

STREAM 2- BDC - F

FUEL DATA ON A NATIONAL SCALE

Improving remote sensing fuel data on a national scale

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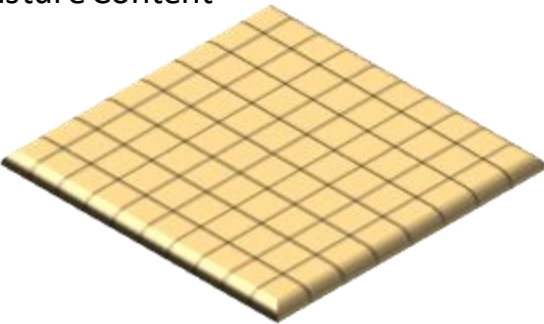
04

Key Takeaway

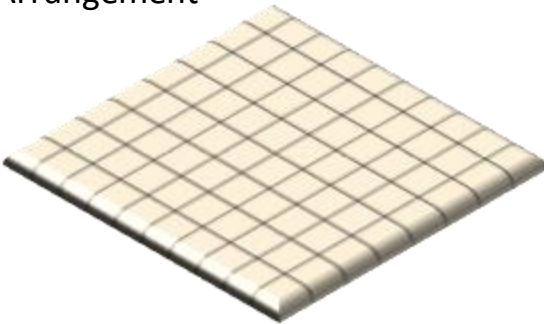


List of the primary fuel attributes

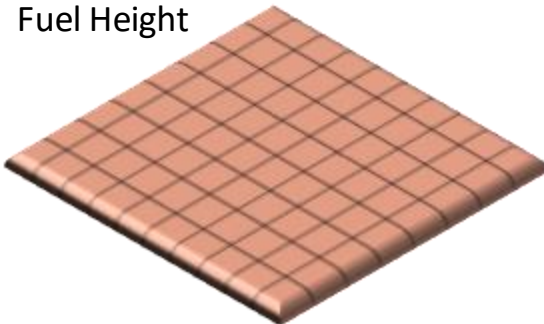
Fuel Moisture Content



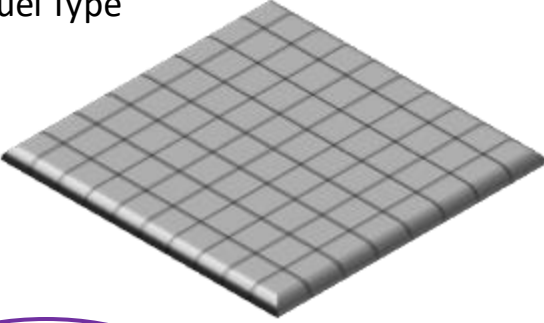
Fuel Arrangement



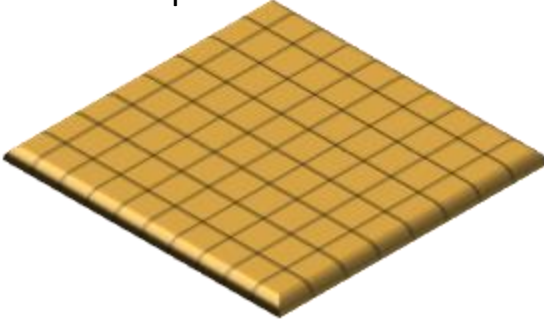
Fuel Height



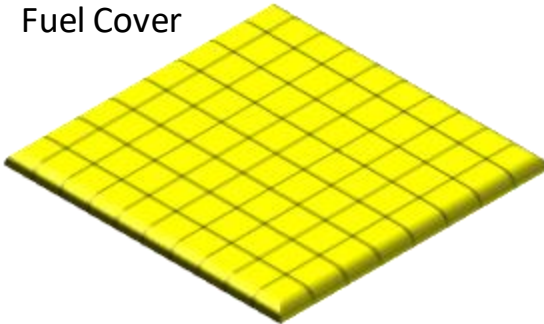
Fuel Type



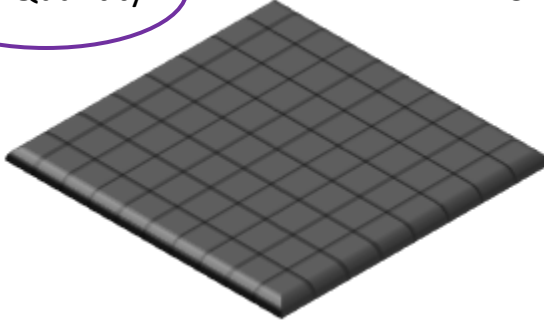
Fuel Size and Shape



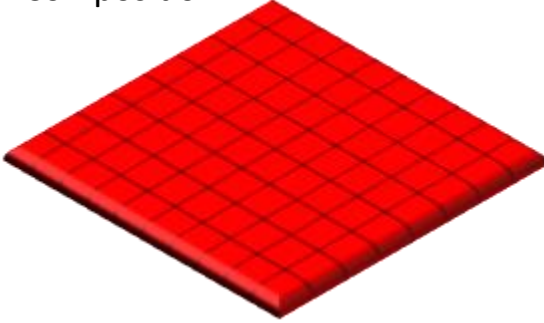
Fuel Cover



Fuel Quantity



Chemical Composition



Creating aggregated and harmonized fuels datasets over Australia



Study objectives

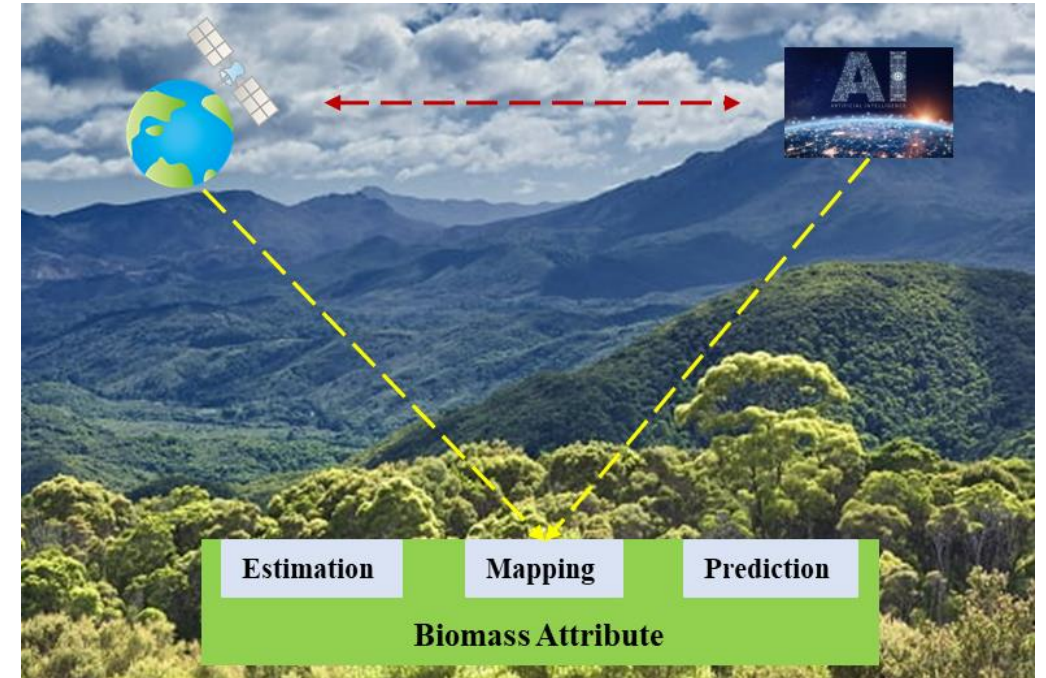
Above Ground Biomass (AGB): The total mass of living or organic material present in the above ground portions of plants and vegetation, including stems, branches, leaves, etc.

- 1 Investigate the combined use of high-resolution satellite missions like Sentinels and GEDI data to create a comprehensive AGB map within a designated study region.
- 2 Explore the capabilities of machine learning models for AGB estimation.



Why accurate biomass estimation?

- ✓ Forest biomass holds critical importance for both carbon sequestration, aiding in mitigating climate change effects, and assessing fuel availability for forest fires.
- ✓ Studying AGB helps gauge the potential impact of wildfires and environmental degradation on climate change, aiding in devising strategies for mitigation and preservation.
- ✓ Assist firefighters in decision-making for prescribed burns and fire spread assessment.



Overall Workflow

Specific tasks...

1. **Machine Learning Model Development:** Experiment with different architectures, hyperparameters, and techniques to find the best configuration and calibrate the model for AGB estimation.
2. **Fuel Type Analysis:** Test the ML model performance across various fuel types.
3. **Integration of Multiple Datasets/factors:** Explore incorporating additional data sources (e.g., optical, SAR, vegetation indices, topographic/textural factors) for accuracy enhancement.



