FEASIBILTY ANALYSIS OF THE IMPLEMENTATION OF NATIONWIDE POINT CLOUD CLASSIFICATION WITH AI

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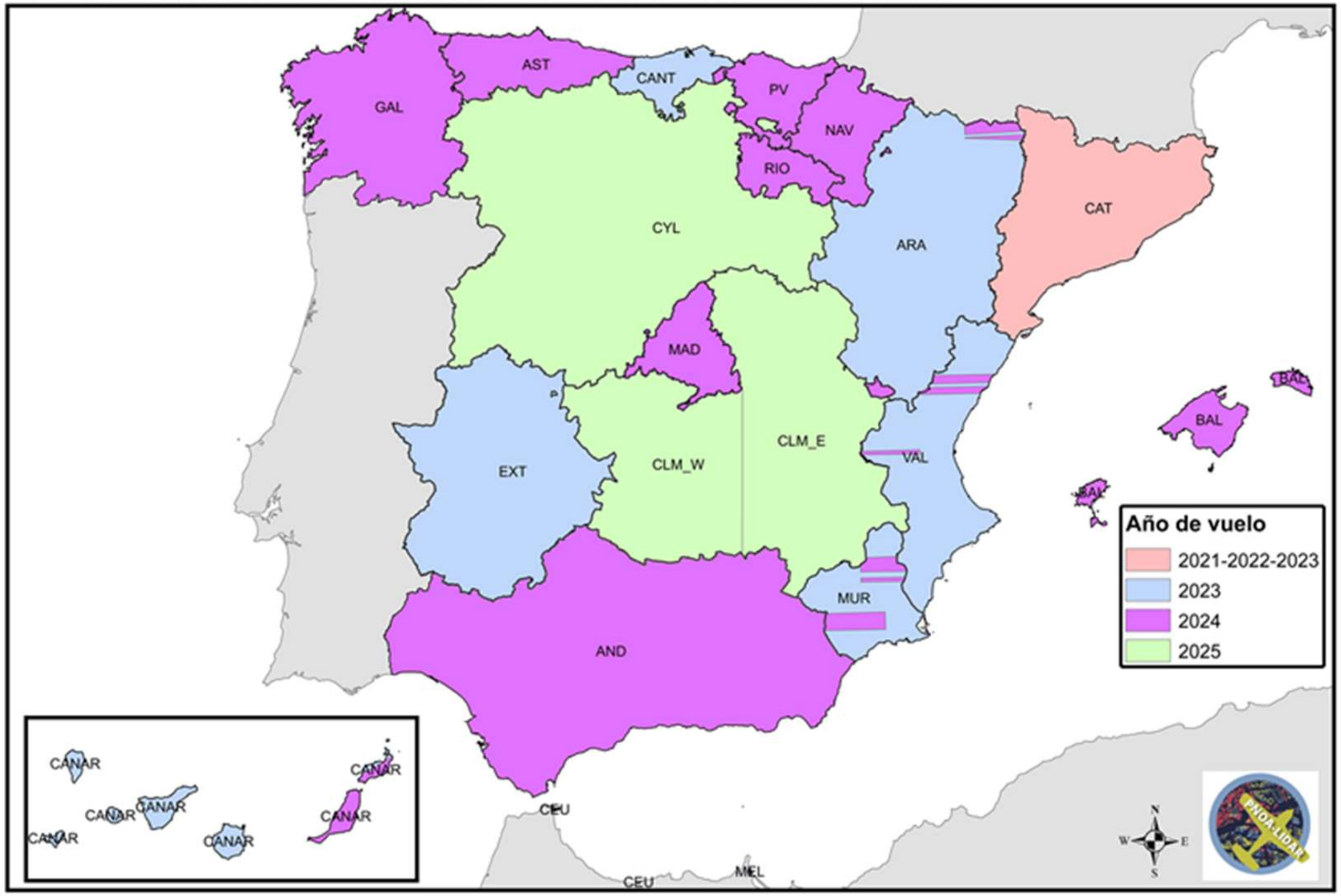
Introduction

SPANISH NATIONAL LIDAR PROGRAM

PROYECTO PNOA-LiDAR: AÑOS DE VUELO 3º COBERTURA



- 2022-2025
- 505.000 km2

(2023-2025 160.000 km2 per year)

