



Taller CR2, Mapas de Cobertura de Suelo

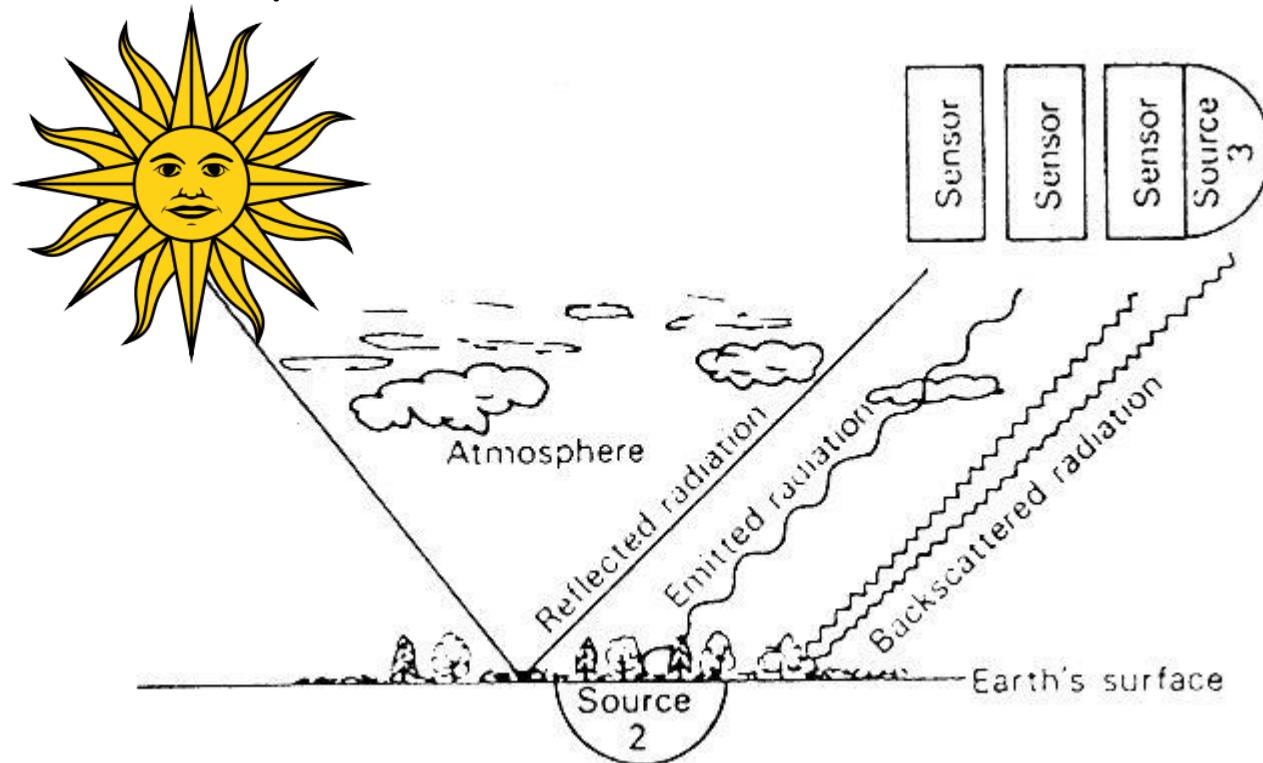
3 de septiembre 2018, Santiago, Chile

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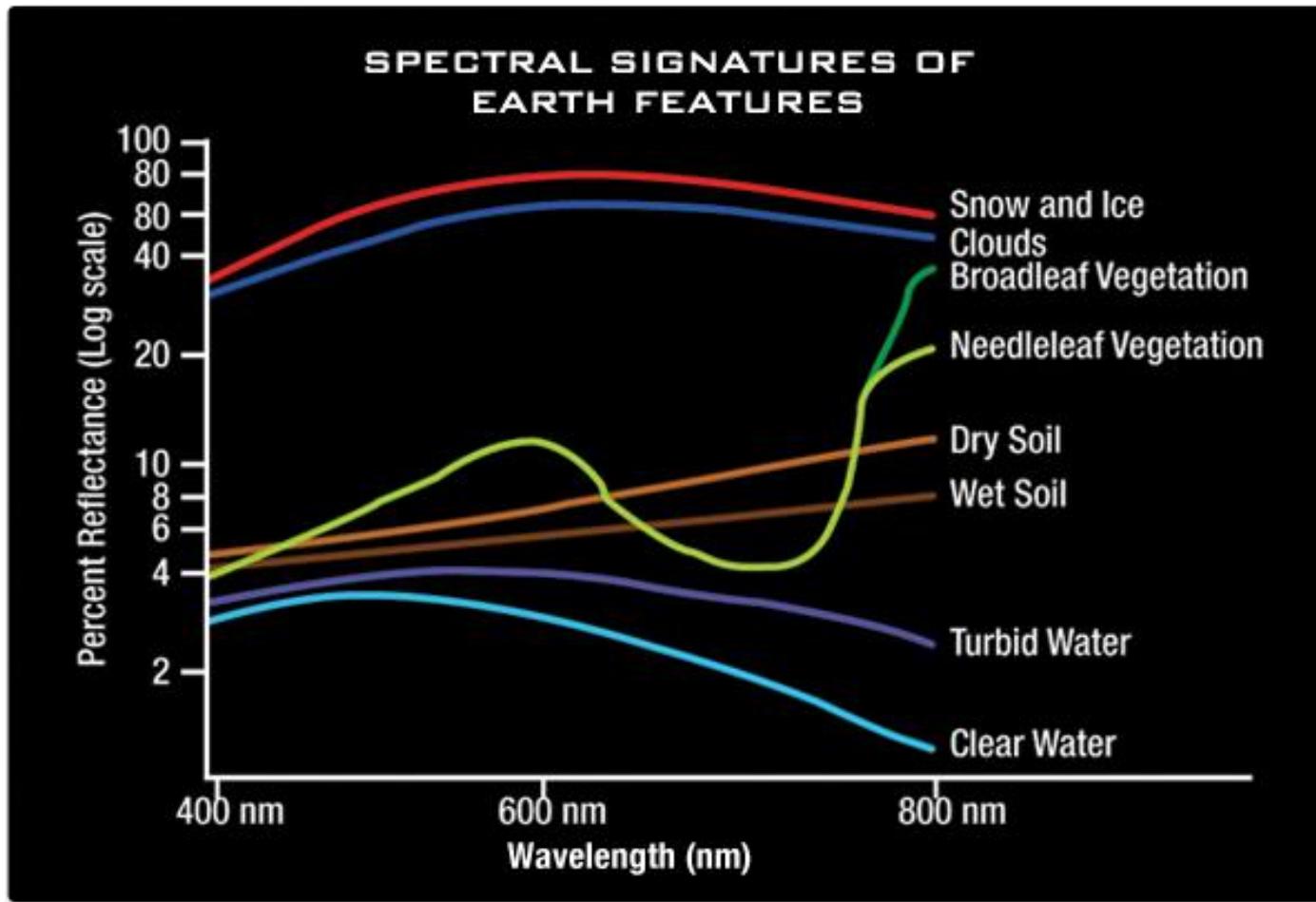
Tipos de teledetección

La superficie terrestre recibe diferentes tipos de radiación (Principalmente desde el sol)



- La superficie terrestre reenvía al espacio **radiación reflejada** (espectro visible) y **Térmica** (emisión) estas son captadas por los sensores remotos