Overall Methodology

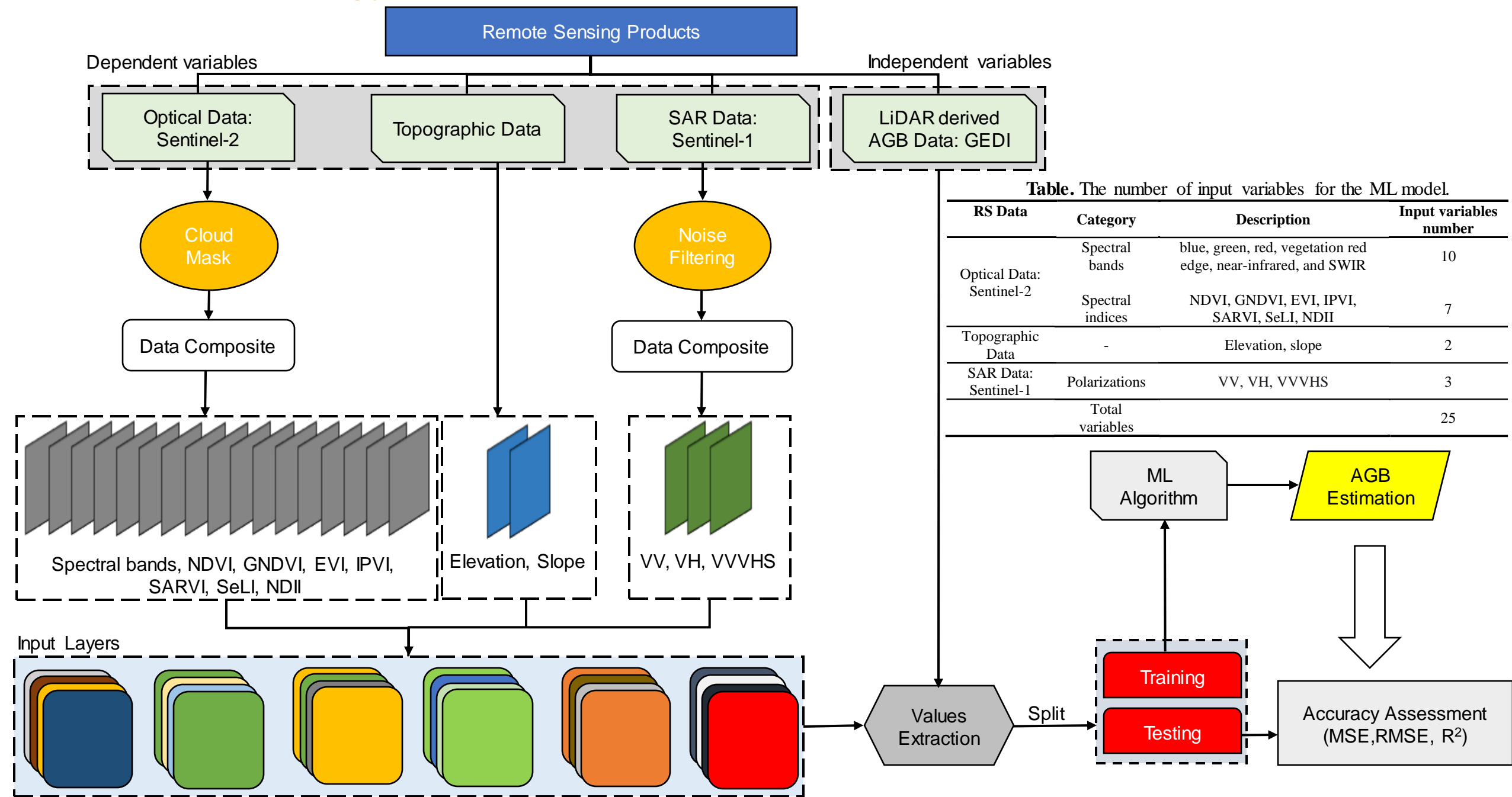
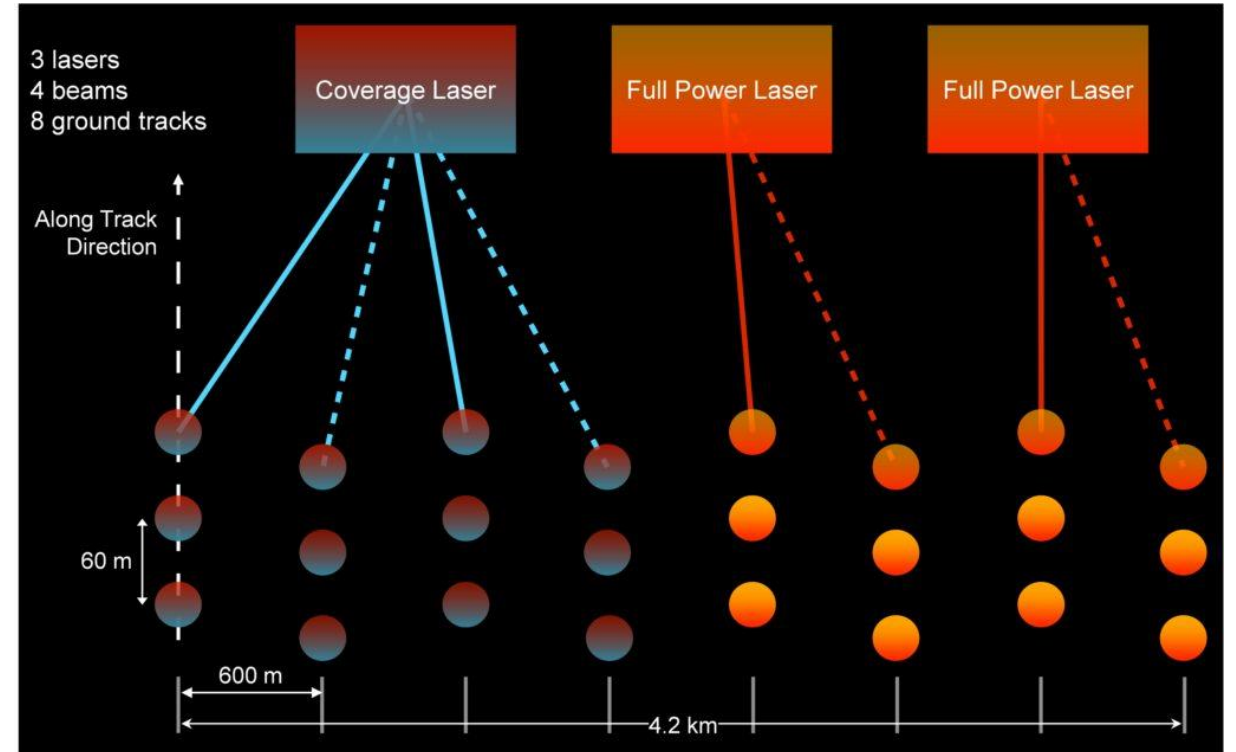
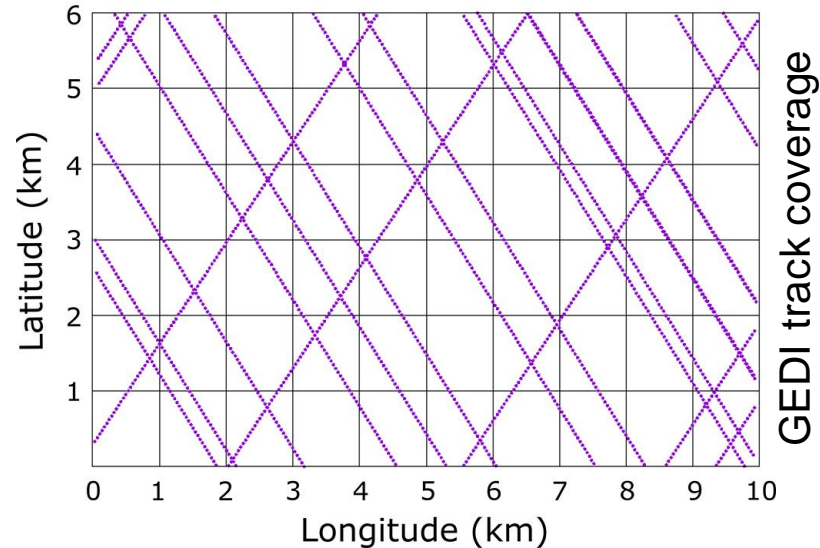


Table. The number of input variables for the ML model.

RS Data	Category	Description	Input variables number
Optical Data: Sentinel-2	Spectral bands	blue, green, red, vegetation red edge, near-infrared, and SWIR	10
	Spectral indices	NDVI, GNDVI, EVI, IPVI, SARVI, SeLI, NDII	7
Topographic Data	-	Elevation, slope	2
SAR Data: Sentinel-1	Polarizations	VV, VH, VVHS	3
Total variables			25

GEDI Data

- ✓ GEDI produces the first high resolution laser ranging observations of the 3D structure of the Earth.
- ✓ GEDI makes precise measurements of forest canopy height, canopy vertical structure, and surface elevation.

