REMOTE SENSING APPLICATIONS IN VIETNAM

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1. Opportunities

Detection and Monitoring

- **Agricultural practices:** Alternate Wetting and Drying & Sowing dates
- **Yield estimation**
- **Environmental pollution:** algae blooms
- **GHG emission estimation:** methane
- **Extreme Events:** droughts, floods, saline intrusion
- **Deforestation monitoring**: evaluating payments for ecosystem services (PES)

Enabled: Large-scale coverage at high frequency

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Satellite Data in Agricultural and Environmental Economics: Theory and Practice

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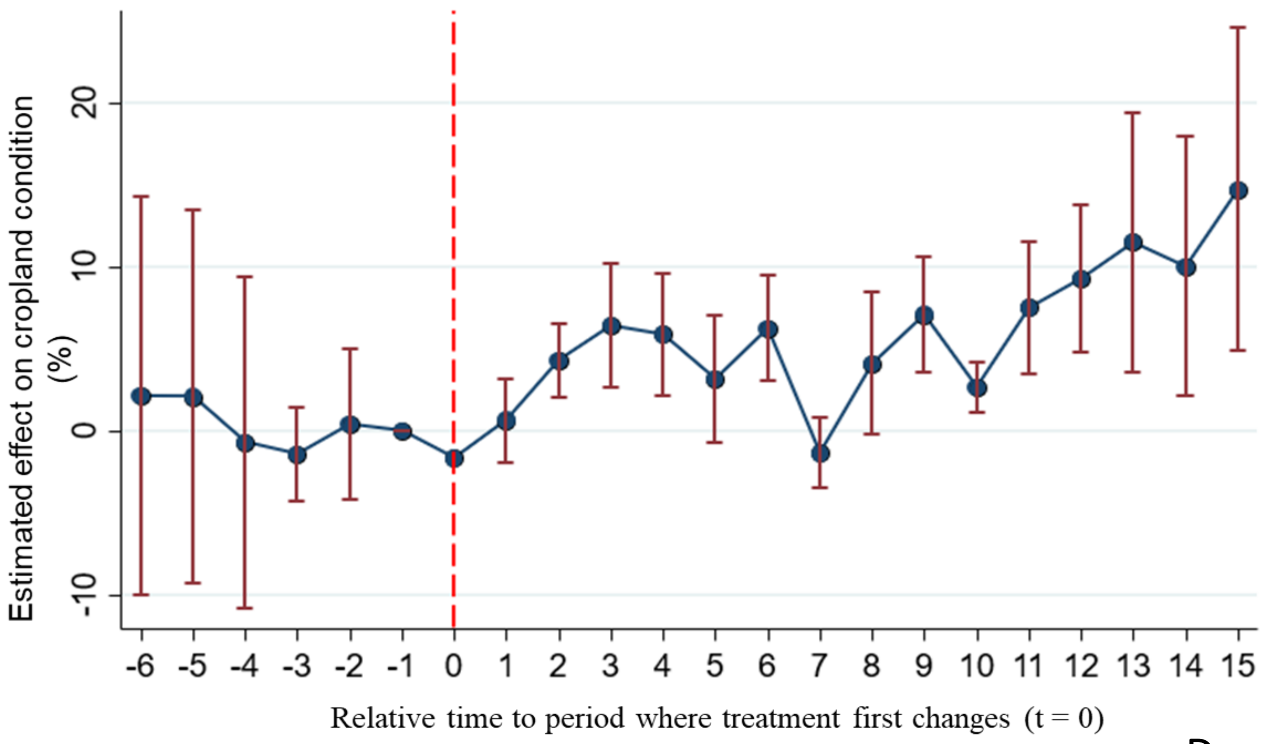
Keywords: causal inference | geospatial analysis | machine learning | measurement error | remote sensing

