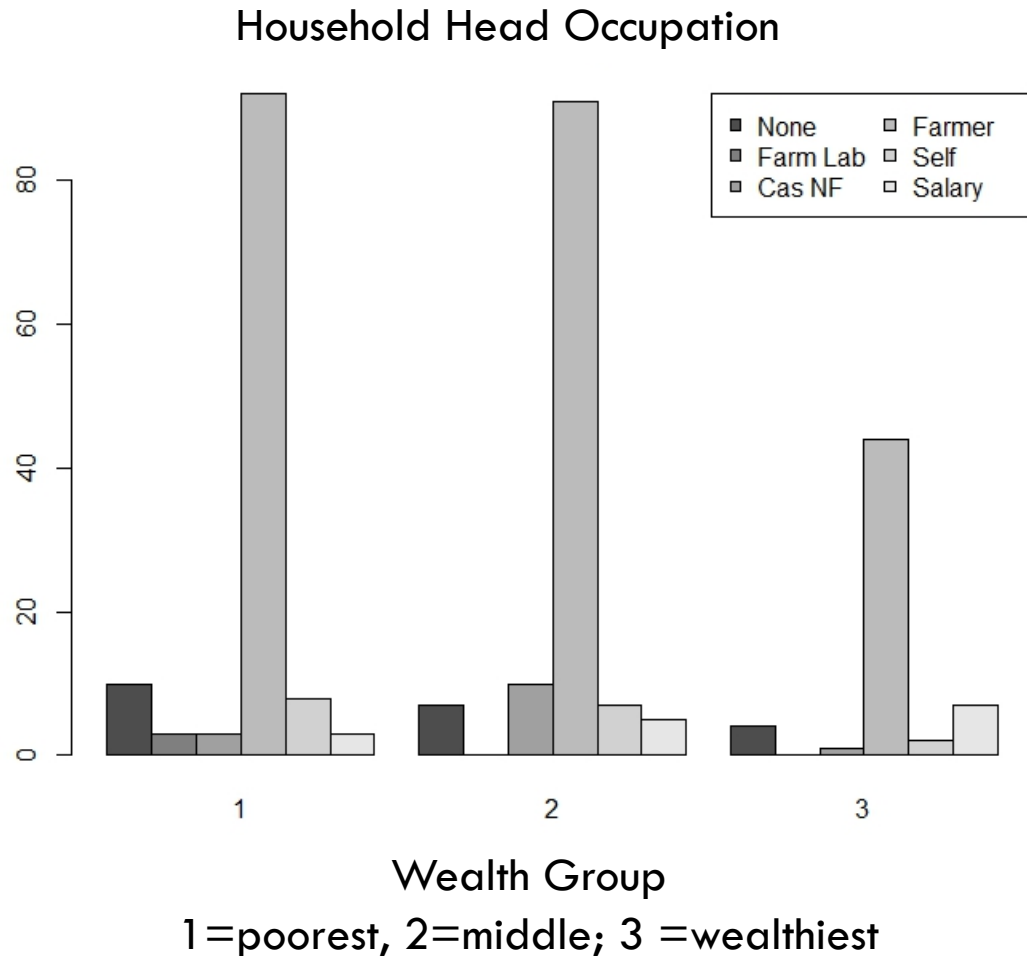
Cannot achieve SDGs if we rely on surveys once every five years.

Without annual data we can see changes have happened but can miss what drives these changes

Can remote sensing data help?

Link to environmental resources

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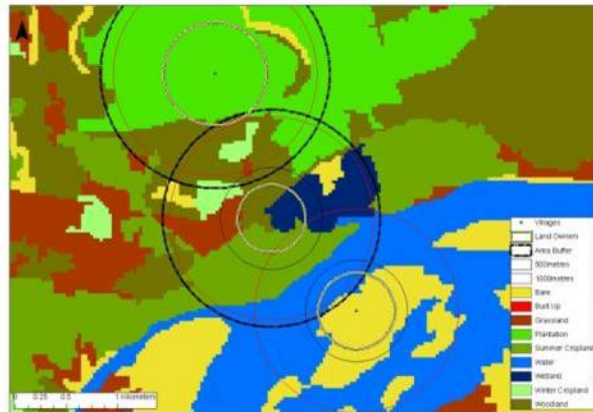


In many rural areas of developing countries agriculture and environmental resources still contribute large amount to livelihoods.