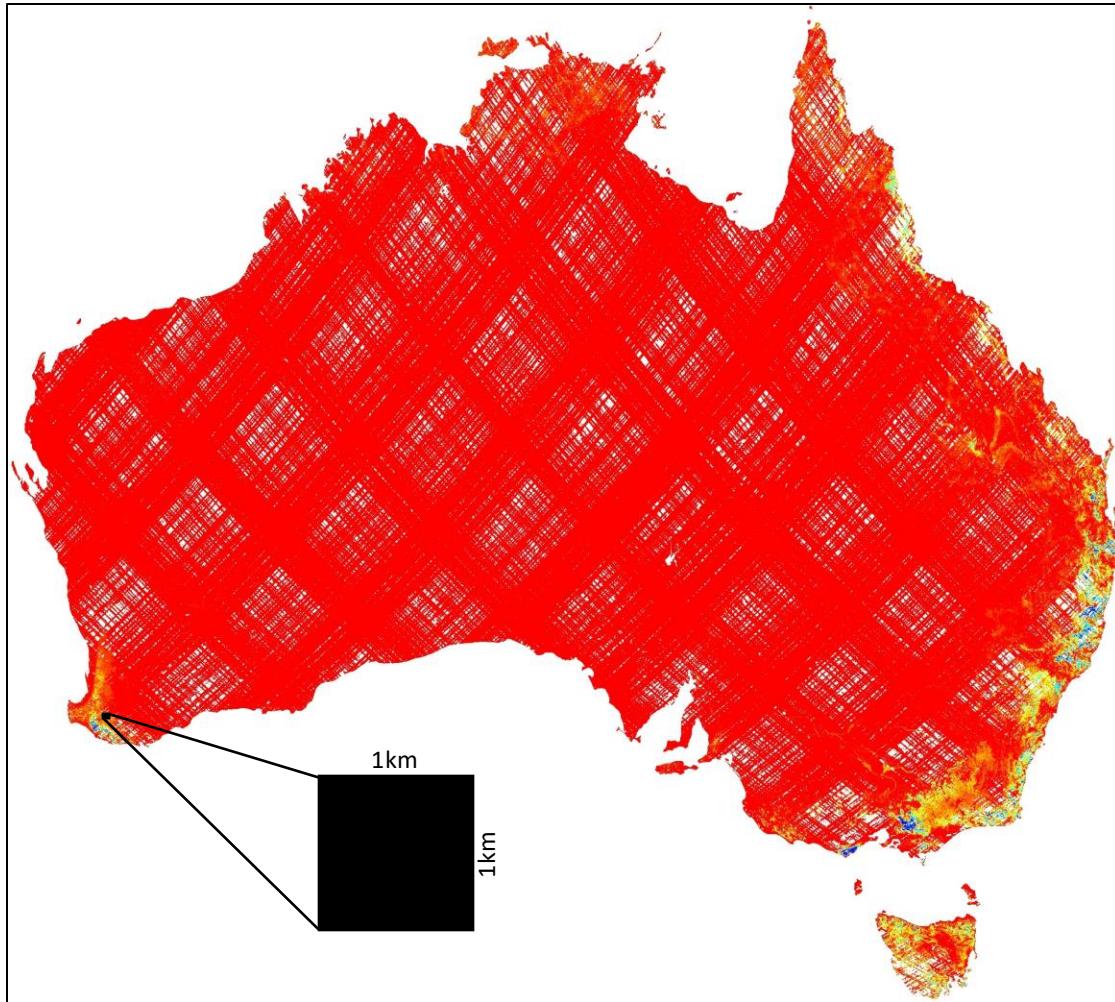


GEDI'S ground sampling pattern (source: gedi.umd.edu)

GEDI Products for Biomass Estimation

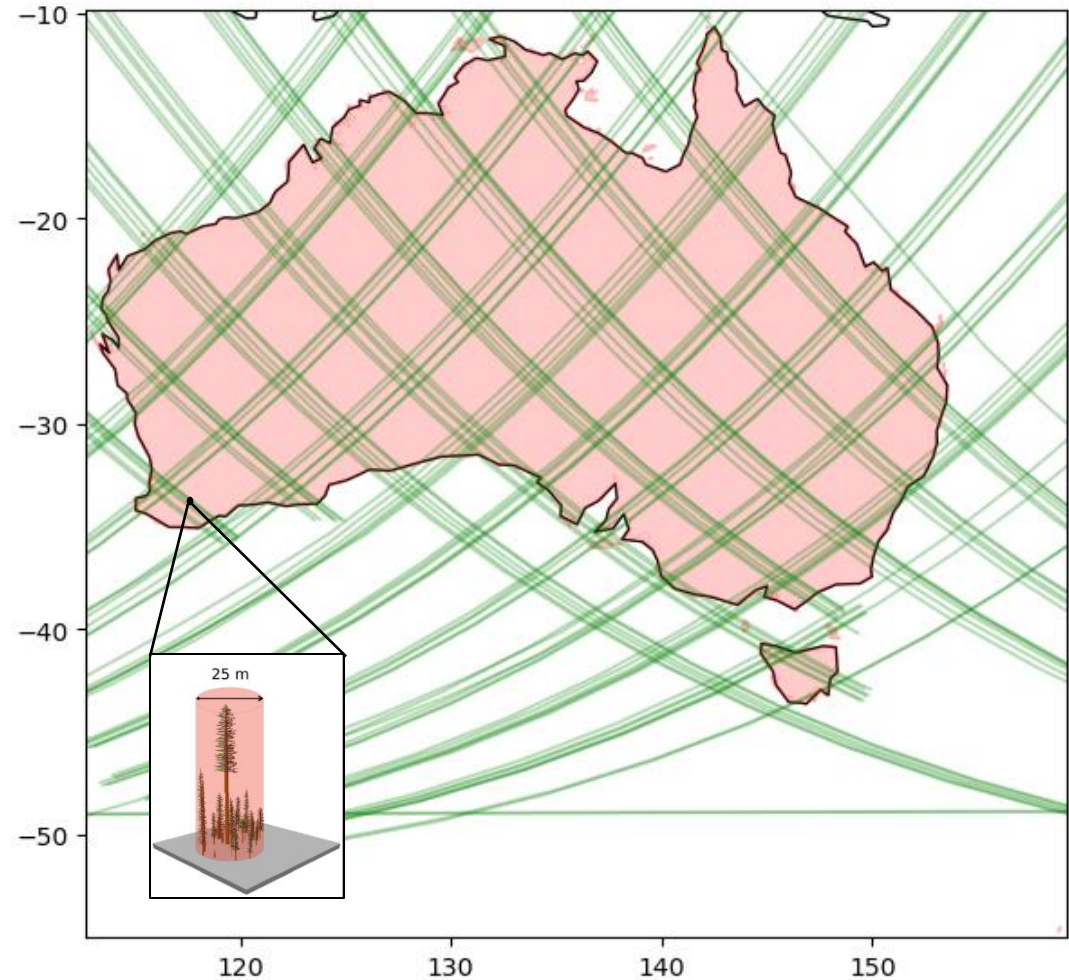
GEDI04_B

- 1x1 km estimates of mean aboveground biomass (AGB) for 2019-04-18 to 2021-08-04.
- Footprint biomass product converts each high-quality waveform to an AGB prediction.

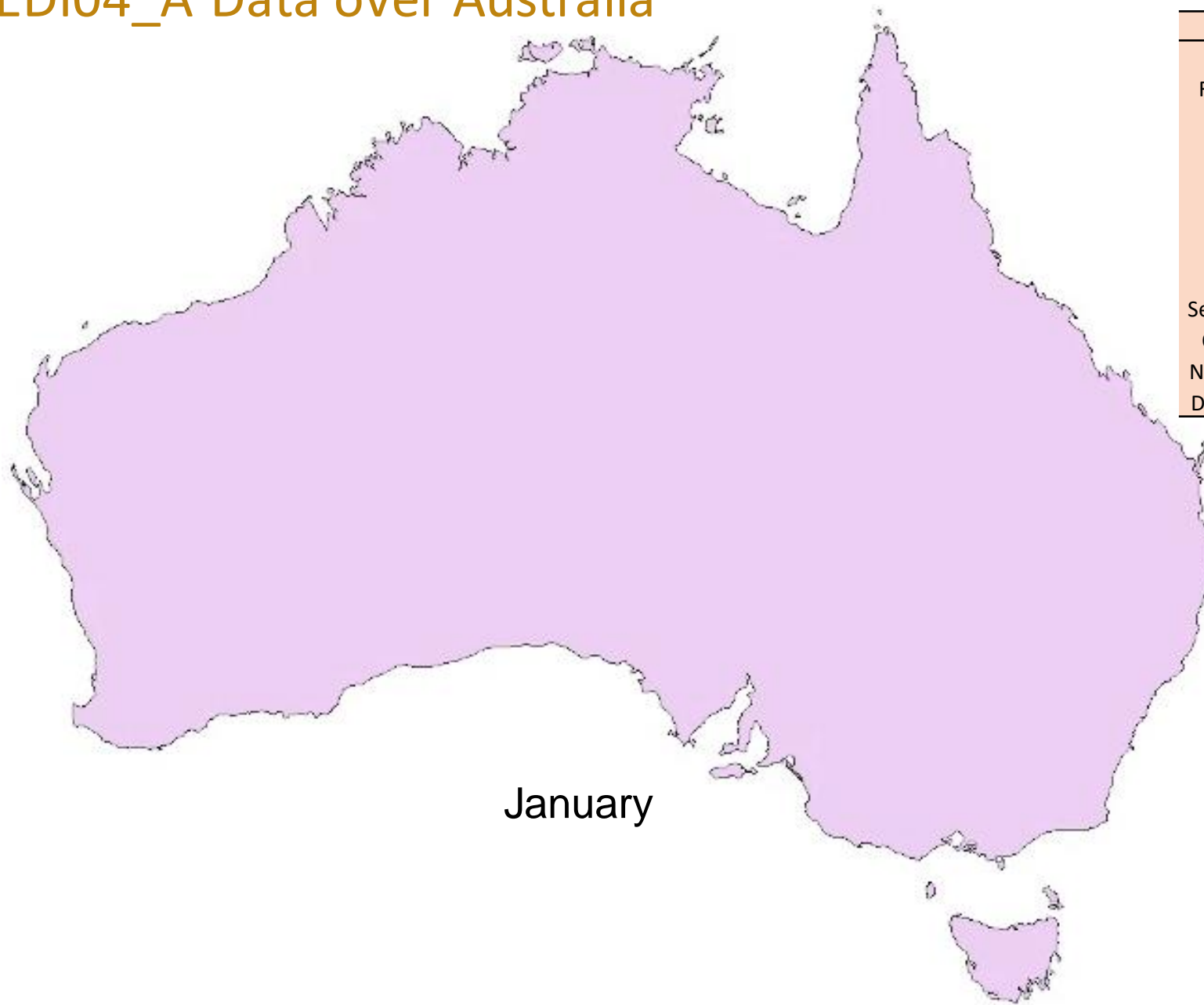


GEDI04_A

- GEDI instrument includes three lasers generating eight beam ground transects, swiftly sampling eight ~25 m footprints.
- The footprints are reported for the period 2019-04-18 to 2023-03-16.



