

SATELLITE DATA IN AGRICULTURAL AND ENVIRONMENTAL ECONOMICS

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ABOUT ME

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- **Bachelors:** Geography
- **Masters:** Geography
- **PhD:** Agricultural Sciences
- **Postdoc:** Land Economics Group



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LAND ECONOMICS GROUP



SESSION STRUCTURE



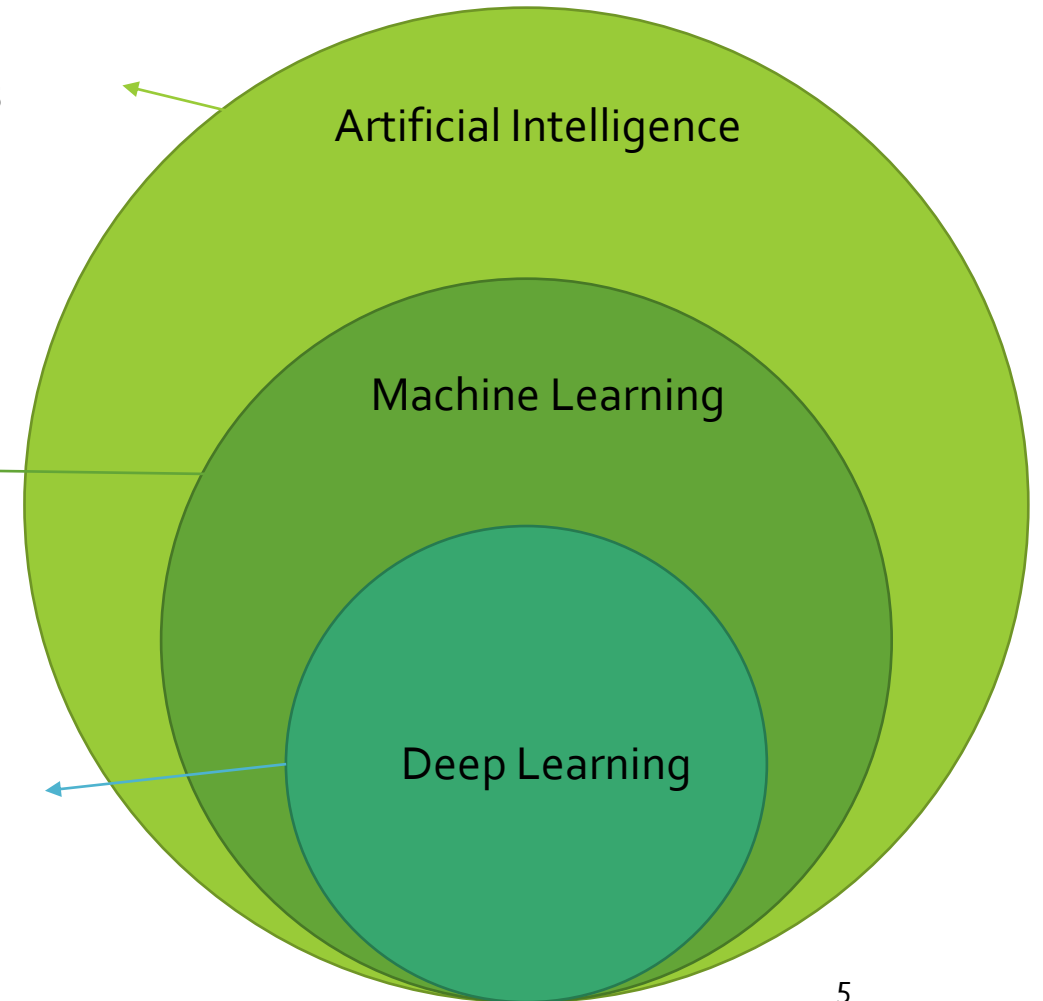
<https://www.teaboard.or.ke/>

AI, ML & DL

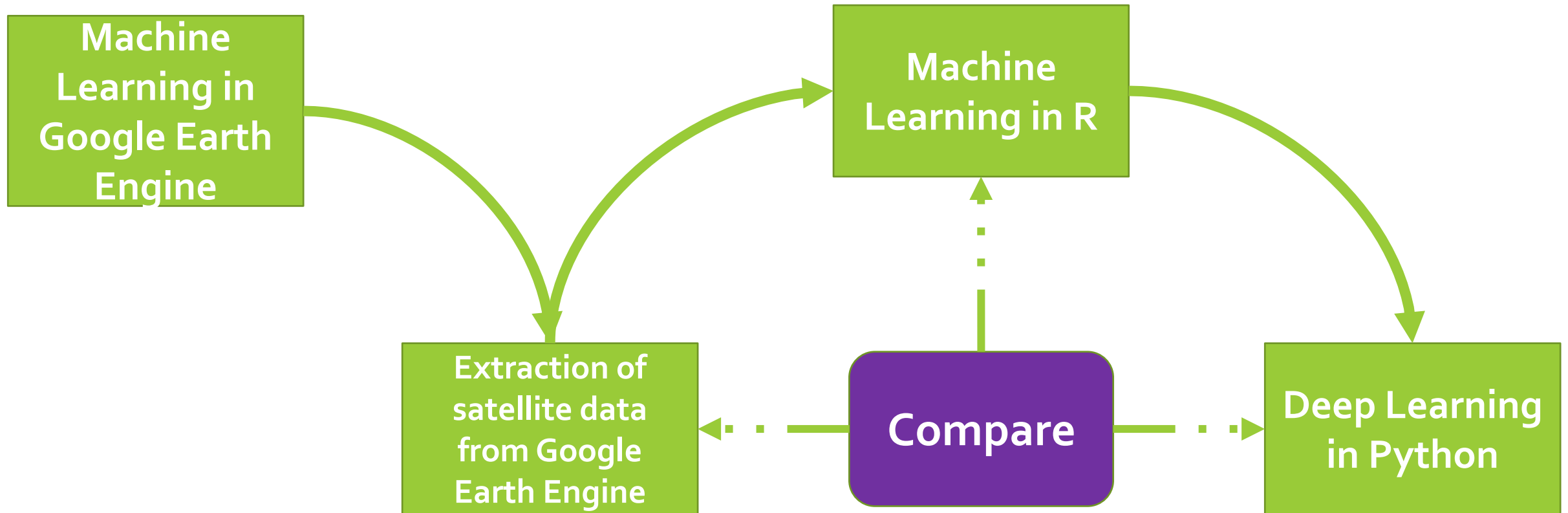
„the effort to **automate intellectual** tasks normally performed by humans‘