So can we say something about socioeconomic conditions by mapping landscapes and changes in landscapes at fine spatial and temporal resolution?

Past studies examining rural wellbeing using EO data

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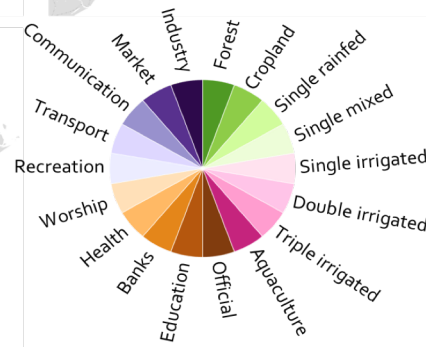
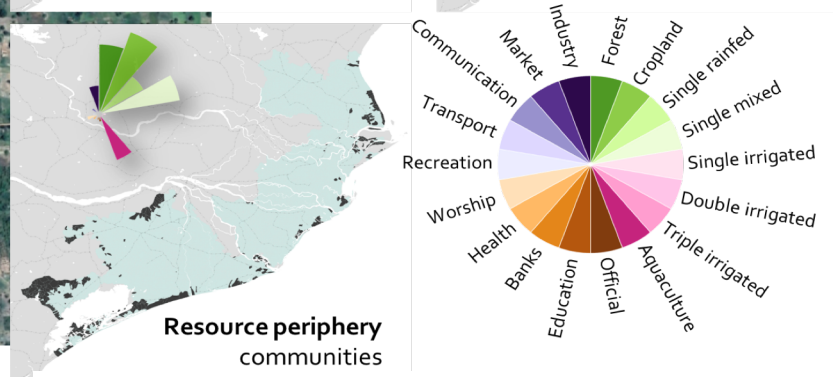
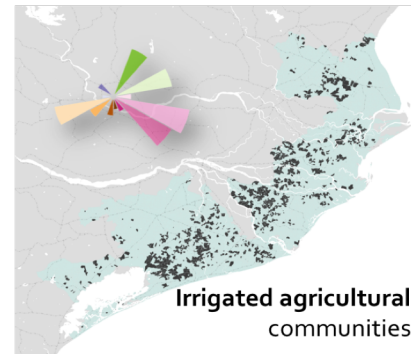
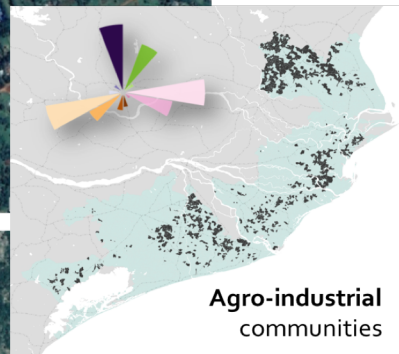
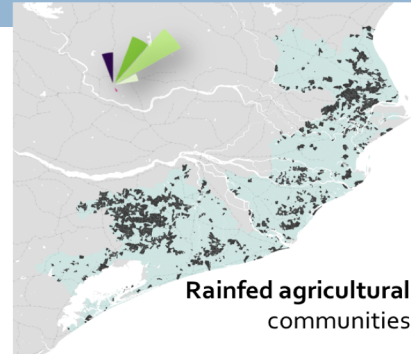
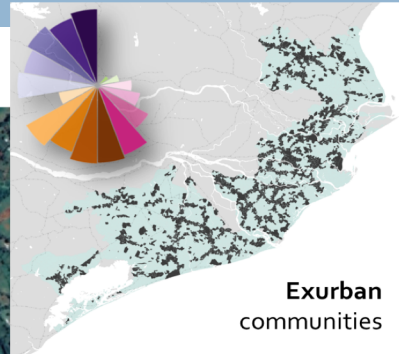


- 53 - 61% accuracy in Assam
 - ▣ Watmough et al. 2016
- 50-61% accuracy in Kenya
 - ▣ Watmough et al. 2019
- 30-50% accuracy in Sri Lanka
 - ▣ Engstrom et al. 2016
- 37-75% accuracy in SSA
 - ▣ Jean et al. 2016

