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Geospatial innovations in agriculture: mapping and monitoring crop yield and nutritional quality to address malnutrition challenges

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Faculty of Geo-Information Science and Earth Observation (ITC),
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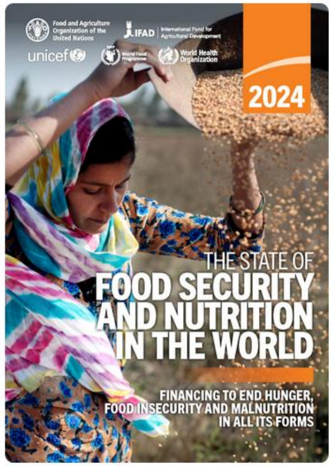
Global burden of malnutrition



733.4 million undernourished people (9.1%)

881 million adults are obese (15.8%)

148 million children under five years of age are stunted (22.3%)

45 million children under five years of age are wasted (6.8%)

37 million children under five years of age are overweight (5.6 %)

Source: 2024 | The State of Food Security and Nutrition in the World (FAO, UNICEF, WFP, WHO, IFAD)

Global challenge of climate change

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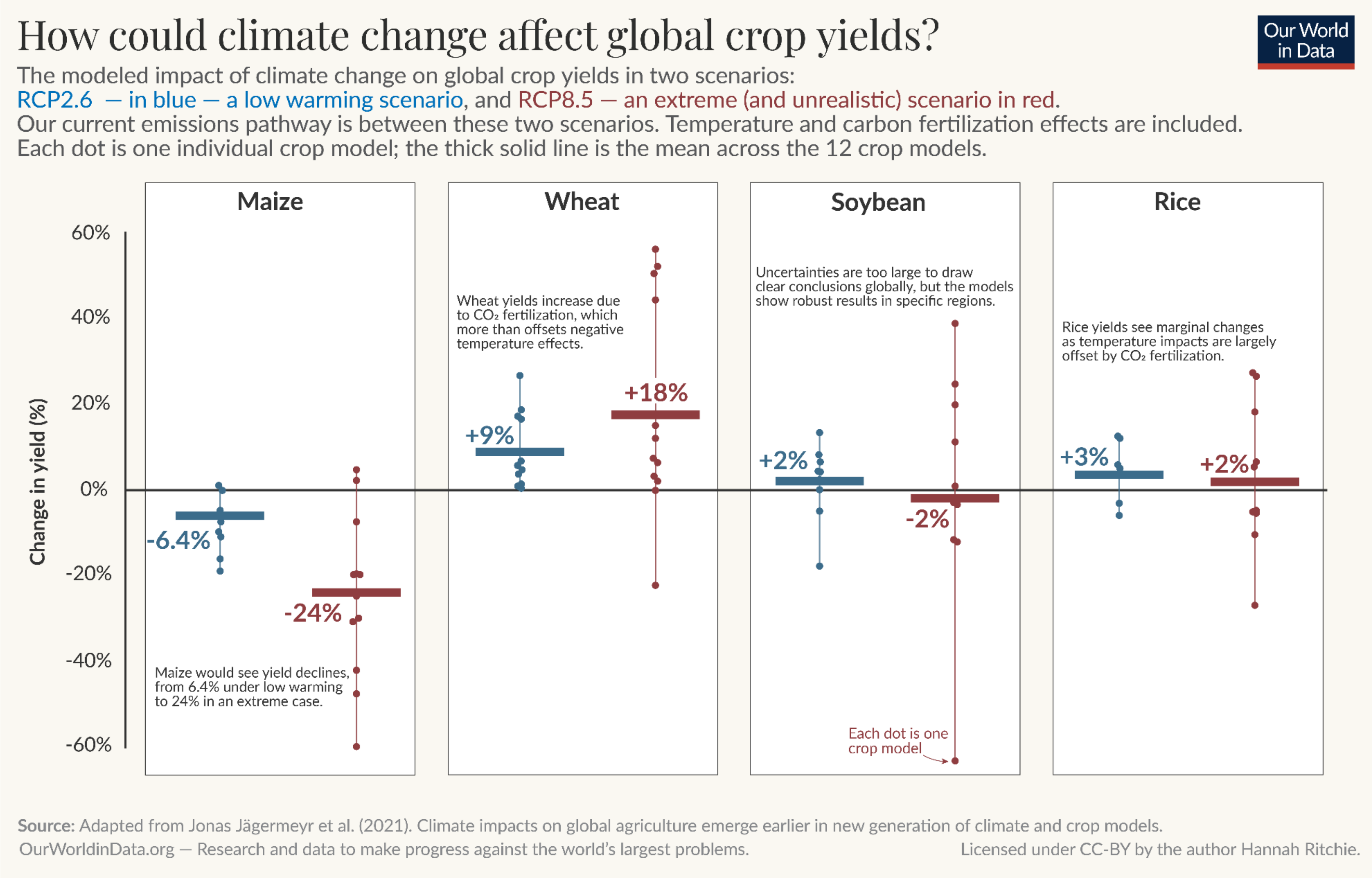
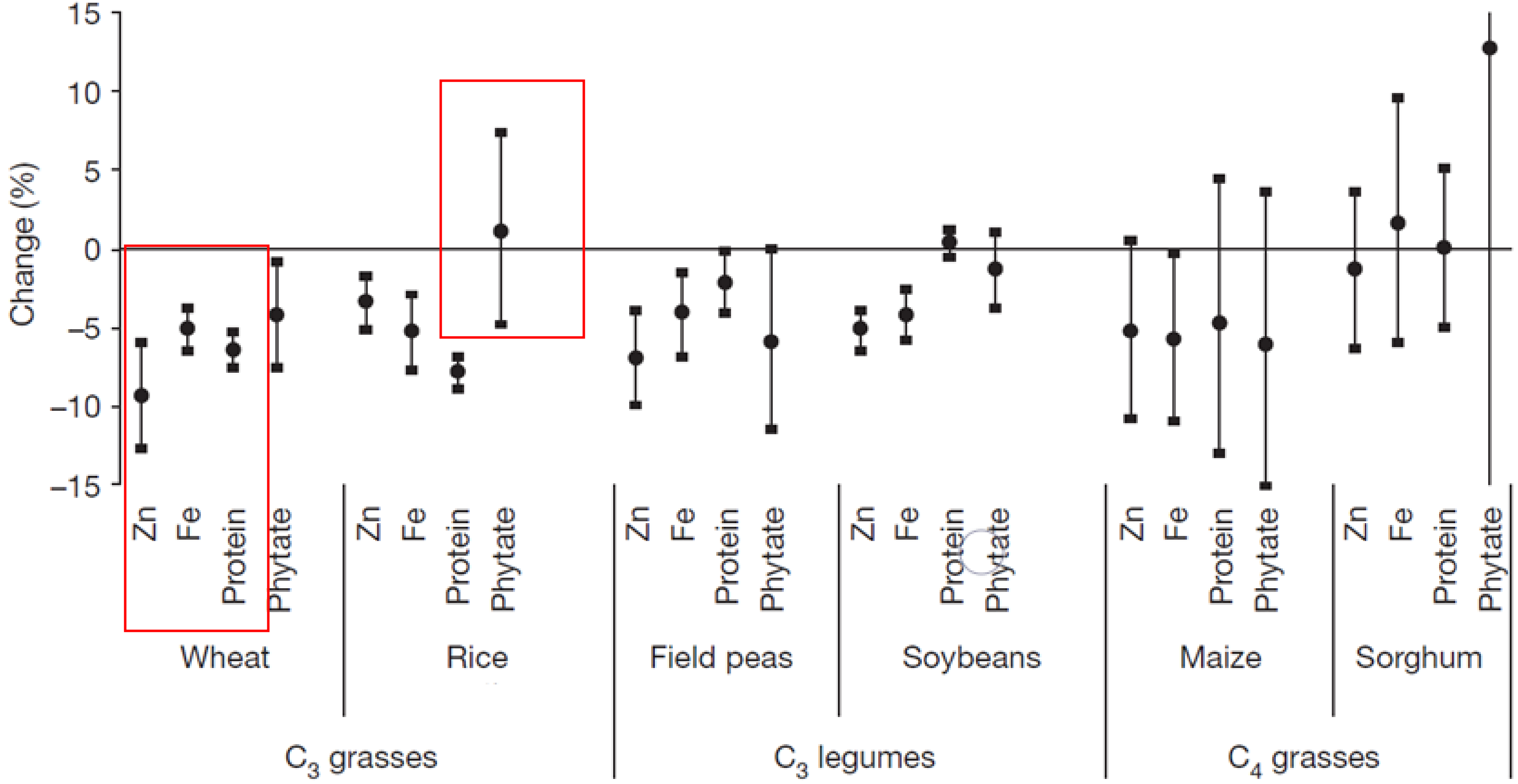


Jägermeyr, J., Müller, C., Ruane, A.C., Elliott, J., Balkovic, J., Castillo, O., Faye, B., …., Rosenzweig, C., 2021. Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. Nature Food 2, 873-885.

