The Geography of Household Finance in Thailand: Access, Vulnerability and Policy Responses

Sommarat Chantarat

Puey Ungphakorn Institute for Economic Research

Bank of Thailand

Finance and Development: Data, Research and Policy Design

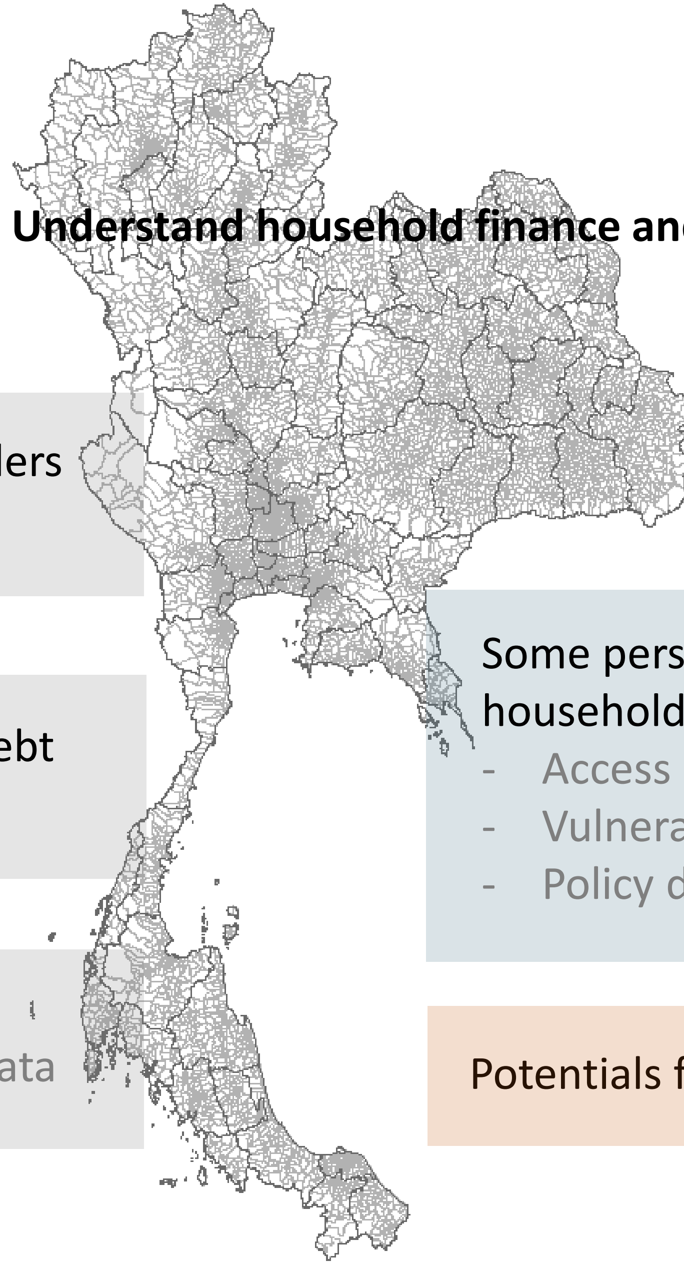
8 June 2017

PIER

PUEY UNGPHAKORN INSTITUTE
FOR ECONOMIC RESEARCH

My talk today

Take stock of our GIS data → Understand household finance and design policy



GIS of financial service providers
- Internet scrapping

+

Geo-referenced household debt
- National credit bureau

+

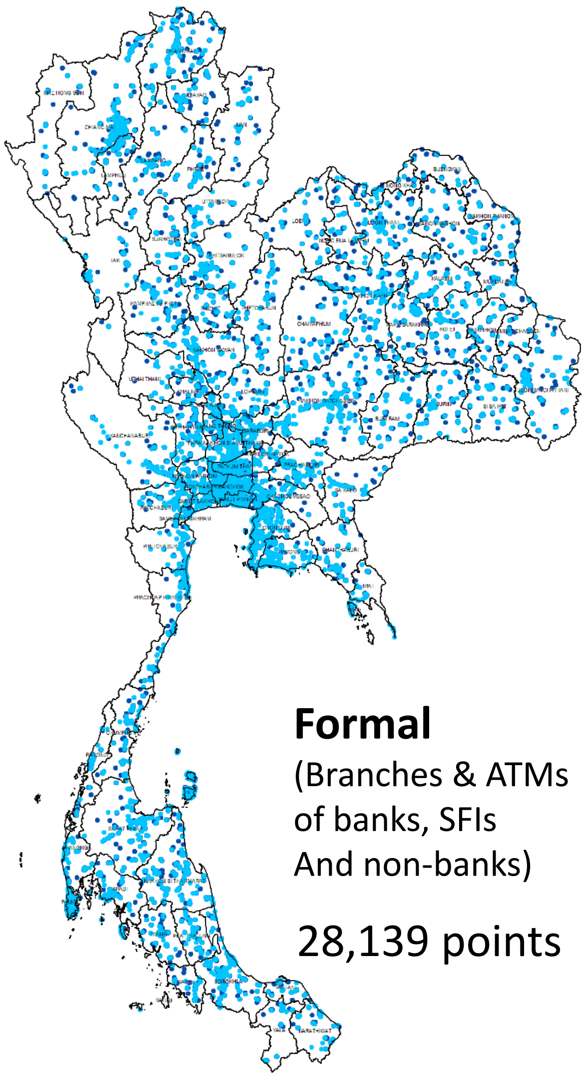
GIS of shocks and exposures
- Satellite-based disasters data

Some perspectives of household finance in Thailand
- Access
- Vulnerability
- Policy design

Potentials for further research

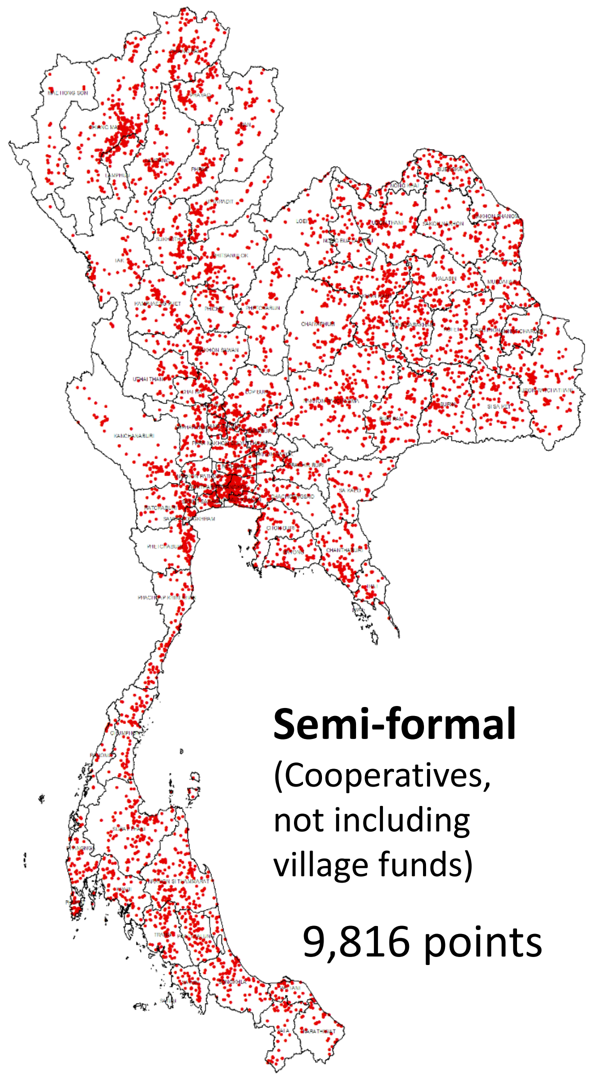
Internet scrapped locations of financial service providers

➢ 41,460 points scrapped from Google Map in July 2016 … but underestimate semi/informal



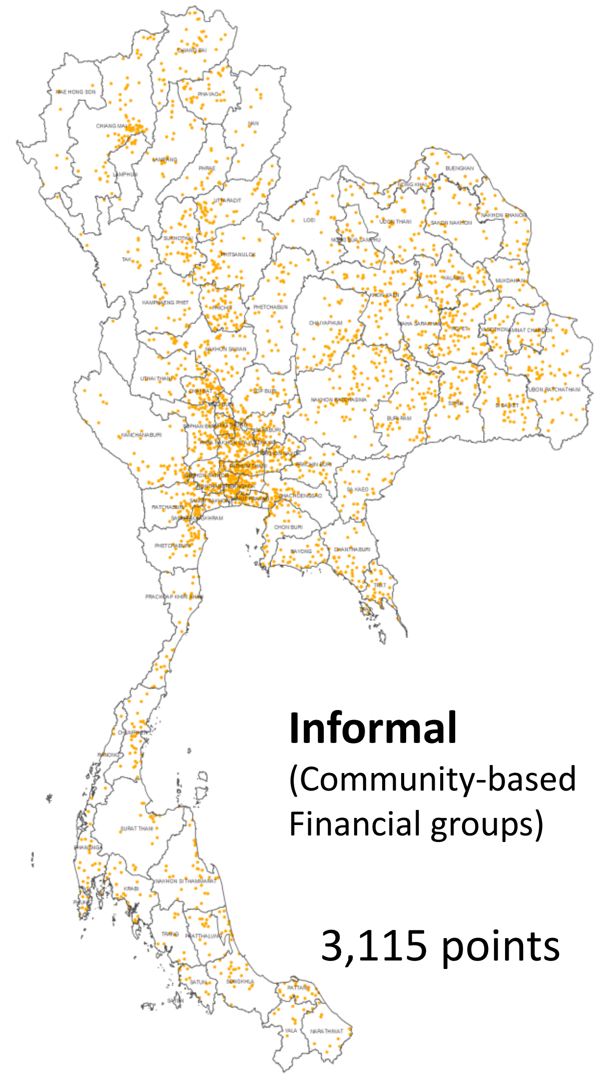
Formal
(Branches & ATMs
of banks, SFIs
And non-banks)

28,139 points



Semi-formal
(Cooperatives,
not including
village funds)

9,816 points



Informal
(Community-based
Financial groups)

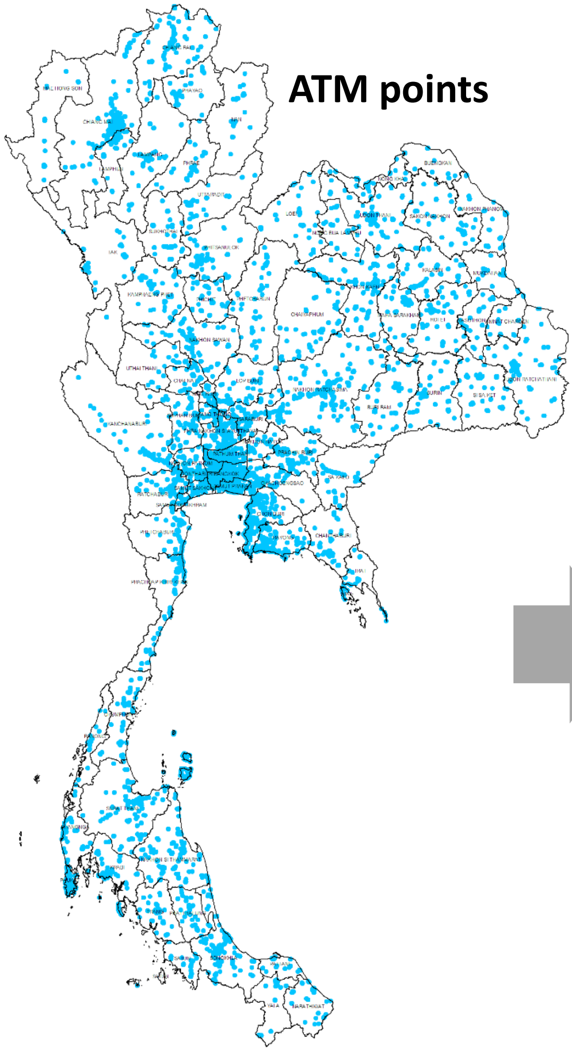
3,115 points

Access

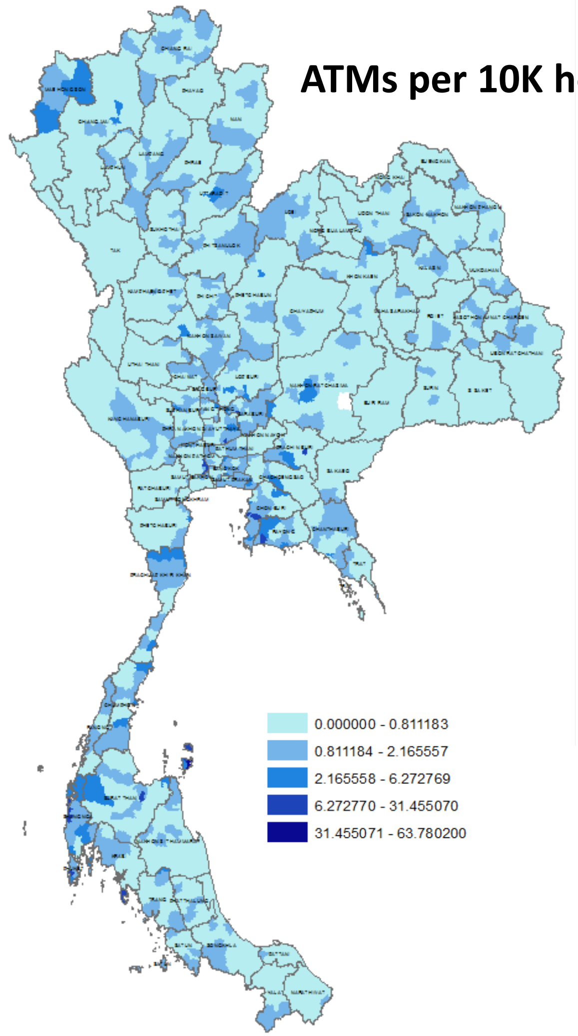
Traditional measure of availability of financial services

