Identifying agroforestry assets from space using Google Earth Engine

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Background

- The stocks and flows of natural capital and many ecosystem services are dependent upon trees
  - Timber and carbon
  - Water quality
  - Crop and pasture productivity
  - Shade and shelter for livestock
  - Habitat
  - Amenity

- Australia's demand for wood will require an additional 400,000 hectares of new plantations by 2030
  - Pro-rated contribution of 50,000 – 100,000 hectares in Tasmania

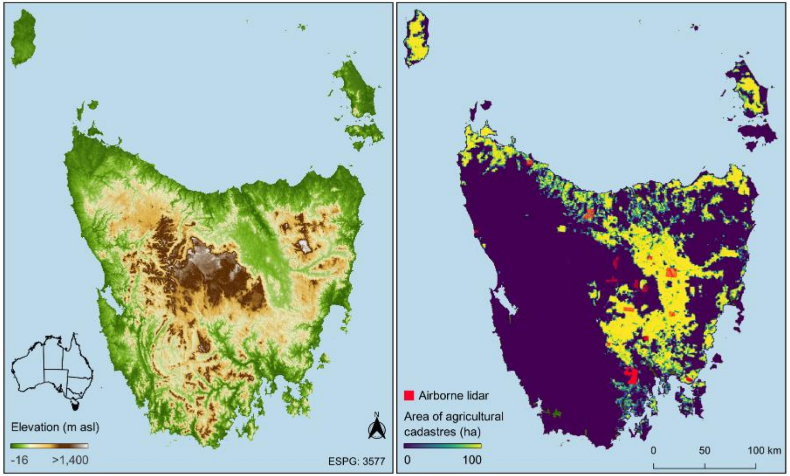
- Farm-forestry, or agroforestry, provides considerable opportunity for expansion (Monckton & Mendham 2022) with additional co-benefits

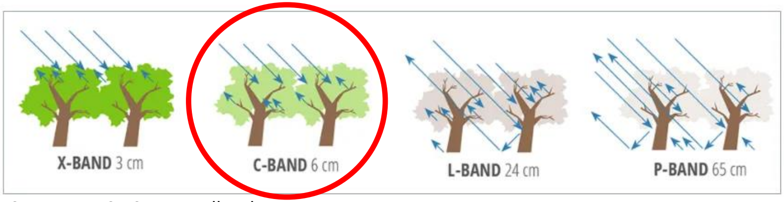
Background

- How can we measure and monitor agroforestry at scale?
- Is it possible to model fine scale features (e.g., shelterbelts, paddock trees) using publicly available (non-commercial) remote sensing data?
- How can radar backscatter contribute to model predictions?
- How does our approach compare against contemporary alternatives?

Methods

- Study site
  - Tasmania
- Dependent variables
  - Woody vegetation classification (> 10 % canopy cover, > 2 m height)
  - Canopy cover fraction (> 2 m height)
- Remote sensing data
  - Airborne lidar (> 500 km^2)
  - Sentinel 2 multispectral imagery
  - Sentinel 1 Synthetic Aperture Radar (C-band ~ 5.6 cm)