Increasing CO2 threatens human nutrition

Percentage change in nutrients at elevated CO2 (= 546–586 p.p.m) relative to the ambient CO2

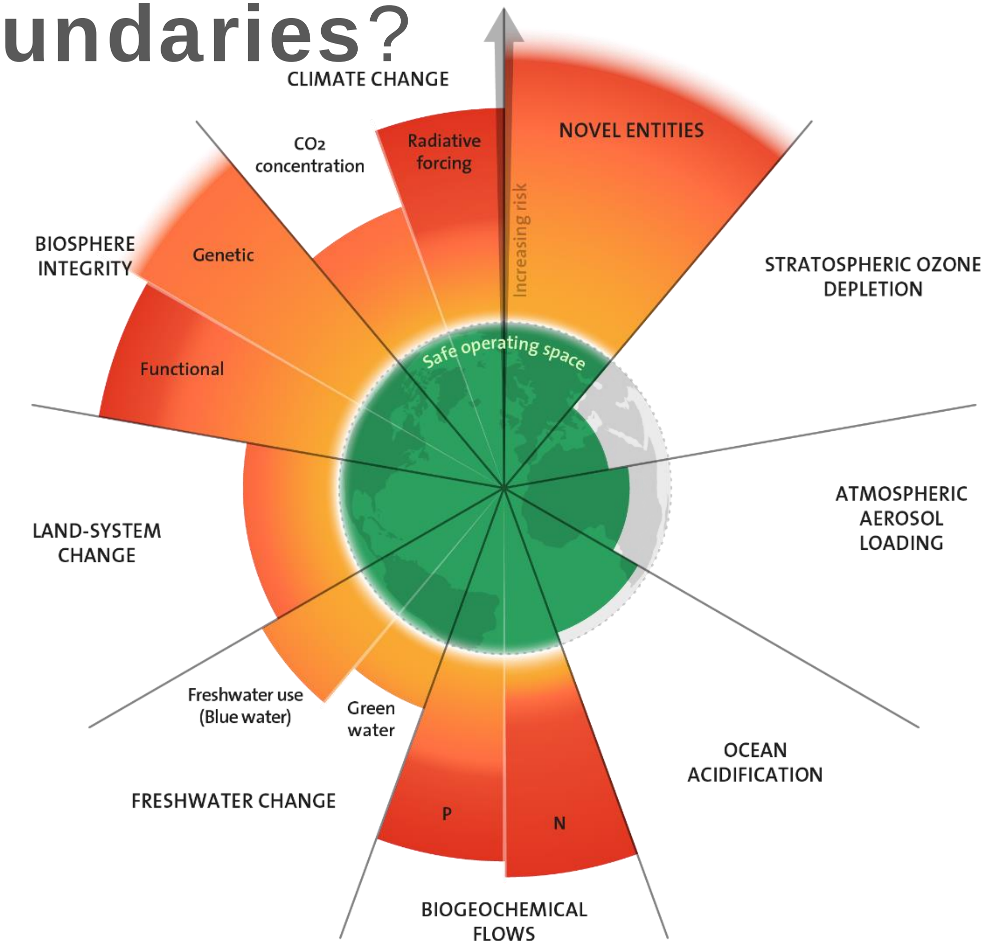


Free-Air Carbon Dioxide Enrichment (FACE)

Myers, S., Zanobetti, A., etc, 2014. Increasing CO2 threatens human nutrition. Nature, 510, 139-142.

Planetary boundaries

EAT Lancet Commission on Food, Planet, Health: Can we feed a future population of 10 billion people a healthy diet within **planetary boundaries**?



Source: Azote for Stockholm Resilience Centre, based on analysis in Richardson et al 2023

UN Sustainable Development Goal 2

End hunger, achieve food security and improve nutrition and promote sustainable agriculture by 2030