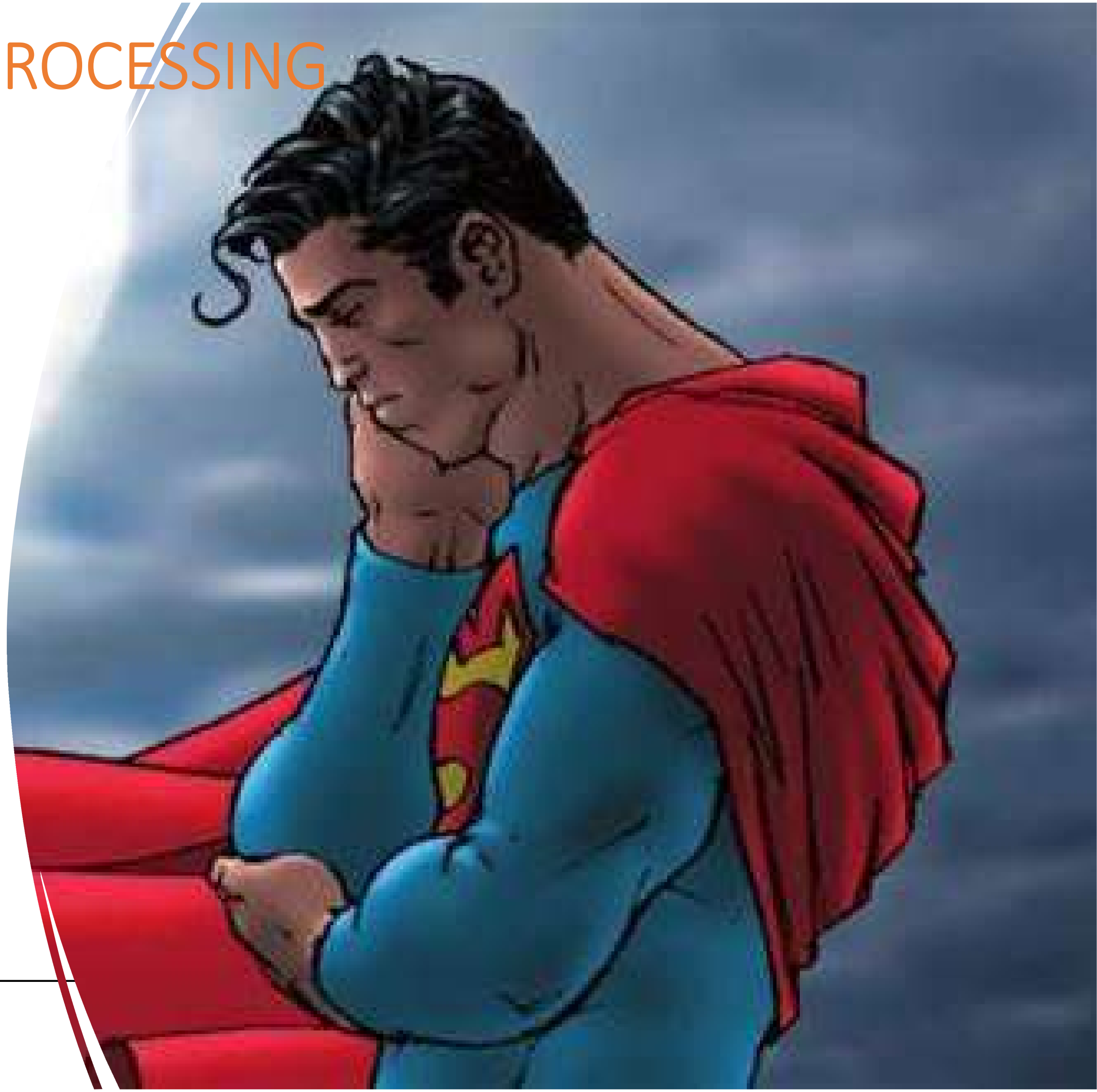
- 5 p/m2
- RMSEz: 10 cm
- RGBI medium format
- GSD 25cm
- Galaxy T2000

(except Catalunya Terrain Mapper)


"TRADITIONAL" PROCESSING
ARTIFICIAL INTELLIGENCE

IA vs TRADITIONAL PROCESSING

- Main problems
  - ➢ Data volume
  - ➢ Heterogeneity: terrains (mediterranean, Atlantic, high mountains etc etc)
- Situation in Europe?
- Our situation?



Feasibility analysis: steps

STEPS

STEP 1: Pilot test → Done

STEP 2: Public Consultation → Done

STEP 3: Bigger and final pilot test → Done

STEP 4: Analysis and comparaison with traditional → In process

STEP 5: Final decision – next steps

STEP 1: Pilot test (done)

- **<u>Goal</u>:** small test to do a first evaluation
- **<u>Compnay:</u>** TRACASA Instrumental S.L. (the same one from the Single Photon test in 2017)
- **<u>AOI:</u>** Region from the 2nd coverage 4-6 p/m2
  - Training 24 km2, Validation 114 km2.
- **<u>Classes</u>**: ground (2), vegetation (3 y 4), buildings (6), electric towers (9), vehicules (10), power lines (11) y bridges (17)
- **<u>F1-Score</u>**:

Zona	Acc	F1 2	F1 3	F1 4	F1 6	F1 9	F1 10	F1 11	F1 17	% Área- Nº puntos
Urbana	99.04	99.66	74.83	97.68	97.91	66.31	93.56	95.57	89.46	5.98% - (55M)
Rural	99.33	99.76	69.86	98.7	97.07	34.64	83.71	93.33	72.58	57.72% - (575M)
Montaña	88.51	92.5	28.49	89.11	81.73	0.78	23.14	1.23	19.43	36.3% - (275M)

STEP 2: Public Consultation (done)

- **Goal**: To asses the level of development and integration of Artificial Intelligence in the processing of point clouds
- **Companies:** 6
- **Conclusion**: A sufficient level of maturity is considered to procceed to step 3