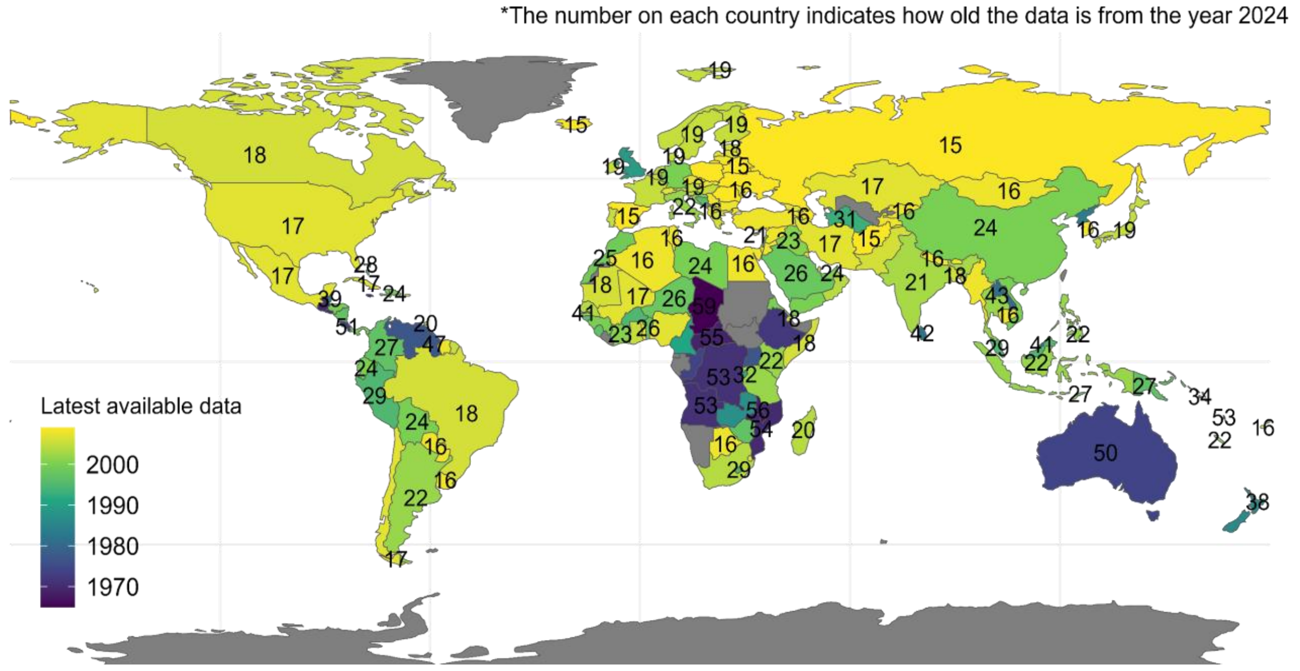
ABSTRACT

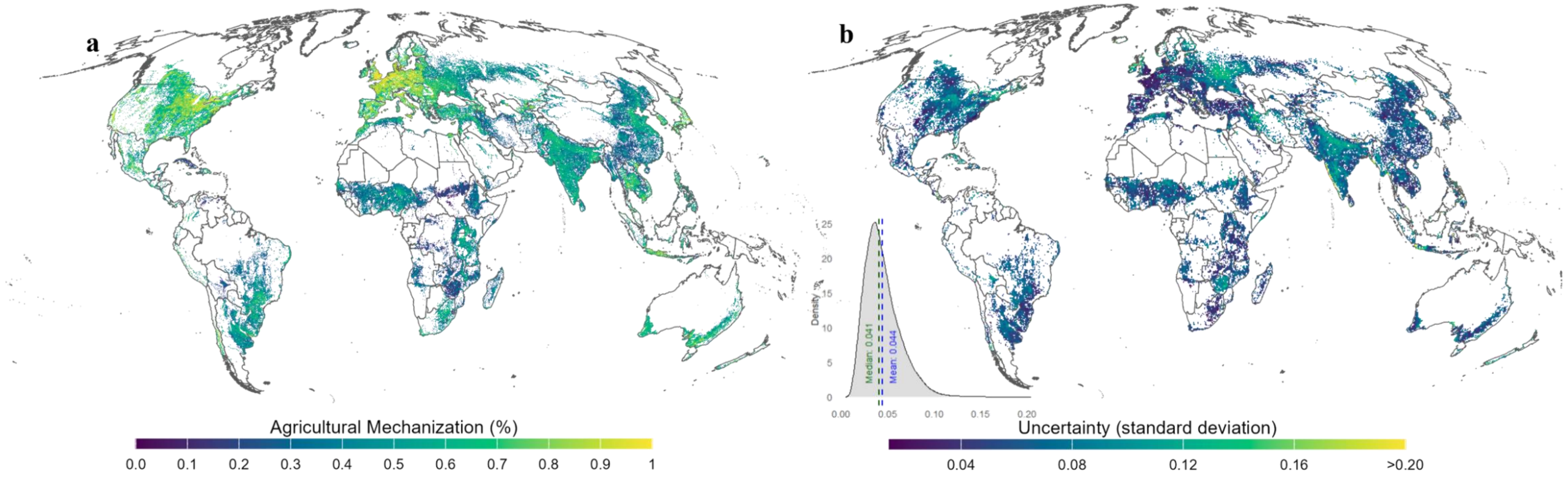
Agricultural and environmental economists are in the fortunate position that a lot of what is happening on the ground is observable from space. Most agricultural production happens in the open and one can see from space when and where innovations are adopted, crop yields change, or forests are converted to pastures, to name just a few examples. However, converting remotely sensed images into measurements of a particular variable is not trivial, as there are more pitfalls and nuances than "meet the eye". Overall, however, research benefits tremendously from advances in available satellite data as well as complementary tools, such as cloud-based platforms, machine learning algorithms, and econometric approaches. Our goal here is to provide agricultural and environmental economists with an accessible introduction to working