Source: NASA SAR Handbook

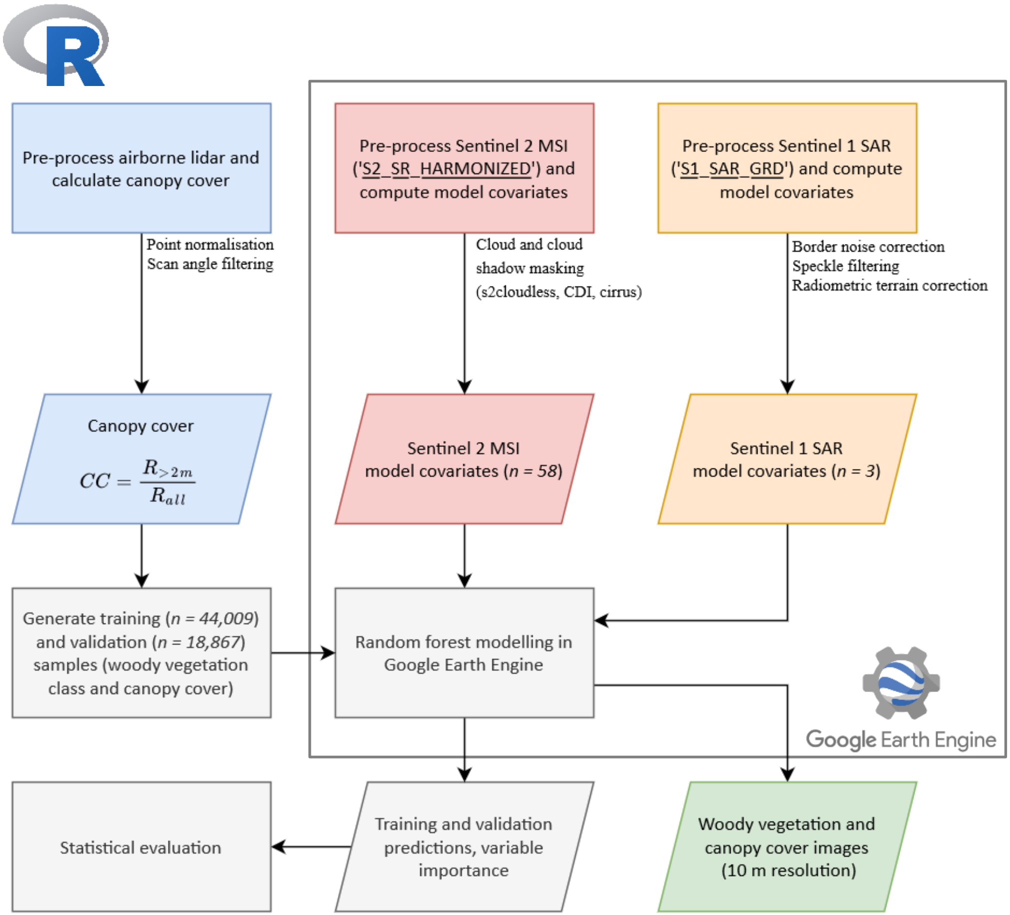
Methods

<u>Two models, one with and one without SAR:</u>

S2: Sentinel 2 MSI covariates only

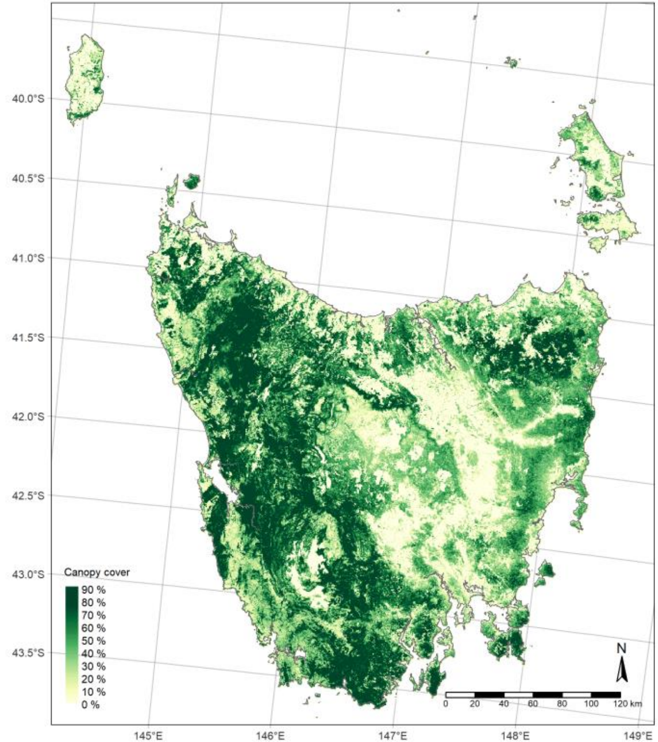
S1S2: Sentinel 1 SAR and Sentinel 2 MSI covariates

Output resolution: 10 m



Results

- Canopy cover (> 2 m height, 2019)
- Training (validation)