Feasibility analysis: step 3-4

Bigger and final pilot test

STEP 3: Bigger Pilot test (done)

- **<u>Goal</u>:** pilot test – real case scenario

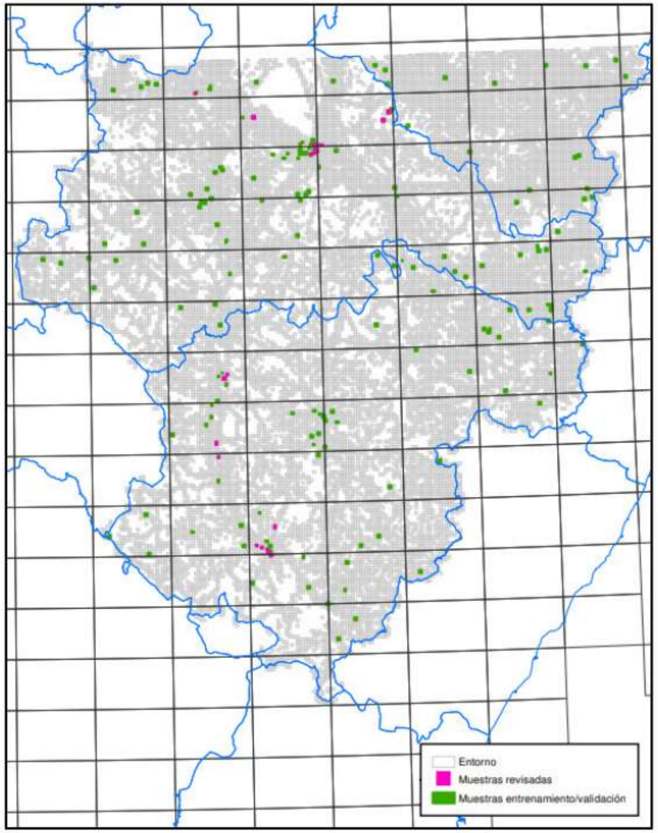
- **<u>Companies:</u>** TRACASA Instrumental S.L. , COTESA-UPV, Tragsatec