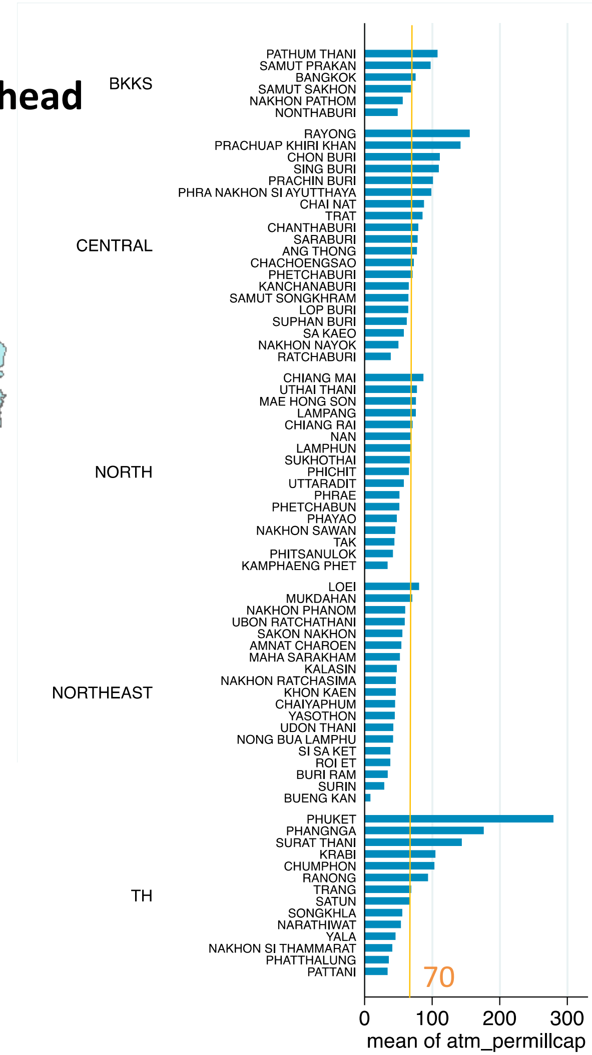
- An average of 1.2 ATMs per 10,000 heads per tambon or 70 ATMs per 1 million heads per province

ATM points



ATMs per 10K head

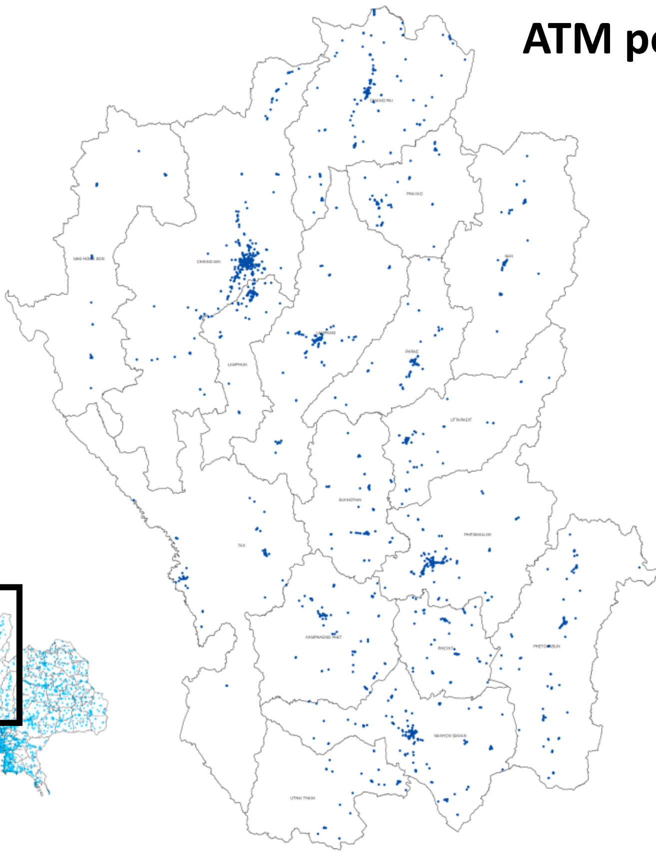


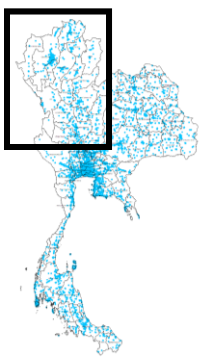


Points data allow us to measure ‘distance’ to financial services

- With village points, we can measure **distance to nearest ATM**, **Number of ATM within X kilometer radius from each village**

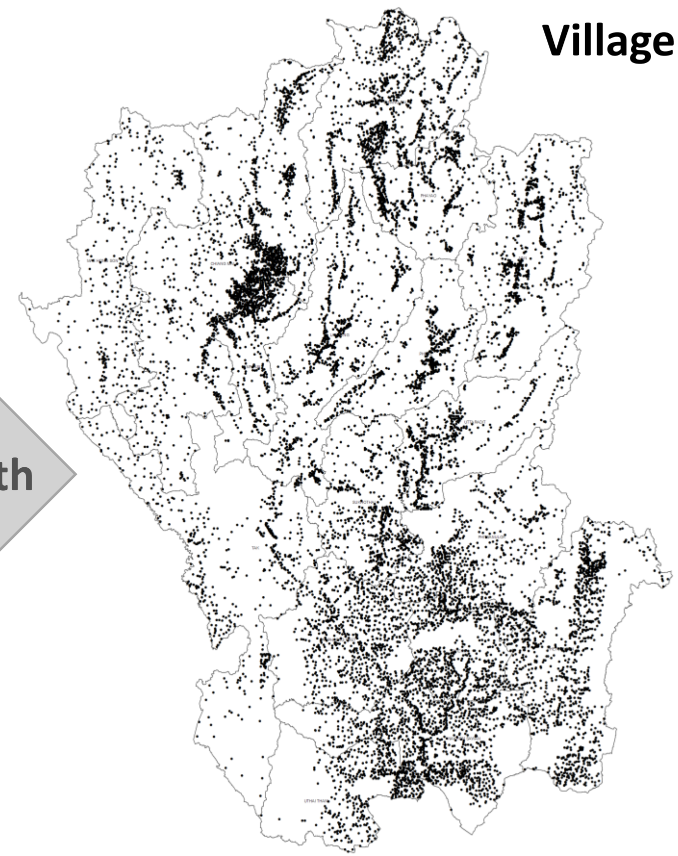
ATM points





Overlay with

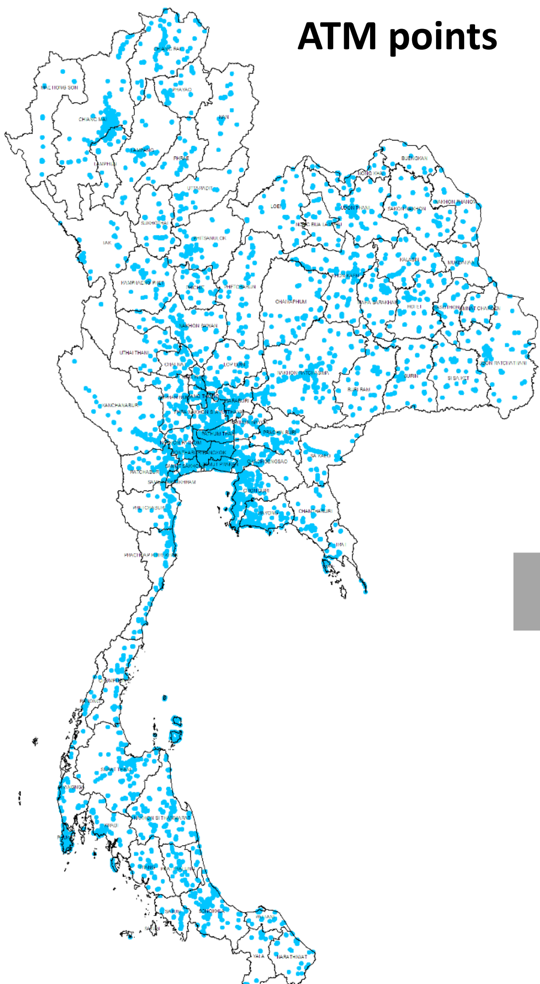
Village points



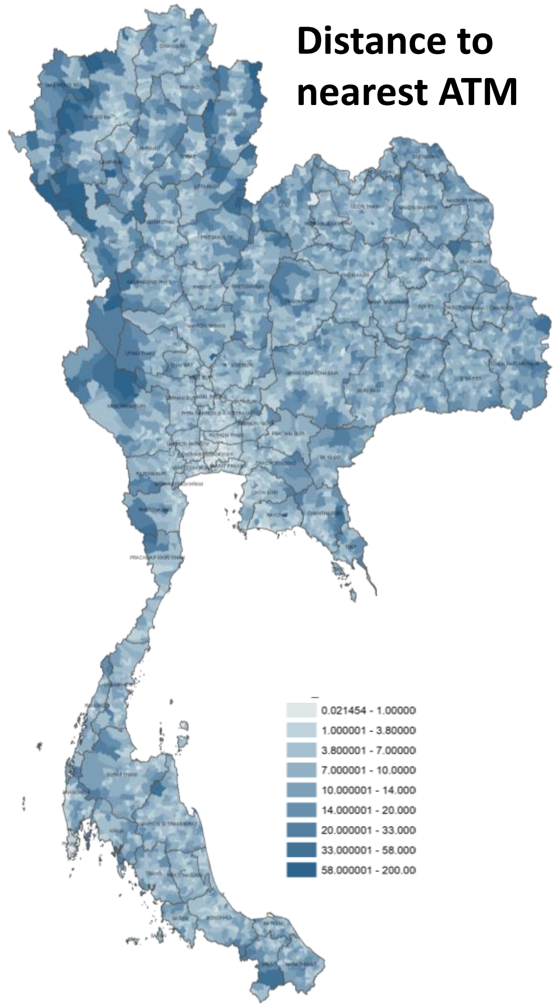
Measuring 'distance' to financial services

- An average of 5.9 km from village to nearest ATM and 0.8 ATM within 5 km radius from a village
- Large variations and very small distance in Bangkok and vicinity…and major cities