Systems and algorithms that enable computers to „**learn**“ and **improve** from experience over time without explicit programming

Subset of ML that uses **neural networks**



SESSION STRUCTURE



WHY ML IN AGRICULTURAL ECONOMICS

- Precision in Agricultural Monitoring & Policy Planning
- Cost-Effective Alternative to Traditional Surveys
- Land Use Change & Environmental Compliance
- Climate Resilience & Risk Management
- e.t.c

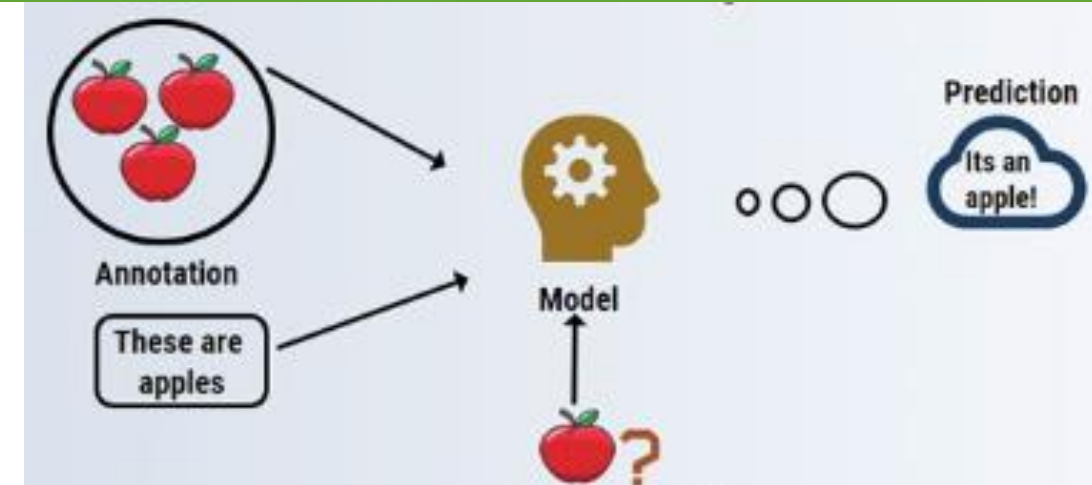
GOOGLE EARTH PRO - TOUR



TYPES OF ML

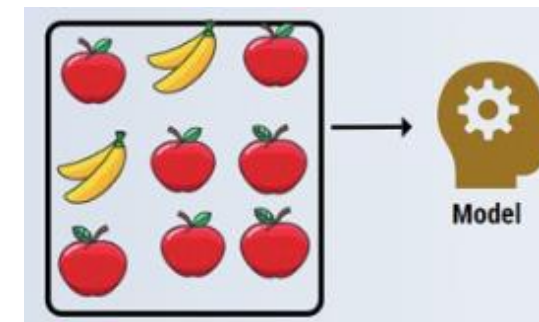
- **Supervised**

Models are trained on labelled data.