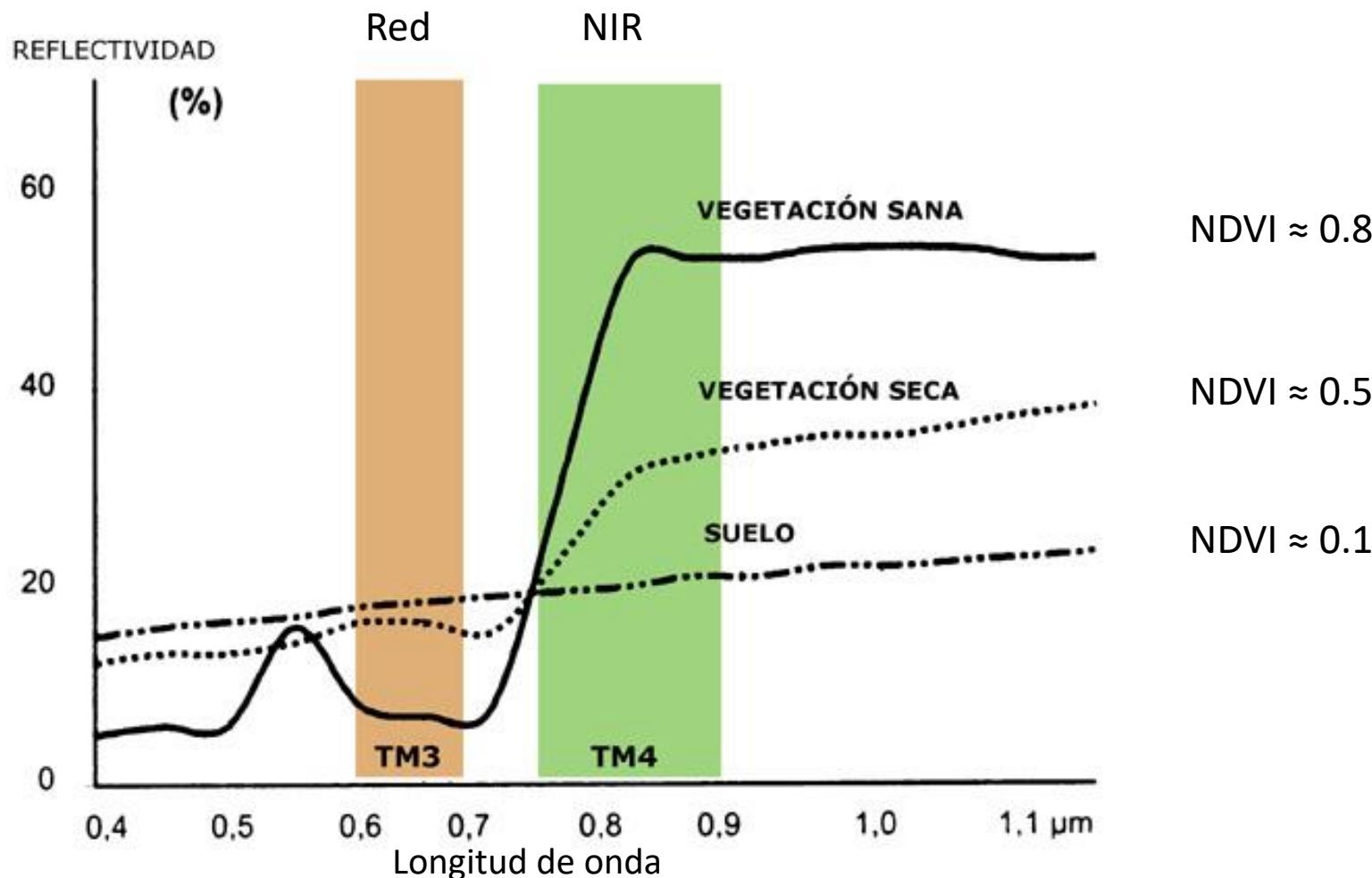
Cada superficie tiene su propia firma espectral