GEDI04_A Data over Australia

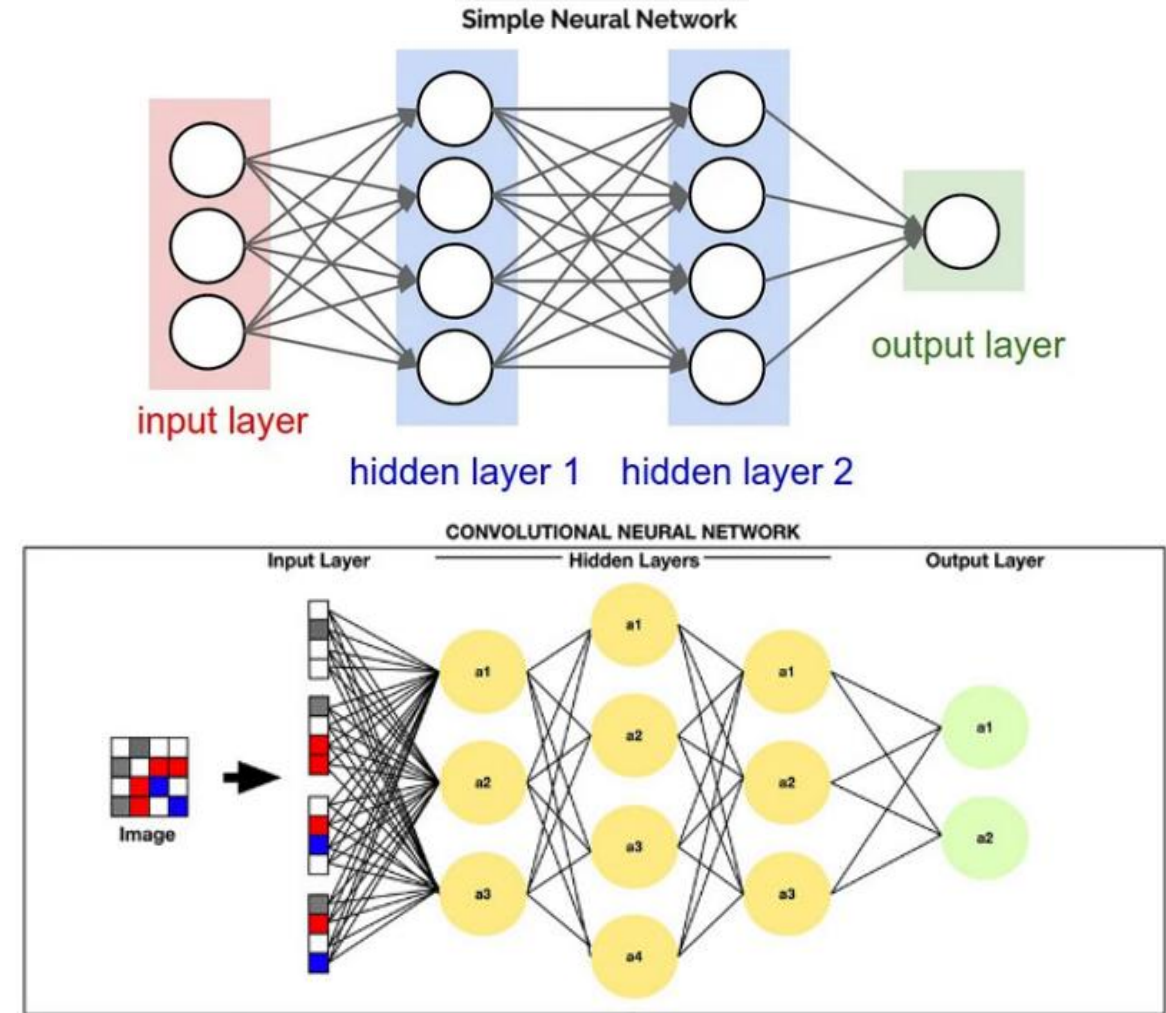
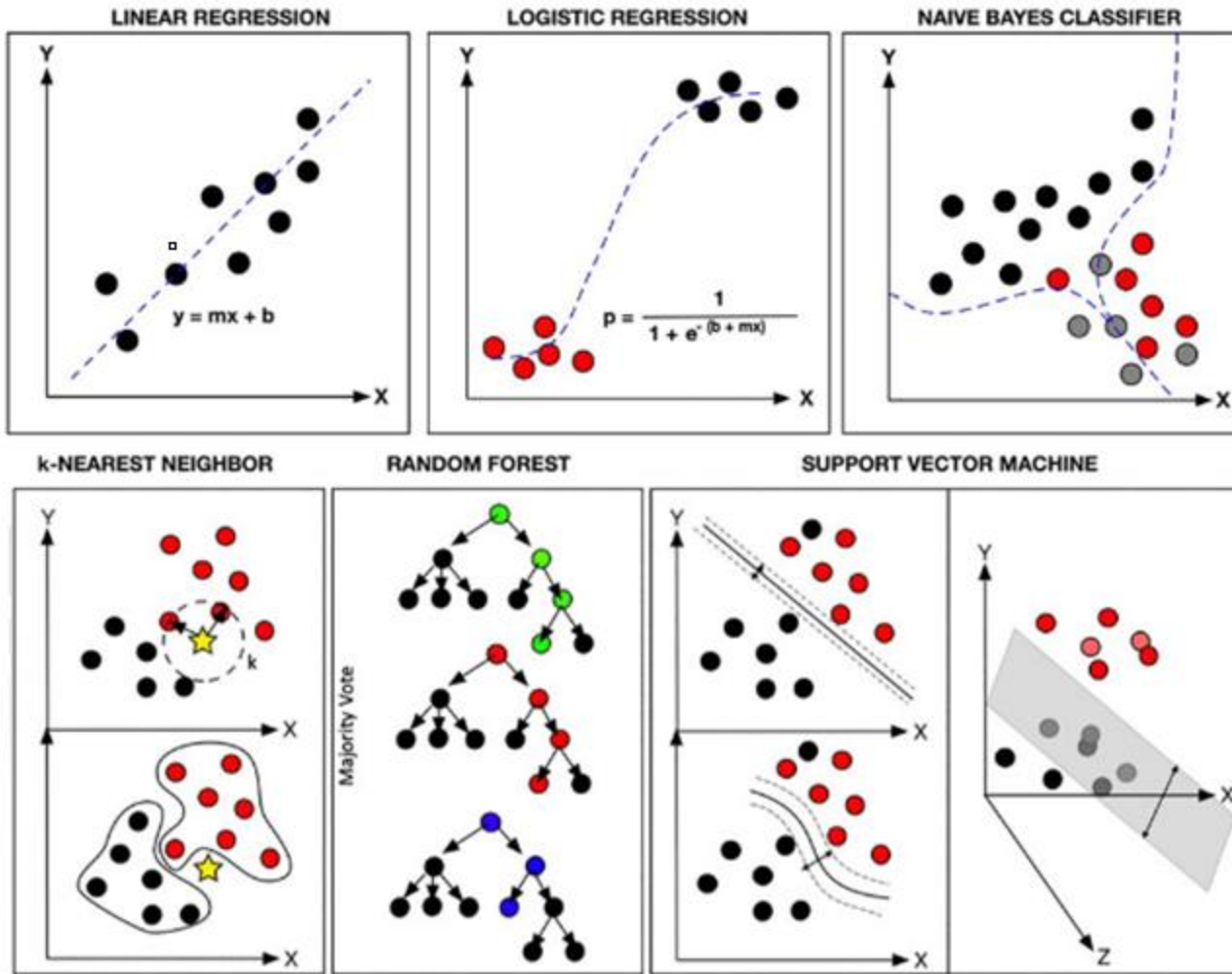


Month	Footprint count	Total granules	Total file size (MB)
January	16186933	108	21806.71075
February	19779400	114	23022.17555
March	23150448	132	25938.51268
April	18766683	118	24879.6168
May	23846991	127	26081.75762
June	29709457	134	29195.61914
July	21271236	146	31203.14102
August	27581806	132	26855.2611
September	26545103	127	25761.76923
October	25147568	130	26005.93536
November	25802644	122	25060.87306
December	21864817	132	26235.30639

Month	Min	Max	Mean	SD
January	0.000007	3731.559	13.20701	66.71496
February	0.000922	6818.86	12.83959	65.98681
March	0.000005	6561.343	12.29655	55.75075
April	0.00002	7094.706	15.04183	61.18093
May	0.000001	6832.327	13.10246	56.81508
June	0.000936	6885.445	15.35616	63.14277
July	0.001161	6573.354	14.0364	59.18473
August	0.000012	7340.935	12.7455	65.44325
September	0.00001	6904.857	11.15539	54.17512
October	0.000008	6901.61	13.48965	67.31401
November	0.00001	6685.175	11.45842	49.76876
December	0.00001	6540.128	12.61129	61.27466