End hunger|End all forms of malnutrition|

Double agricultural productivity and incomes|

Ensure sustainable food production systems|

Maintain the genetic diversity of seeds, plants, and animals

Food security challenges

Decision making is under deep uncertainty

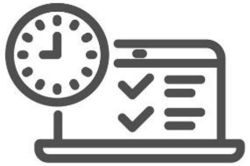

http://unsplash.com

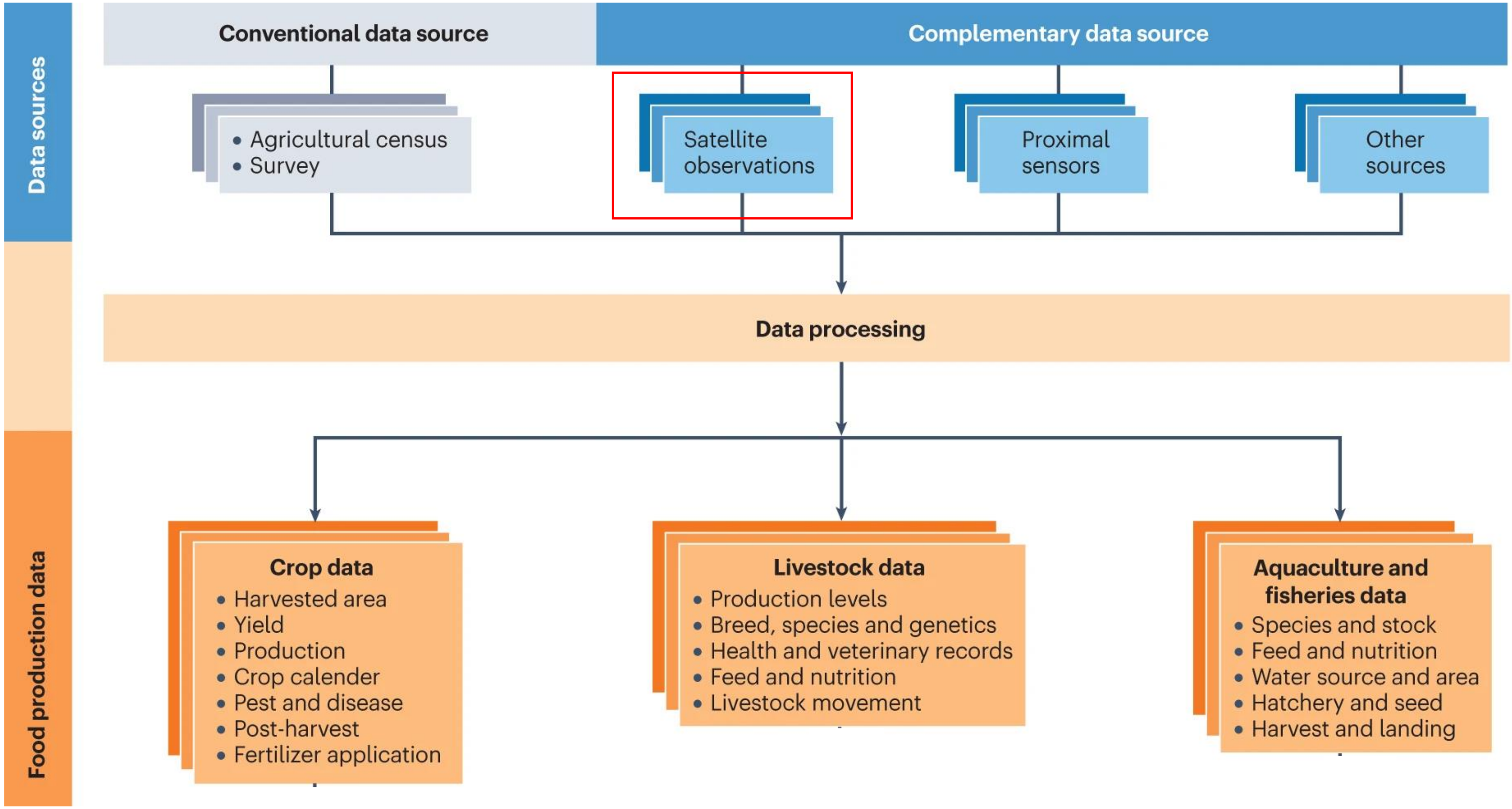
Food production data

DETAILED

ACCURATE

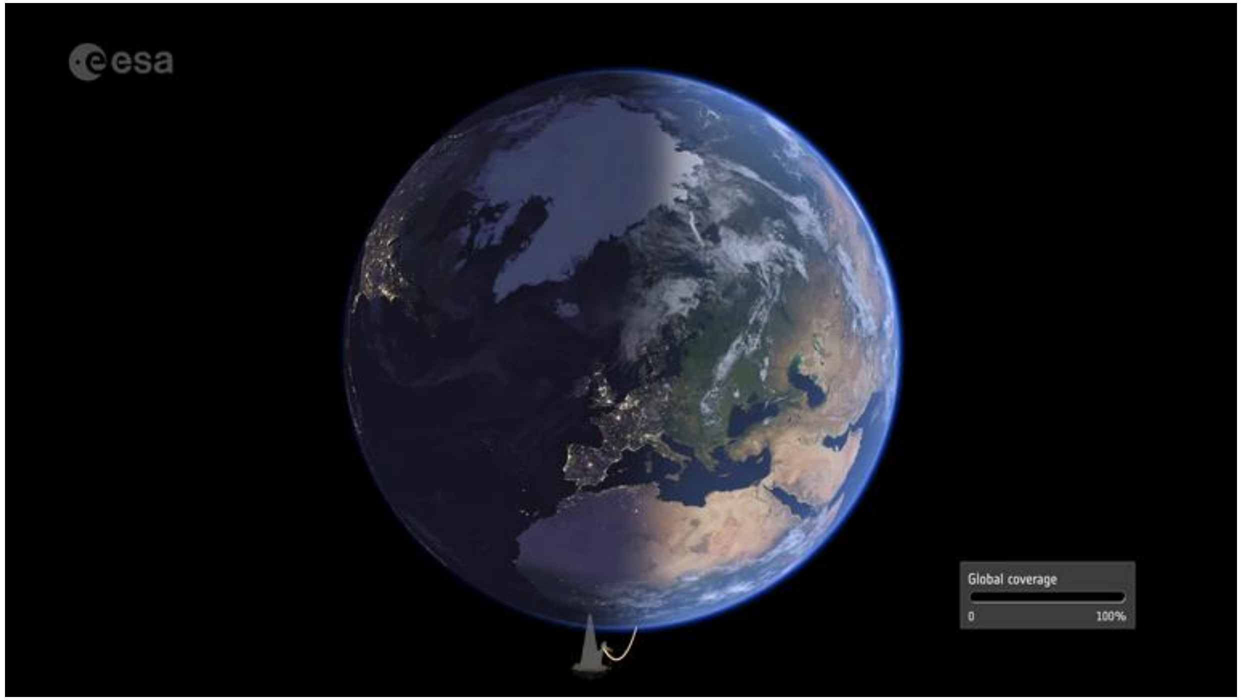
UP-TO-DATE

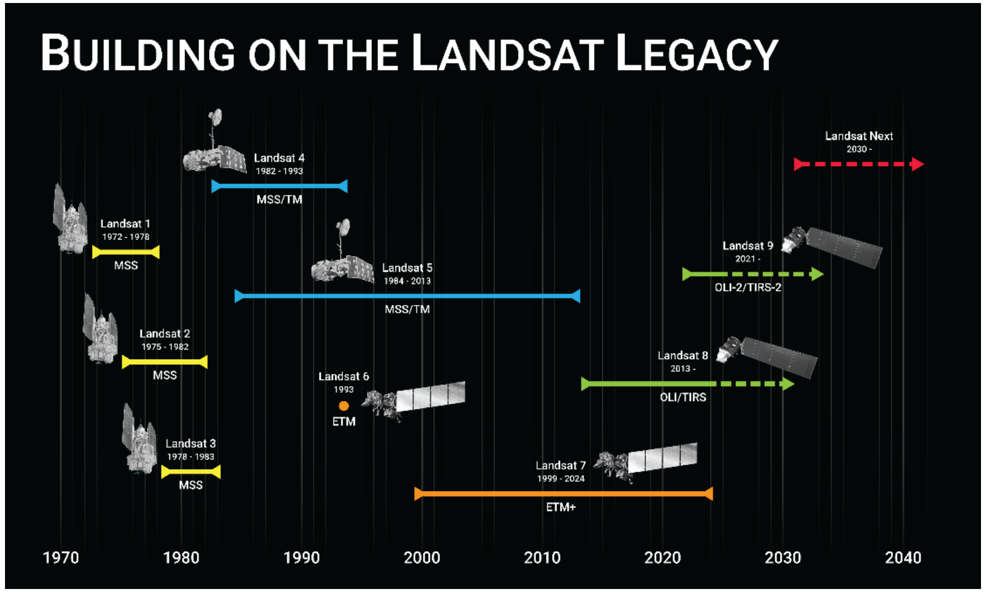


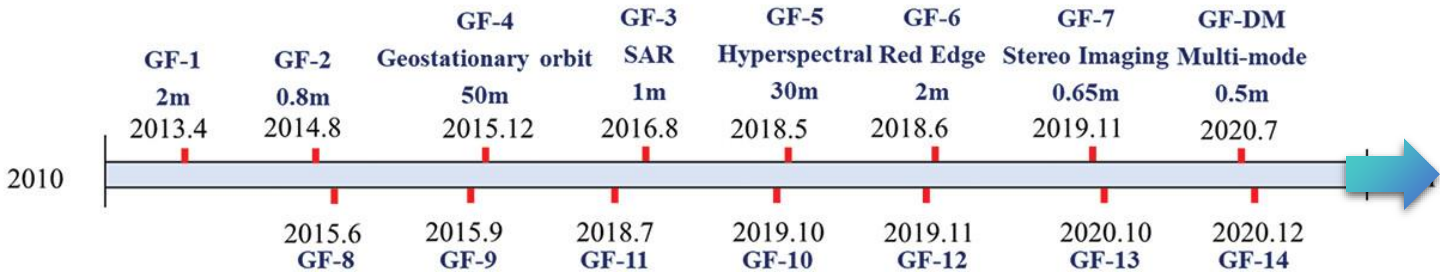


Source: Kebede, E.A., Abou Ali, H., Clavelle, T., Froehlich, H.E., Gephart, J.A., Hartman, S., Herrero, M., Kerner, H., Mehta, P., Nakalembe, C., Ray, D.K., Siebert, S., Thornton, P., Davis, K.F., 2024. Assessing and addressing the global state of food production data scarcity. Nature Reviews Earth & Environment.