S1 and S2 best performance

Region	Model	R^2	CCC	RMSE	MAE	Bias	Mean
All points	S1S2 CC	0.92 (0.83)	0.96 (0.91)	0.09 (0.13)	0.05 (0.08)	0.00 (0.00)	0.27 (0.27)
n = 44,009 (18,867)	S2 CC	0.91 (0.81)	0.95 (0.90)	0.09 (0.13)	0.06 (0.09)	0.00 (0.00)	0.27 (0.27)

Results

- Woody vegetation binary classification (10 % cover at > 2 m height)
- Training (validation)

Direct classification provides well-balanced prediction

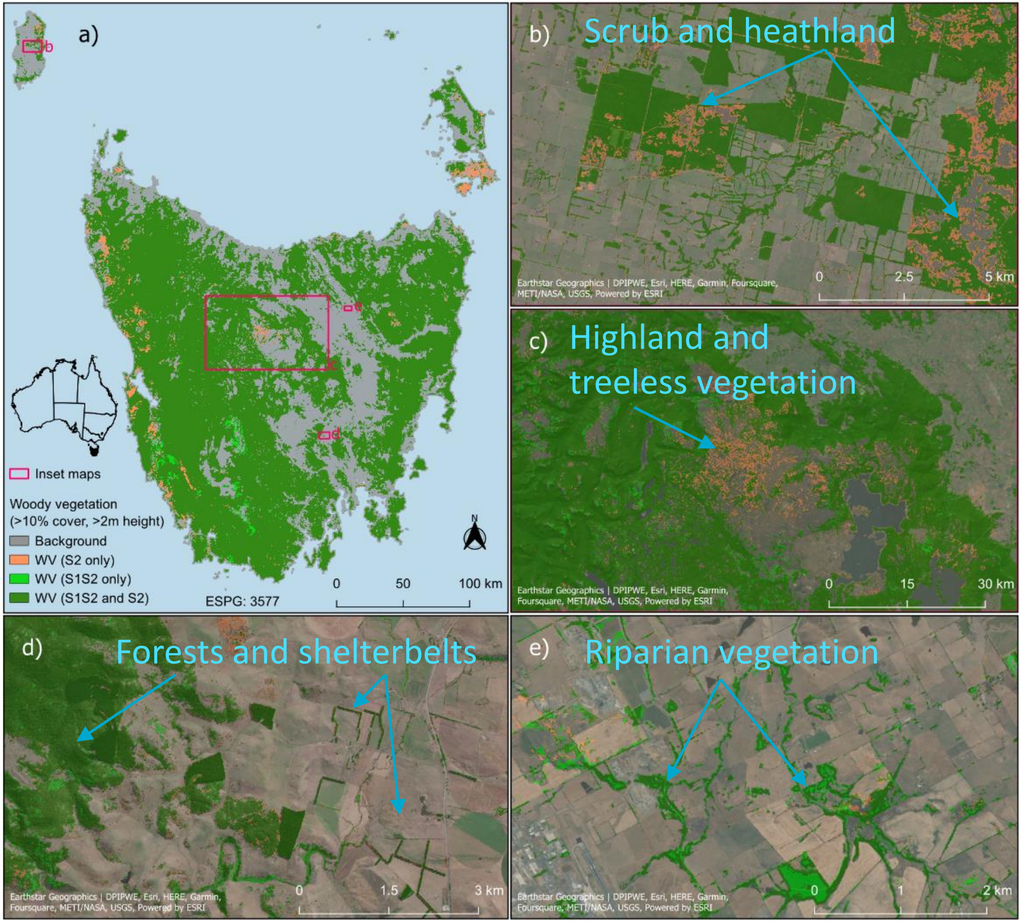
S1 and S2 best performance

Region	Model	Overall accuracy	Kappa	Sensitivity	Specificity	Precision	Prevalence
All points	S1S2 WV10	0.97 (0.94)	0.93 (0.87)	0.97 (0.94)	0.97 (0.94)	0.97 (0.94)	0.50 (0.50)
n = 44,009 (18,867)	S2 WV10	0.96 (0.93)	0.93 (0.86)	0.96 (0.93)	0.97 (0.93)	0.97 (0.93)	0.50 (0.50)
	S1S2 CC T10	0.95 (0.93)	0.90 (0.86)	0.99 (0.97)	0.91 (0.89)	0.92 (0.90)	0.50 (0.50)
	S2 CC T10	0.94 (0.91)	0.88 (0.83)	0.99 (0.97)	0.89 (0.86)	0.90 (0.87)	0.50 (0.50)

