# 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
- <u>Dependent variables</u>
  - Woody vegetation classification (> 10 % canopy cover, > 2 m height)
  - Canopy cover fraction (> 2 m height)



- <u>Remote sensing data</u>
  - Airborne lidar (> 500 km<sup>2</sup>)
  - Sentinel 2 multispectral imagery
  - Sentinel 1 Synthetic Aperture Radar (C-band ~ 5.6 cm)





### Methods

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

**S2:** Sentinel 2 MSI covariates only

**\$1\$2:** Sentinel 1 SAR and Sentinel 2 MSI covariates

Output resolution: 10 m





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



#### S1 and S2 best performance

Region	Model	R <sup>2</sup>	ссс	RMSE	MAE	Bias	Mean
All points	\$1\$2 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)



• Woody vegetation binary classification (10 % cover at > 2 m height)

S1 and S2 best performance

• Training (validation)

Direct classification provides well-balanced prediction

Region	Model 🚽	Overall accuracy	Карра	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)



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





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



Canopy cover (> 2 m height)



- S1S2 vs NCAS (Landsat) on King Island, 2019
- S1S2 provides sharper image, better delineates shelterbelts and shows lower woody cover in scrubs and heathlands



5-19% cover ≥ 20% cover

≤ 5% cover
≥ 10% cover



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, noncommercial 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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#### 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



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



Sampled regions in Tasmanian agricultural cadastres (2001-2022)



- 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

VH-	5.43		8.11	
NDVLM -	2.41	2.31	9.13	10.56
NDVLM E2::	4.69	1.01	7.60	0.12
NDVIME3µ=	1.00	1.04	7.69	9.12
- VV	3.27		4.74	
B3 M -	3,79	3.19	2.37	3.27
P12 M E20 -	1.59	1 79	4.22	4.60
BIZ WF3µ-	1.50	1.70	4,33	4.35
B12 M -	1.67	1.70	4.70	4.14
B4 M F3u -	1.93	2.45	4.05	3.66
B11 M -	1.84	3.28	2 32	3.71
D4 M FOU	0.01	0.57	0.70	0.00
B1MF3µ-	2.21	2.57	2.79	3.30
B11 M F3µ -	1.94	3.32	1.77	2.77
B1 M -	1.96	2.32	2.18	2.56
P2 M E20 -	1.66	2.58	1.68	2.69
D2 MT 5µ	1.00	2.00	1.00	2.00
B3 M F3H -	1.53	2.26	1.99	2.49
B4 M -	2.19	1.96	2.26	1.57
RVI-	2.49		0.98	
P2 M E2 a -	0.44	2.42	0.95	1.45
D3 M F 30 -	2.11	2.40	0.00	1.45
NDVI min -	1.54	1.91	1.49	1.81
B2 M F3σ -	2.00	2.54	0.76	1.43
EVIM-	1.65	1.92	1.59	1.48
DO M	4.00	4.00	1.40	1.01
B2 M -	1.63	1.92	1.49	1.61
B4 M F3σ -	1.83	2.32	0.90	1.44
B5 M F3u -	1.61	2.00	1.38	1.49
B8 M E3g =	1.82	2.16	0.92	1.38
DOMITOO	0.00	2.10	0.02	1.00
B2 M-	2.00	1.80	0.99	1.29
B8 M -	1.53	1.41	1.43	1.69
B1σ-	1.29	1.40	1.51	1.79
EV/LM E20 -	1.59	1.42	4.94	4.74
EVINFSH-	1.00	1.42	1.21	1.7.1
B12 M F3σ -	1.26	1.50	1.20	1.65
G EVI min -	1.70	1.95	0.89	1.05
NDVIG-	1.48	1.87	1.16	1.08
NDVI ME20-	4.69	1 79	1.07	1.07
S NDVIM F30 -	1.55	1.70	1.07	1.07
B1MF30-	1.48	1.41	1.20	1.22
B2 σ -	1.17	1.46	1.09	1.38
B9 M E3σ =	1.54	1.89	0.77	0.90
B5 M E3 a =	1.63	1.69	0.72	0.76
D0 M T 30 -	1.00	1.00	0.72	0.70
Ba W F3h -	1.45	1.42	0.99	0.79
B11 M F3σ -	1.28	1.39	0.89	1.03
EVI or -	1.57	1.60	0.66	0.66
DOA ME20-	4.64	4 64	0.52	0.77
DOA INT SO	1.01	1.04	0.00	0.71
EVIM F30 -	1.54	1.55	0.53	0.72
B9 M -	1.34	1.55	0.73	0.70
B6 M E3σ -	1.44	1.49	0.59	0.80
P7 M E2 a -	4.24	4.70	0.50	0.90
B7 M F30 -	1.31	1.70	0.50	0.60
B0 M -	1.11	1.09	0.83	0.98
B12 σ -	1.13	1.30	0.71	0.82
B6 M F3u -	1.20	1.14	0.78	0.76
B11 g =	1.95	1.18	0.60	0.66
DITO	1.55	1.10	0.03	0.00
Β4 σ -	1.29	1.19	0.63	0.71
B8A M -	1.08	1.34	0.58	0.67
B7 M -	1.00	1.15	0.71	0.77
P9 g -	1.10	4.94	0.50	0.64
000	1.10	1.21	0.55	0.04
Ba Q -	1.02	1.16	0.65	0.76
B3 σ -	1.08	1.13	0.66	0.70
B5 σ -	1.14	1.11	0.67	0.63
P7 M E2	0.08	1.19	0.69	0.69
Brivirou-	0.90	1.18	0.09	0.09
Β6 σ =	0.99	1.08	0.56	0.64
B8A M F3u -	1.08	1.07	0.58	0.51
B8A -	1.04	1.02	0.52	0.54
D8 M E2	0.00	0.06	0.56	0.56
DO IVI FOH	0.99	0.90	0.00	0.50
Β7 σ -	0.92	0.96	0.47	0.54
	S162 W0/10	S2 W///10	8182.00	82.00
	5152 WV10	52 WV IU	5152 00	52 00
		Mo	del	







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