Ambitious pursuit of Earth Observation missions







Source: European Space Agency (ESA), NASA
Li, D., Wang, M., Guo, H., Jin, W., On China's earth observation system: mission, vision and application. Geo-spatial Information Science, 1-19.

Remote sensing technology devs.

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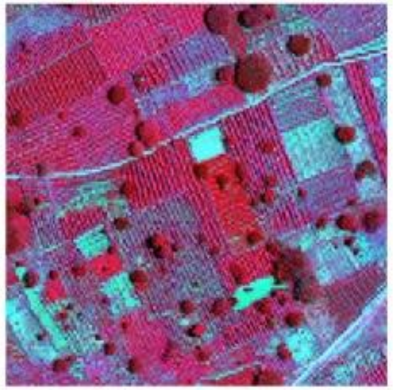
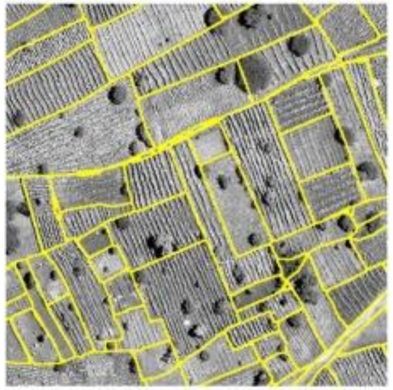
Spatial resolution

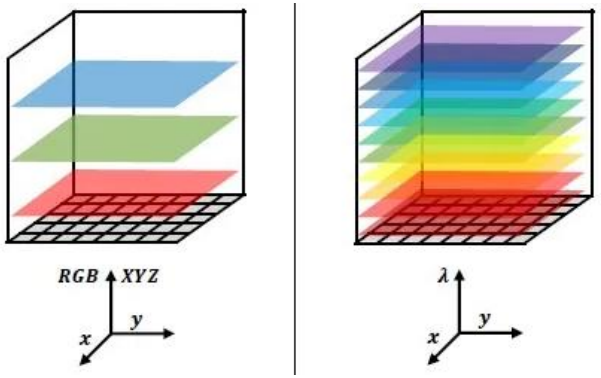


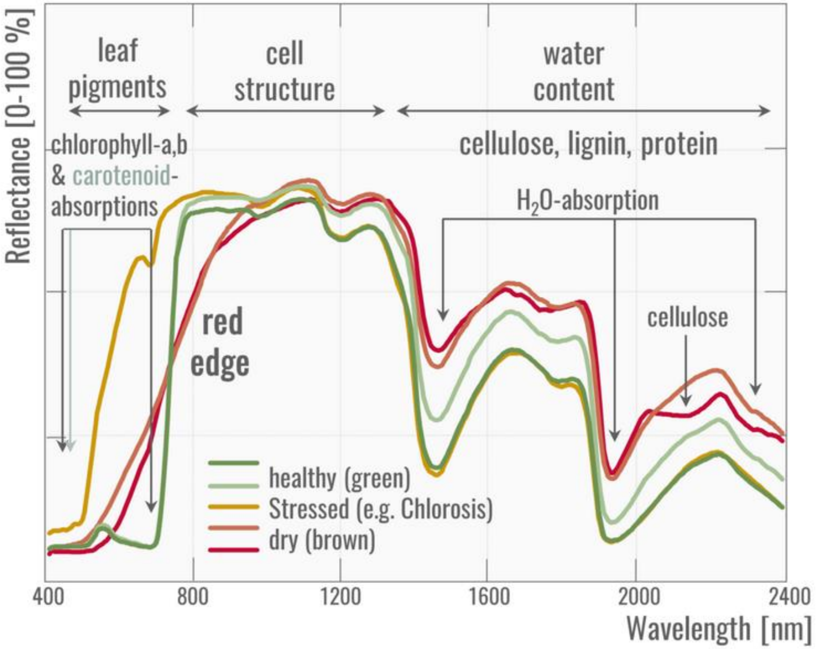
Multispectral bands 7, 5, 3



PAN + reference boundaries

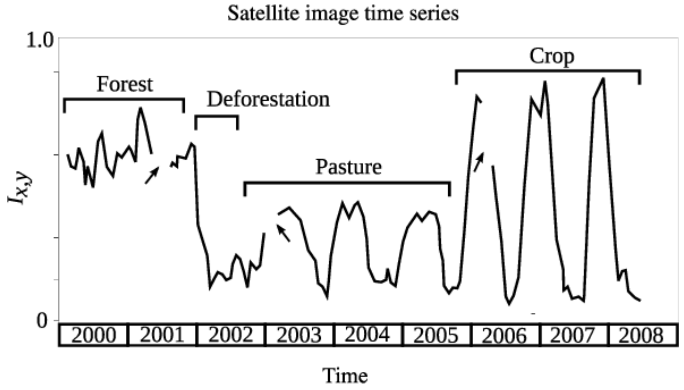
Spectral resolution





Source: eo-college.org

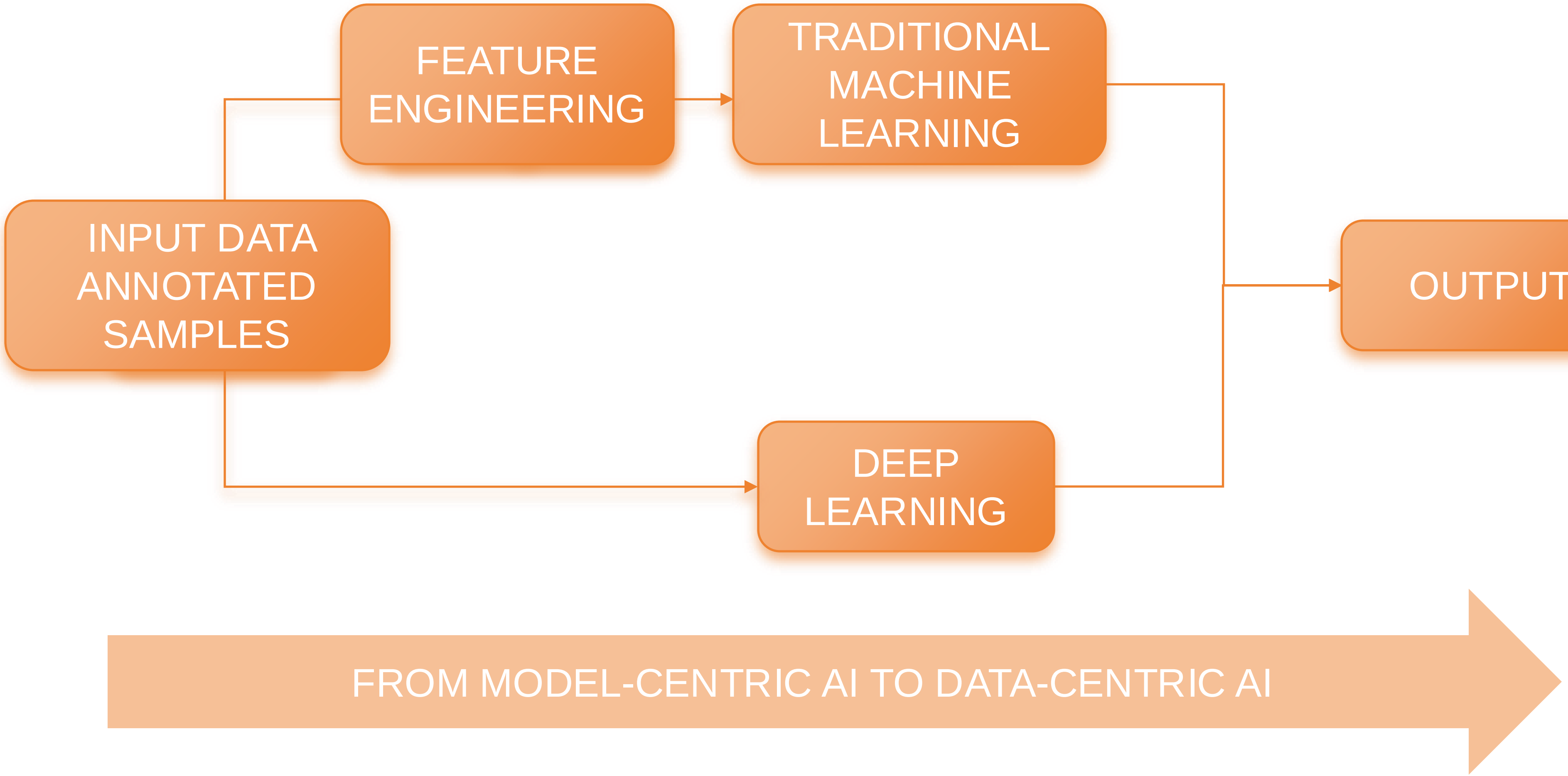
Temporal resolution



Source: Maus et al. 2016

Persello, C., Tolpekin, V.A., Bergado, J.R., de By, R.A., 2019. Delineation of agricultural fields in smallholder farms from satellite images using fully convolutional networks and combinatorial grouping. Remote Sensing of Environment 231, 111253.

