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INTEGRATING DRONE-BASED REMOTE SENSING, MACHINE LEARNING AND BAYESIAN MODELING TO ADVANCE PRECISION AGRICULTURE

Dissertation presented to University of Palermo, Palermo, ITALY

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1 Background & Review

Rationale and aim

Crop management must become more precise, efficient and sustainable under climatic pressure, input scarcity and strong within-field spatial variability. This thesis integrates **UAV remote sensing**, **machine learning** and **Bayesian modelling** into a unified framework for precision agriculture across horticultural, arable and perennial systems in Europe.

Premise: high-resolution UAV data become far more valuable when coupled with algorithms that model nonlinear relationships, preserve spatial structure and explicitly quantify uncertainty.

PRISMA systematic review: UAVs in vegetable crops

864 records identified → **132** studies included (2018–2023)

- **Crop health and stress monitoring** was the most studied application domain; **Solanaceae** the most investigated crop family.
- **Uses:** crop and weed detection, phenotyping, disease scouting, water management, biomass and yield estimation, aerial spraying.
- **Benefits:** earlier stress diagnosis and targeted interventions that cut fertiliser, herbicide, pesticide and water use.
- **Limitations:** preprocessing complexity, data fusion, interpretation and operational scalability.

RGB · Multispectral · Hyperspectral · Thermal · LiDAR

2 Precision Nitrogen Management in Potato

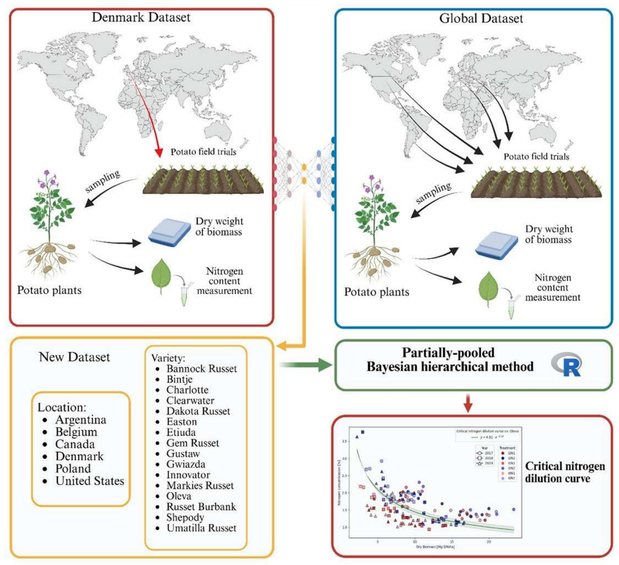


Fig. 1 – Multi-site potato dataset and partially pooled Bayesian estimation of the critical N dilution curve.

Bayesian modelling of Nitrogen Dilution

A partially pooled hierarchical Bayesian model estimated the **critical N dilution curve** from multi-year trials, giving robust **Nitrogen Nutrition Index (NNI)** values even with heterogeneous, partially imbalanced data (Fig. 1).

From UAV spectra to NNI maps

NNI was linked to UAV multispectral data through six machine-learning models; **Gaussian Process Regression** performed best.

0.83 R^2 (GPR) · **0.10** RMSE (NNI) · **28** NNI maps at 0.04–0.09 m

Maps tracked within-season N dynamics, separated management regimes and revealed strong intra-field variability in N requirement.