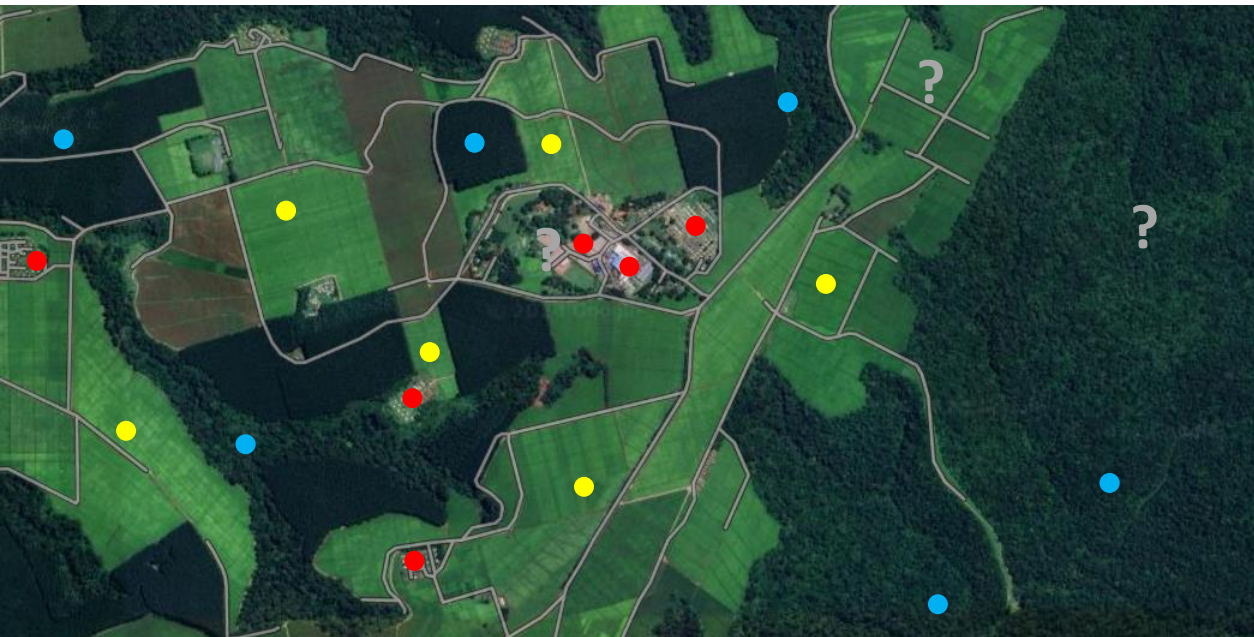
- **Unsupervised**

Models are trained on un-labelled data (without explicit output).



TYPES OF ML

- Supervised



Yellow = Tea, Blue = Forest, and Red = Buildings

- Unsupervised



e.g, group pixels into three classes ($k = 3$)