Machine learning devs.

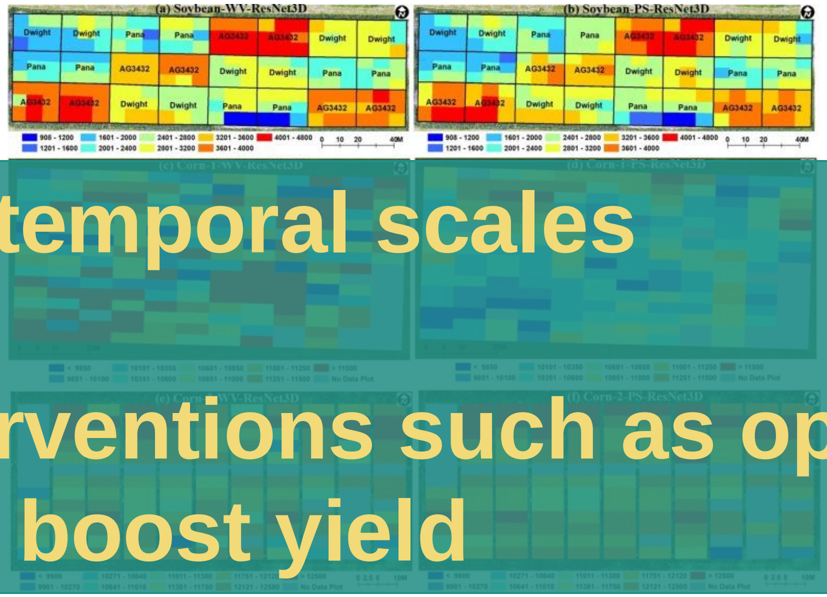


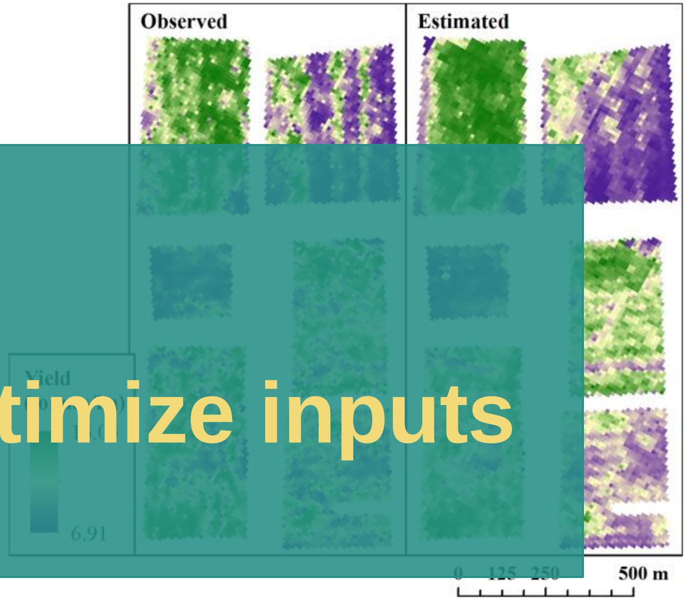
Remote Sensing & Food Production

Crop yield estimation

Spatial resolution:
Within field
Field level
Landscape, Regional and Global levels

Temporal resolution:
end of season, within-season, trends



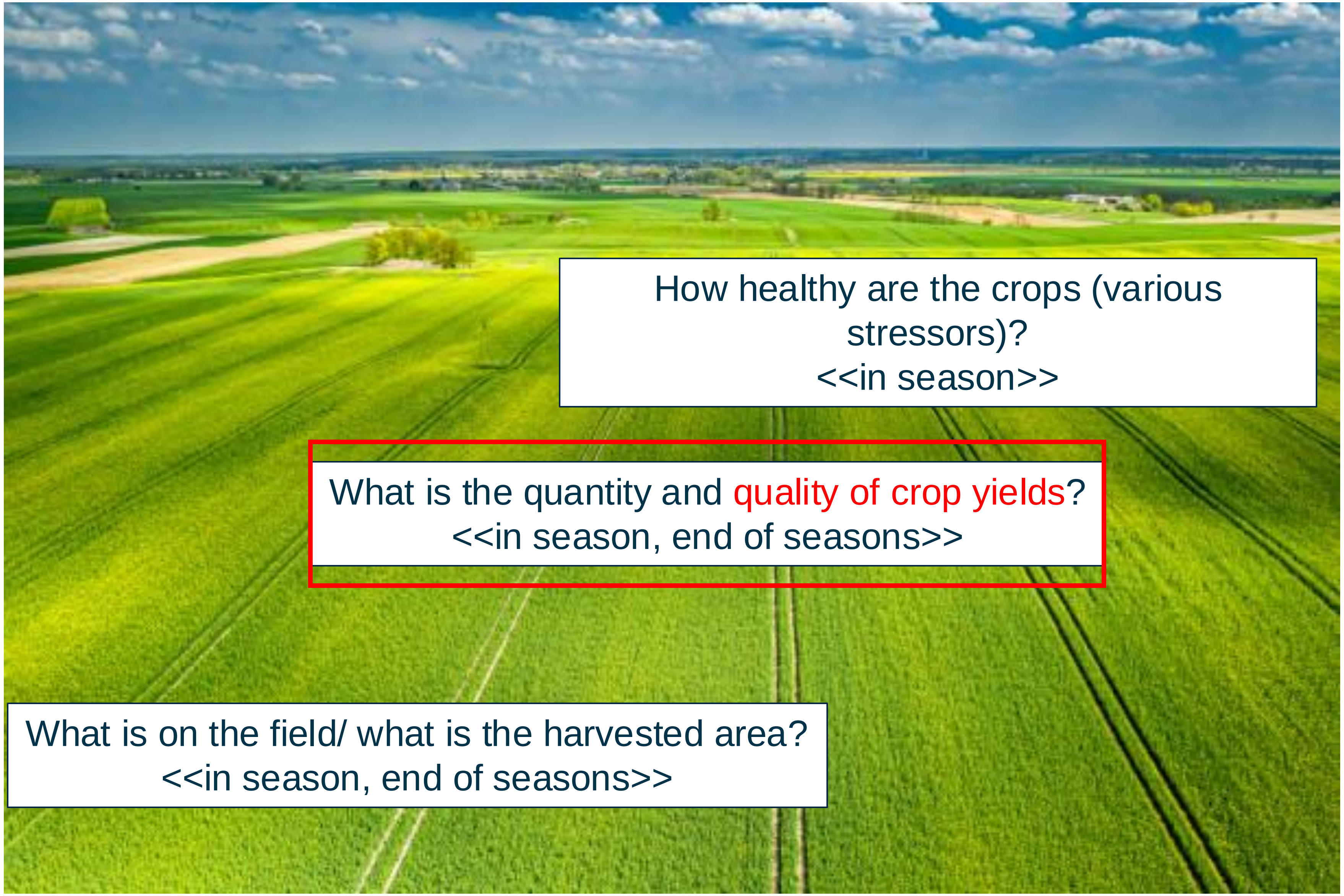


Various spatial and temporal scales

Before harvest: interventions such as optimize inputs (water, fertilizers) to boost yield