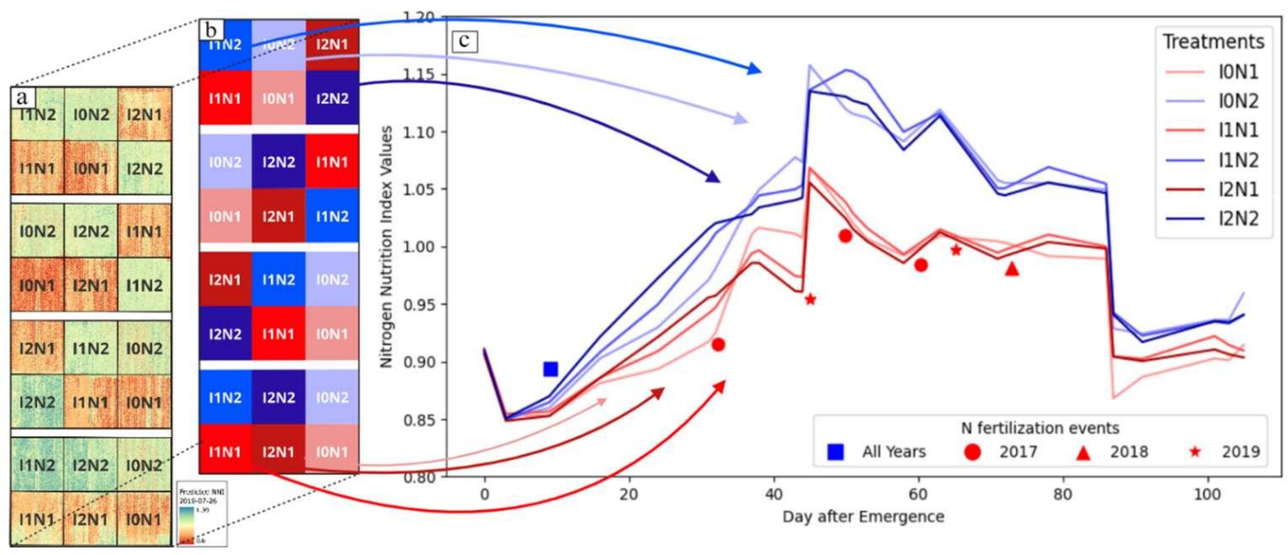


Fig. 2 – (a) UAV-predicted NNI map; (b) experimental treatments (I0–I2 × N1–N2); (c) within-season NNI dynamics per treatment with N fertilisation events.

3 Perennial Crops

Vineyards

- Multispectral and thermal imagery captured stable patterns of canopy vigour and temperature.
- Hyperspectral reflectance improved discrimination of grapevine varieties.
- UAV-LiDAR reconstructed canopy architecture; point density was strongly associated with canopy and leaf area.
- Pruning weight related to multispectral indices, especially before ripening, and was mapped by regression and ordinary kriging.

Olive groves

- Multispectral surveys detected vigour responses to pruning and supported tree-level analysis of canopy condition.

Importance of ground-truth data

In vertically shoot-positioned vineyards, contiguous **1-m canopy segments** outperformed vine-based sampling across linear, machine-learning and Bayesian models and reduced posterior uncertainty: accuracy depends on matching the sampling unit to the UAV canopy footprint.

0.78–0.84 R^2, 1-m segments · **≈0.26** RMSE, kg m^{-1}

4 Bayesian Vineyard Yield Mapping

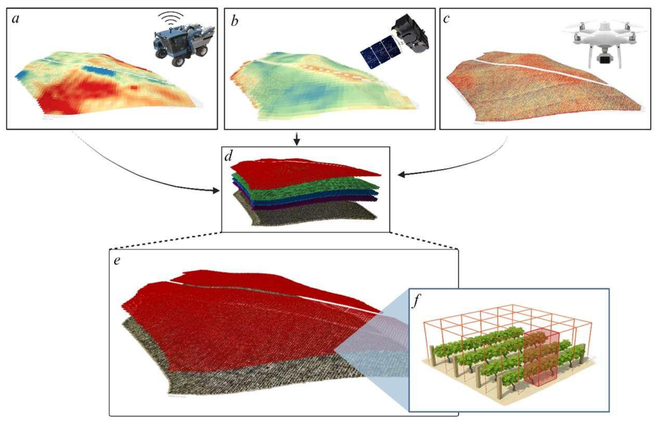


Fig. 3 – Harvester telemetry (a), Sentinel-2 (b) and UAV NDVI (c) stacked (d) and fused at vine level (e–f).