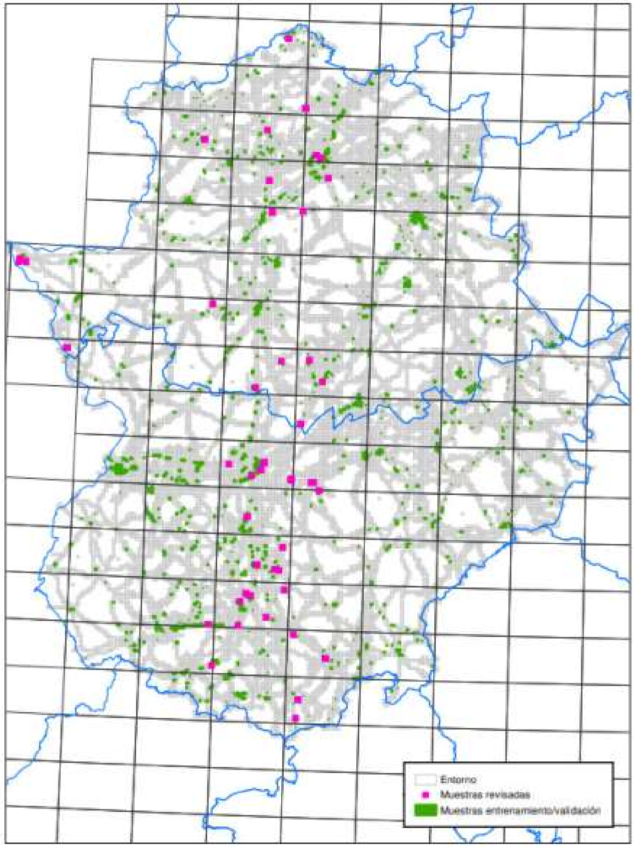
AREA OF INTEREST

42.000 km2

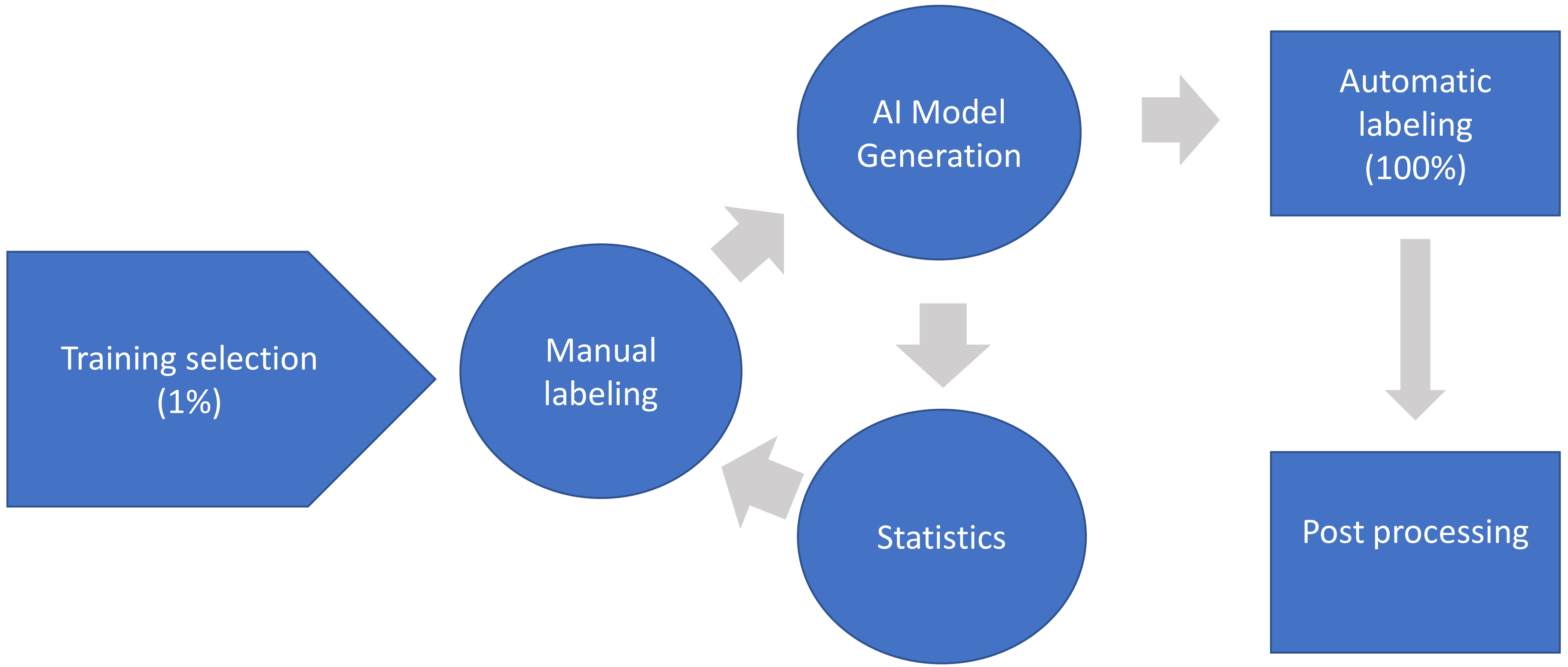
Aragón: Orographic complexity, landscape variability

Extremadura: A homogeneous plain framed by mountain ranges





METHODOLOGY AI



METHODOLOGY AI: training

	MODELO DASET 1	MODELO DATASET 2
Surface (Km2)	25	264,03
Points	220.207.985	1.868.680.199
Samples	10.000	380
Samples size (km2)	0,25	69,48
Methodology	FRACTAL: IGN France	partially random
Time (hours)	69	733
Training time (h/GPU)	120	192
Inference time (h/GPU) (20K km)	700	3.660

METHODOLOGY AI: training

Advantages of the Fractal Methodology (IGN France - IGNF/FRACTAL)

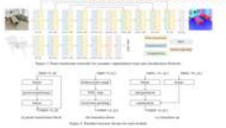
•Corrects class imbalance -> optimizes model training.
•Increases the representativeness of minority classes: bridges, towers, vehicles, etc.
•Enhances the representation of challenging landscapes and surfaces for AI classification models, such as mountainous areas, coasts, or complex urban scenes.
•Corrects implicit spatial autocorrelation in geographic data by seeking the widest spatial distribution of samples, maximizing diversity within each scenario type and globally.
•Employs a simple yet effective sampling scheme that consists of directed sampling followed by completion sampling.
•Defines a reference split into training, validation, and testing datasets with a ratio of 80/10/10. Training and testing areas are sampled independently using the same sampling parameters. Validation patches are sampled from training areas with spatial stratification, independently for each type of scene.
•Achieves the widest possible spatial distribution for each type of scene and ensures equal representation of all landscapes.
•Better performance: minimizes manual labeling times and GPU processing times.

METHODOLOGY AI: DL architectures

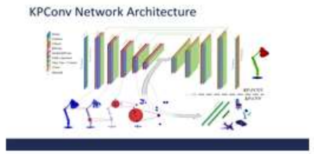
POINTCEPT
Point Cloud Perception Codebase