- If can predict poverty from RS data can consider using it to fill some gaps in socioeconomic datasets

Complexity: different methods across space and time

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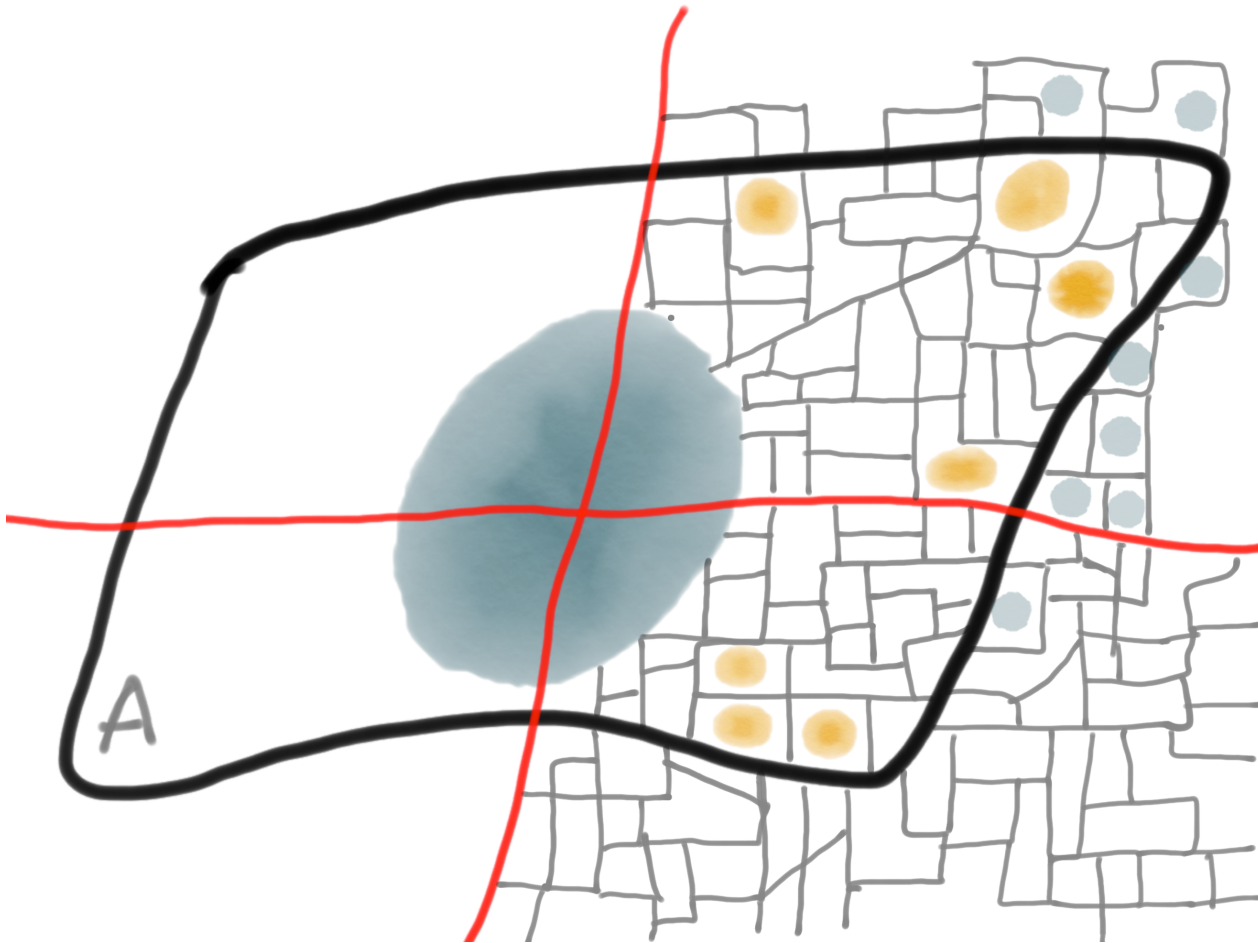
Communities and regions differ

Some are isolated, some well connected,
some rely on agriculture some on forestry

Need to consider this when using EO data to
estimate socioeconomic conditions as we need
to identify different characteristics in data.