Thresholding CC less performant, less well-balanced (tends to overpredict)

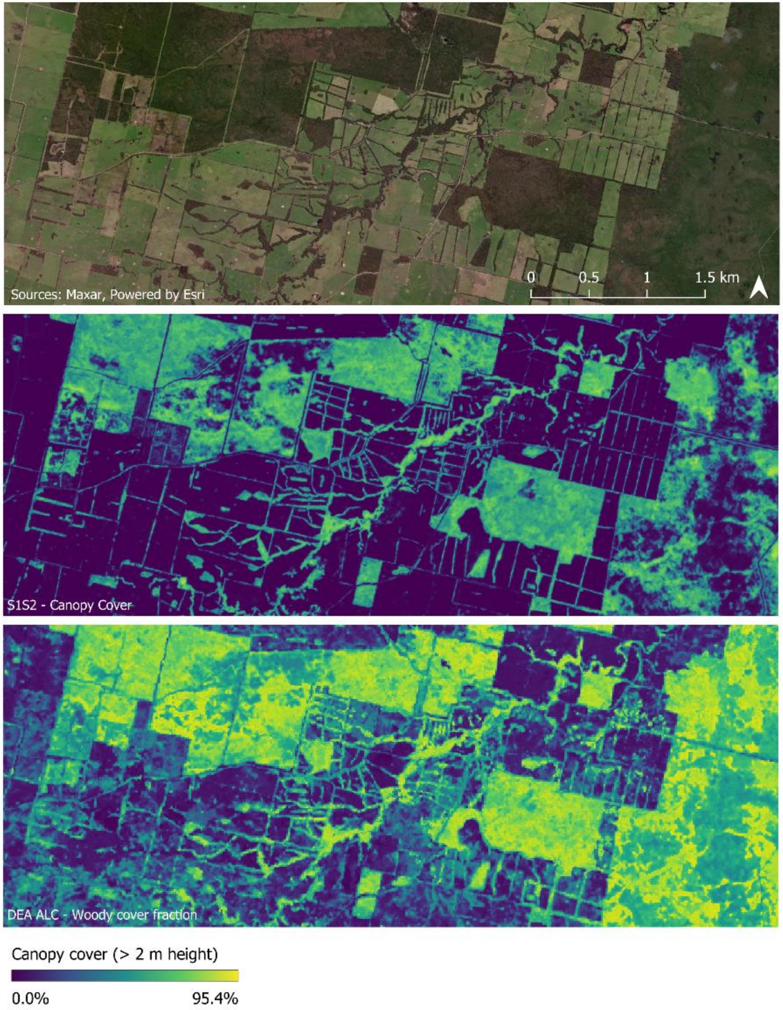
Results

- SAR predictions lower in ecosystems with less woody cover (b, c)
- SAR predicts increased woody cover in riparian vegetation (e)



Results

- S1S2 vs DEA ALC (Landsat) on King Island, 2019
- S1S2 provides sharper image, shows lower woody cover in paddocks, scrubs and heathlands