OPEN3D

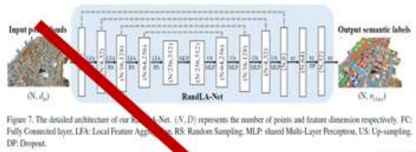
Point Transformer



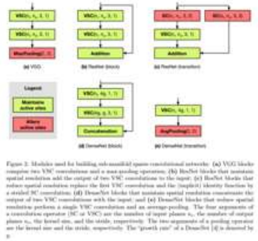
KpConv



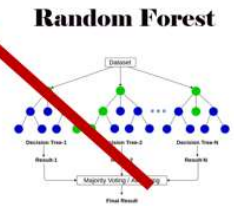
RandLA-Net



SparseConvNet

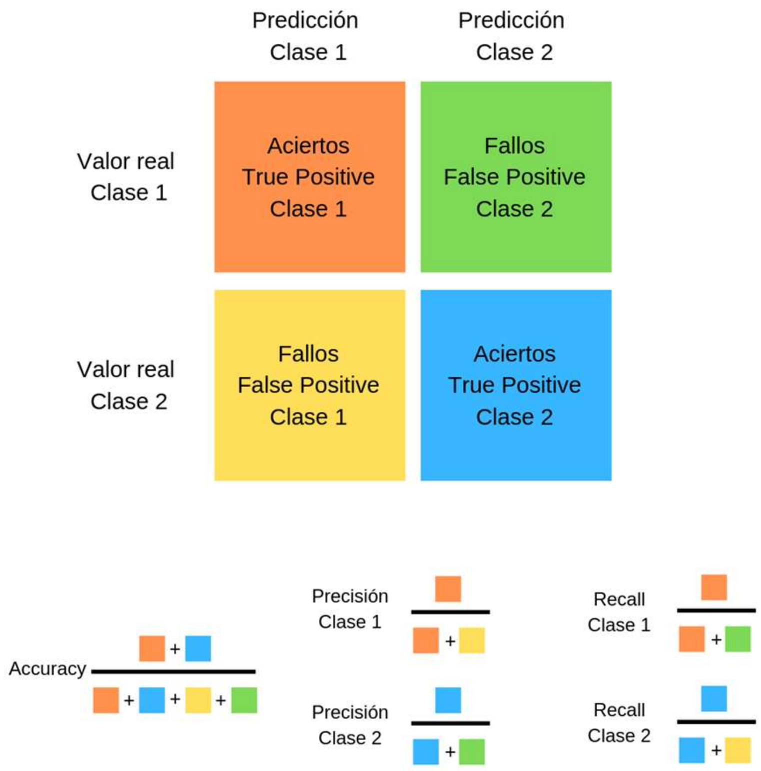


Random Forest



KpConv and Point Transformer

Statistics



Métrica	Formula	Descripción
Accuracy	$\frac{TP + TN}{Total\ samples}$	Porcentaje de acierto general
Precision	$\frac{TP}{TP + FP}$	Precisión sobre las muestras positivas
Recall	$\frac{TP}{TP + FN}$	Proporción de ejemplos positivos clasificados correctamente, con respecto a todos los ejemplos positivos predichos.
F1 score	$2 * \frac{precision * recall}{precisio + recall}$	La media armónica entre la precisión y el Recall. Nos indica como de preciso y robusto es nuestra predicción.

Tabla 1 - Métricas comunes en algoritmos de aprendizaje

Statistics

Predicción

Verdad campo	2	3	4	5	6	10	11	14	15	17	64	67	68	Total	f1
2	936 M	2M	887m	67m	752m	415m	1,33M	-	-	76m	14m	49m	2m	942M	**99**
3	4M	13,7M	1,69M	8m	38m	-	-	-	-	-	5m	6m	-	19,5M	**75,2**
4	1,05M	1,13M	68M	754m	232m	-	-	-	-	-	111m	19m	-	71M	**95,2**
5	140m	16m	788m	179M	382m	-	-	8m	16m	-	25m	3m	1m	180M	**99,3**
6	609m	17m	120m	187m	66,8M	-	-	18m	106m	25m	74m	21m	7m	68M	**97,9**
10	395m	-	-	-	2m	613m	2m	1m	-	18m	-	-	-	1M	**58,4**
11	6,6M	-	-	-	5m	25m	9,35M	-	-	18m	-	-	-	16M	**70,1**
14	-	-	-	2m	1m	-	-	479m	12m	-	-	-	-	495m	**94,2**
15	2m	2m	3m	11m	9m	-	-	13m	88m	-	-	-	1m	131m	**48,7**
17	125m	-	2m	2m	86m	12m	31m	-	-	662m	-	-	1m	924m	**76,7**
64	19m	2m	37m	9m	105m	-	-	-	-	3m	1,63M	1m	5m	1,8M	**88,5**
67	19m	27m	6m	12m	61m	-	-	-	-	-	11m	8,36M	-	8,5M	**98,6**
68	2m	-	-	1m	5m	-	-	1m	7m	-	-	-	78m	97m	**80,7**

"M" : *millón* "f1" : *f1-score*
"m" : *miles* "-" : *menos de 1000 puntos*

Clase 2: Suelo
Clase 3: veg baja
Clase 4: veg media/alta
Clase 6:Edificio
Clase 10: Vías Ferrocarril
Clase 11: Carreteras
Clase 14: Cables eléctricos
Clase 15: Torres eléctricas
Clase 17: Puentes
Clase 64: Vehículos
Clase 67: Placas solares
Clase 68: Aerogeneradores