QGIS- TOUR

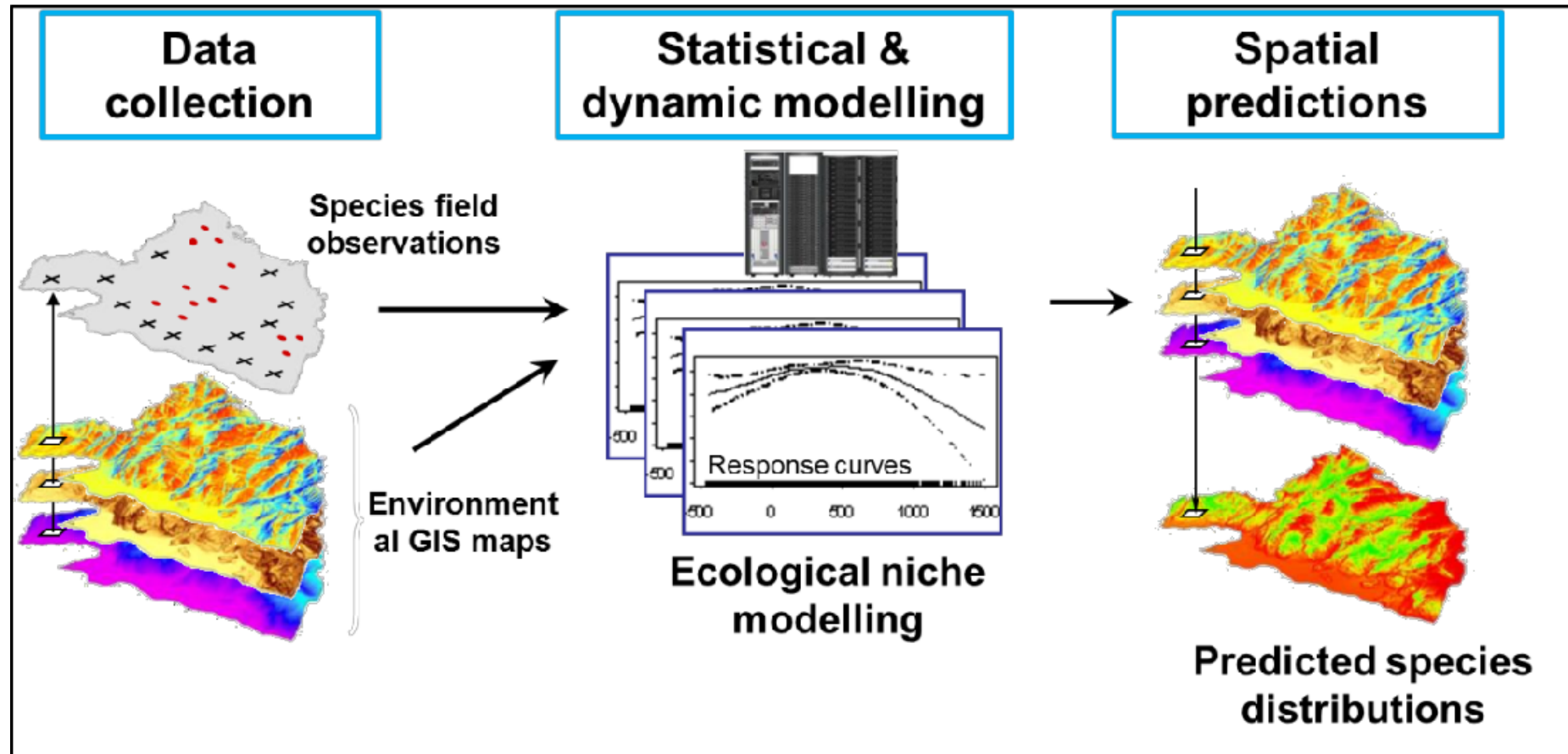


USE OF ML & DL IN AGRICULTURE

- Invasive species mapping
- **Cropland mapping**
- Weed detection
- Disease/pest detection
- Yield prediction
- Quality grading
- Weather monitoring/prediction
- Organic carbon prediction



USE OF ML & DL IN AGRICULTURE



USE OF ML & DL IN AGRICULTURE

- **Cropland mapping**

Define region of interest | Obtain coordinates of known plantations | Obtain satellite and related variables |
Build a model to associate the two | Evaluate the model | Make predictions

	longitude	latitude	B2	B3	B4	B5	B6	B7	B8	B8A	B11	B12
1	4168785	-39235	0.0301	0.0661	0.0325	0.1059	0.3268	0.4021	0.4462	0.4390	0.1834	0.0848
2	4168795	-39235	0.0308	0.0664	0.0331	0.1123	0.3264	0.4008	0.4367	0.4289	0.1897	0.0892
3	4168805	-39235	0.0305	0.0672	0.0330	0.1125	0.3273	0.4008	0.4395	0.4295	0.1902	0.0892
4	4168815	-39235	0.0299	0.0670	0.0331	0.1150	0.3363	0.4116	0.4461	0.4433	0.1936	0.0926
5	4168825	-39235	0.0302	0.0687	0.0336	0.1152	0.3375	0.4116	0.4502	0.4439	0.1939	0.0922
6	4168835	-39235	0.0298	0.0682	0.0349	0.1243	0.3264	0.3895	0.4527	0.4210	0.2034	0.1042
7	4168725	-39245	0.0311	0.0697	0.0336	0.1187	0.3577	0.4428	0.4641	0.4749	0.1795	0.0795
8	4168735	-39245	0.0303	0.0690	0.0310	0.1195	0.3627	0.4466	0.4606	0.4788	0.1771	0.0765
9	4168745	-39245	0.0295	0.0674	0.0303	0.1195	0.3627	0.4466	0.4566	0.4788	0.1771	0.0768
10	4168755	-39245	0.0289	0.0687	0.0292	0.1204	0.3623	0.4499	0.4678	0.4818	0.1725	0.0742