Common Machine Learning Models

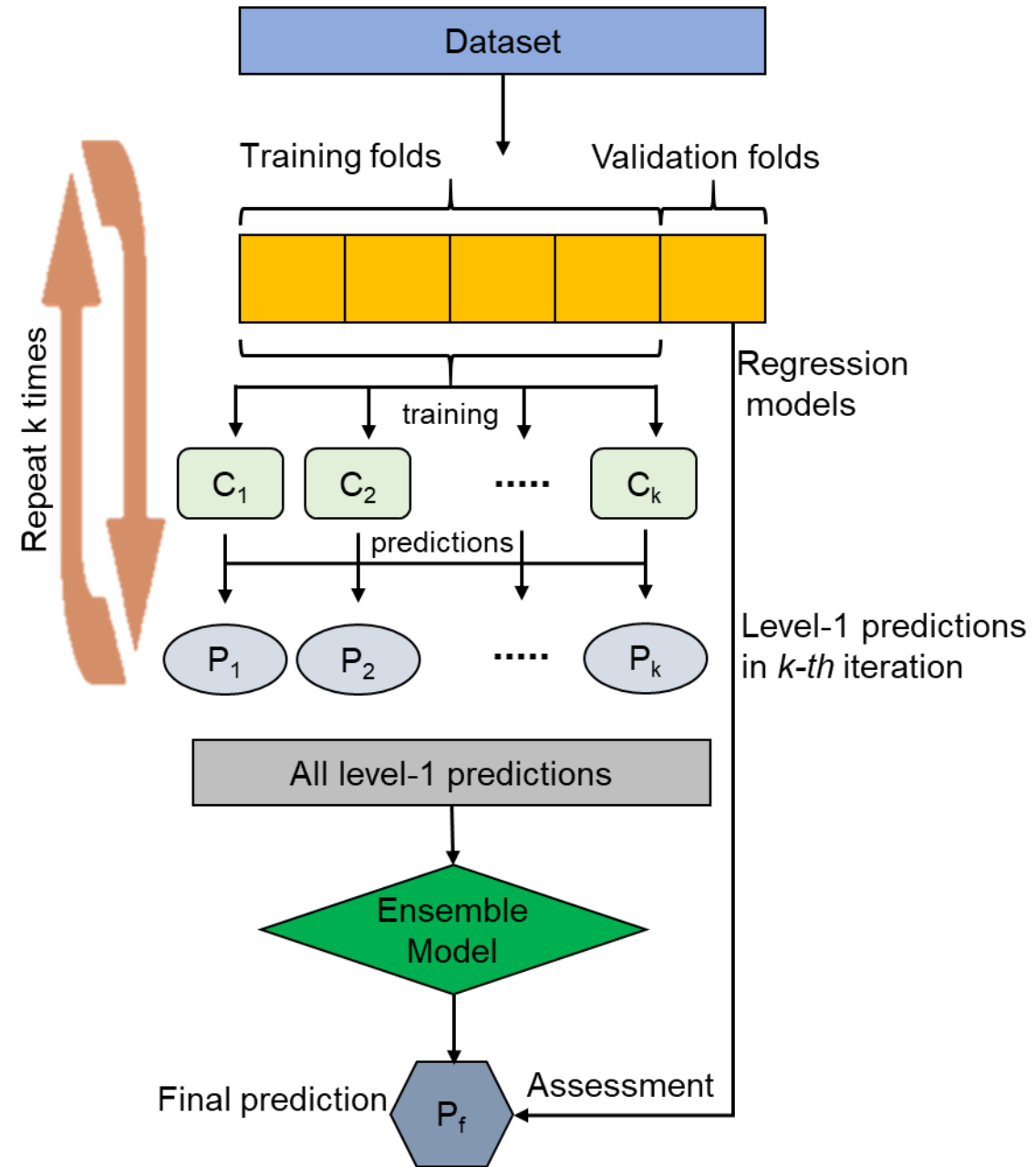


Source: Rashidi et al., (2019)