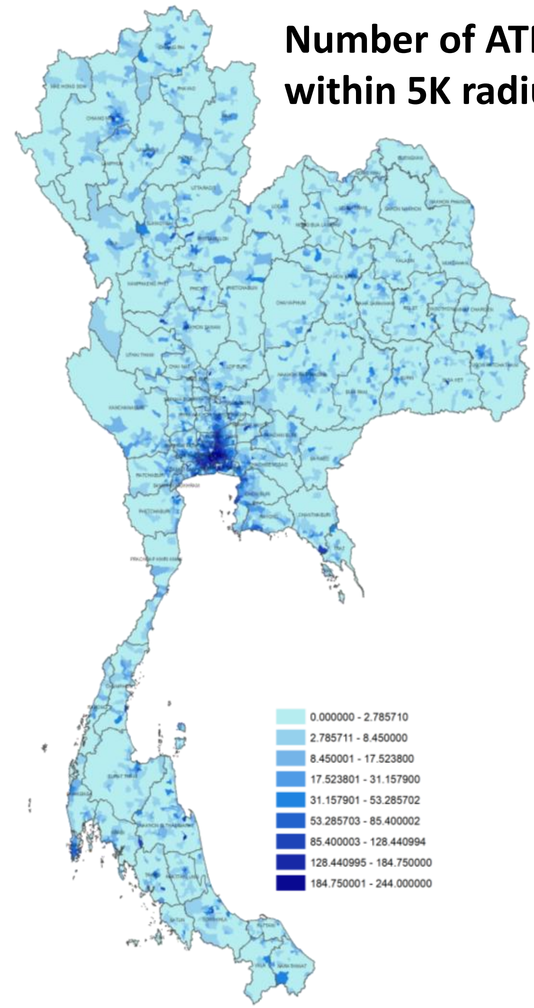
ATM points



Distance to nearest ATM



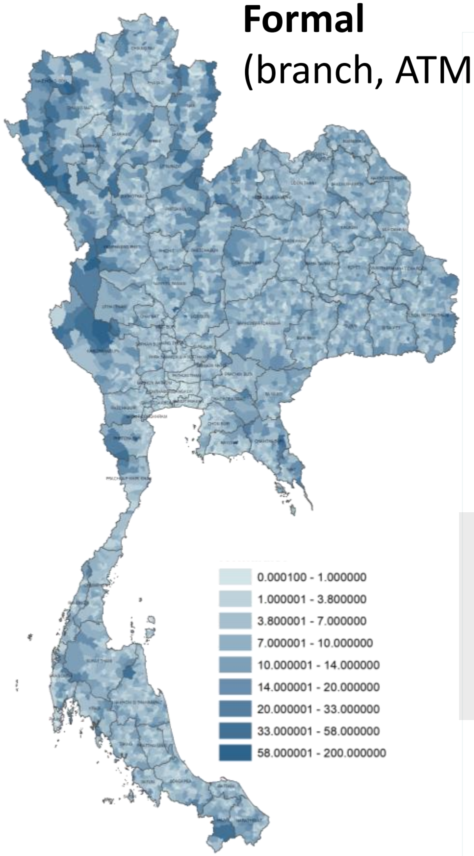
Number of ATMs within 5K radius

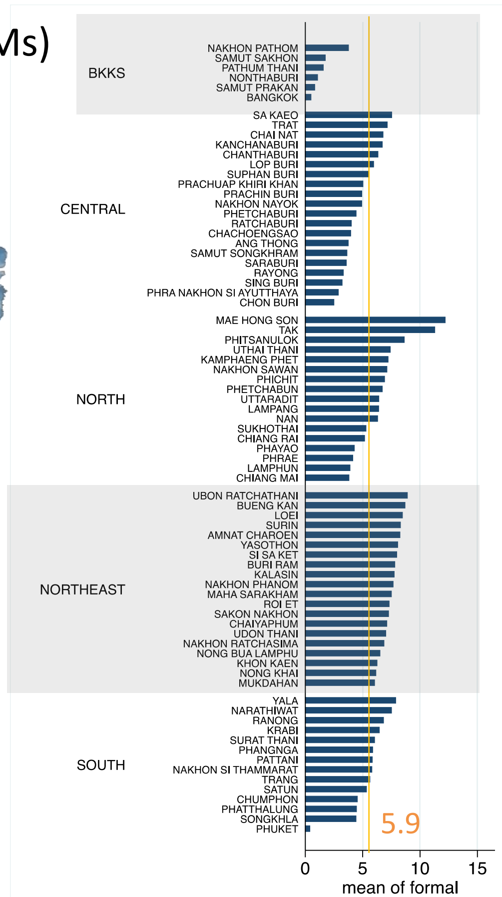


Access
Shorter distance to semi/informal services overall

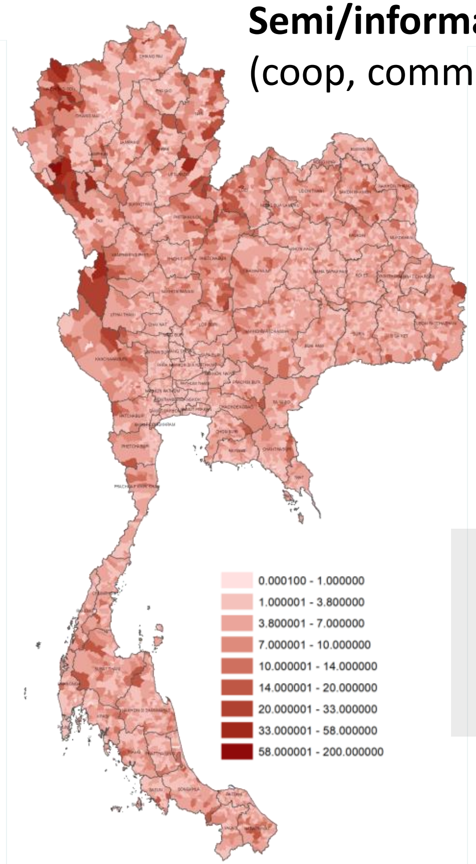
- **100% closer to semi/informal than formal services**: could be larger given the presence of village funds
- Distance to any service among the shortest in Bkk and vicinity and longest in Northeast and North

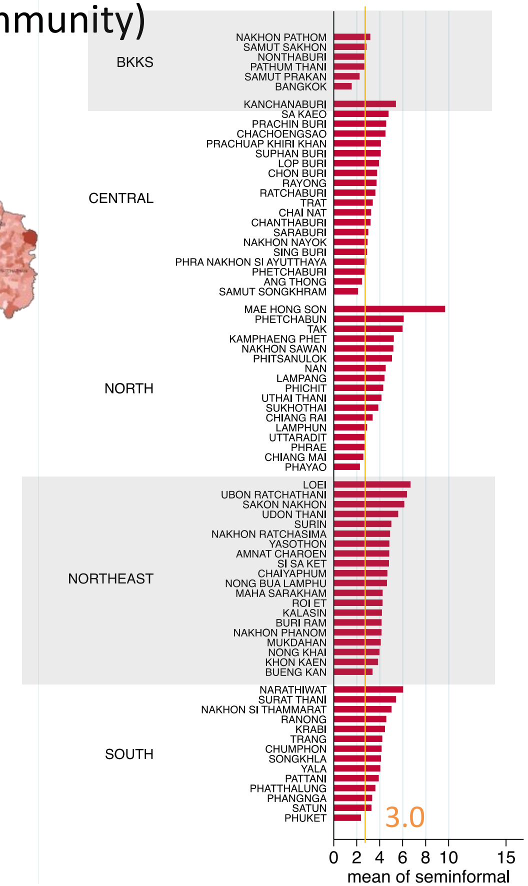
Formal
(branch, ATMs)





Semi/informal
(coop, community)

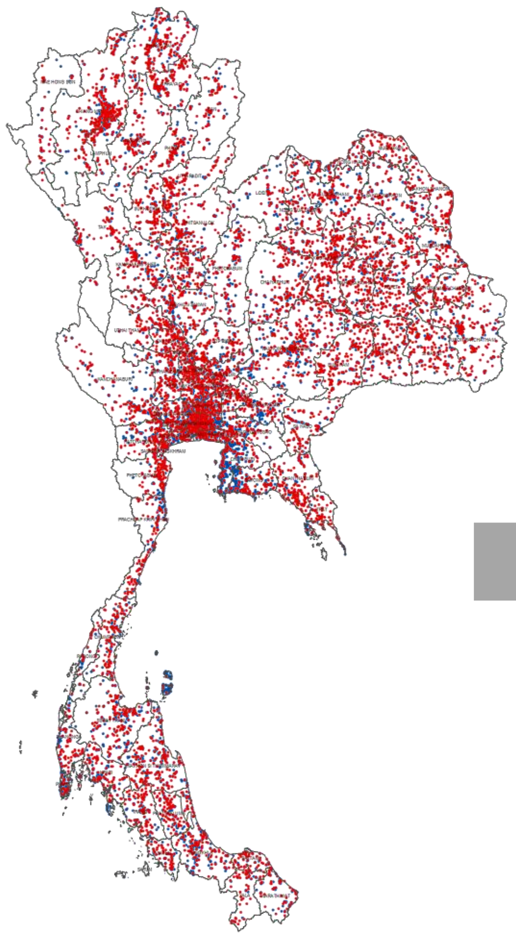




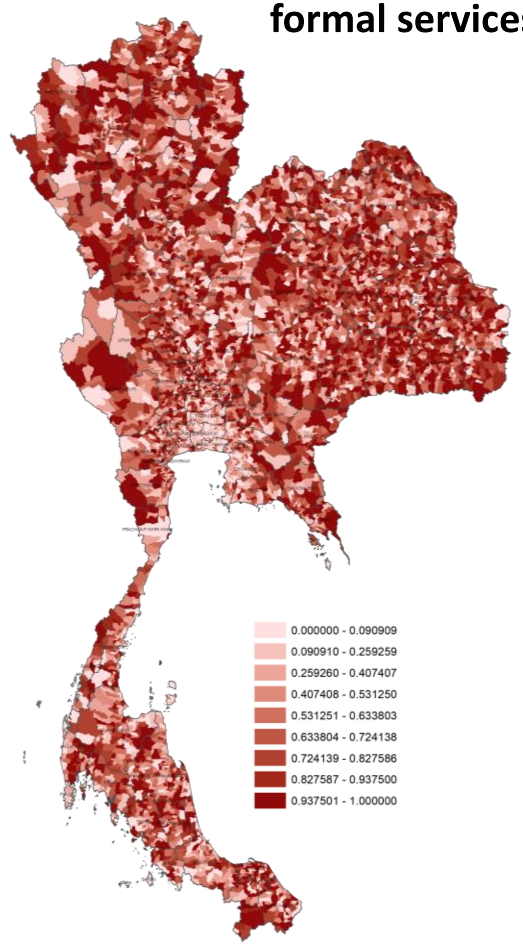
Semi/informal 'relatively closer' especially in rural villages

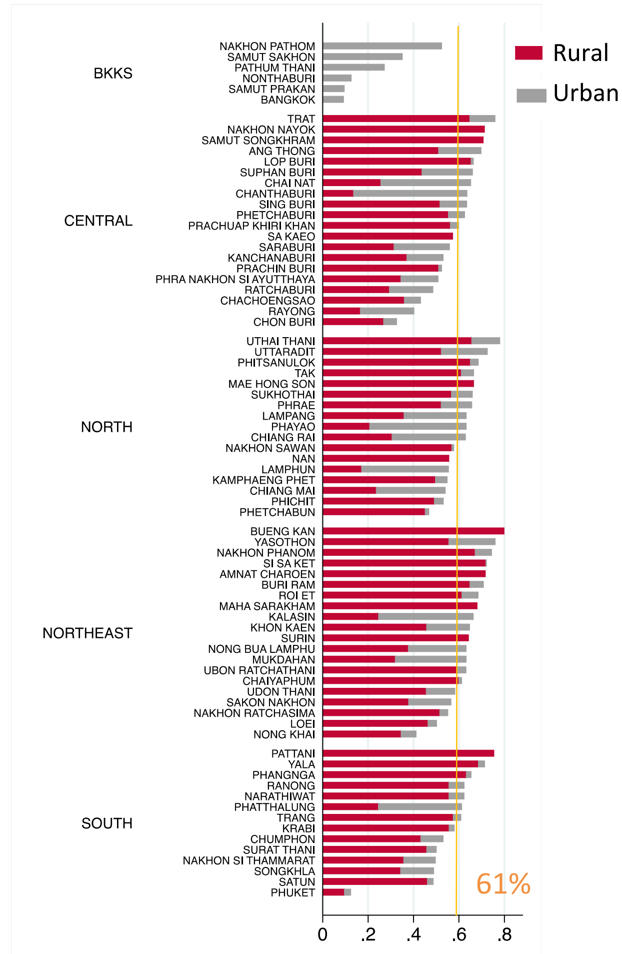
- **Comparing within a village,** 61% of villages closer to semi/informal, majority of which are in rural