DATA

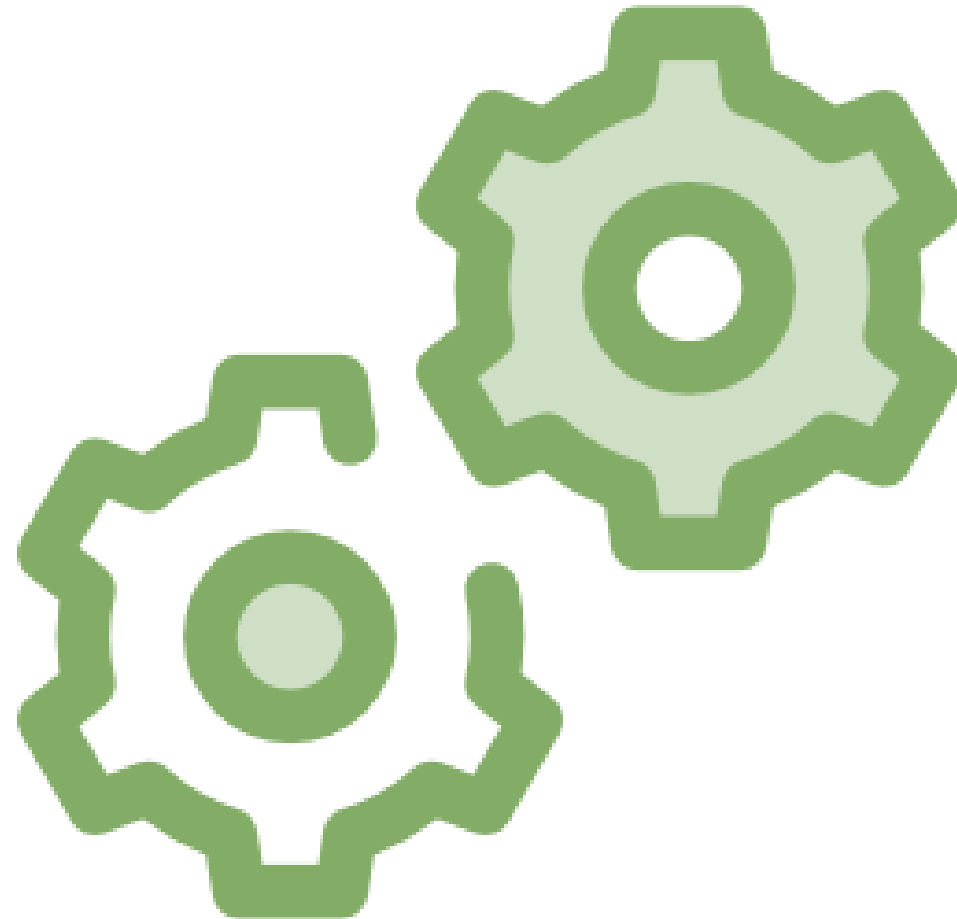
Clean the data/preprocess the data

- Handle NA, duplicates, outliers
- Partition the data
(train-test, usually 80% - 20%)
- For 20 rows, testing will take 4 rows.
- $20\% \text{ of } 20 = 4$
- Normalize the data

id	x1	x2	x3	x4	y
1	12	338	8	49	1
2	14	1687	8	30	1
3	17	580	3	56	0
4	13	1292	5	50	0
5	23	1521	4	10	0
6	15	792	6	25	0
7	15	132	5	29	0
8	20	701	6	56	1
9	12	1267	3	57	1
10	26	1297	6	35	0
11	16	217	8	53	0
12	17	1278	1	45	0
13	26	1648	6	20	0
14	23	1742	3	29	1
15	28	1087	2	60	1
16	28	1427	5	59	0
17	27	1545	3	28	0
18	22	609	5	19	0
19	22	653	7	27	1
20	12	236	1	31	1