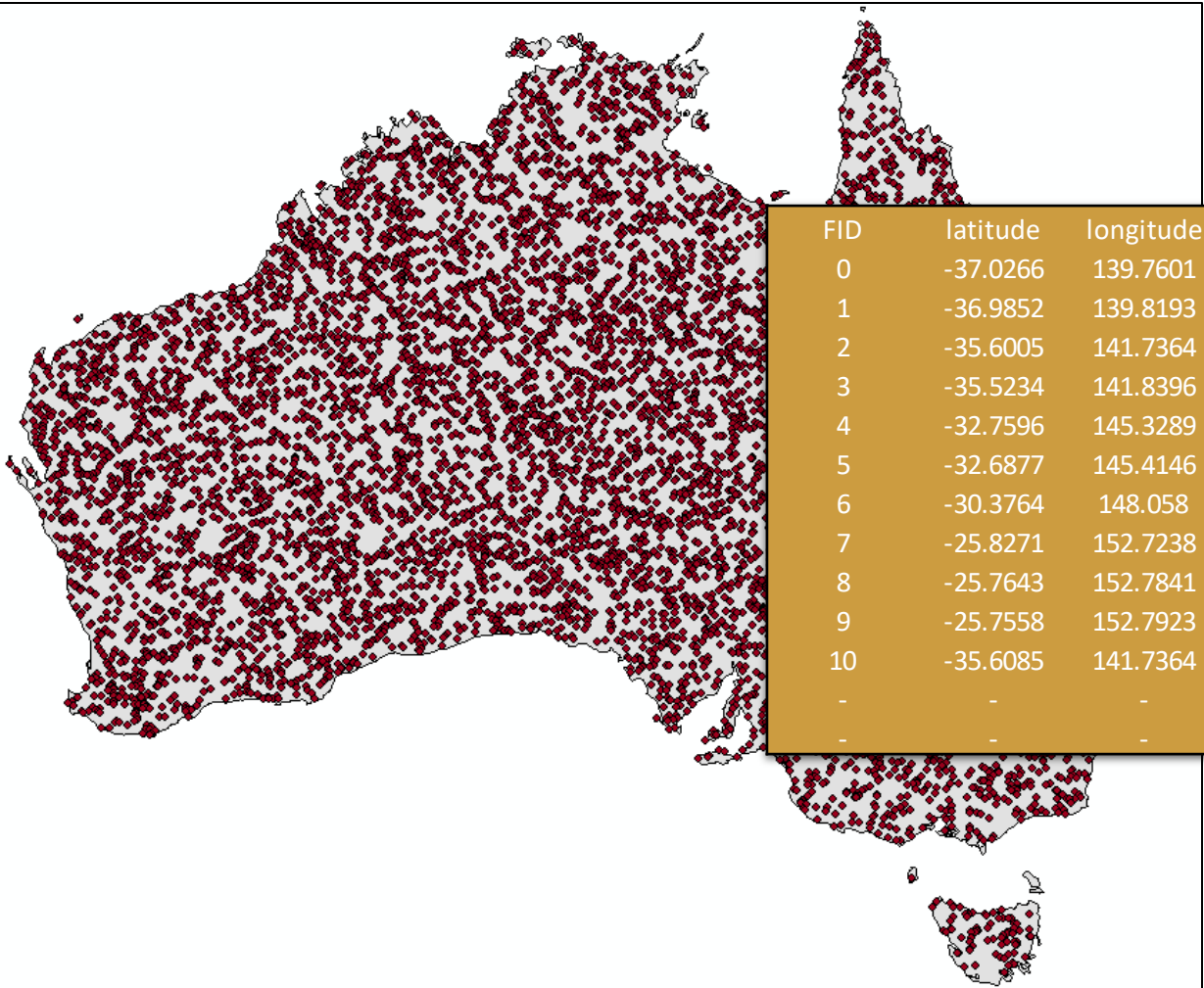
Model Structure

Ensemble regression model:
Random forest + Gradient boosting

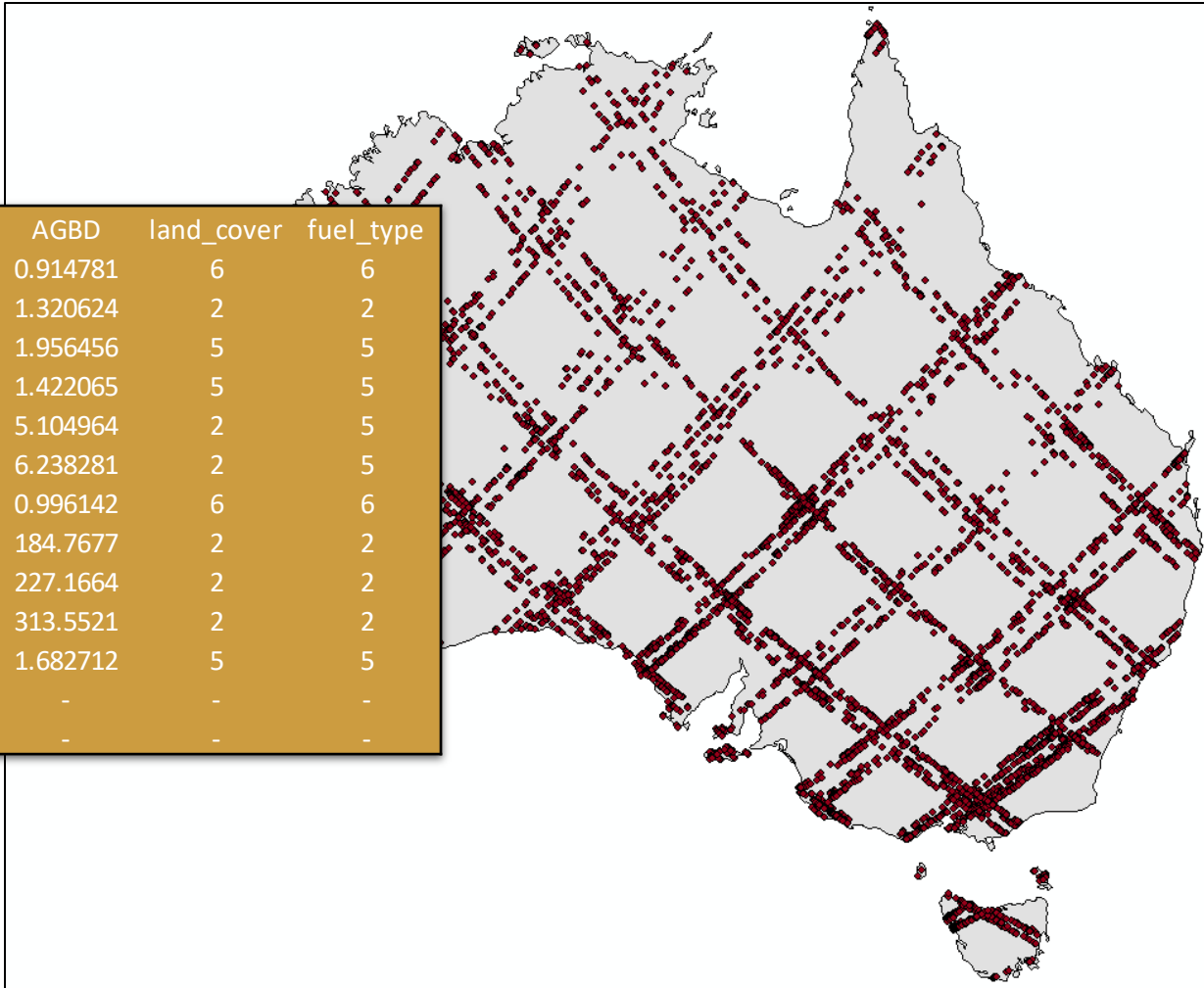


GEDI-generated Training Dataset

GEDI04_B

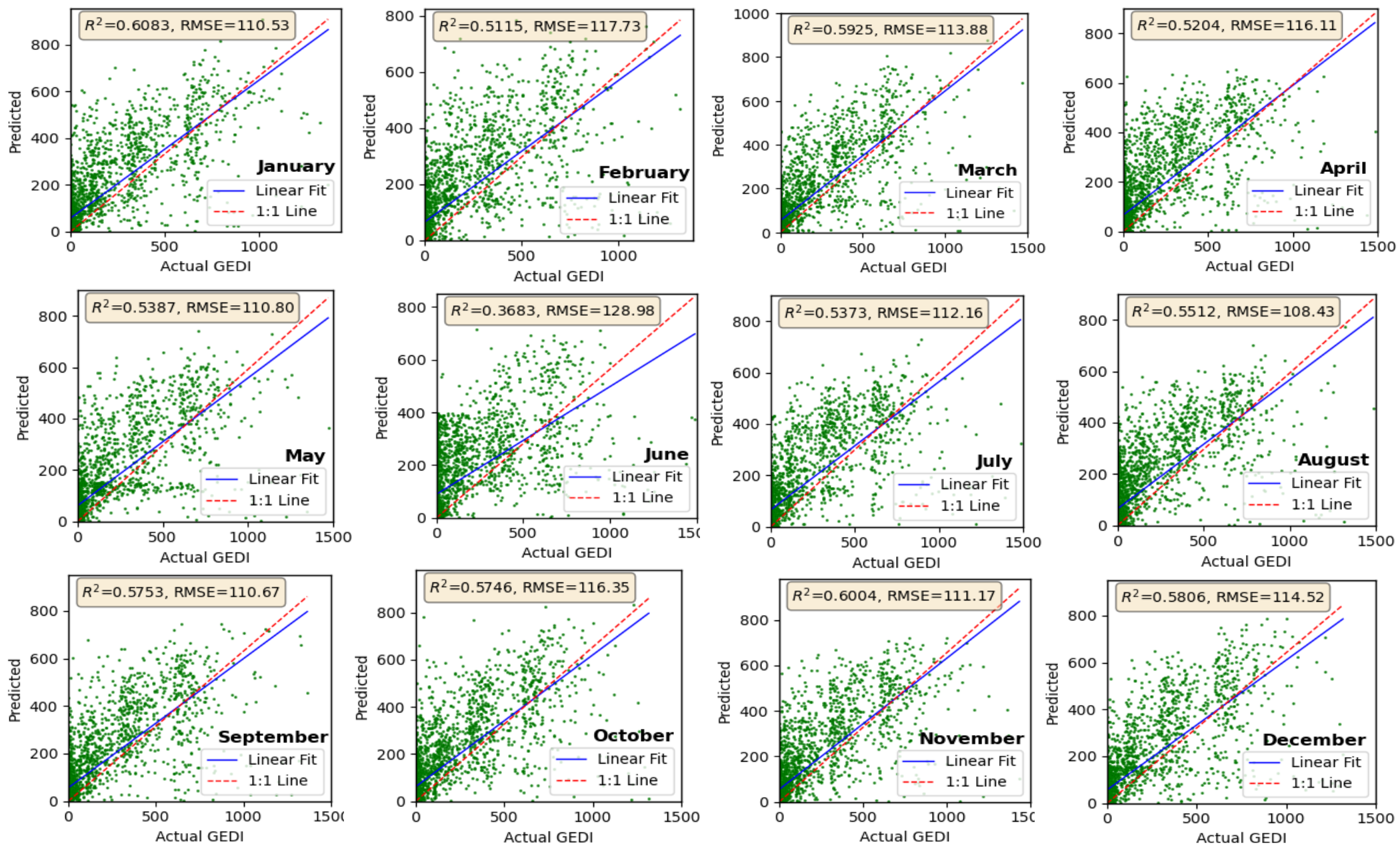


GEDI04_A



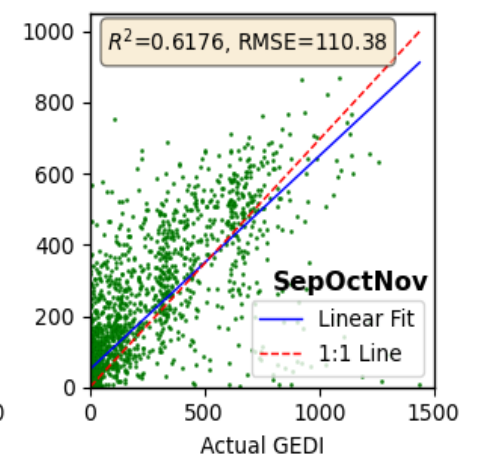
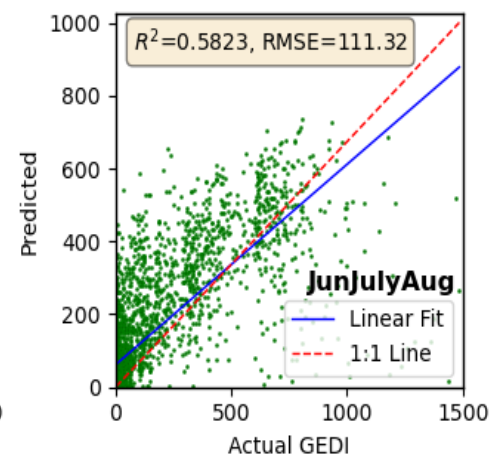
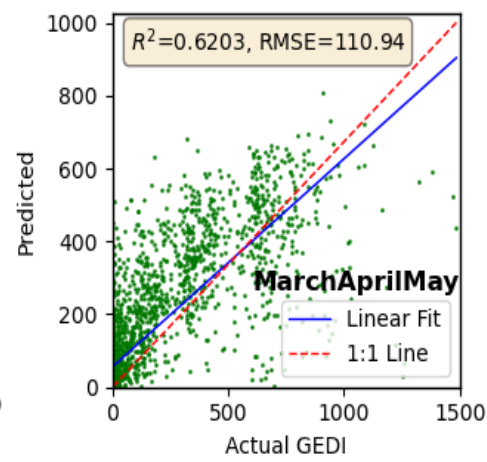
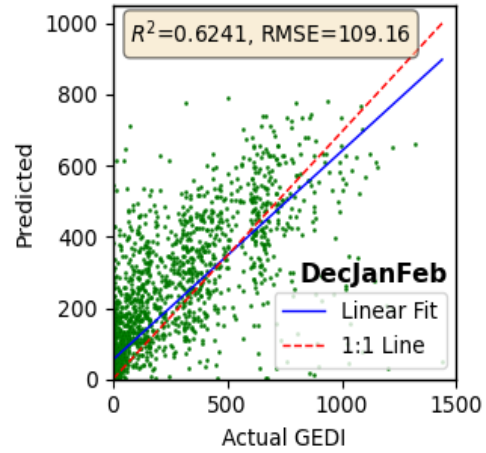
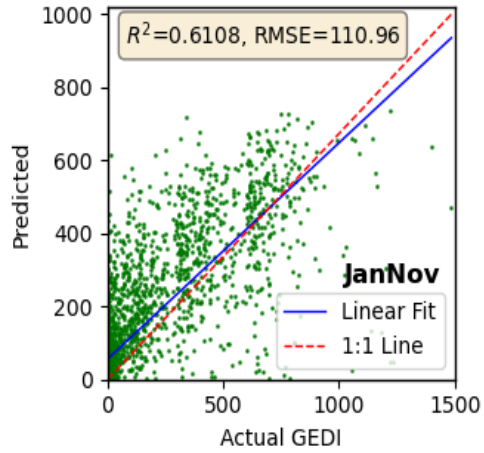
FID	latitude	longitude	AGBD	land_cover	fuel_type
0	-37.0266	139.7601	0.914781	6	6
1	-36.9852	139.8193	1.320624	2	2
2	-35.6005	141.7364	1.956456	5	5
3	-35.5234	141.8396	1.422065	5	5
4	-32.7596	145.3289	5.104964	2	5
5	-32.6877	145.4146	6.238281	2	5
6	-30.3764	148.058	0.996142	6	6
7	-25.8271	152.7238	184.7677	2	2
8	-25.7643	152.7841	227.1664	2	2
9	-25.7558	152.7923	313.5521	2	2
10	-35.6085	141.7364	1.682712	5	5
-	-	-	-	-	-
-	-	-	-	-	-