Herramientas: indicador de reflectancia

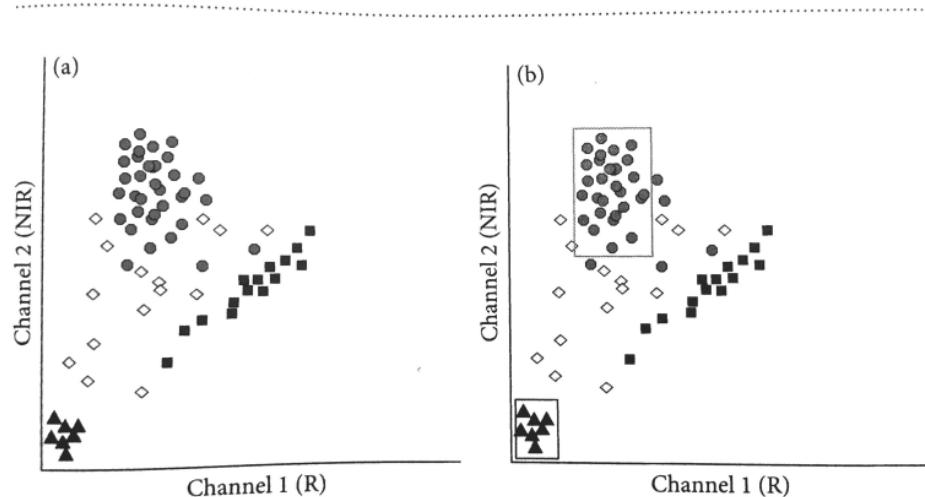
Índices espectrales ejemplo del NDVI

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}}$$



Clasificación no supervisada

- Los pixeles son clasificados únicamente basados en sus estadísticas espectrales
- Se agrupan en base a un numero de clases espectrales pre-definidas



- El algoritmo actúa en forma iterativa colocando pixeles en cada grupo hasta que se obtengan los grupos mas claros posibles

Se pueden usar para agrupar características fisiológicas (suelos , humedad entre otros...)

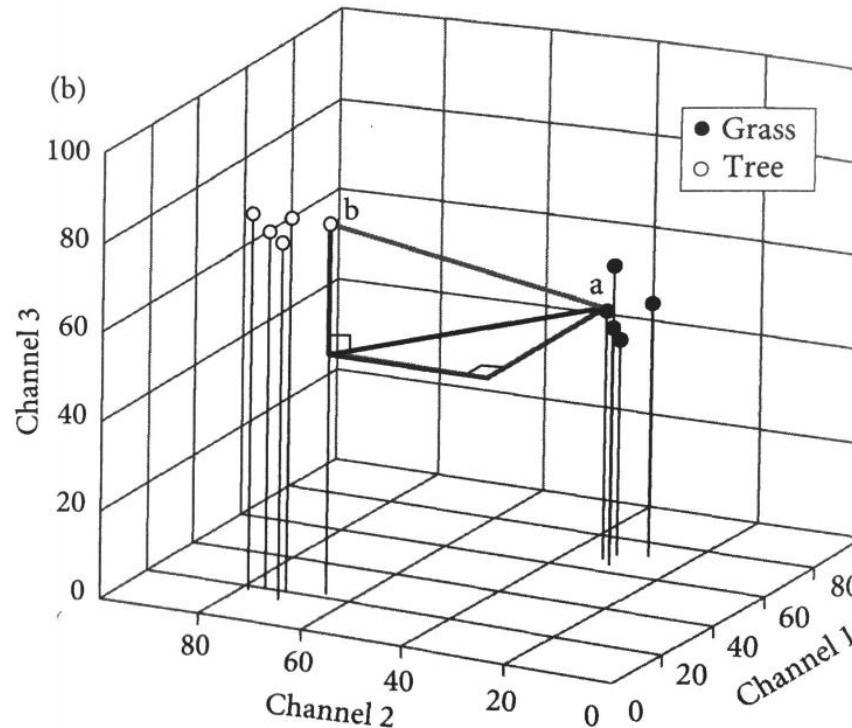
$$D_{ab} = \sqrt{\sum_{i=1}^n (a_i - b_i)^2},$$