with satellite data, show-case applications, discuss pitfalls and available solutions, and emphasize the best practices. This is supported by extensive supporting information, where we describe how to create different variables, common workflows, and a discussion of required resources and skills. Last but not least, example data and reproducible codes are made available online.

JEL Classification: Q5, Q10, Q15, C31, R10



Dureti et al. (under review)



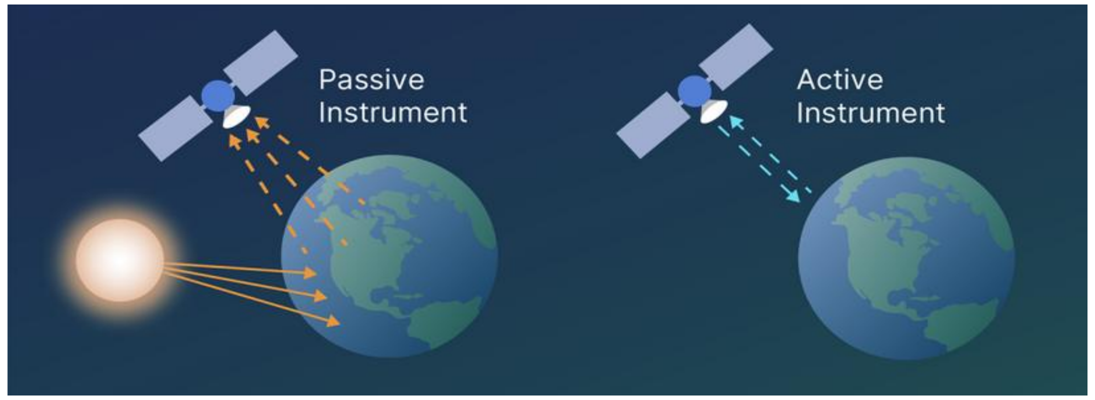


Roman et al. (under review)

2. Challenge

In tropical Vietnam, persistent cloud cover hinders the continuous collection of good optical data

- Although there are methods to harmonize freely available Landsat and Sentinel-2 data for synchronous use, and to use commercial data (PlanetScope, WorldView, Pléiades…), there likely remain issues with observations in the wet season (relevant for monitoring AWD, e.g.)