Hunt, M.L., Blackburn, G.A., Carrasco, L., Redhead, J.W., Rowland, C.S., 2019. High resolution wheat yield mapping using Sentinel-2. Remote Sensing of Environment 233, 111410.
Marshall, M., Belgiu, M., Boschetti, M., Pepe, M., Stein, A., Nelson, A., 2022. Field-level crop yield estimation with PRISMA and Sentinel-2. ISPRS Journal of Photogrammetry and Remote Sensing 187, 191-210.
Sagan, V., Maimaitijiang, M., Bhadra, S., Maimaitiyiming, M., Brown, D.R., Sidike, P., Fritschi, F.B., 2021. Field-scale crop yield prediction using multi-temporal WorldView-3 and PlanetScope satellite data and deep learning. ISPRS Journal of Photogrammetry and Remote Sensing 174, 265-281.

Remote Sensing & Food Production



How healthy are the crops (various stressors)?
<<in season>>

What is the quantity and quality of crop yields?
<<in season, end of seasons>>

What is on the field/ what is the harvested area?
<<in season, end of seasons>>

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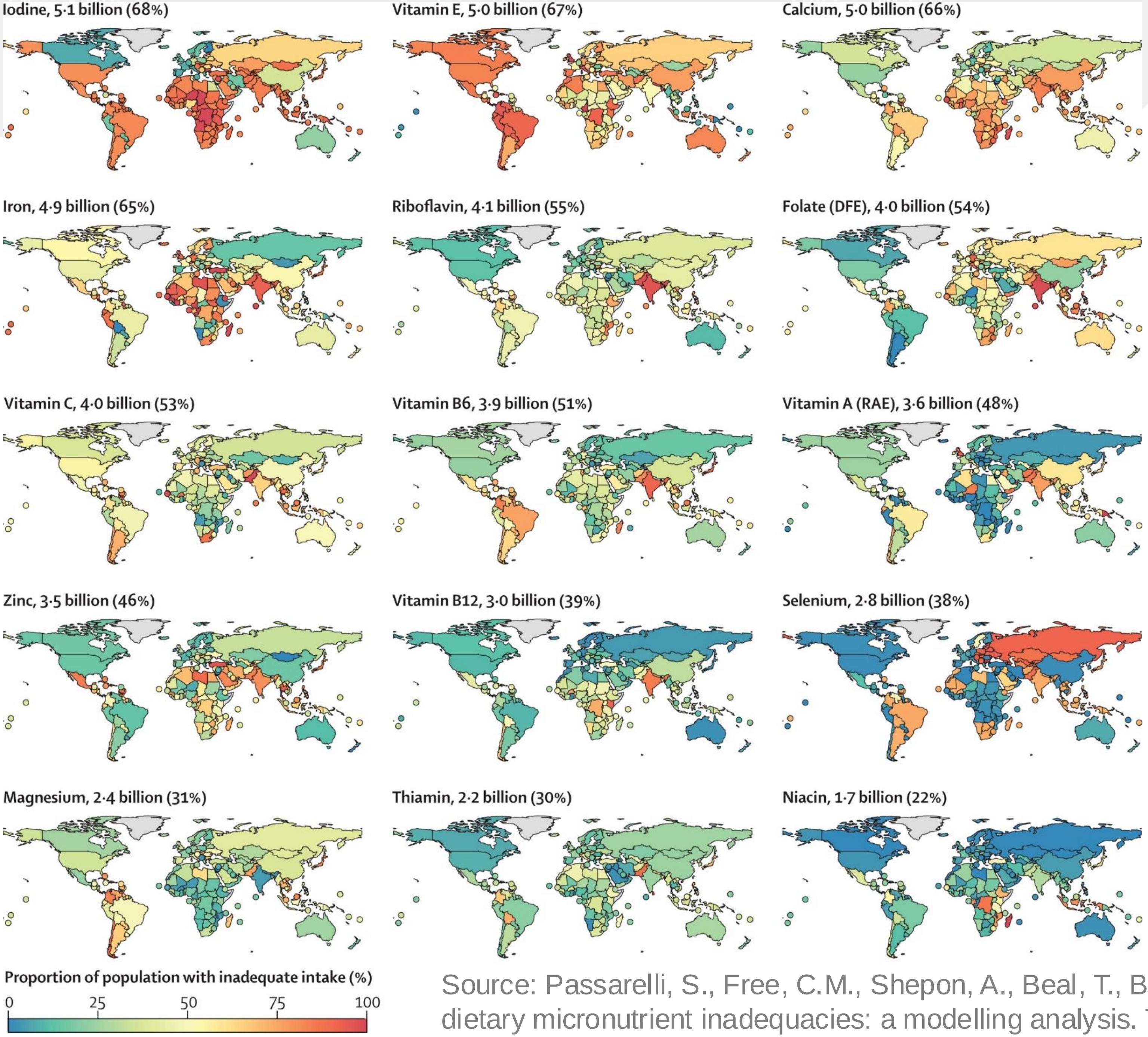
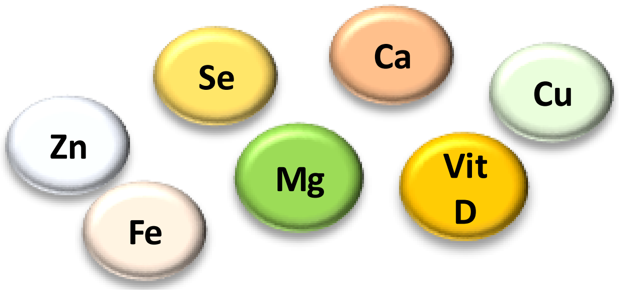
Estimated prevalence of nutrient intake inadequacies in 2018



Source: Passarelli, S., Free, C.M., Shepon, A., Beal, T., Batis, C., Golden, C.D., 2024. Global estimation of dietary micronutrient inadequacies: a modelling analysis. The Lancet Global Health 12, e1590-e1599.

Micronutrient deficiencies

"Hidden Hunger"