Métodos mas conocidos:
K-mean, ISODATA, SOM

Clasificación no supervisada

Distancia euclídea
en un espacio
multidimensional

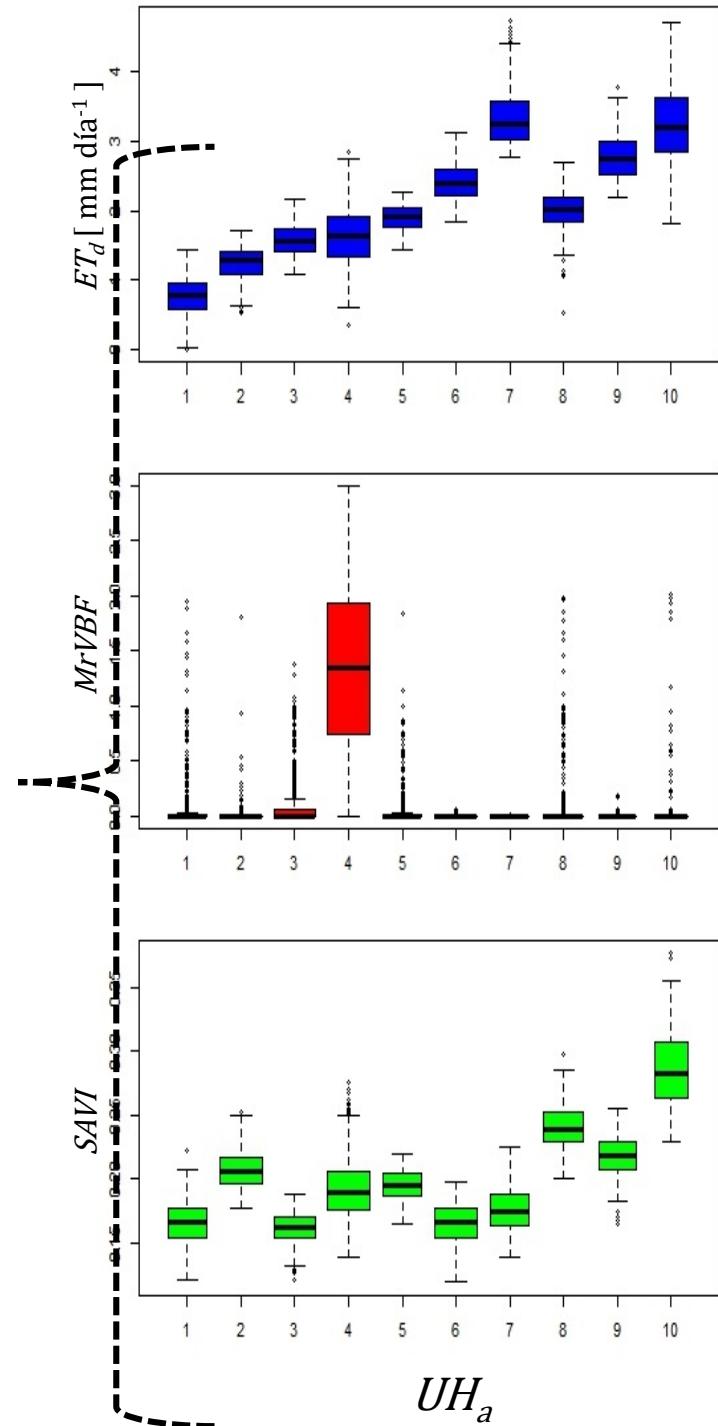
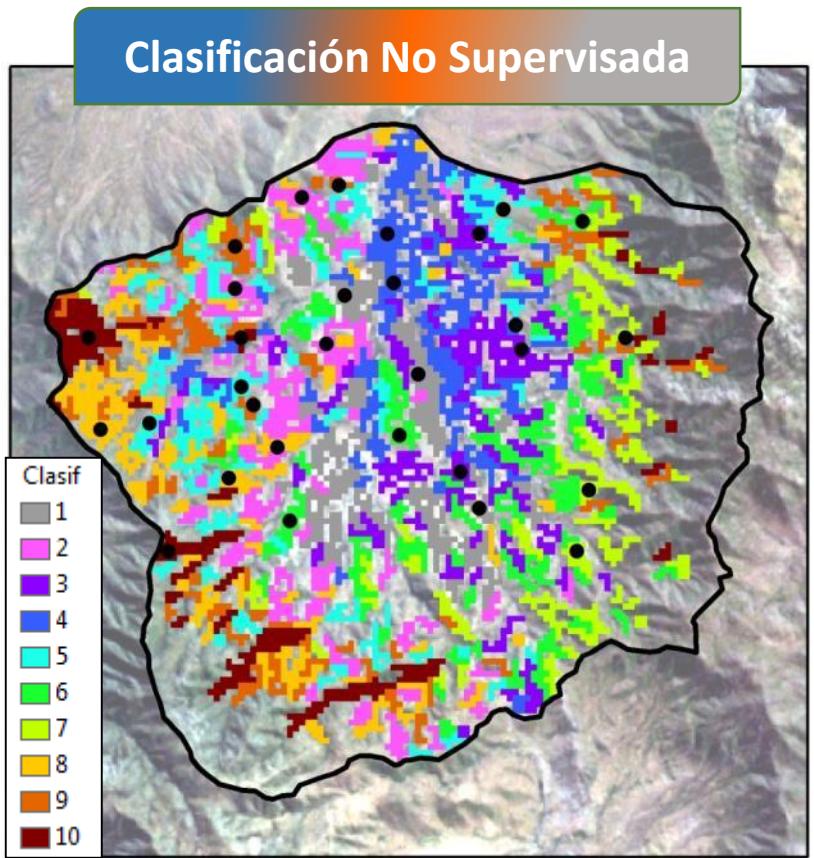
$$D_{ab} = \sqrt{\sum_{i=1}^n (a_i - b_i)^2},$$