Complexity

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Watmough & Marcinko (in review)

Existing approaches do not always consider complexity.

The village boundary (black line) would be the extent of the analysis so anything within this polygon would be considered as part of the model to estimate poverty/wellbeing anything outside of the black line would be considered to belong to a different village or if not in a village boundary may be ignored. The fields with blue dots are owned by households belonging to village A but are outside of the boundary so these would be dropped from the analysis whilst fields inside the village boundary with orange dots are owned by households in neighbouring villages but these would be linked to village A in the statistical models

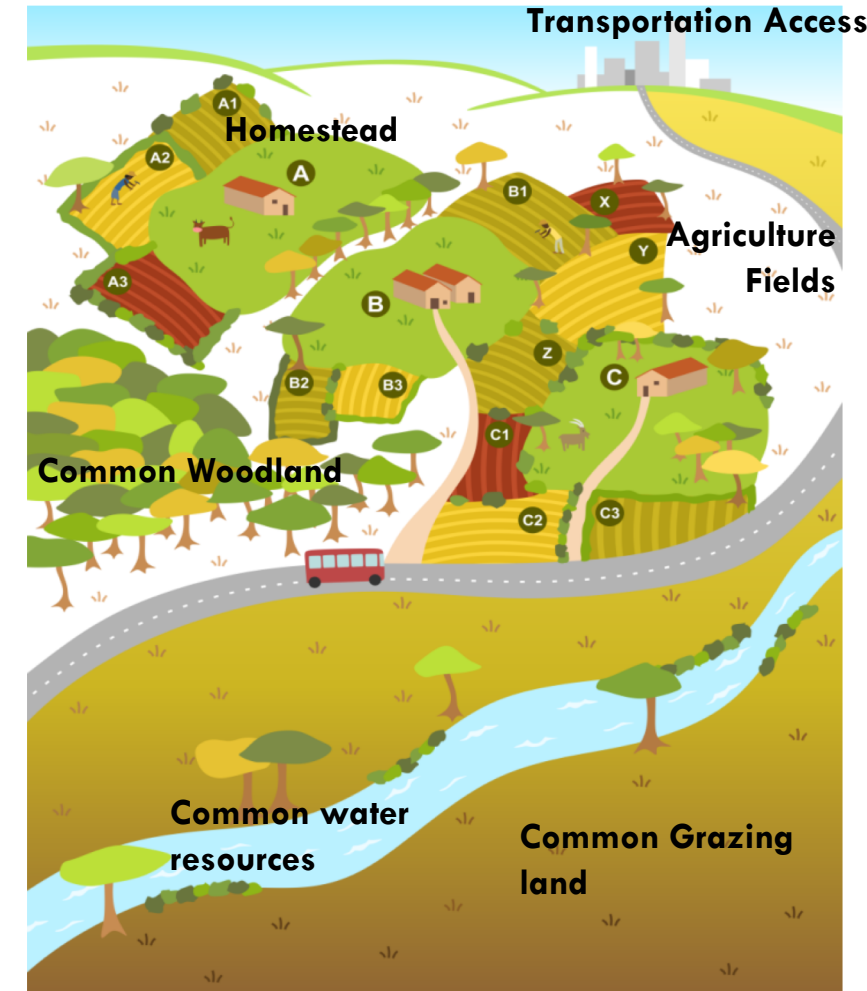
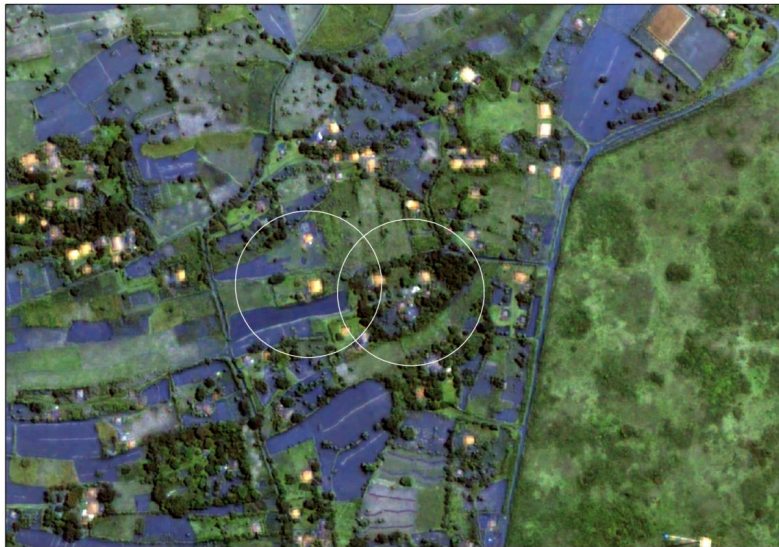
Multi-level approaches needed