Monthly Model Performance on AGB Estimation

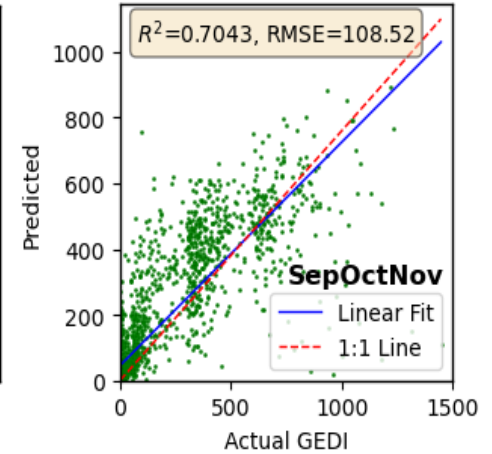
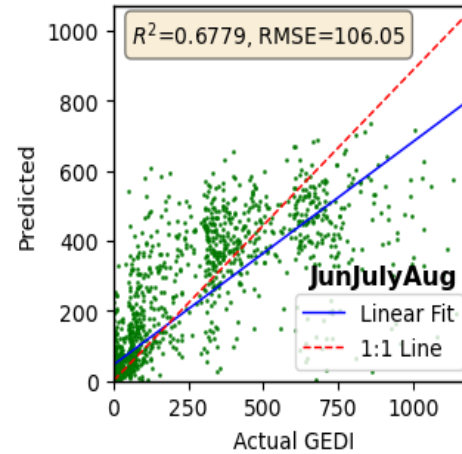
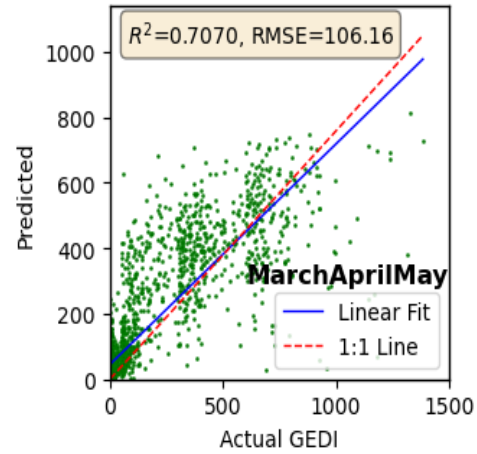
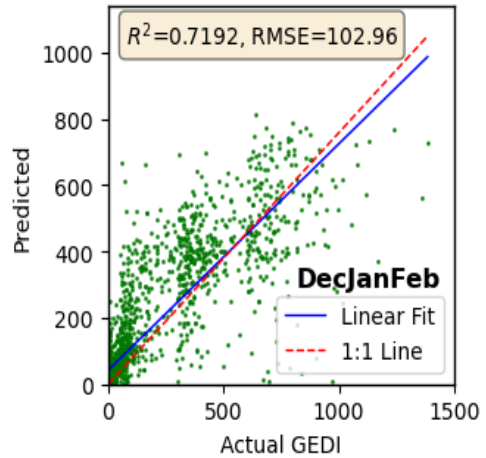
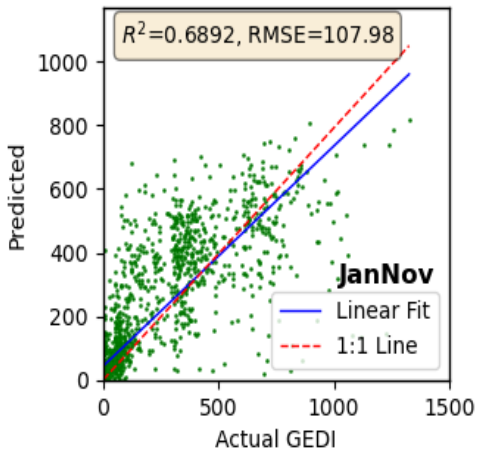


Aggregated Timeframe Analysis: Combined Bi-Monthly and Tri-Monthly Model Performance