	channel 1	channel 2	channel 3	$\Sigma(a-b)^2$	D_{ab}
a	65	32	50		
b	22	66	60		
a-b	43	-34	-10		
$(a-b)^2$	1849	1156	100	3105	55.7

Utilización de calcificación ISODATA para seleccionar puntos de muestreo

Elección de los puntos de muestreo



UH_a

Clasificación Supervisada

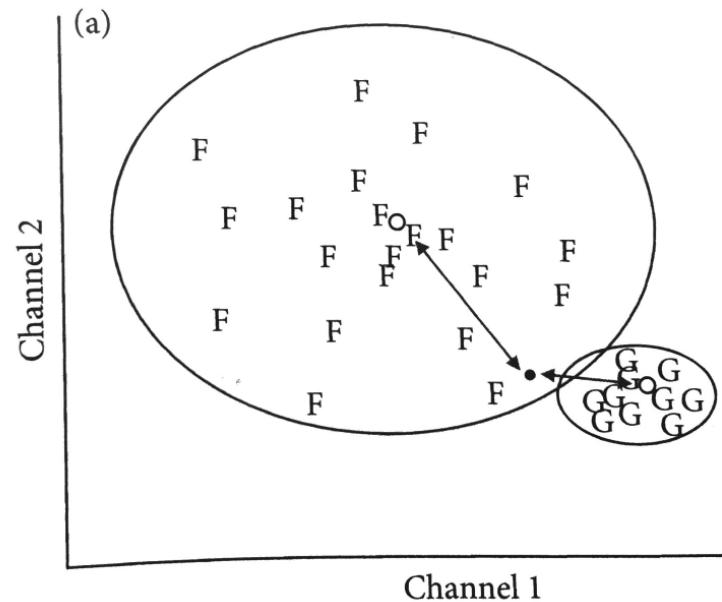
Parte del supuesto que se pueden identificar áreas (o pixeles) que pueden ser asignadas a un tipo de superficie conocido.

Se debe seleccionar un set de entrenamiento a partir de datos conocidos (terreno o alta resolución). Esta selección esta condicionada por dos factores:

- Pixeles muy homogéneos dentro de la clase
- Cada clase debe ser espectralmente diferente (Índice Divergencia Transformada, IDT, u otro método de evaluación)

Se suele seleccionar un numero de pixeles de entrenamiento $>n+1$ (n numero de bandas) con ojala al menos 10 pixeles por cada banda

Dentro de los métodos probabilísticos están los paramétricos y los no paramétricos:
El más conocido es el maximum-likelihood (Probabilidad) y también el de mínima distancia