Results

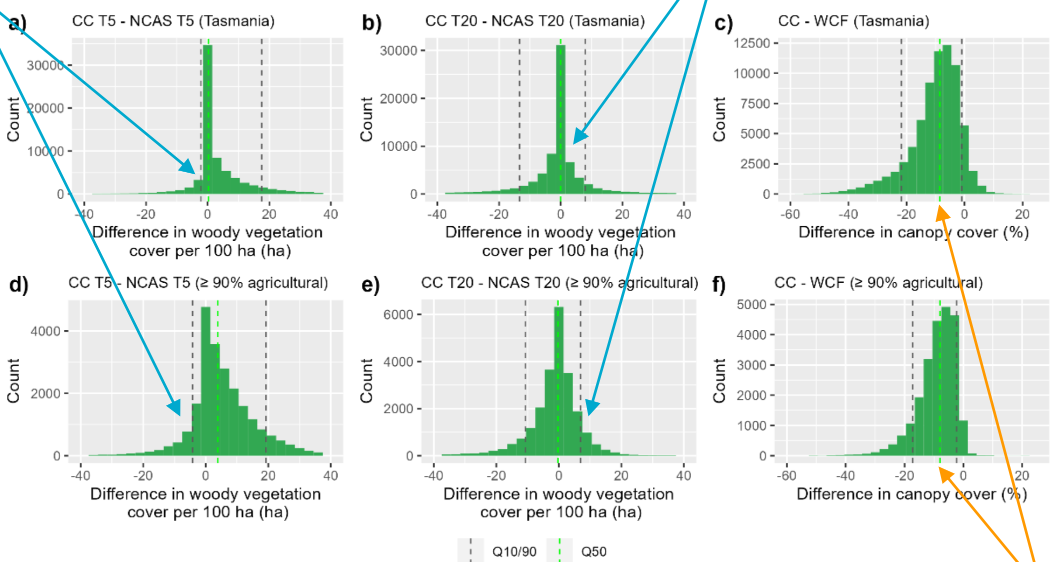
- S1S2 vs NCAS (Landsat) on King Island, 2019

- S1S2 provides sharper image, better delineates shelterbelts and shows lower woody cover in scrubs and heathlands

Results

S1S2 predicts more woody vegetation than NCAS at 5% threshold (sparse or greater), particularly in agricultural areas

S1S2 unbiased in comparison to NCAS at 20% thresholds for Tasmania (97% of area) and agricultural areas (96% of area)



DEA ALC woody cover fraction consistently overpredicts in comparison to S1S2

Discussion and conclusion

- Woody vegetation modelling can be improved using publicly available, non-commercial data from multiple sensors
- Addition of SAR only shows a small statistical improvement, but analysis of S1S2/S2 differences demonstrate spatial clustering associated with different ecosystem types
- Important to align sensor data with seasonal phenology
    - Unbiased compared to NCAS @ 20% (also centred on late summer)
    - Large deviations (20%+) from DEA ALC WCF
- Sentinel improves detection of assets at farm scale, but finer resolutions would also be useful (CSIRO-ANU-NASA collaboration using Planet imagery, airborne lidar)
- Potential next steps include regional statistics, morphological analyses to infer function (e.g., shelterbelts, block plantations, riparian vegetation)