Formal vs. Semi/informal



% of village with shorter distance to semi/informal relative to formal services

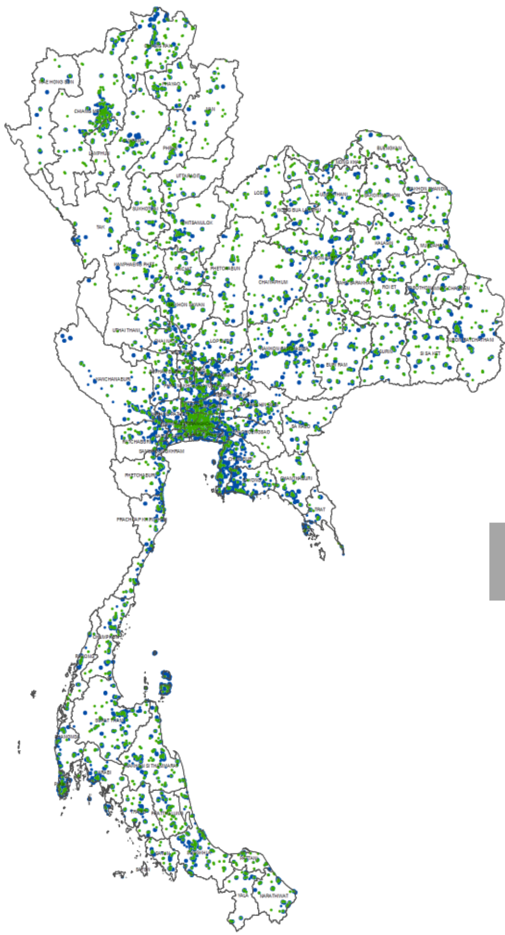




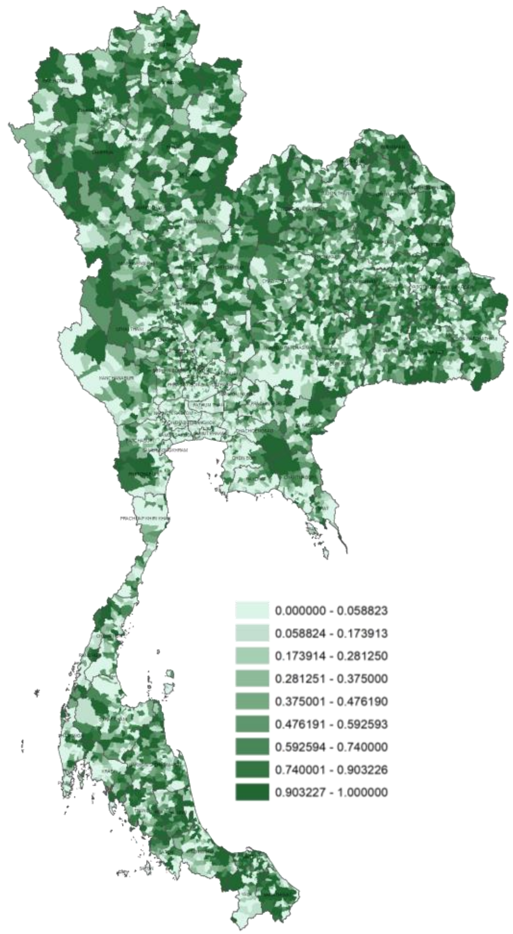
SFIs reaching out 'relatively closer' especially in rural

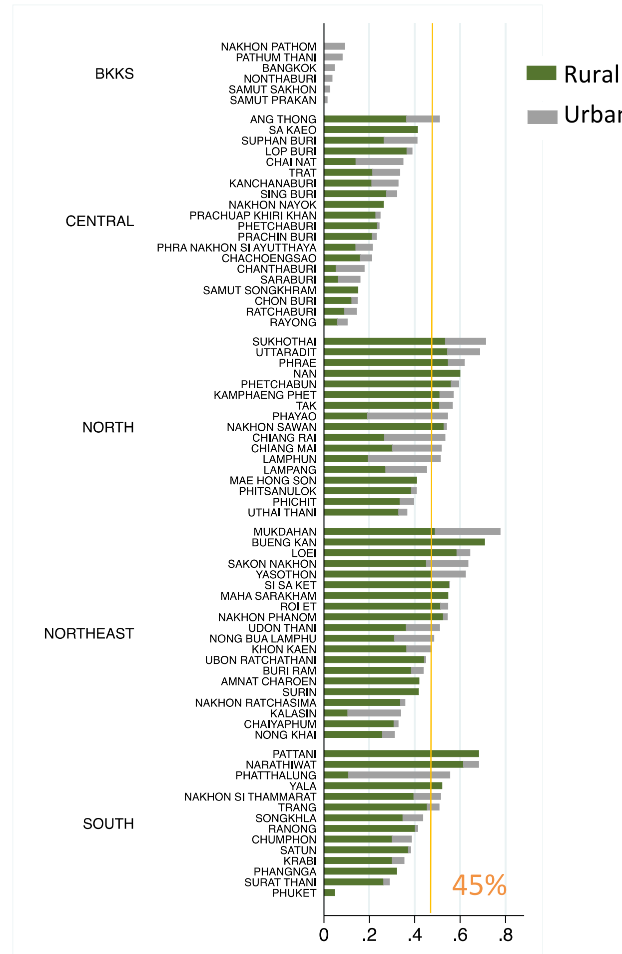
- 45% of villages closer to SFIs, majority of which are in rural especially in the North and Northeast

Banks vs. SFIs



% of village with shorter distance to SFIs relative to banks



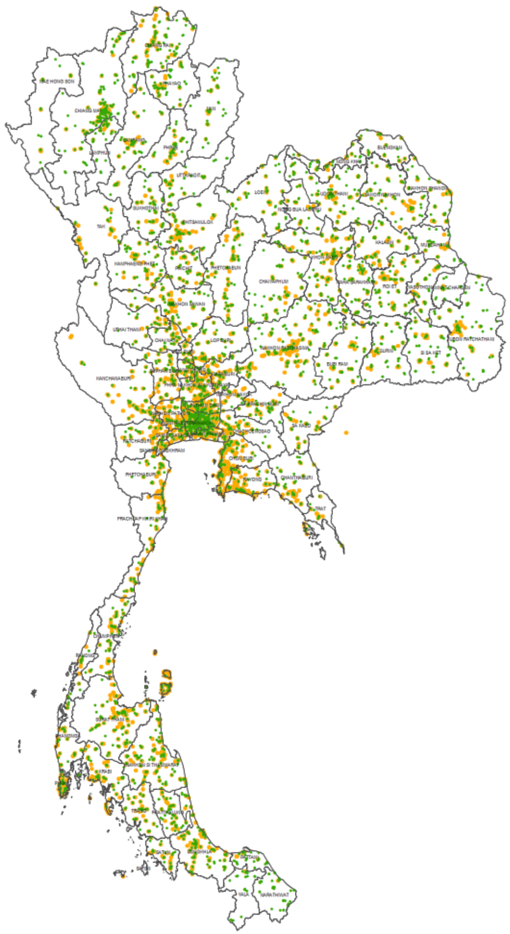


PUEY UNGPHAKORN INSTITUTE FOR ECONOMIC RESEARCH

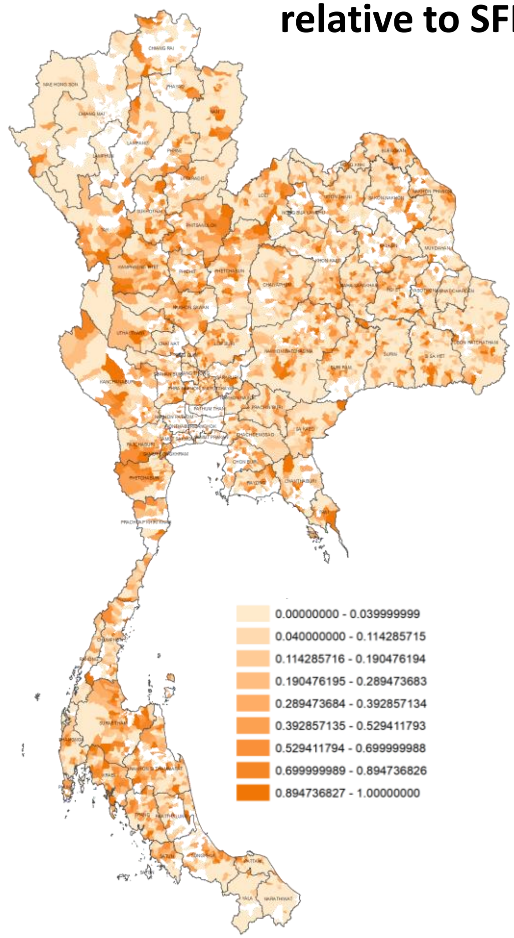
Limited roles of non-traditional service providers in rural

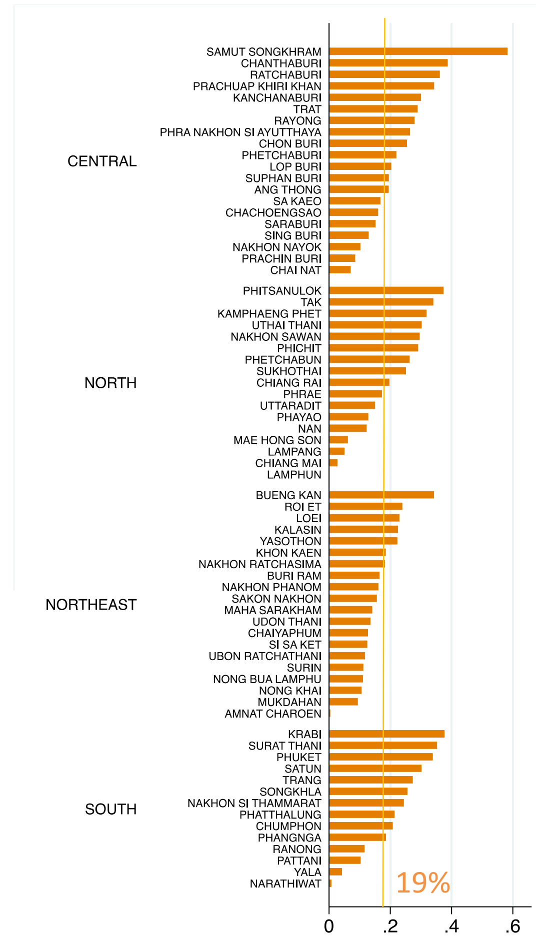
- Non-traditional service providers like 7/11 and other convenient stores could only reach closer than SFIs in 19% of the rural villages