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Double (or worse) counting...

If using radial buffer zones around communities can end up with the same environmental resources linked to multiple households even though only one household is benefitting from these resources.

Watmough et al. 2019 tried to overcome this and had some success but complex to implement.



Watmough et al. 2019

So need multiple EO data sources...

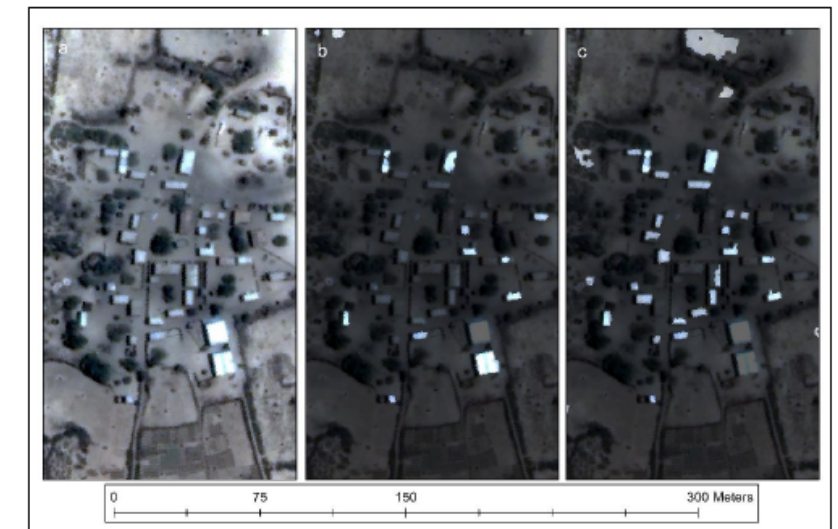
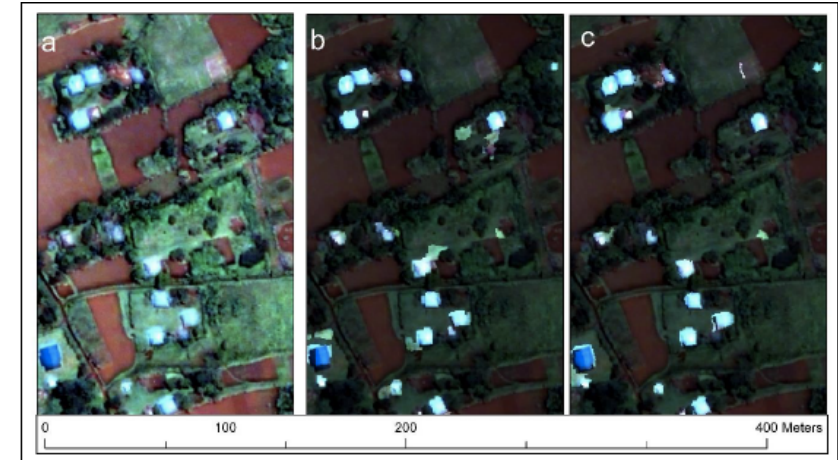
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Level	Metric	Source	Proxy for
1 Homestead	% cover of; trees, grass, water, agriculture	Hi-res LULC map	Natural and Physical Capitals
1 Homestead	% cover of building, building area (m ²)	Hi-res LULC map	Financial &/or human capital
2 Agriculture	% cover of Agriculture	Hi-res LULC map	Physical Capital
3 CPR Resources	% cover of woodland, grassland, water	Hi-res LULC map	Natural Capital
3 CPR resources	Number of homesteads	Hi-res LULC map	Social capital
4 Village	Distance to all weather road	Hi-res LULC map	Physical capital
4 Village	Annual Length of Growing Season in 2005 and 2006	MODIS NDVI time series	Physical Capital

What should we look for?