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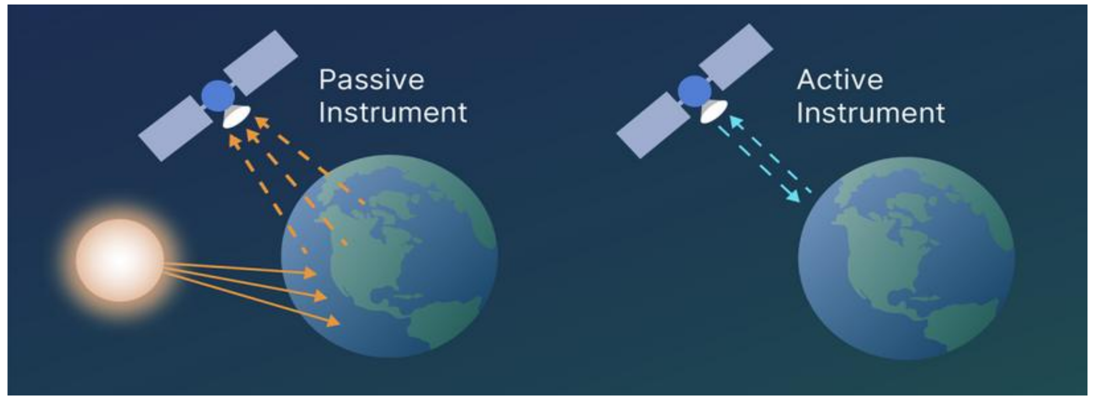
- Option: use of active data, especially Sentinel-1 SAR (10m), which penetrates clouds and ensures consistent observations
  - SAR is sensitive to object structure, allowing crop and growth stage differentiation - but cannot provide vegetation indices as proxies for e.g. photosynthetic activity, greenness, vegetation water content