Thank you

Environment
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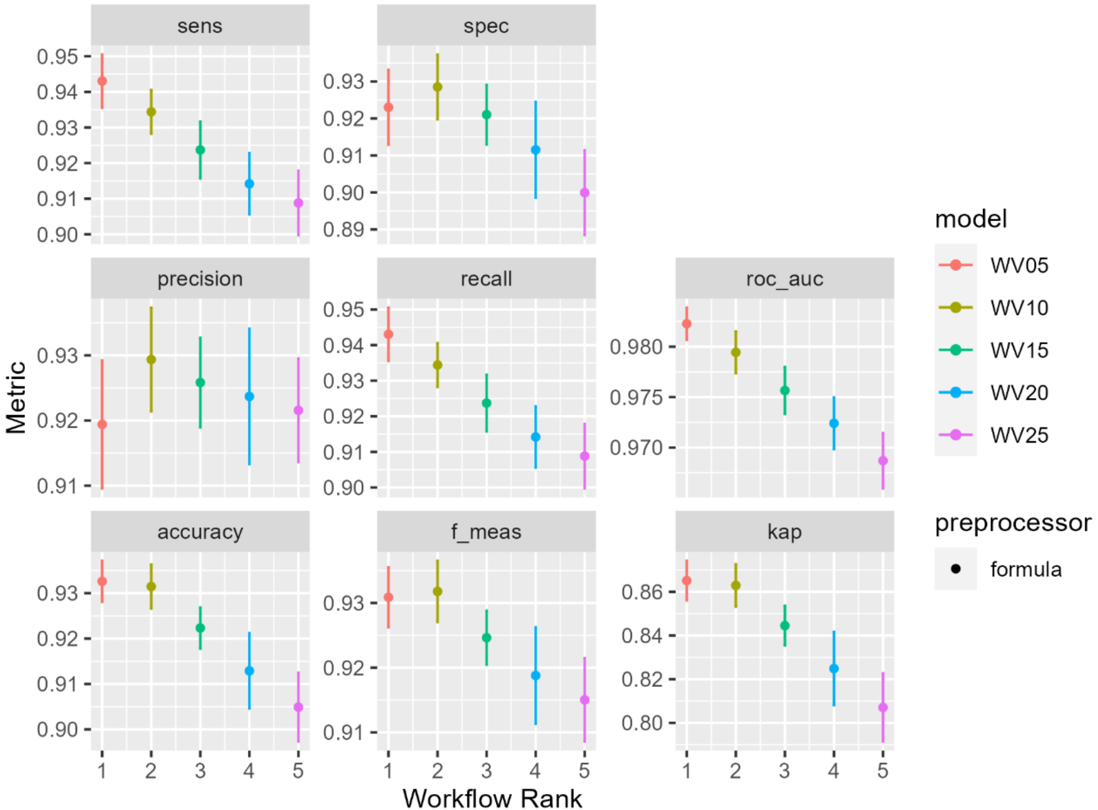
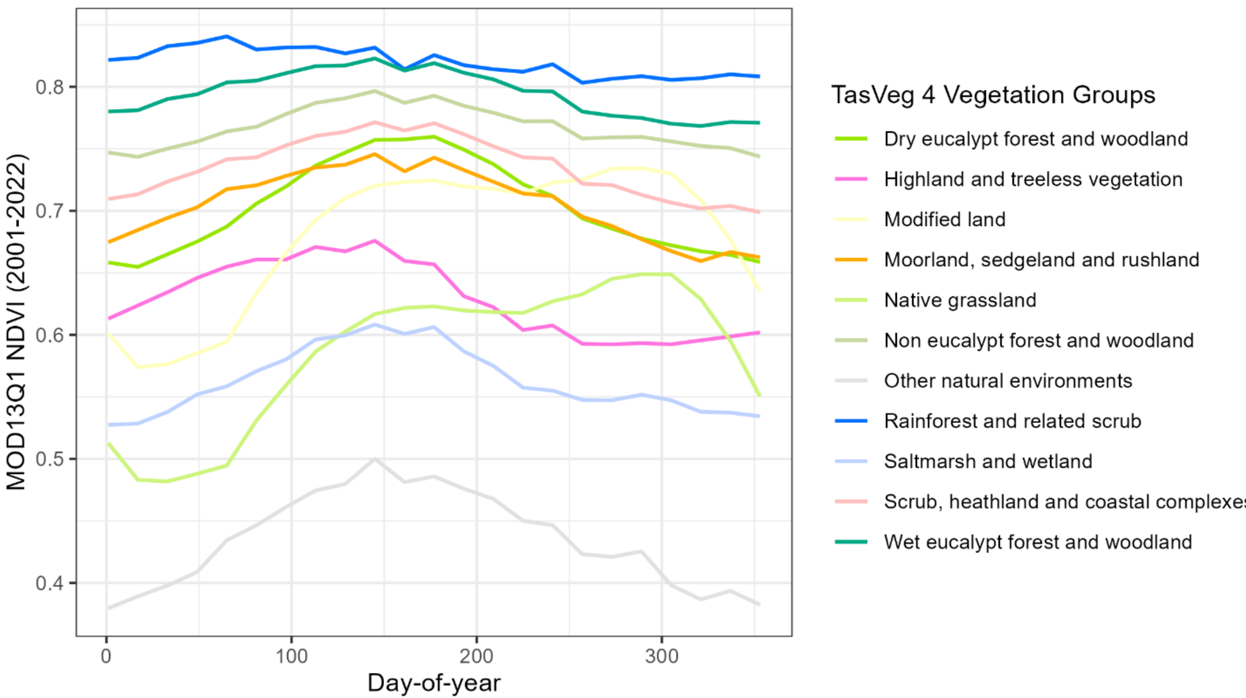
Methods


sens
spec
precision
recall
roc_auc
accuracy
f_meas
kap
Metric
Workflow Rank
model
WV05
WV10
WV15
WV20
WV25
preprocessor
formula