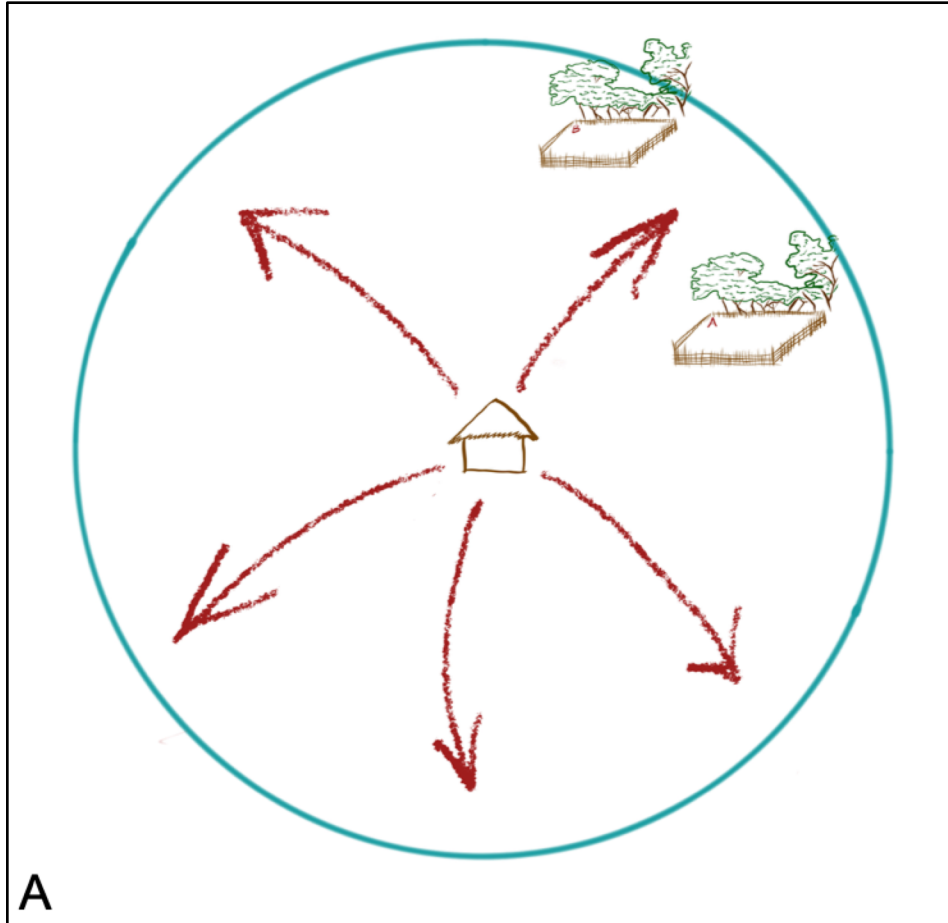
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- Standardised approaches?
- Standardised metrics from EO data?
- Buildings are not seasonal so should be consistent overtime.
 - ▣ Is this something to focus on?
 - ▣ Roof material type might be better but what about change over time, once have a good roof it doesnt change?
- Need other ideas for measuring change in socioeconomics from EO data



Next steps: How people interact with the land?

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We often look at how far households travel to fields or to collect fire wood and use this to identify the area around the households that should be considered.

But its unlikely households travel 5 km in any direction as fields could be in one particular direction.

Can we use volunteered geographic data or mobile phone tracking to identify household movements? Is this ethical?

It would certainly help refine the models.

Summary

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- Cannot achieve SDGs if we rely on surveys once everyone 5 years.
- EO data increasingly used to look at wellbeing from space
- But need to think how this can be used to policy
- Power to provide data at high frequency and in fine spatial resolution to support decision making.

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