Serious mental & physical health problems

Diets rely heavily on staple crops

Spatial variation of crop nutrients

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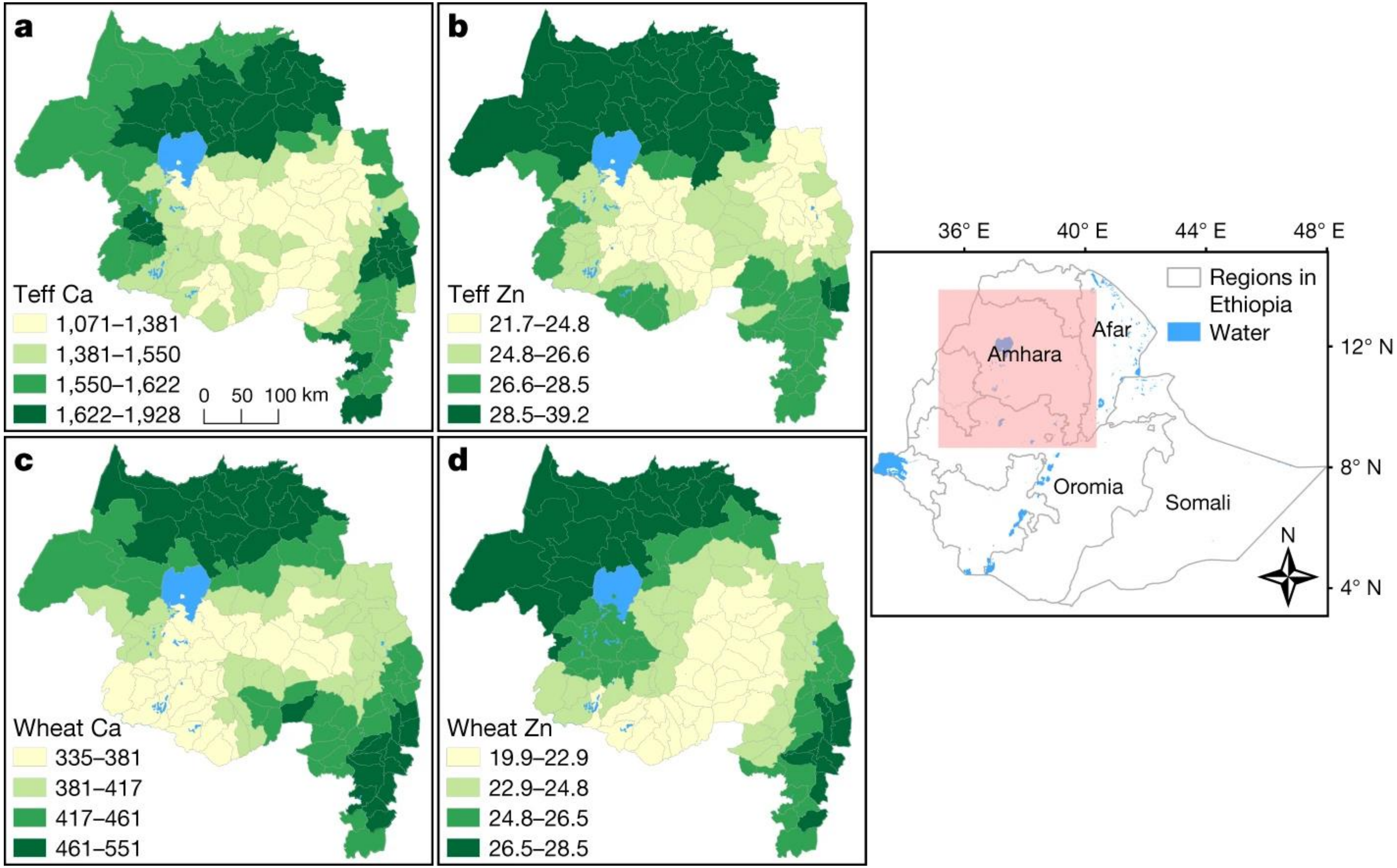


Gashu, D., Nalivata, P.C., ….., Broadley, M.R. (2021). The nutritional quality of cereals varies geospatially in Ethiopia and Malawi. Nature, 594, 71-76

Spatial variation of crop nutrients

	Midland	Highland	Upper highland	EAR
Energy (kcal)	2234.3	3453	4431.6	2869.7
Protein (g)	62.7	98.6	107.8	51.9
Fat (g)	20.1	27.5	30.4	85.5
Carbohydrate (utilizable) (g)	431.8	667.8	873.7	148.1
Fiber (g)	37.5	68.8	112	31.5
Calcium (mg)	169	196.6	250.7	700.1
Iron (mg)	35.9	57.3	105.5	12.1
Zinc (mg)	15.4	26.1	38.7	11.3
Vitamin A (μg RAE)	36.5	86.6	146.2	625.6
Folic acid (μg)	363	541.2	296.7	329.9
Vitamin C (mg)	5.1	9.4	8.9	38.6

Note: Values are production.

Abbreviation: EAR, estimated average requirement.

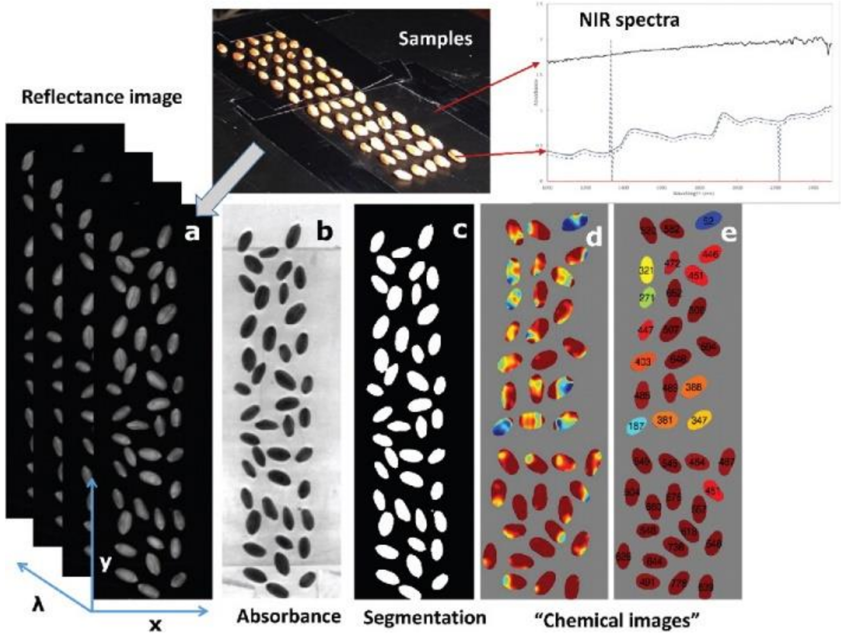
Energy and nutrient per capita production in South Wollo, Ethiopia

Guja-Bayu, H., Belgiu, M., Embibel, L., Baye, K., Stein, A. 2023, **Examining energy and nutrient production across the different agro-ecological zones in rural Ethiopia using statistical methods**, Food Science and Nutrition, https://doi.org/10.1002/fsn3.3676

Crop nutrient data?

Wet Chemistry

Hyperspectral imaging technology



Time-consuming & expensive

After harvest

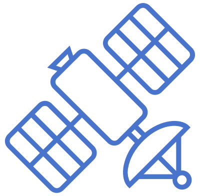
Caporaso, N., Whitworth, M.B., Fisk, I.D., 2018. Near-Infrared spectroscopy and hyperspectral imaging for non-destructive quality assessment of cereal grains. Applied Spectroscopy Reviews 53, 667-687.