GEDI04_A



GEDI04_B



Model Performance on Seasonal AGB Mapping over Australia

DecJanFeb

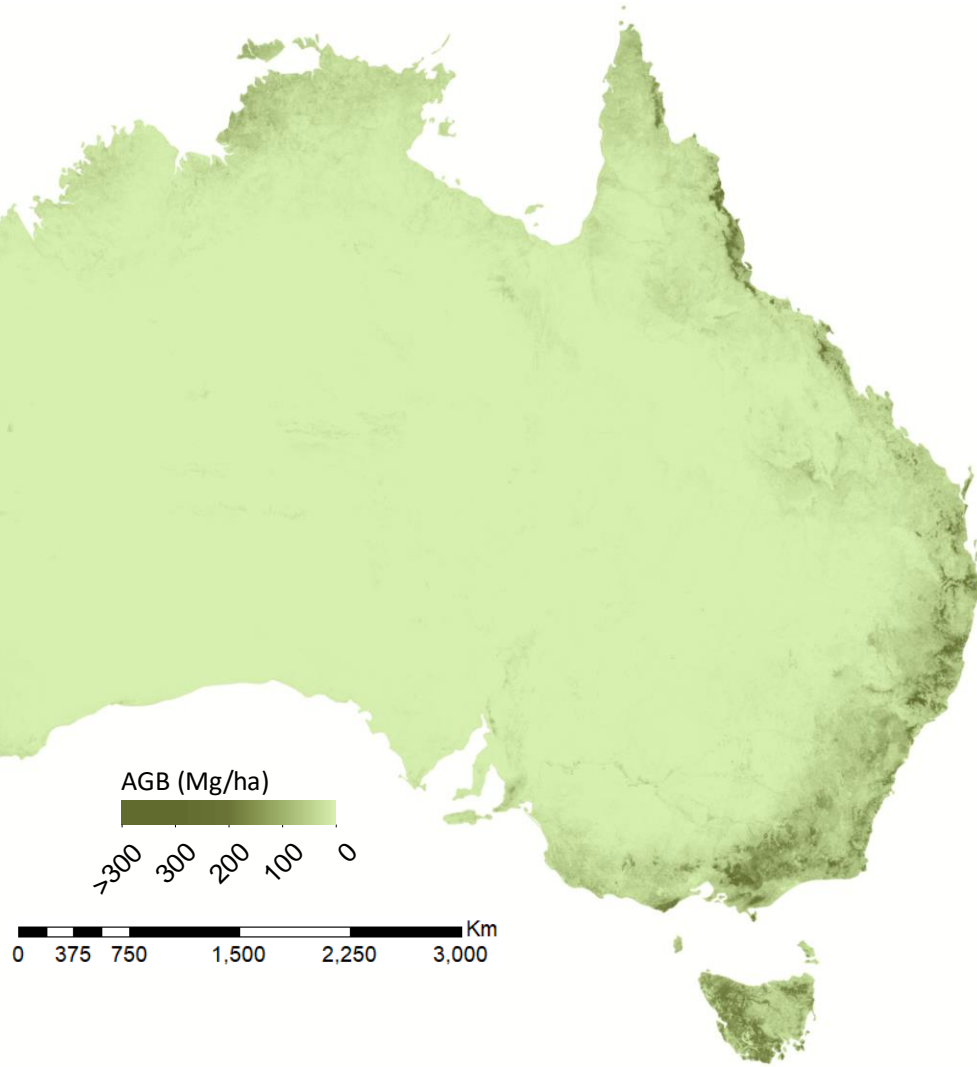


Fig 1. AGB Spatial Distribution Map from GEDIL4A

DecJanFeb

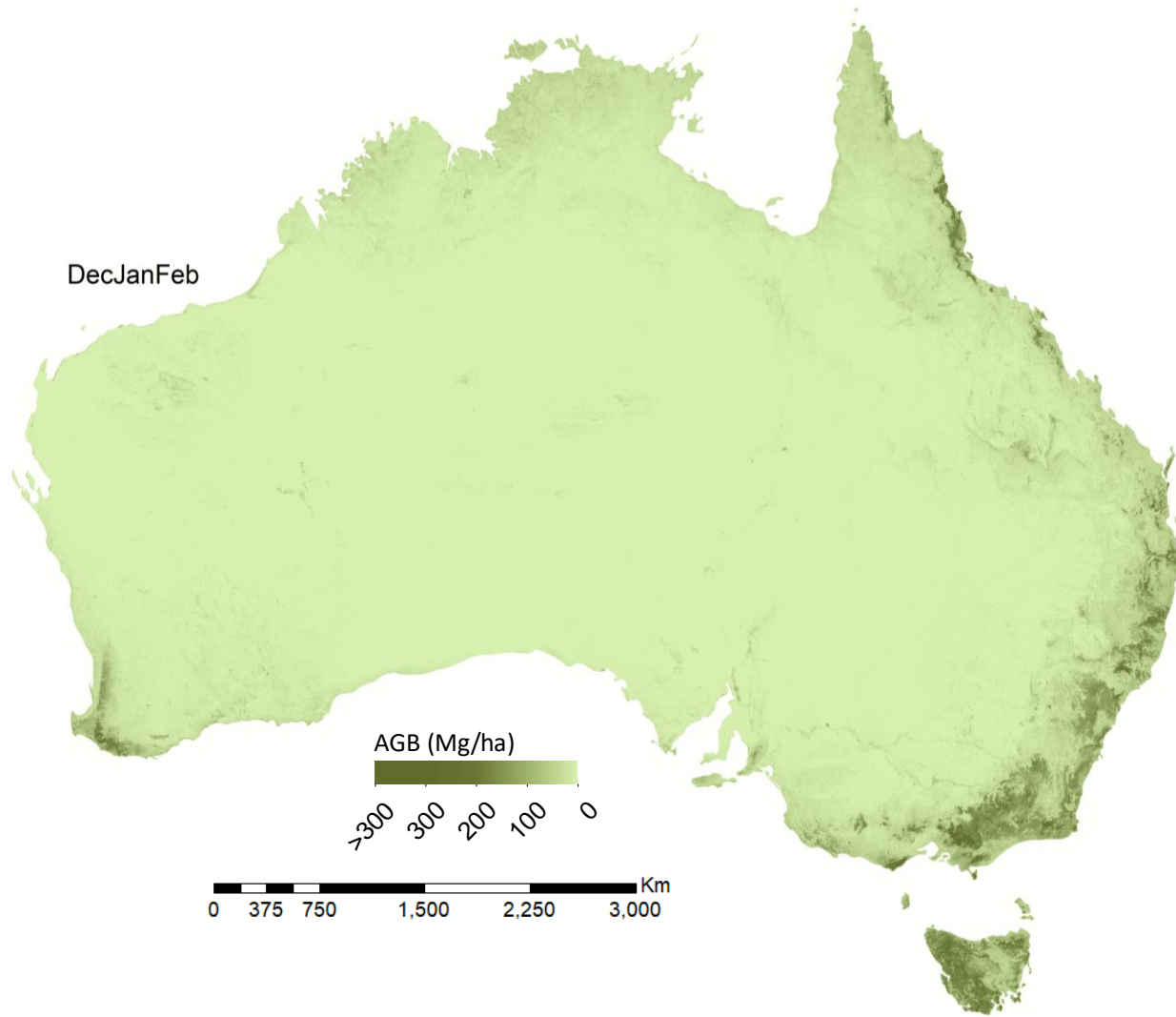
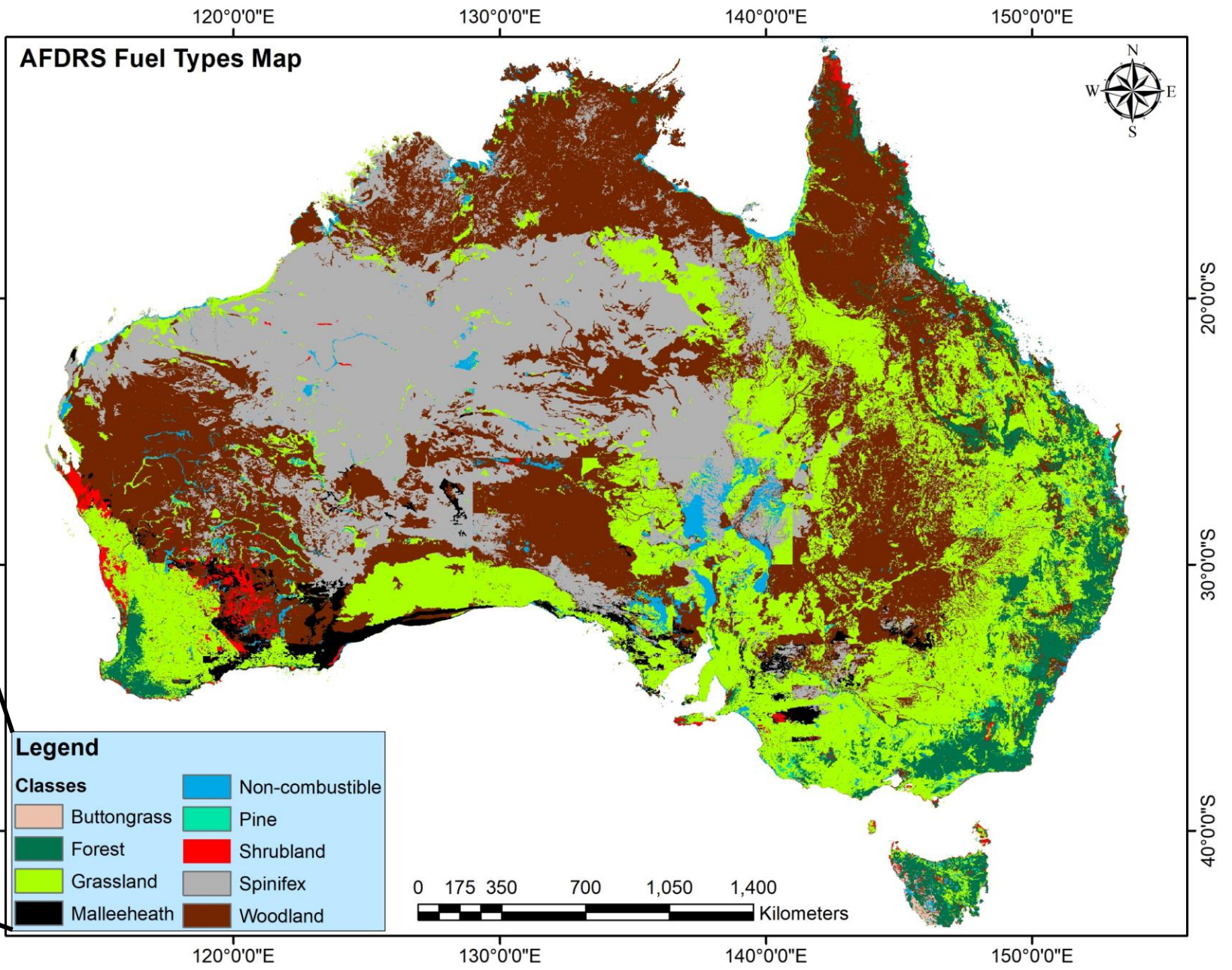


Fig 2. AGB Spatial Distribution Map from GEDIL4B



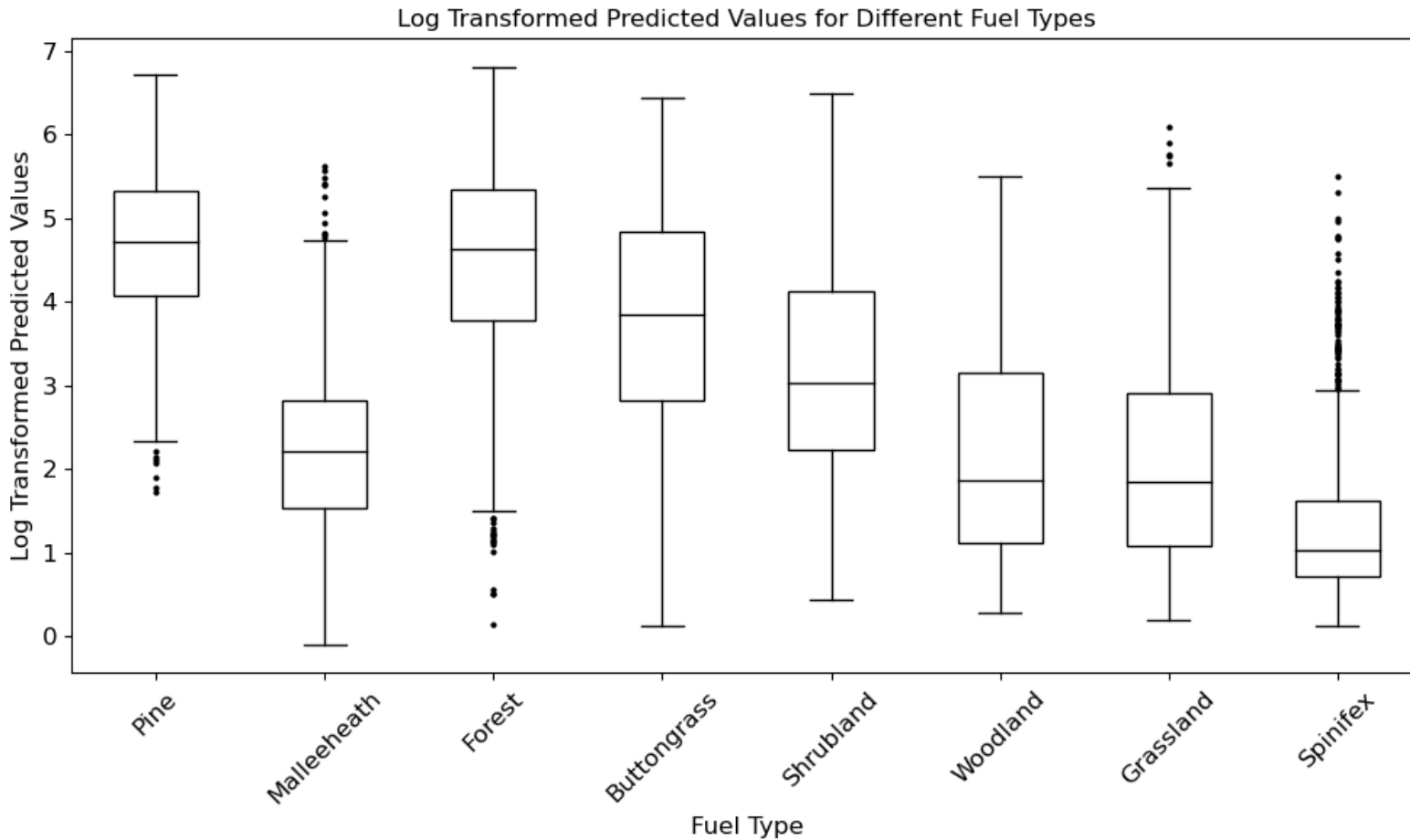
Australian Fire Danger Rating System (AFDRS) Fuel Type Map

Class_id	Pixel_count	Fuel_type	Area_km ²
1	245859	Forest	472842.6516
2	8294	Pine	15951.24422
3	1593896	Woodland	3065423.723
4	1147464	Spinifex	2206833.675
5	98521	Malleeheath	189478.2411
6	1217496	Grassland	2341521.103
7	46832	Shrubland	90068.56394
8	113263	Non-combustible	217830.4526
9	4781	Buttongrass	9194.947988



Model Performance on AGB Estimation for Different AFDRS Fuel Types

Fuel Type	Statistical Measures		
	MSE	RMSE	R ²
Pine	6898.38	83.05	0.53
Malleeheath	234.49	15.31	0.56
Forest	6987.40	83.59	0.67
Buttongrass	6864.31	82.85	0.42
Shrubland	4335.99	65.84	0.42
Woodland	507.10	22.51	0.44
Grassland	998.14	31.59	0.35
Spinifex	175.27	13.23	0.36



Key Takeaway

- ✓ **Machine learning (ML) models** have showcased proficiency in estimating biomass when analysing big remote sensing (RS) data across large-scale areas, such as Australia.
- ✓ **RS data (e.g., optical and SAR)** has enhanced biomass estimation, yet further exploration is necessary for other SAR data types in L and P-bands.
- ✓ **GEDI data availability**, offering lidar-based measurements of vegetation height and structure, has paved the way for biomass research in large-scale areas. Further research is warranted for retrieving other fuels attributes.
- ✓ Having **accurate, fine-scale, and up-to-date fuel type maps** would be highly beneficial for precise model investigations into biomass estimation across various fuel types.
- ✓ Recent and **accurate AGB validation data** are essential for verifying the outcomes of the ML model and RS data in estimating fuel attributes.






Thank you for listening

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