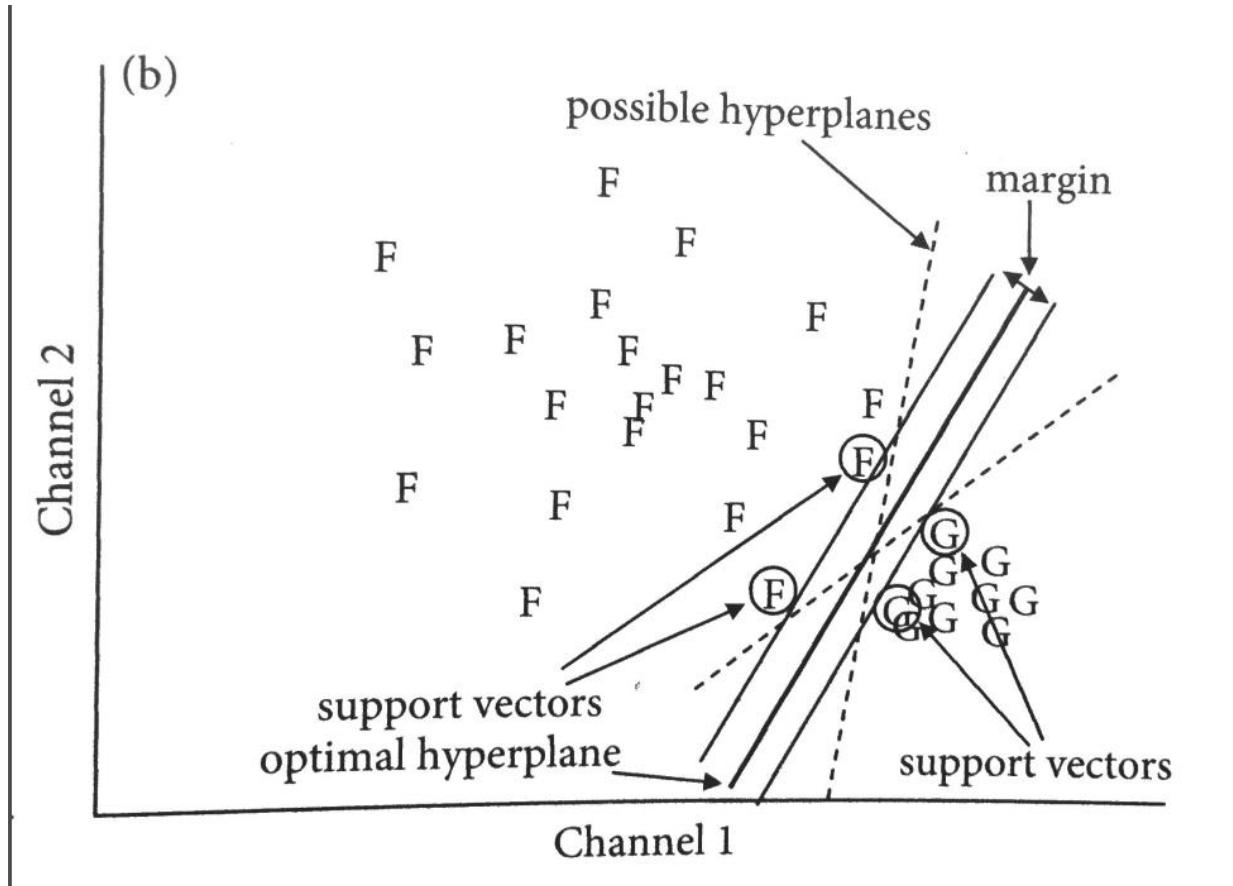


Se clasifica un pixel en base a su relación al centroide:

- Distancia
- **Probabilidad**

Clasificación Supervisada

Métodos no paramétricos están k nearest-neighbour, Artificial Neural Network, Support Vector Machines