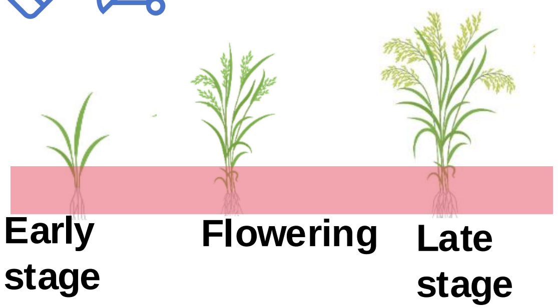
Data on crop nutrient

Crop grain samples

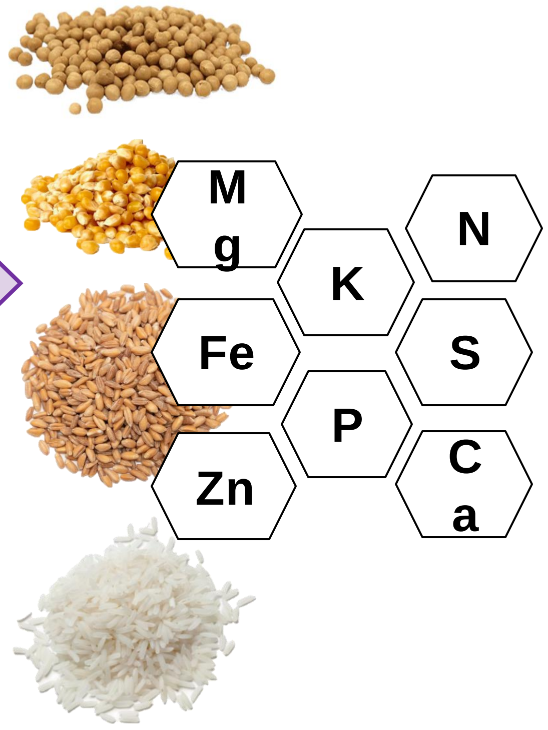
Satellite Images

Spatial co-variates

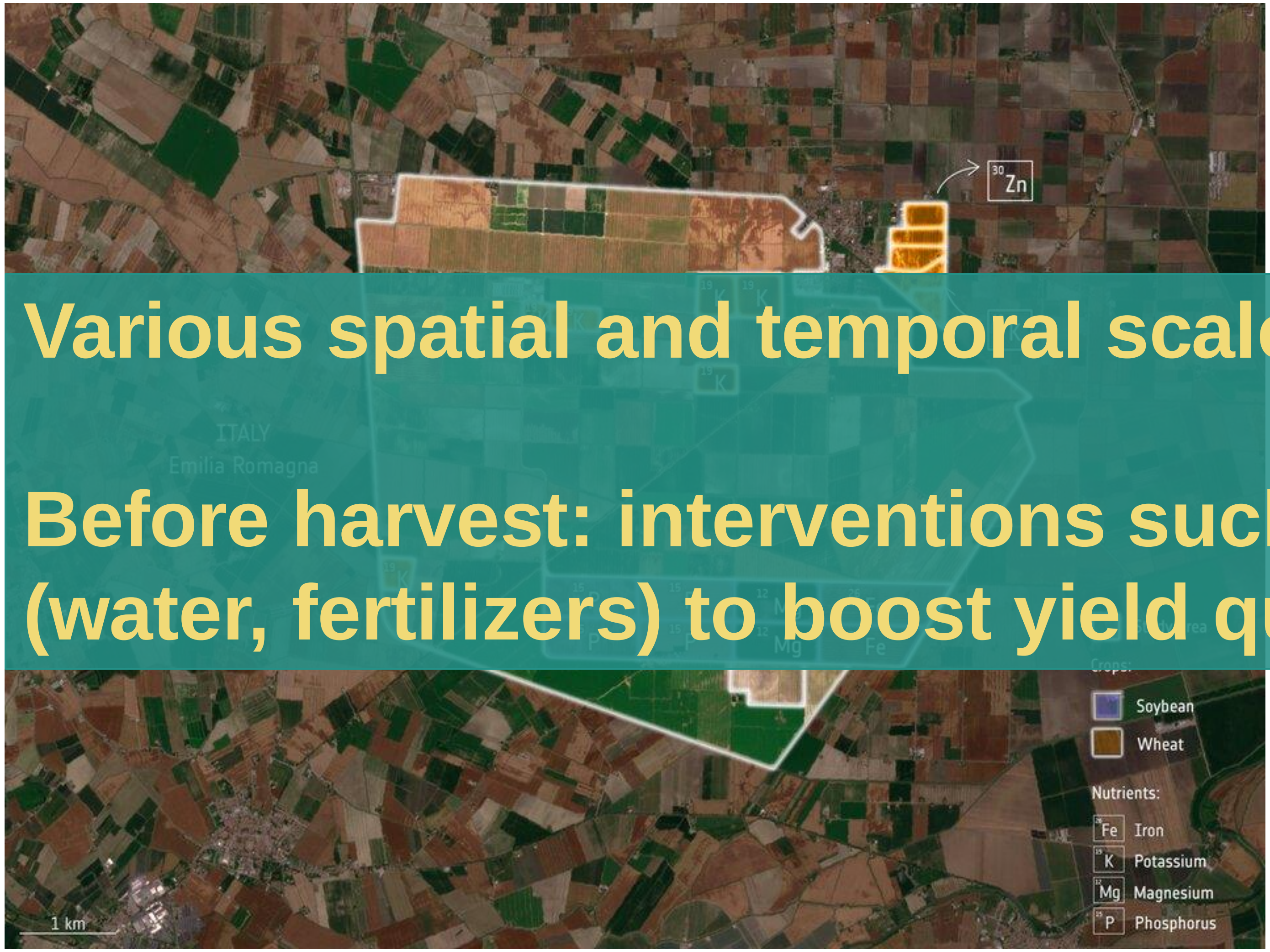


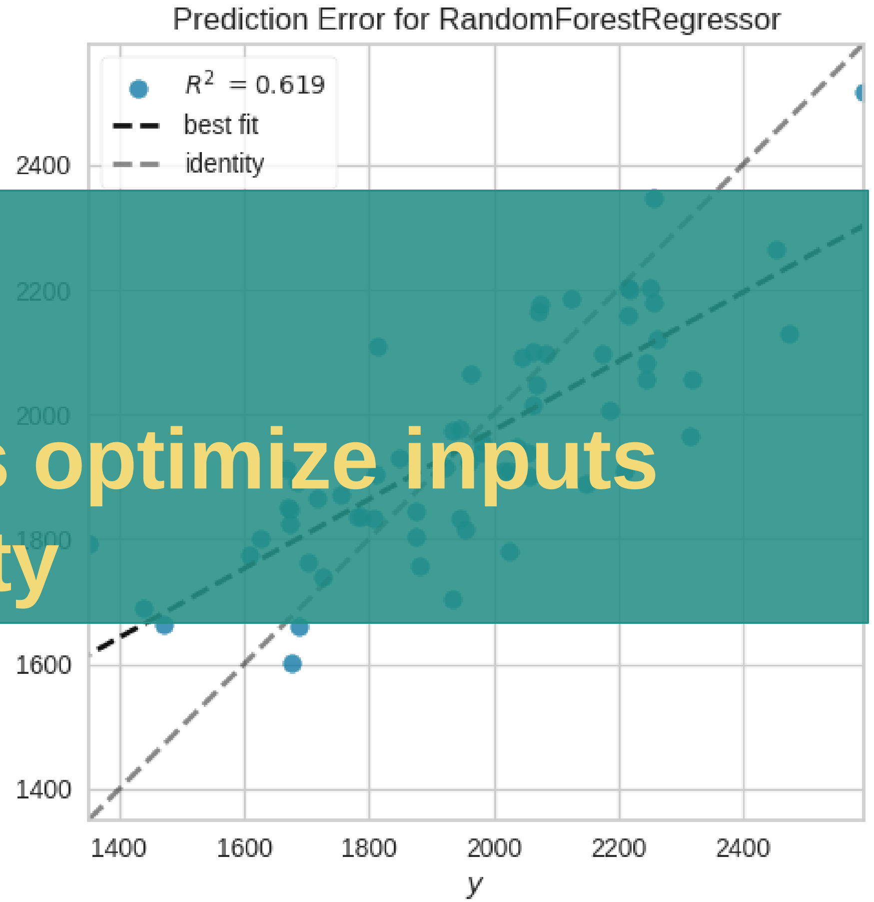


Machine learning



Crop nutrient data





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Before harvest: interventions such as optimize inputs (water, fertilizers) to boost yield quality

Belgiu, M., Marshall, M., Boschetti, M., Pepe, M., Stein, A., Nelson, A., 2023. PRISMA and Sentinel-2 spectral response to the nutrient composition of grains. Remote Sens. Environ. 292, 113567.

Reality check: bridging idealism with reality

Local vs global levels

Geographic bias: studies focused on developed countries

Inconsistencies and inaccuracies: prevalent in developing regions

Genetics * Environment * Management (GEM)

What do we need?

High quality and representative annotated data

Agriculture Digital Twins | Benchmark datasets

Hybrid approaches: process-based and machine learning

Multi-disciplinary teams and studies

What do we need?

- Machine learning based implementations evaluated using metrics beyond F1 or R^2 scores:

  number of saved lives

  income

  # of organizations that reuse the data or model

to **reduce the uncertainties in our decision making**

Wagstaff, K, 2012. Machine learning that matters. Proceedings of the Twenty-Ninth International Conference on Machine Learning (ICML), p. 529-536

THANK YOU