SFIs vs. Convenient stores



% of rural village with shorter distance to convenient stores relative to SFIs

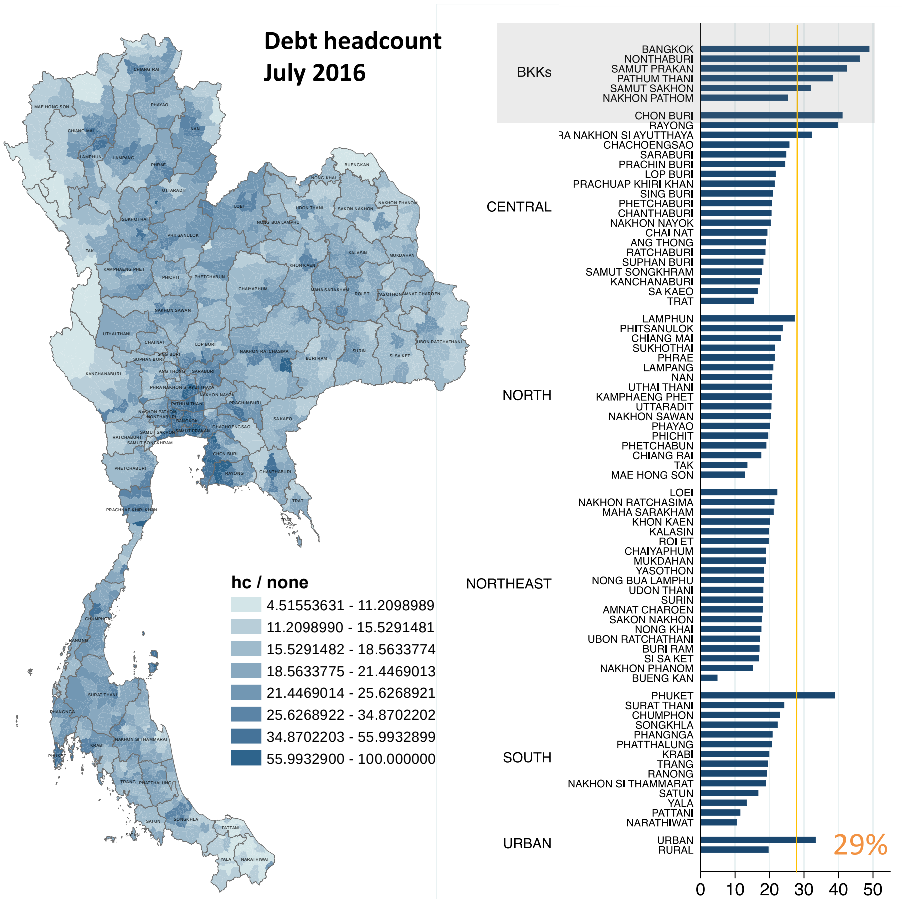


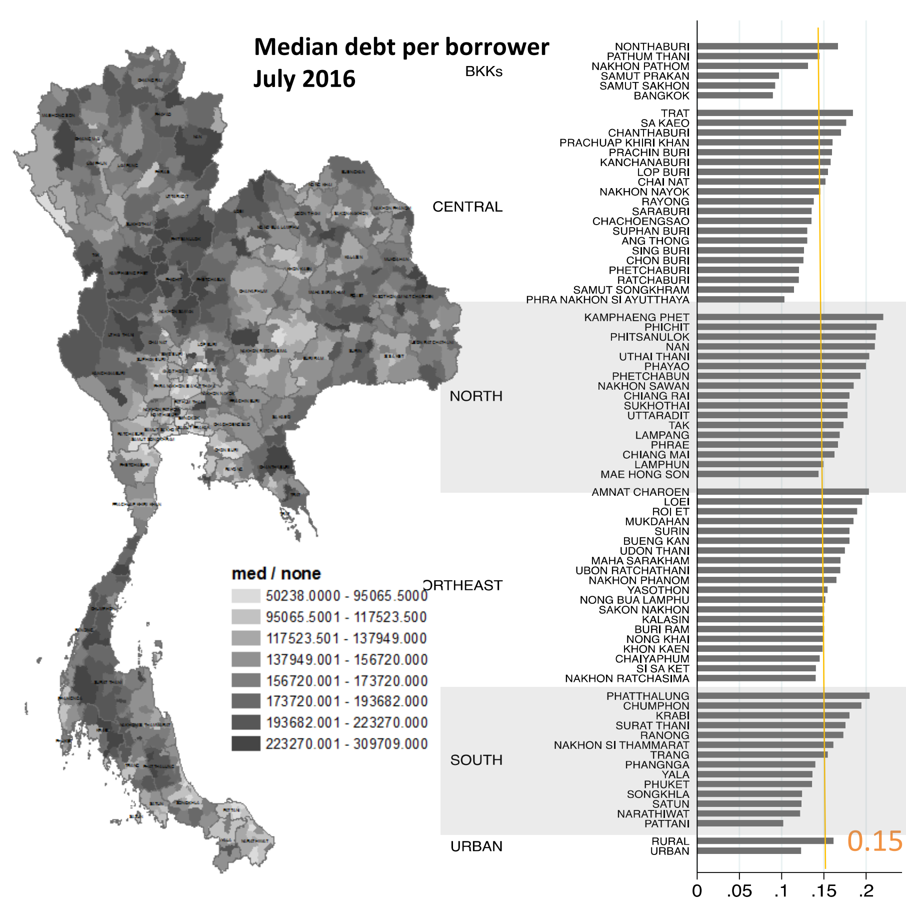


How might 'distance' determine access?

Geo-referenced household debt from National Credit Bureau

- **Consumer loan-level data**: cover ~19 million borrowers in formal institutions (~87% of total household debt), available with borrower's postcode
- 29% of Thai population have debt from formal institutions…High debt prevalence in Bangkok and vicinity and urban areas (where formal services are 'relatively closer')



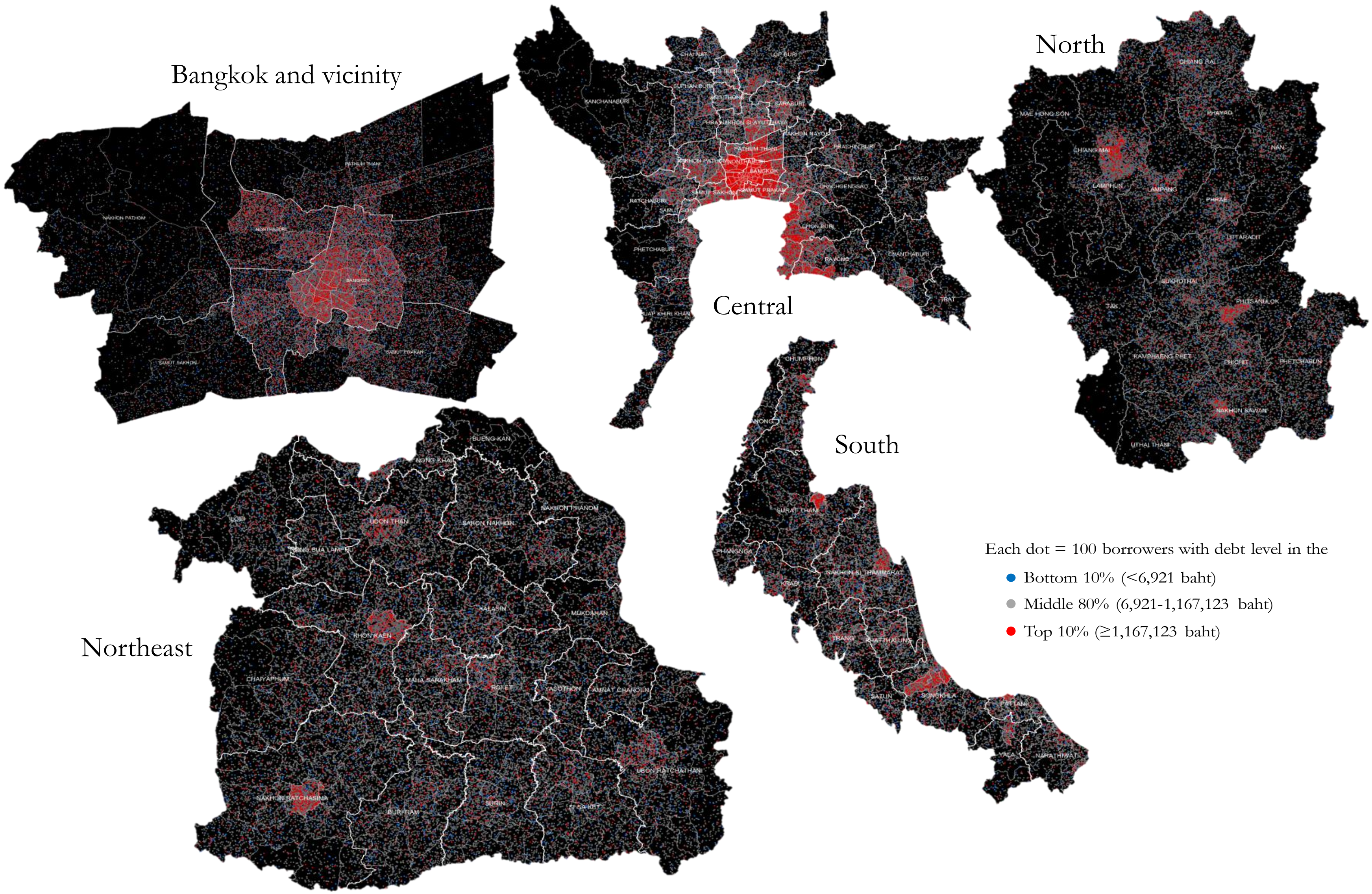


PIER

PUEY UNGPHAKORN INSTITUTE FOR ECONOMIC RESEARCH

Thailand’s household debt are largely concentrated

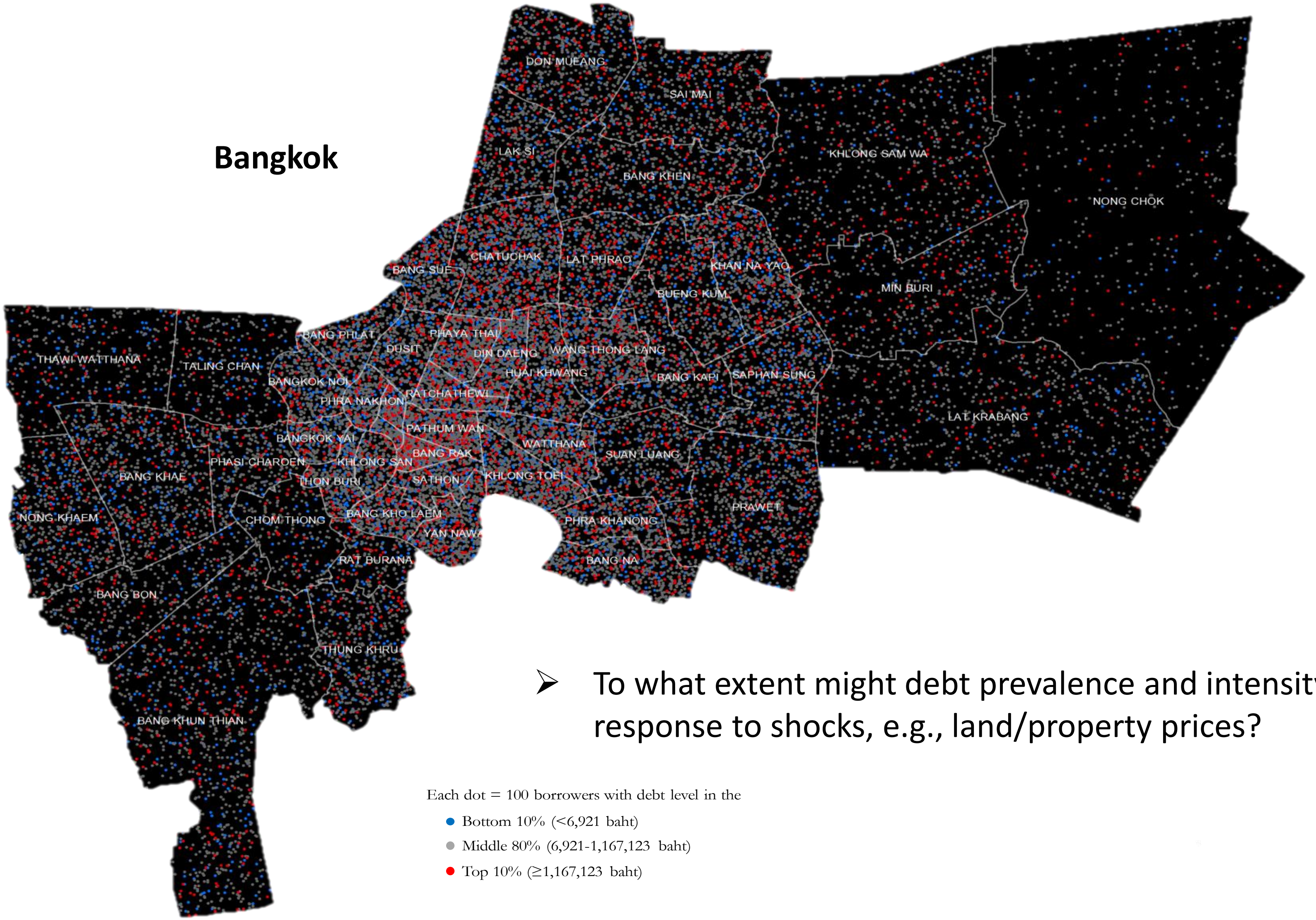
- Top 10% borrowers occupy ~60% of total debt and concentrated in big cities and urban areas