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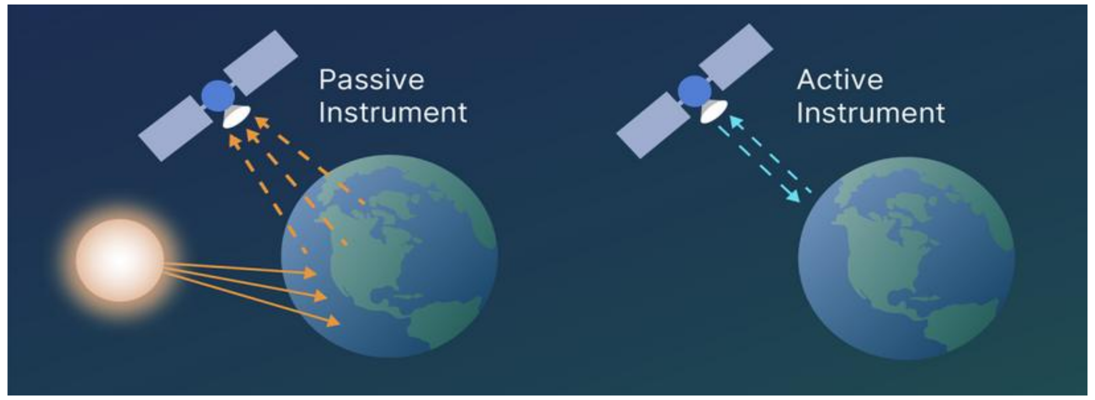
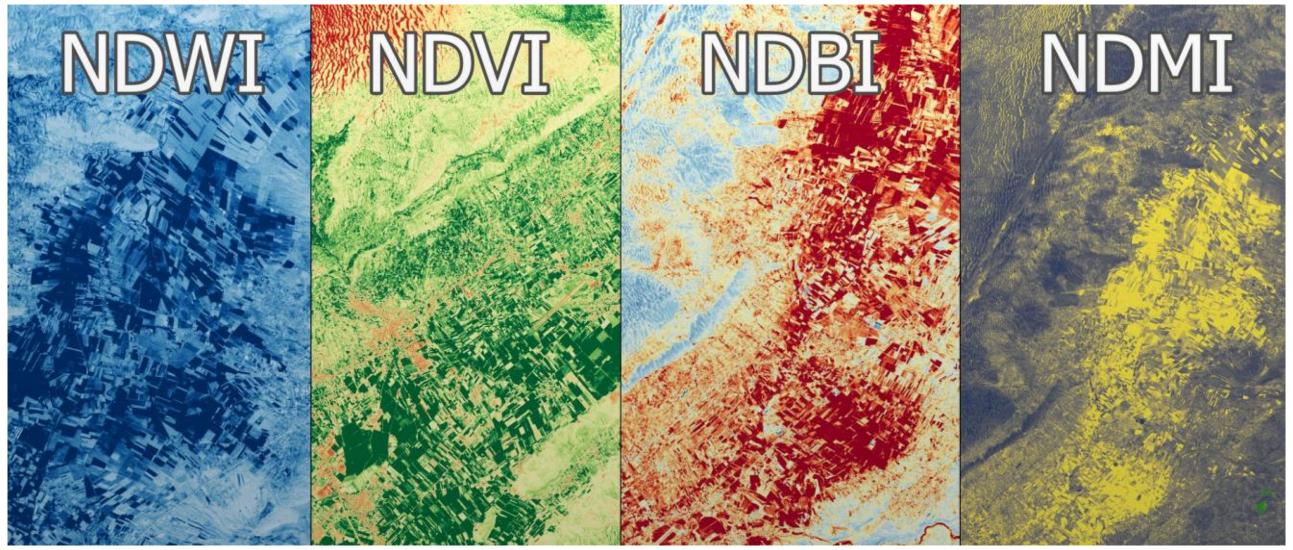
- Possibility to combine active and passive data for improved rice mapping (Aziz et al. 2023, Gao et al. 2023, Ginting et al. 2024, Ngo et al. 2024)