Statistics, results

	Extremadura				Aragón				
	MODELO DASET 1				MODELO DATASET 2				
	KPConv		Point Transformer	KPConv	KPConv		Point Transformer	KPConv	Average F1
CLASES	DL		DL	DL+PP	DL		DL	DL+PP	DL
Ground	90,69			91,20	99,00			99,00	
Railway	80,54	89,60	95,30	83,00	58,40	97,92	98,78	62,10	**95,40**
Roads	79,48			82,00	70,10			71,50	
Veg. Low	33,31			44,50	75,20			75,20	
Veg. Medium	85,88	73,59	91,22	87,00	95,20	95,81	96,11	95,20	**89,18**
Veg. High	97,15			97,00	99,30			99,30	
Buildings	95,85		96,05	96,70	97,90		97,62	98,00	**96,86**
Water	96,09			94,50				74,70	**96,09**
Bridges	88,57		83,18	91,80	76,70		71,38	80,00	**79,96**
Vehicules	74,41		77,72	86,90	88,50		89,41	88,50	**82,51**
Electrical Towers	78,01		91,14	82,70	48,70		57,58	68,20	**68,86**
Power lines	91,60		96,73	93,10	94,20		96,60	94,20	**94,78**
Solar paneles	87,45		85,83	87,80	98,60		98,70	98,60	**92,64**
Wind turbines	67,74		90,85	94,10	80,70		96,34	91,00	**83,91**
F1 General	**84,29**		**84,13**		**86,56**		**86,87**		
F1 Basic classes	**86,35**		**94,19**		**97,21**		**97,50**		
F1 Advanced classes	**83,41**		**87,58**		**81,23**		**85,00**		

METHODOLOGY AI: postprocessing

Tests to improve results without manual editing using decision trees based on spatial GIS analysis, clustering, outlier detection, etc.

Advantages:

•In terms of metrics, they generally provide a small improvement.

•They are useful for correcting gross and isolated errors or those with low occurrence, improving the visual appearance of the cloud.

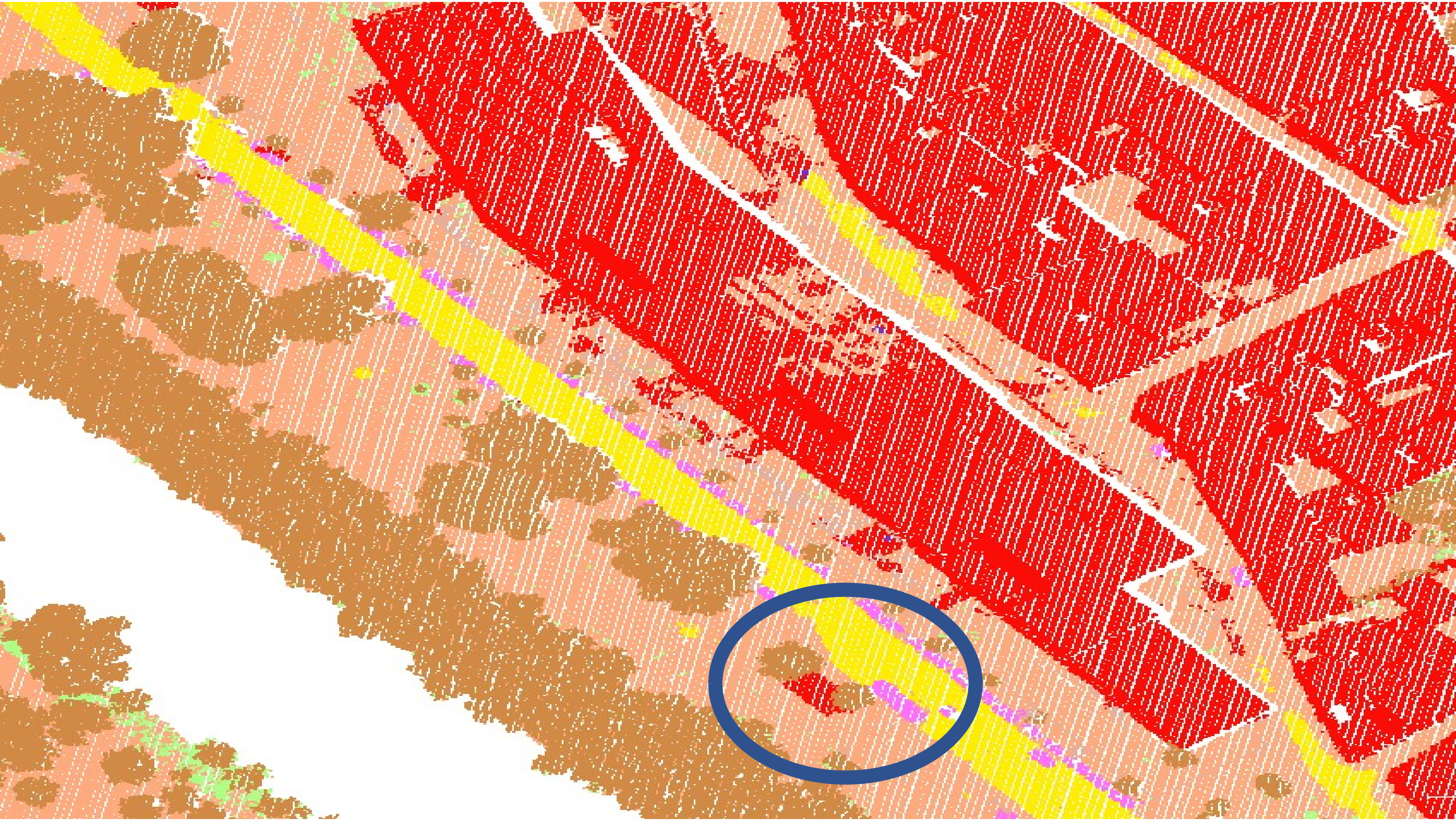
•They are applied specifically to each class.