Access

…And great variations within province

Bangkok

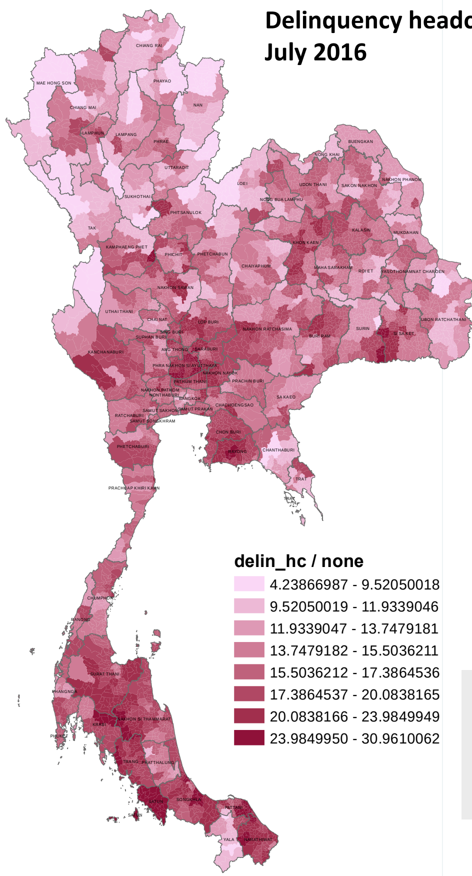


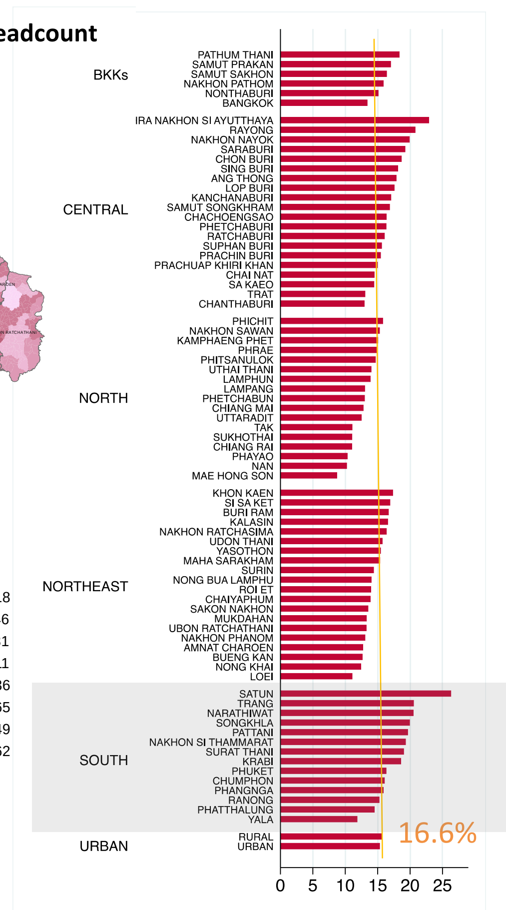
➢ To what extent might debt prevalence and intensity response to shocks, e.g., land/property prices?

Each dot = 100 borrowers with debt level in the
- Bottom 10% (<6,921 baht)
- Middle 80% (6,921-1,167,123 baht)
- Top 10% (≥1,167,123 baht)

Large geographical variations in delinquency

- 16.6% of borrowers have delinquent debt (more than 90 days overdue)
- High delinquency in the South (and deep South) and Central





- What drives these geographical variations in delinquency?

PUEY UNGPHAKORN INSTITUTE FOR ECONOMIC RESEARCH

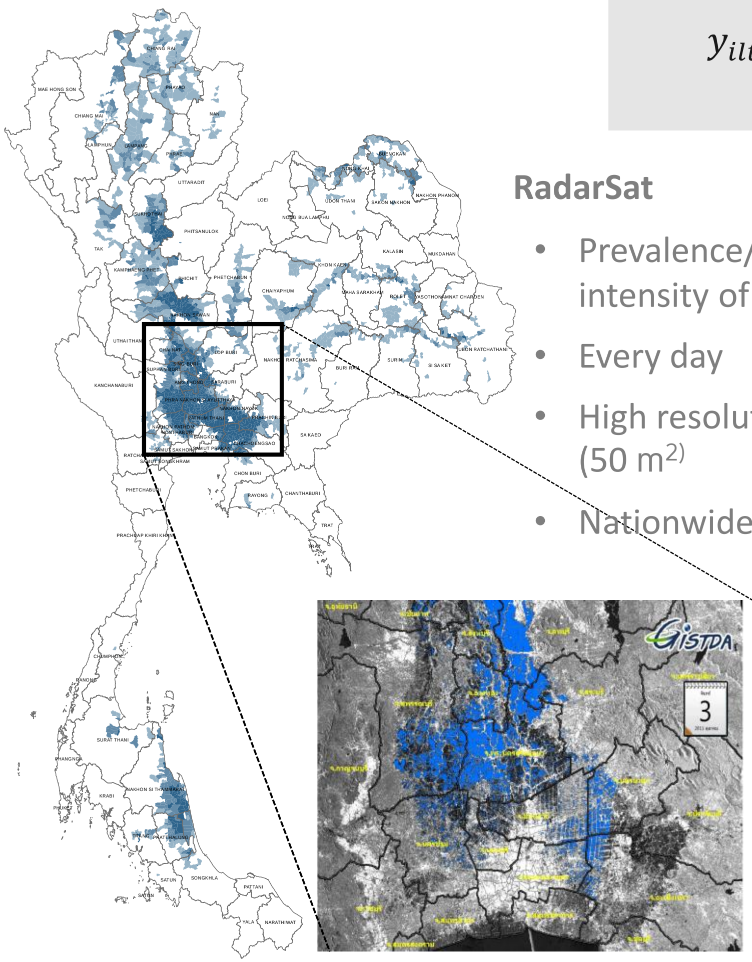
PIER

What could potentially cause high delinquency?
Largely vulnerable to disasters

Quantifying impacts of the mega flood 2011 on delinquency using high frequency satellite data

- The mega flood caused significant and long lasting impacts on delinquency

$$y_{ilt} = \sum_{\tau} \beta^{\tau} flood_l * mtsinceflood_{\tau} + mt_t + \varphi_i + \sum \alpha X_{lt} + \varepsilon_{ilt}$$



RadarSat

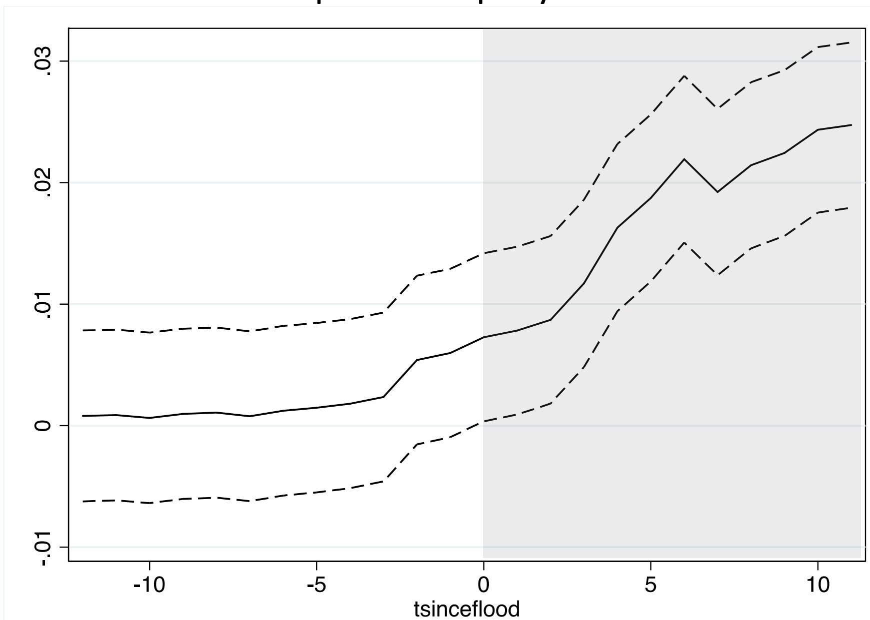
- Prevalence/ intensity of flood
- Every day
- High resolution (50 m2))
- Nationwide

Flood starts

Pre-flood monthly loan data 1 year	Post-flood monthly loan data 1 year

Month

Impacts on delinquency headcount



Developing satellite-based agricultural risk information

- Can satellite data be used to generate better agricultural risk information for rice farmers?
- Potentials to crowd in sustainable agricultural finance? (crop insurance, risk-contingent credit)

Satellite data
- MODIS NDVI
- RADARSAT

+

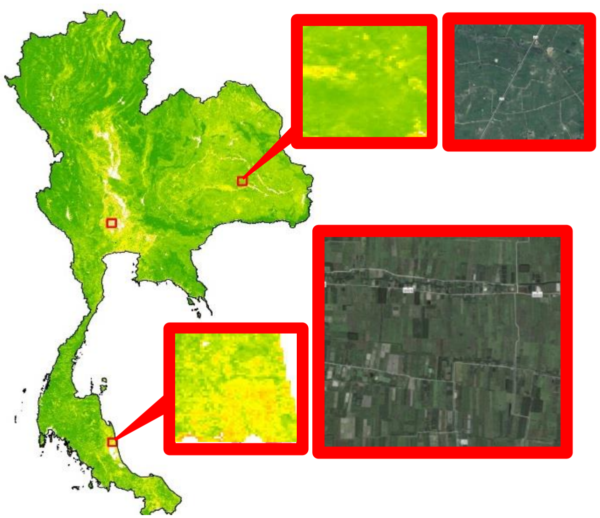
GIS data
- Irrigation
- Altitude

→

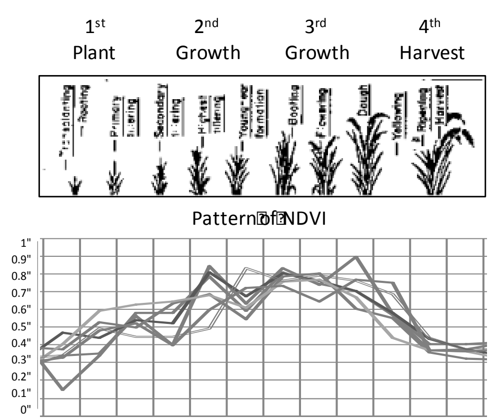
Household data
- 31,295 rice farmers
- Nationwide
- 10 yrs

Normalized Difference Vegetation Index (NDVI) from NASA MODIS

- Reflect health and cycle of vegetation
- Every 8 days from 2000-present
- Cover nationwide
- 1 pixel = area of 250 m^2 or 40 rai
- 2,260,778 pixels nationwide



Rice growth stage(s)

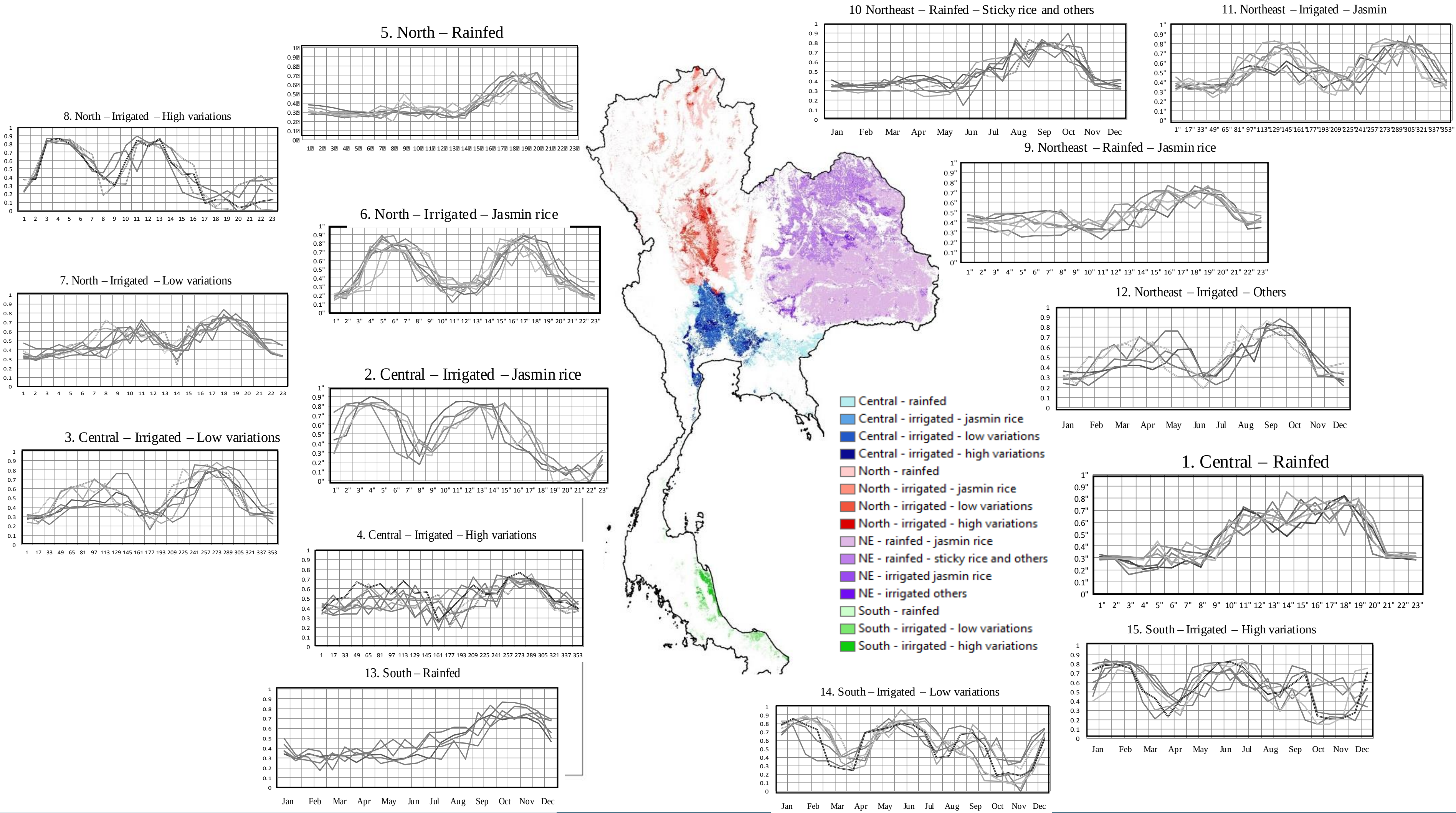


Rice growth stage from Murphy (1998)