MODEL FITTING

- Variable selection
- Multi-collinearity check
- Tuning model (e.g. for extrapolation)
- Variable importance
- Model selection strategy
- Ensemble procedure



MODEL ASSESSMENT

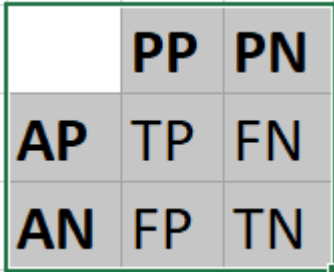
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2	14	1687	8	30	1
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19	22	653	7	27	1
20	12	236	1	31	1

\hat{y}
1
0
1
0
0
1
0
0
0
1
0
1
1
0
0
1
0
1

y	\hat{y}	Prediction
1	1	TP
1	0	FN
0	1	FP
0	0	TN

Prediction
TP
FN
FP
TN
TN
FP
TN
TP
TP
FN
TN
TP
TP
TN
TN
FP
FN
TP

MODEL ASSESSMENT

Precision	Recall/Sensitivity /True positive rate	Loss	F1 Score	Confusion matrix	Accuracy
$TP / (TP + FP)$	$TP / (TP + FN)$	MSE MAE	$2 * (Precision * Recall) / (Precision + Recall)$		$(TP + TN) / (TP + FP + TN + FN)$
$5 / (5 + 4)$ $= 0.556$	$5 / (5 + 3)$ $= 0.625$	Cross-entropy loss Hinge loss	$2 * (0.556 * 0.625) / (0.556 + 0.625)$ $= 0.588$		Overall correctness of the model

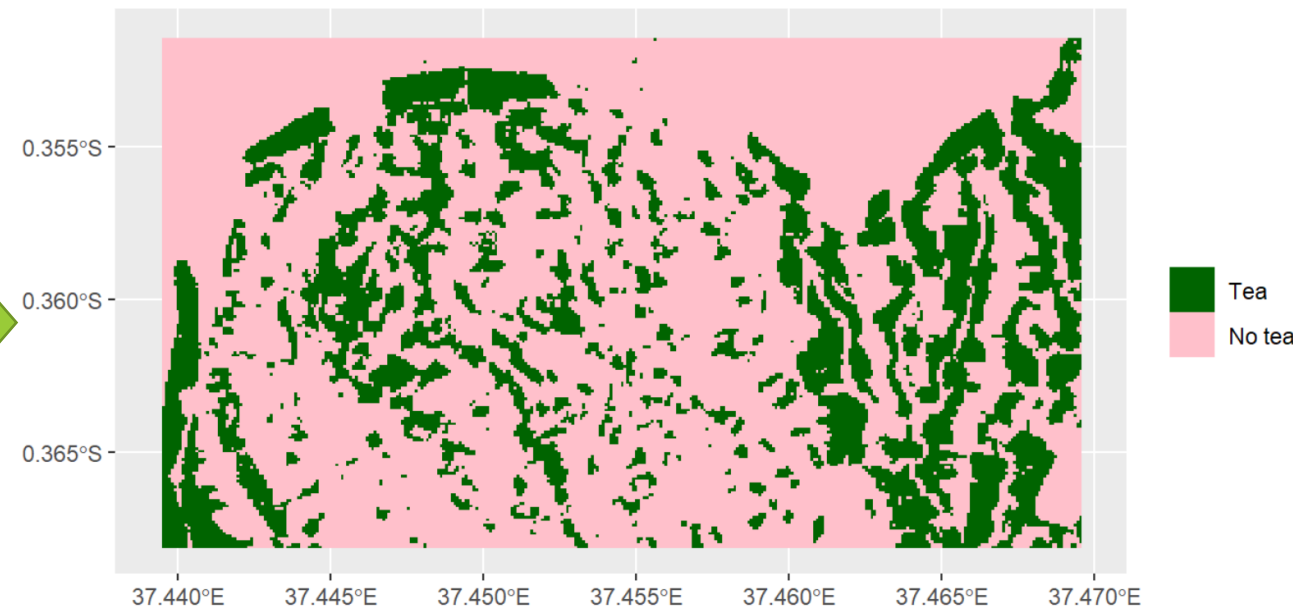
This can also come from actual field visits or use of experts.

PREDICTION

Training region, Study Area



Tea Map



https://github.com/Wycology/ml_tea_mapping

TUTORIAL

geodata

terra

tidyterra

tidyverse

sdm

usdm

forestdata

THANK YOU