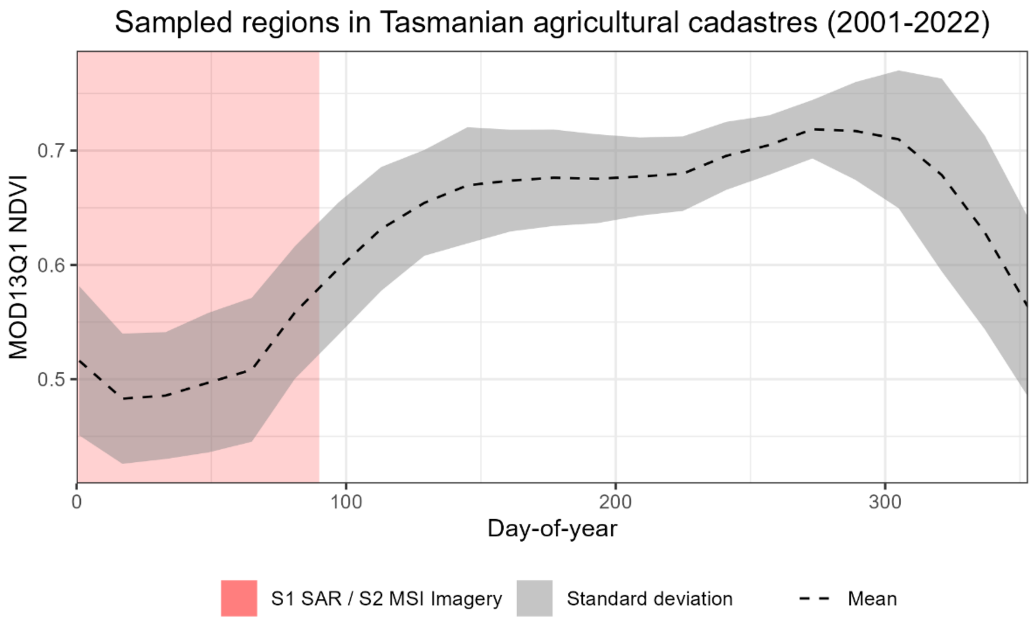
Methods



MOD13Q1 NDVI (2001-2022)
0.8
0.7
0.6
0.5
0.4
0
100
200
300
Day-of-year
TasVeg 4 Vegetation Groups
Dry eucalypt forest and woodland
Highland and treeless vegetation
Modified land
Moorland, sedgeland and rushland
Native grassland
Non eucalypt forest and woodland
Other natural environments
Rainforest and related scrub
Saltmarsh and wetland
Scrub, heathland and coastal complexes
Wet eucalypt forest and woodland