Using GIS and satellite data in policy design

Step 1: Detecting rice area and homogeneous zones

- Cluster analysis based on NDVI patterns and other GIS data results in 15 distinct production zones each with distinct crop cycle in a year

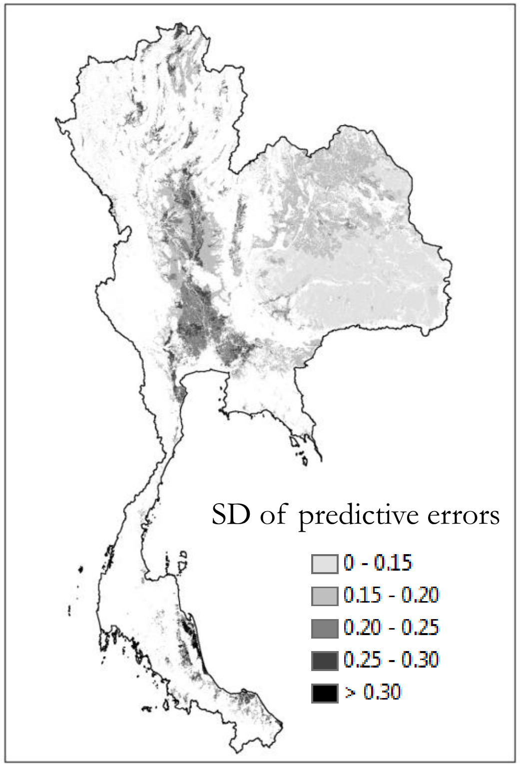


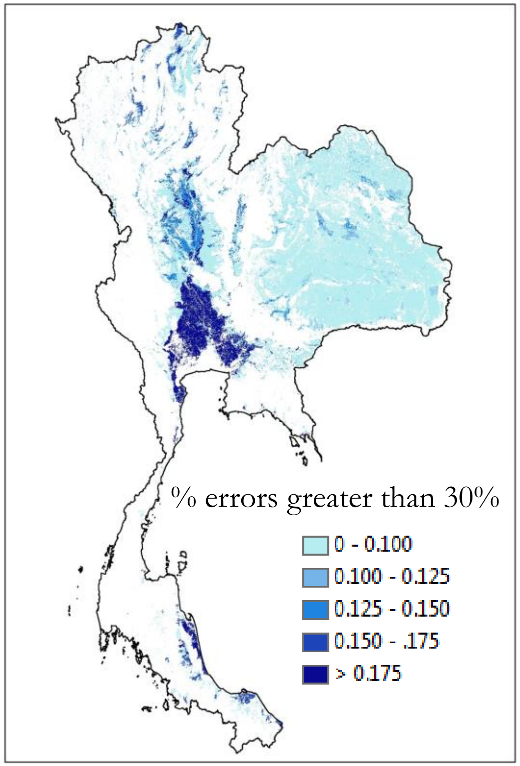
Using GIS and satellite data in policy design

Step 2: Estimating production loss function for each zone

➢ Estimate for each zone:

Farmer's actual losses = f (NDVI, Flood index) + error

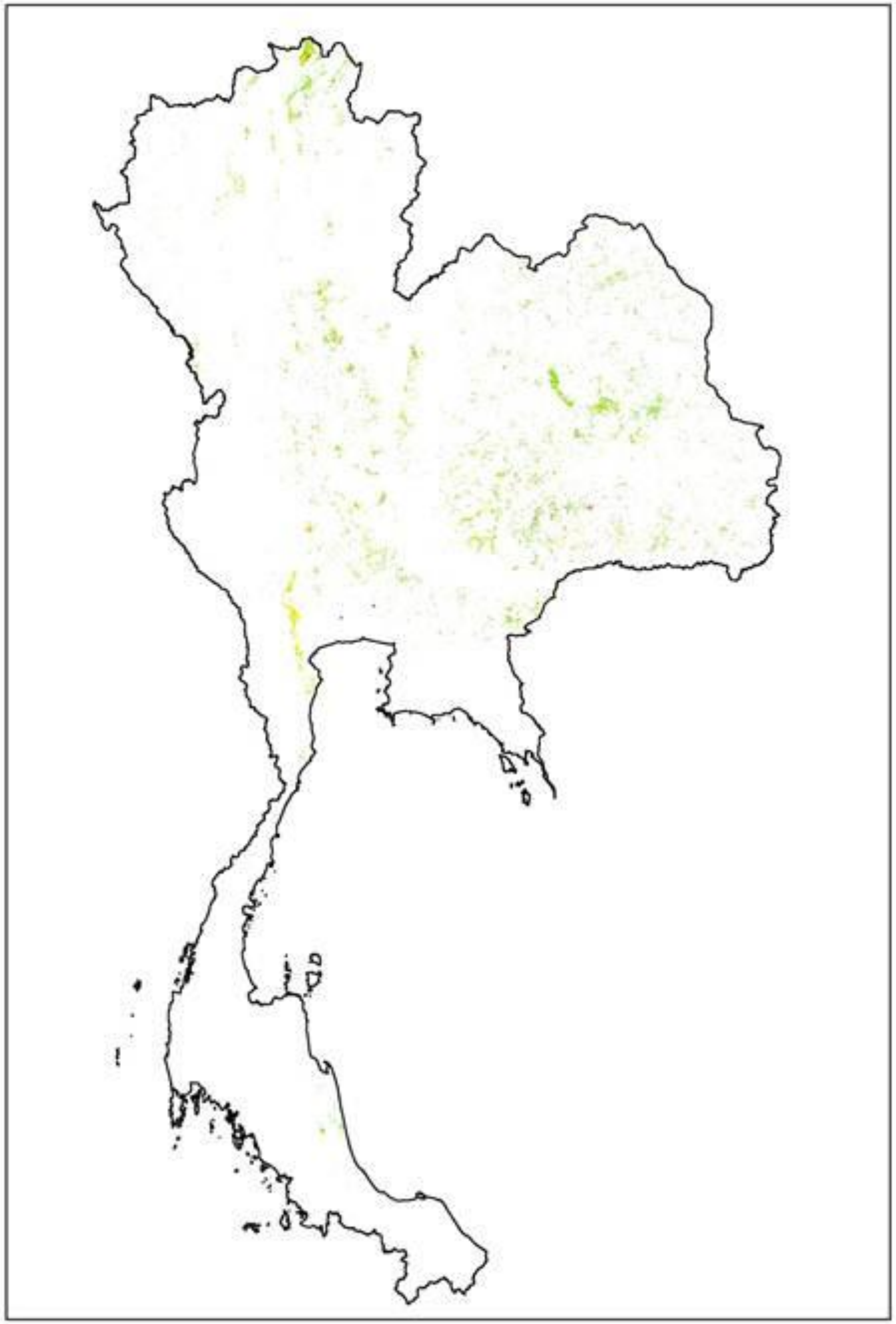




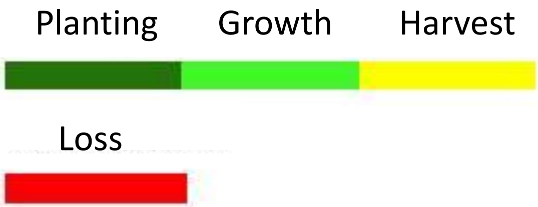
➢ Estimation errors

- Estimate well in rainfed area but less well in the more heterogeneous irrigated areas
- Most of predictive errors lie within +-20% and are especially low during the extreme losses

Estimated crop cycles and losses at pixel level (selected months)



May 2016



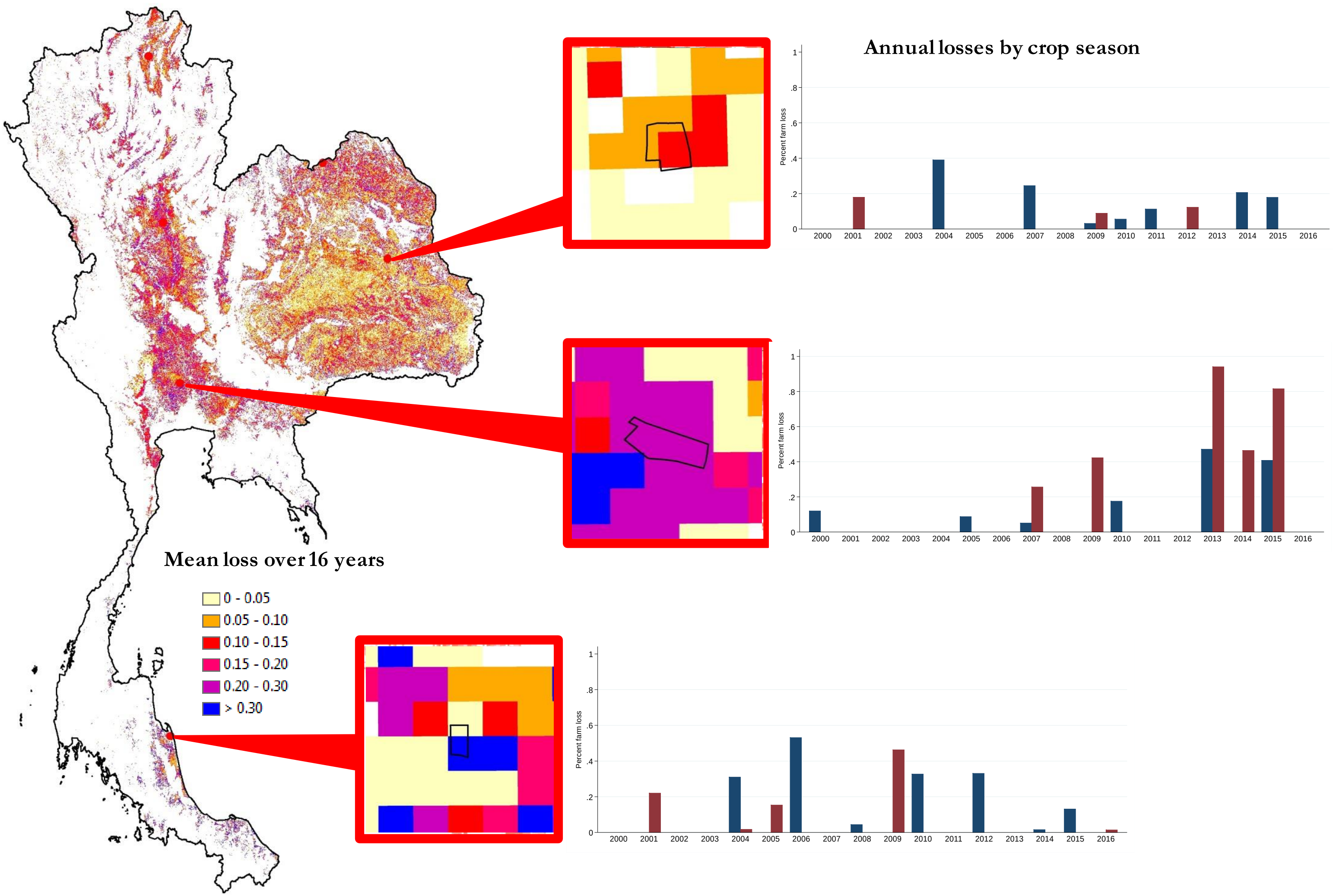
PUEY UNGPHAKORN INSTITUTE FOR ECONOMIC RESEARCH

PIER

Using GIS and satellite data in policy design

Satellite-based agricultural risk mapping

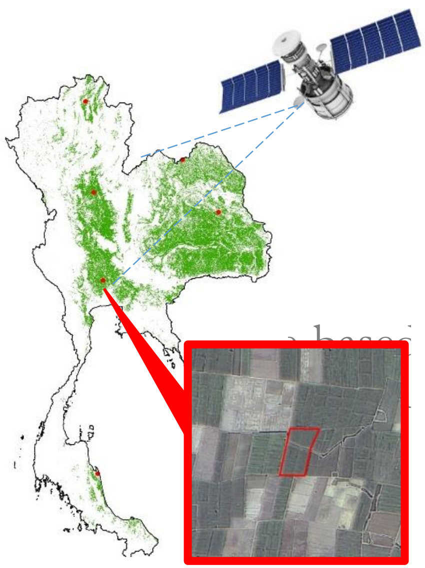
- Accurate, micro level (40 Rai per pixel), long historical data, near real time, transparent