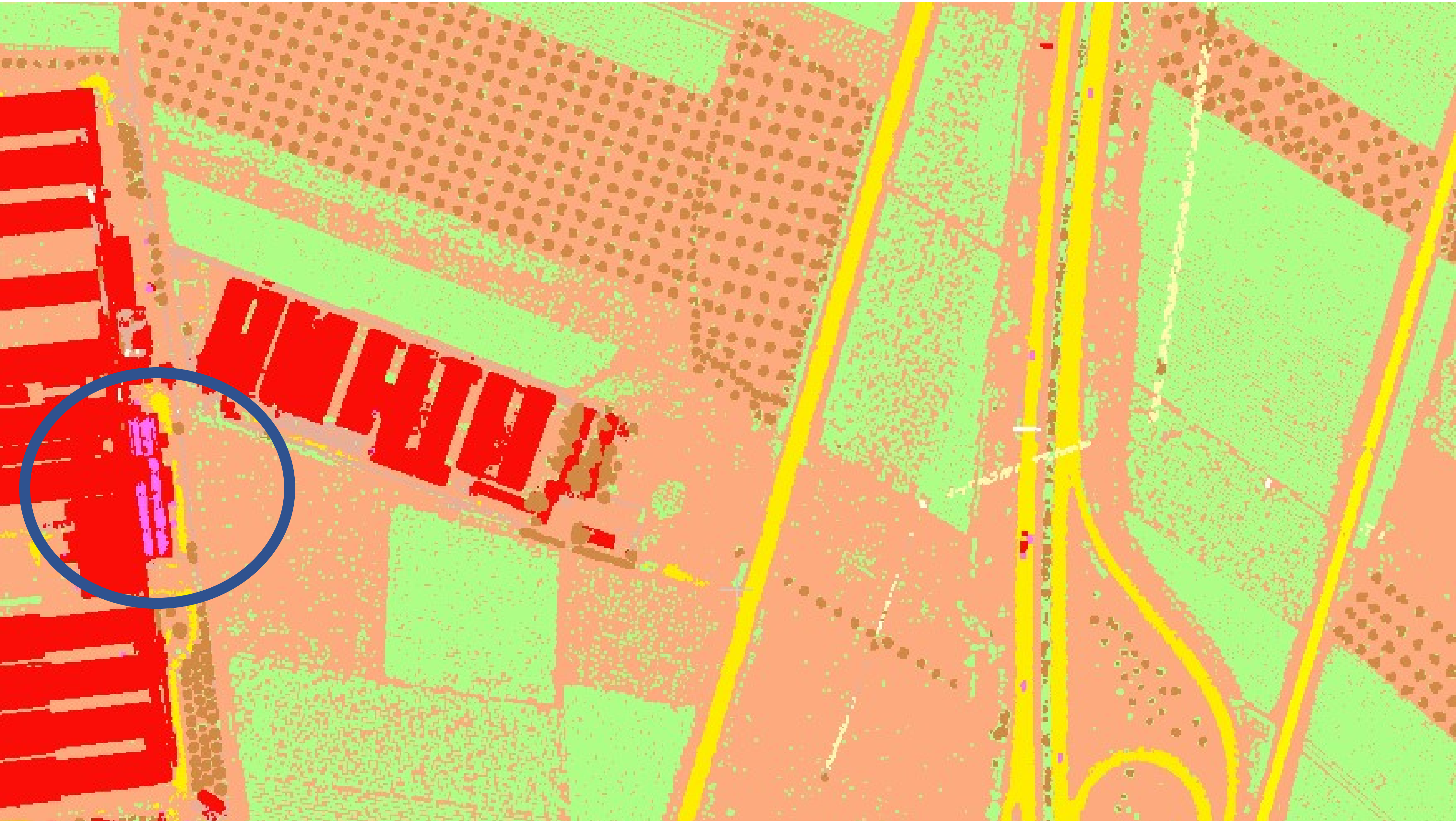
•Better results are achieved in classes corresponding to specific, advanced, or minority geographic phenomena or entities.

Disadvantages:

•High computational cost in post-processing (CPU).

•It is important to find a balance between execution time and the improvement obtained, especially in very large study areas.





METHODOLOGY AI: Model Transference

Tests for transferring models to other geographical areas with different characteristics: Cantabria: high mountains with cliffed coasts

Results:

•Similar metrics in orographically equivalent areas.

•Need for retraining with new samples in areas with typologies not present in the initial dataset: coast, cliffed coast, high mountain rocky areas.

•Profitability of reuse: Significant cost reduction compared to conventional classification or training a new model from scratch.

Future expectations:

•Having several pre-trained models (4-5) to cover the specificities of the entire peninsula: Cantabrian coast, central plateau, Mediterranean front, Pyrenees, etc.

•Savings in the training phase as more pre-trained models become available in production.

Conclusions and lessons learned

•The selection procedure published by IGN France seems appropriate, reducing labeling costs.

•Dataset sizes of 0.15%-0.30% of the surface area seem sufficient to achieve results.