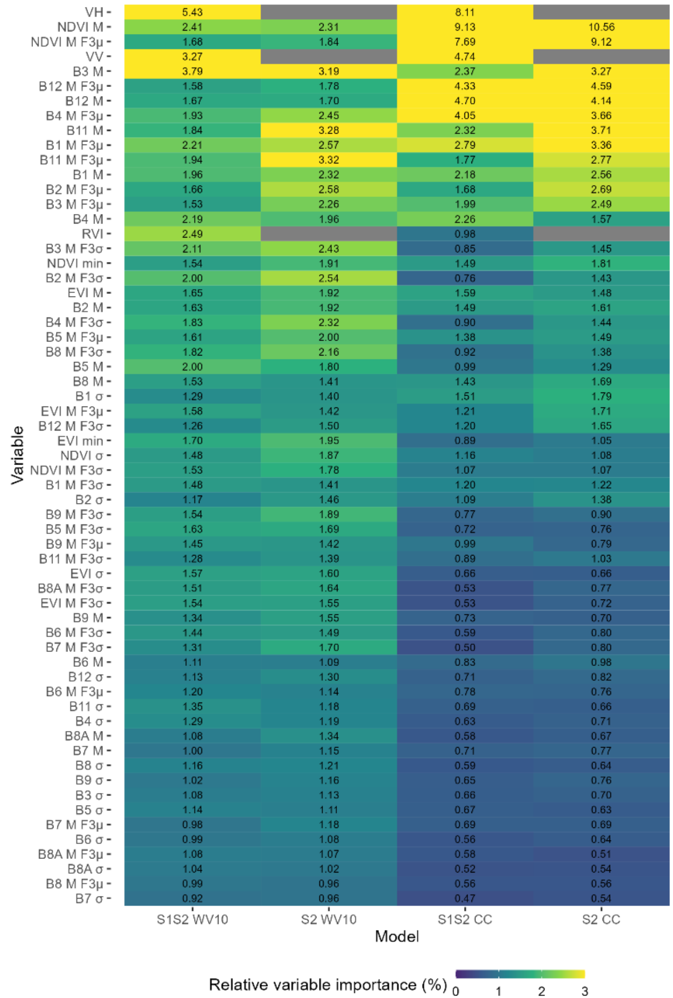
Methods

- Lidar acquisitions 01/Jan/2019 to 20/Apr/2019
- Imagery aligned to late summer period, enhances separability of vegetation types

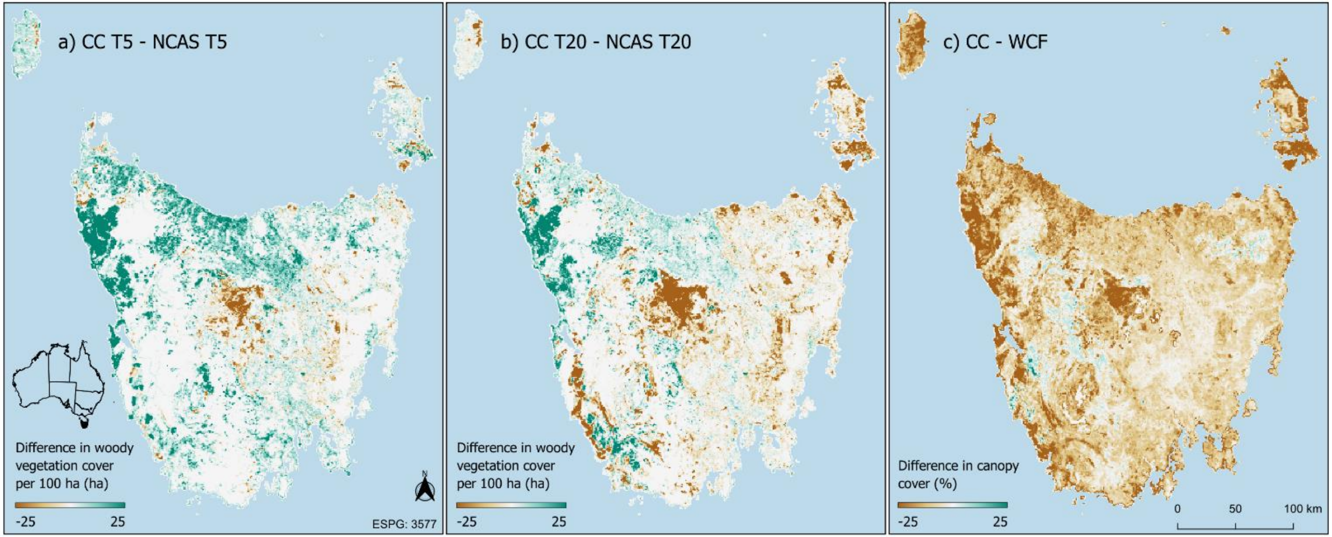


Results

- Radar backscatter (VV/VH), NDVI, green (B3), red (B4) and SWIR (B11/B12) consistently among most important variables
- Texture metrics (i.e., moving window averages) improved model, particularly for CC



Results



a) CC T5 - NCAS T5
Difference in woody vegetation cover per 100 ha (ha)
-25
25
ESPG: 3577
b) CC T20 - NCAS T20
Difference in woody vegetation cover per 100 ha (ha)
-25
25
c) CC - WCF
Difference in canopy cover (%)
-25
25
0
50
100 km

Results

- S1S2 predicts lower canopy cover in vegetation groups where fewer trees are expected*