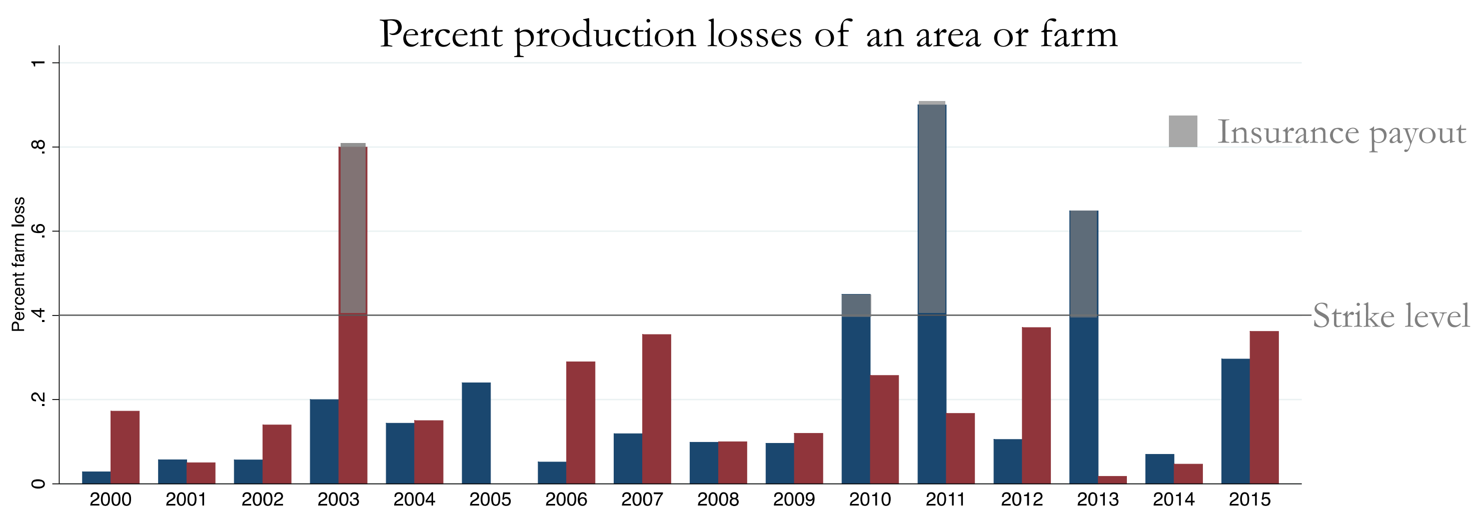


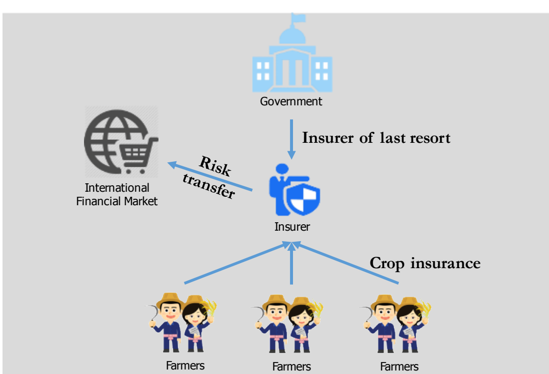
Using GIS and satellite data in policy design

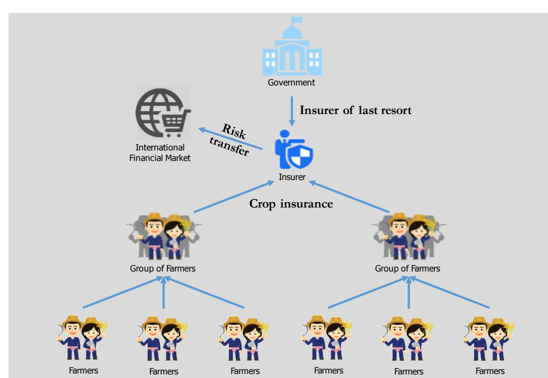
Better risk information for better design of financial contracts

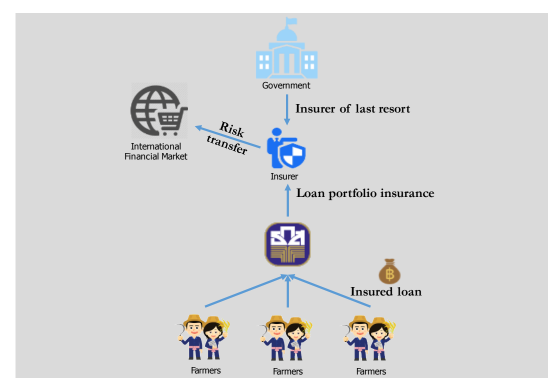
- **Satellite-based crop insurance and/or risk contingent credit contracts** can be designed and priced for farmers, groups/cooperatives, BAAC





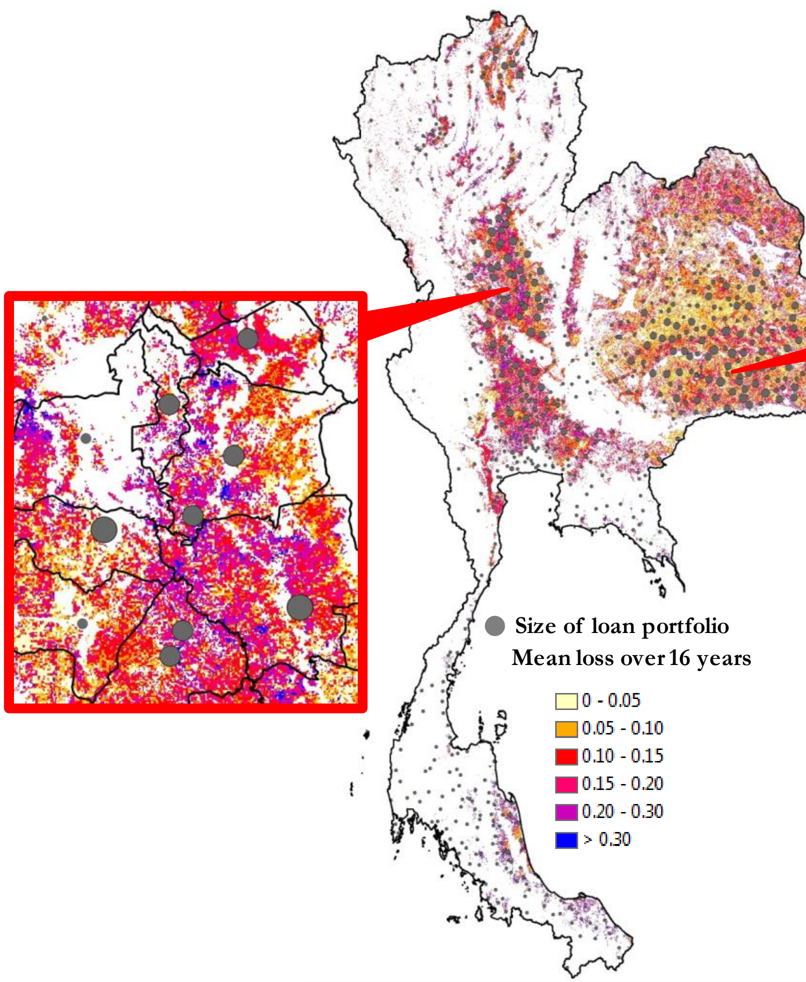


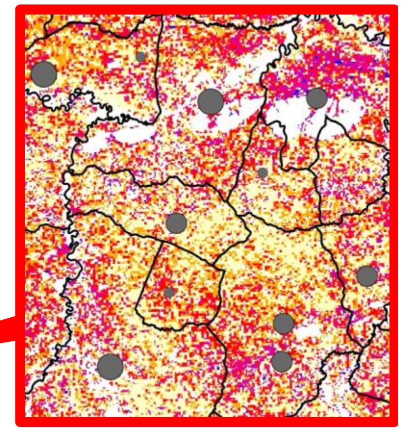




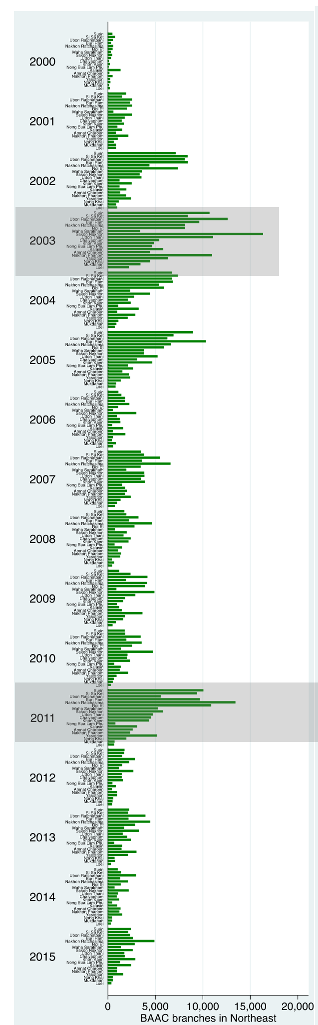
Using GIS and satellite data in policy design
And to better quantify systematic risk to financial system

- Aggregate production losses of each branch of BAAC (portfolio credit risk) appears highly covariate within and even across regions → threat to financial stability?

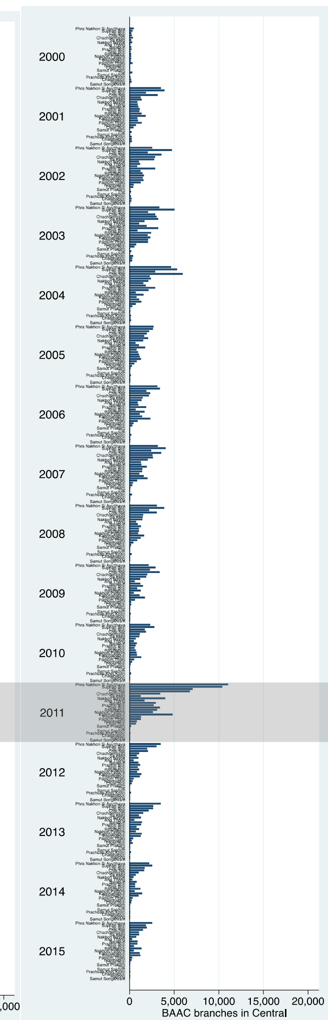




Branches in Central



Branches in Northeast



- How can we use this risk information to better manage systemic risk to financial system?

Take aways

(Hopefully) My talk displays the power of GIS data

In understanding some aspects of household finance in Thailand

- Large presence of service providers but large variations in ‘distance’
- Semi/informal institutions and SFIs can reach closer to rural
- Access to credit moderate with large concentration and delinquency
- Still largely vulnerable to big shocks

In designing policy

- GIS/satellite data powerful in providing granular level information but with large coverage → necessary data to resolve asymmetric information

Further research bringing all these GIS data together

- How distance determine access?
- What factors affect vulnerability of household and financial system?
- How else can we use GIS data to resolve information asymmetry?

References

1. **Mapping Financial Inclusion in Thailand**

   Chantarat, Lamsam and Rittinon (PIER DP, 2017)

2. **Microscoping View of Household Debt through the Lens of National Credit Bureau**

   Chantarat, Lamsam, Samphantharak and Tangsawasdirat (PIER DP, 2017)

3. **Household Debt, Policies and Shocks: Evidence from National Credit Bureau Data**

   Chantarat and Samphantharak (PIER DP, 2017)

4. **Farmers and Pixels: Toward Sustainable Agricultural Finance with Space Technology**

   Chantarat, Rakwatin and Charumilind (PIER DP, 2017)

5. **Floods and Farmers: Evidence from the Field in Thailand**

   Chantarat, Lertamphainont and Samphantharak (PIER DP, 2016)