•Precise specification of classes

•Good results in basic classes. For advanced classes, there is more room for improvement with post-processing.

•Supervised quality control of samples and manual editing of gross errors and specific cases is necessary.

•Model transfer to other territories is possible by retraining specific characteristics. The training process is expected to decrease progressively as new retrained models become available. It might be necessary to have several models to cover the entire peninsula (Cantabrian region, central area, mountains, Mediterranean coast, Atlantic coast).

Conclusions and lessons learned

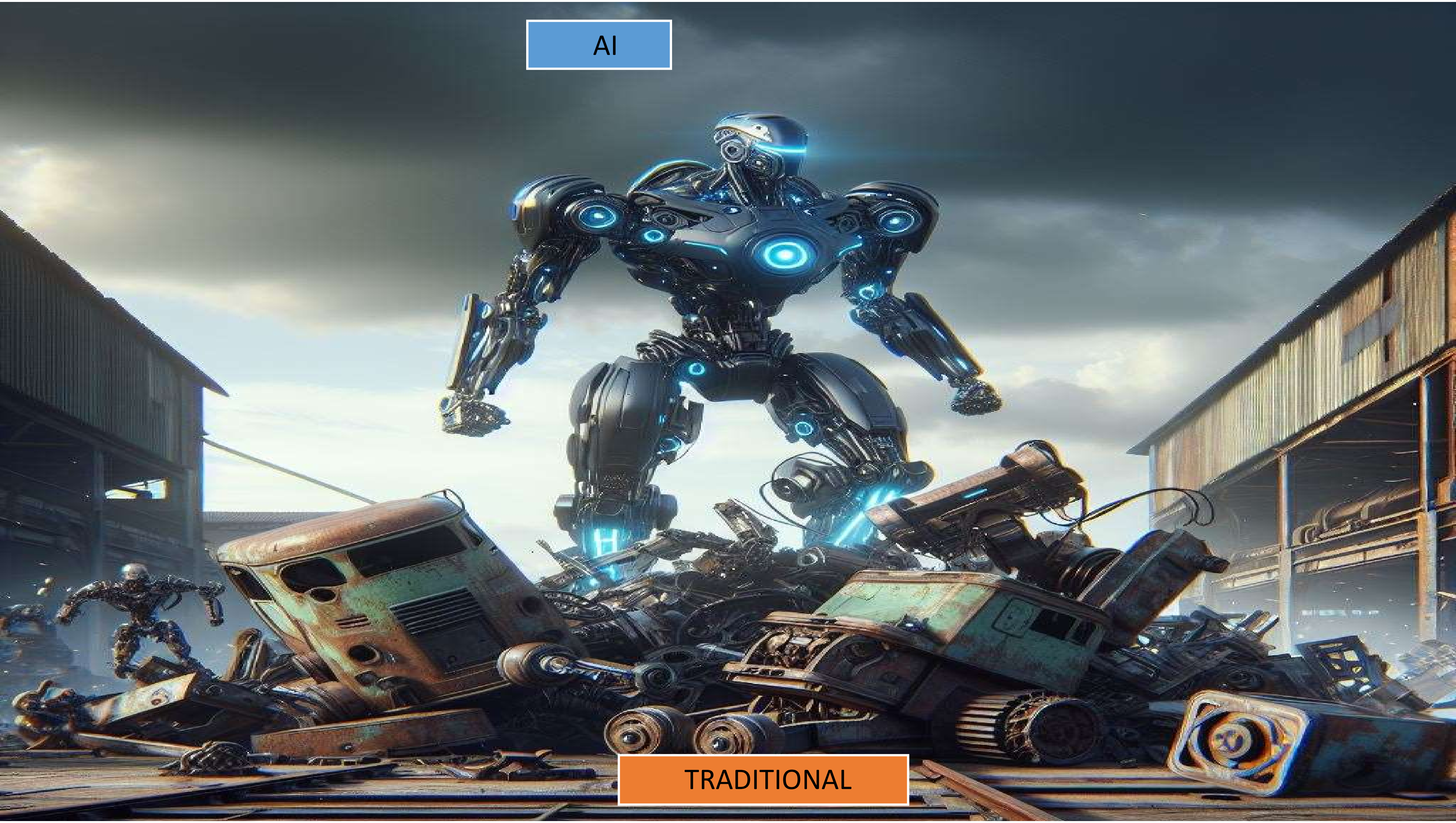
	Traditional	AI
Basic Classes	Same	Ground, vegetation, buildings, bridges
Advance classes	non	Water, vehicules, electrical towers, power lines, solar panels, wind turbines
F1 Basic classes	95-97	95
Manual work	Most of the work	some postprocessing needed
Cost	10€ per km2	Tender 6,6 € per km2 Final price: dataset 1 (4,5€) - dataset 2 (5,71€)
Time	?	?

Feasibility analysis: step 5

Decision

STEP 5: Decision – next steps

- No clear decision made yet, but we believe it is the way to go.
  - Technical analysis is still being conducted
  - Bureaucratic complications
- Cantabria (5.000 km2): some advanced classes are being processed with DL
- Navarra (10.000 km2): will be processed with DL
- Analysing a tender for production for a large area


AI
TRADITIONAL

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