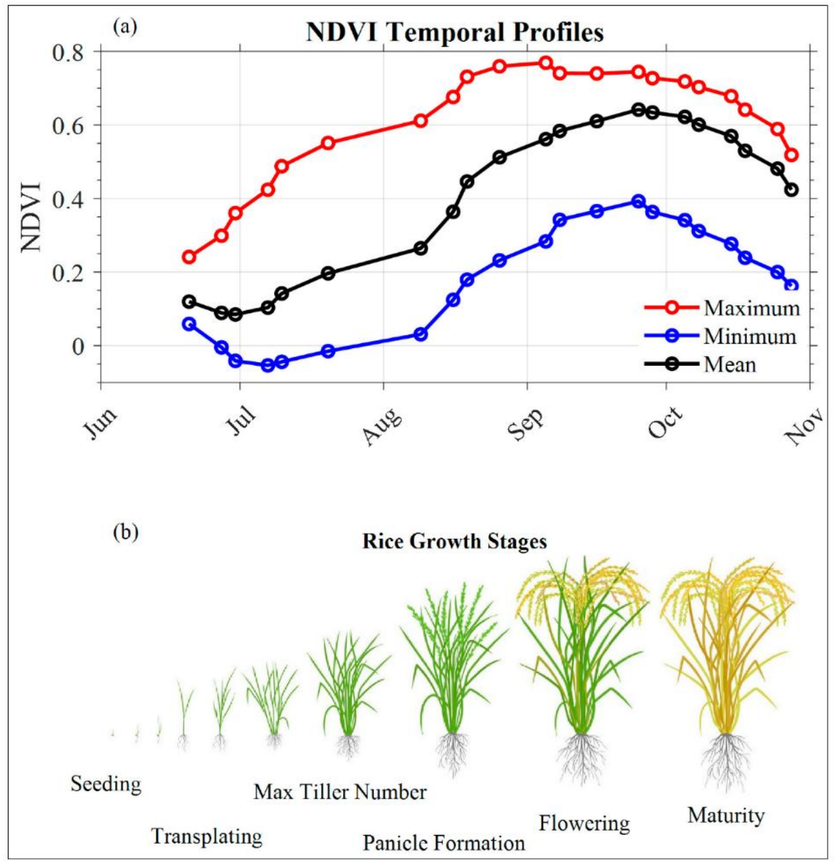


Vegetation indices from optical data:



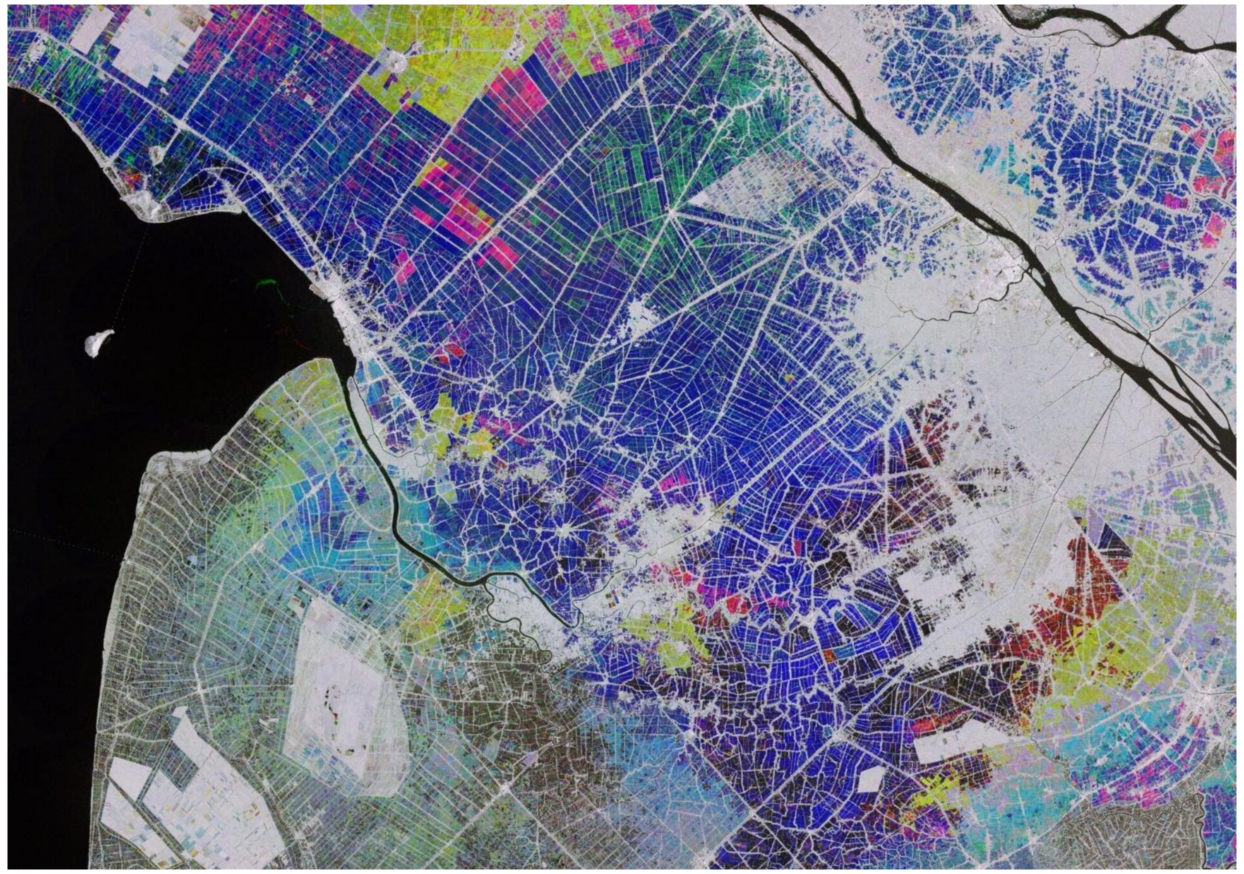
Source: Gilles Tounsi / www.limko.cm

Time series of NDVI over rice plot:



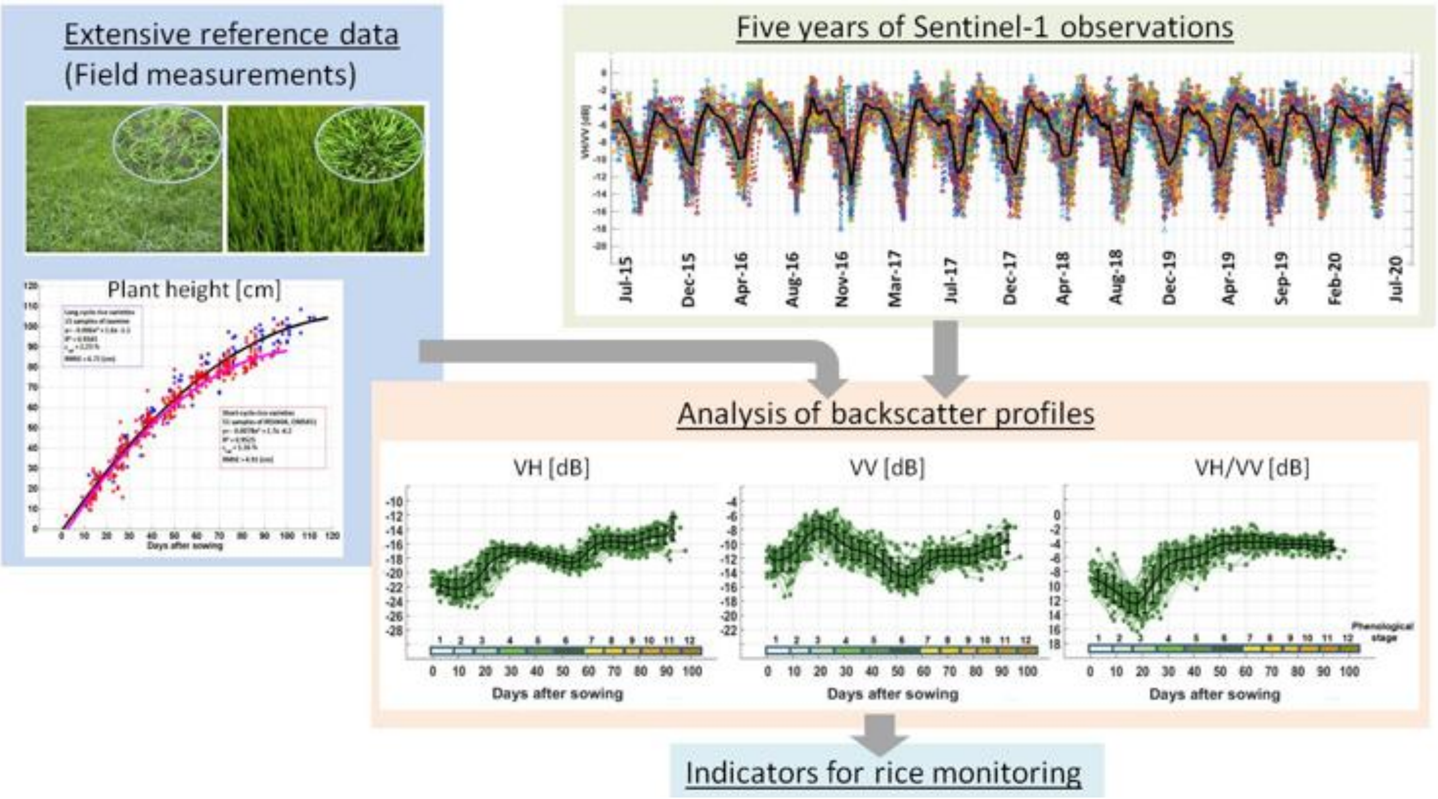
Source: Nazir et al. 2021

Backscatter from three S1 radar acquisitions shows changes between:



Source: [S1 Applications]

Time Series of S1 over rice plot:

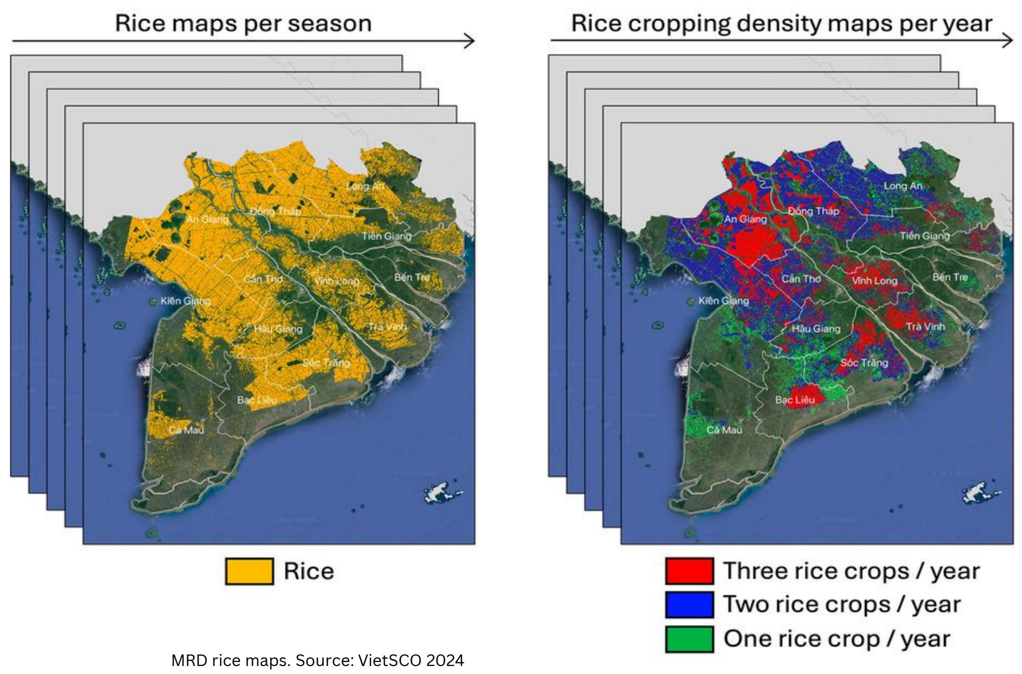


Source: Phan et al. 2021

3. Mapping of rice areas, and growing practices in Vietnam

Various initiatives have mapped rice distribution, cropping intensity, and practices in Vietnam and other rice regions, e.g.:

- Vimesco-Rice (SCO 2024) used Sentinel-1 SAR to map seasonal rice in the MRD (2020) and cropping intensity (2018–2023), achieving high accuracy
- Mérimée (SCO 2024), the follow-up, targets irrigation monitoring in the MRD to assess AWD adoption and methane emissions
- Similar, GEORICE (ESA 2020) mapped rice area and phenological stages in the MRD using Sentinel-1
- Gao et al. (2023) offer a fully automated rice mapping framework
- Ginting et al. (2024) also provide a map for paddy rice cropping intensity across SEA



MRD rice maps. Source: VietSCO 2024

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  - Modelling of Regional Economic Potential using Machine Learning
- Mechanization and Laser Land Levelling
  - Instrumental Variables for Adoption and Yield Measurement for Impact Evaluation

Thank You and Please Get in Touch!

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