Multi-source hierarchical Bayesian model

A partially pooled model in **brms** fused UAV NDVI, Sentinel-2 NDVI and grape-harvester telemetry into high-resolution yield maps with explicit prediction uncertainty (Fig. 3).

0.83 R^2, training · **0.26** RMSE, kg $vine^{-1}$

0.78 R^2, independent validation · **–15%** yield in 2023 (drought, heat)

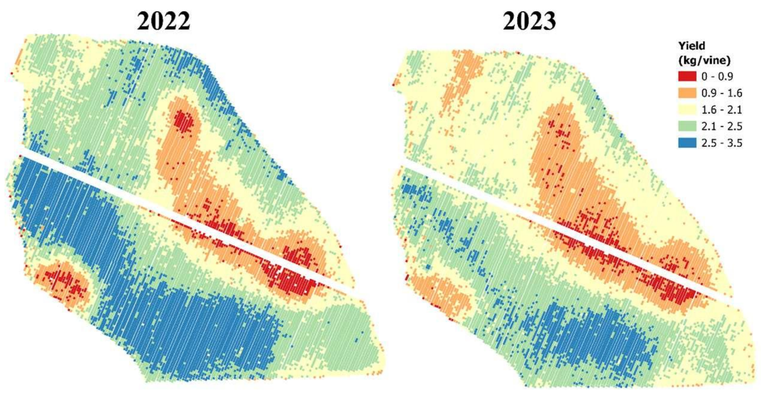


Fig. 4 – Predicted yield (kg $vine^{-1}$): ~15% decline in 2023, with stable spatial patterns linked to pedological variability.

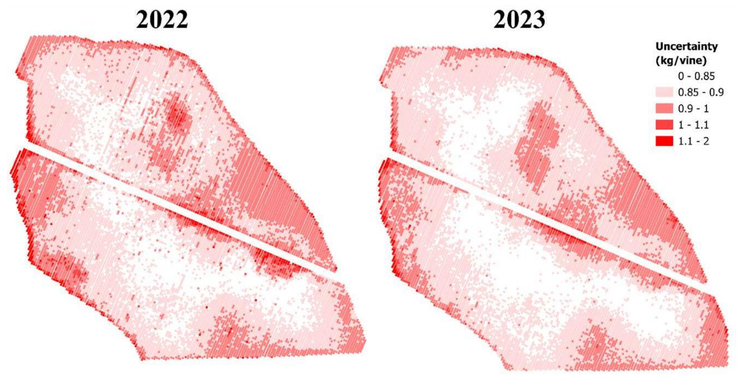


Fig. 5 – Prediction uncertainty rises near field boundaries and where predictors diverge, guiding targeted field inspections.

5 From Maps to Decisions

Drone products act as **decision layers**, not only diagnostic layers, informing fertilisation, pruning, irrigation and harvest.

- **Potato:** NNI and N-requirement estimates converted into prescription maps for variable-rate fertilisation.
- **Olive orchards:** GIS-based fertilisation driven by UAV multispectral imagery.

–24% / –33% N use of GIS-based strategies vs uniform fertilisation

6 Final Remarks

Conclusions and outlook

UAV sensing, machine learning and Bayesian modelling together provide a robust, scalable basis for spatially explicit, uncertainty-aware and operationally relevant precision agriculture. Next steps: standardised, automated preprocessing; multi-site validation across crops and environments; stronger multi-sensor fusion; user-friendly tools that embed recommendations and uncertainty into farm workflows.

Strength points

- **Innovation:** integrated UAV–ML–Bayesian framework for agricultural mechanisation.
- **Originality:** remote-sensing data turned into yield, N-status and variable-rate prescription maps.
- **Transfer:** practical support for fertilisation, irrigation, pruning and harvest.
- **Farmer benefits:** lower inputs, fewer losses, better timing and transparent decisions.