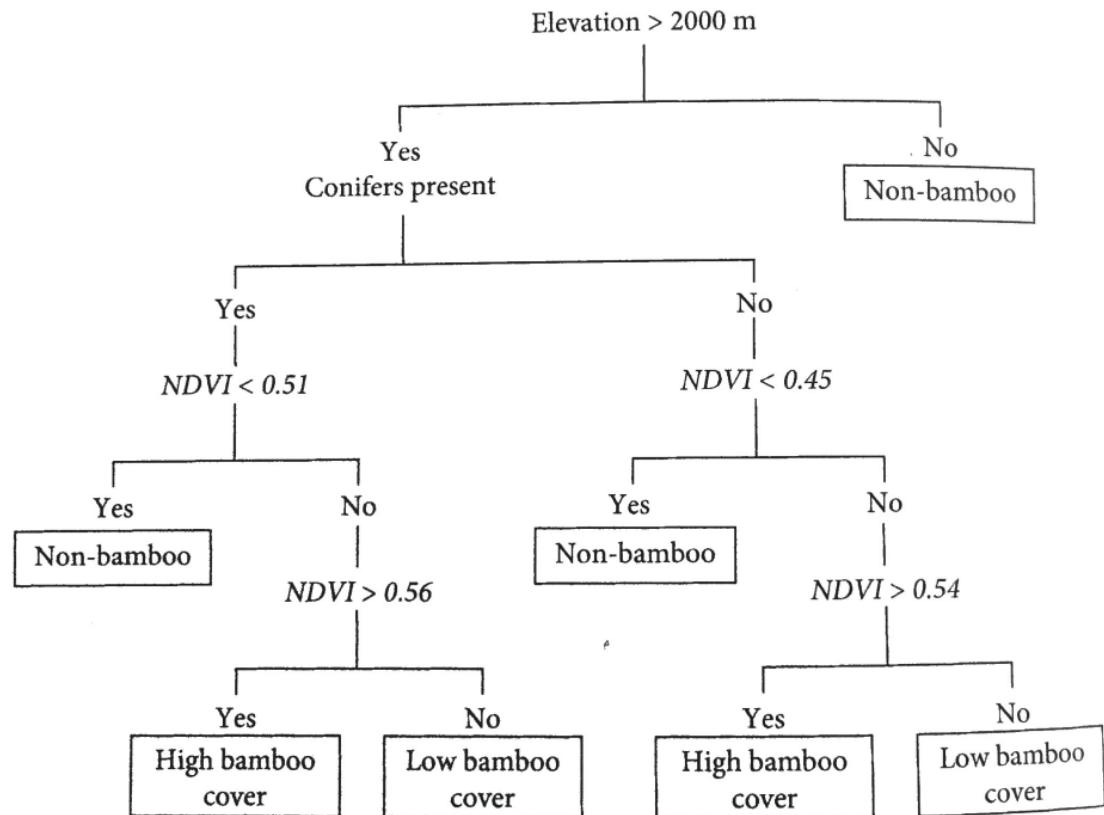
Support vector machines (SVM)

Clasificación por arboles de decisión

Clasificador por arboles de decisión:

Conjunto de decisiones binarias para obtener una clasificación

Método flexible que no requiere de supuestos paramétricos, se ve favorecido en situaciones de pixeles mixtos



Aplicación de Objetos para mejorar clasificaciones

OBIA (Object Base Image analysis)

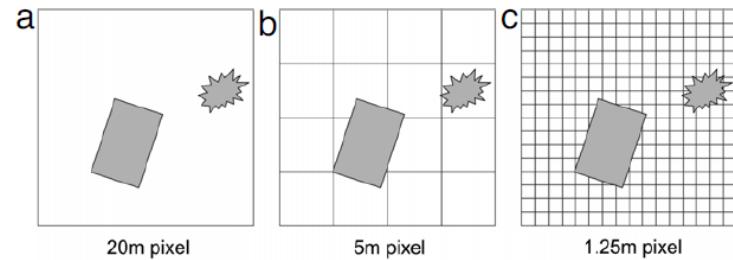


Fig. 1. Relationship between objects under consideration and spatial resolution: (a) low resolution: pixels significantly larger than objects, sub-pixel techniques needed. (b) medium resolution: pixel and objects sizes are of the same order, pixel-by-pixel techniques are appropriate. (c) high resolution: pixels are significantly smaller than object, regionalisation of pixels into groups of pixels and finally objects is needed.

What's wrong with pixels ?

Blaschke 2010

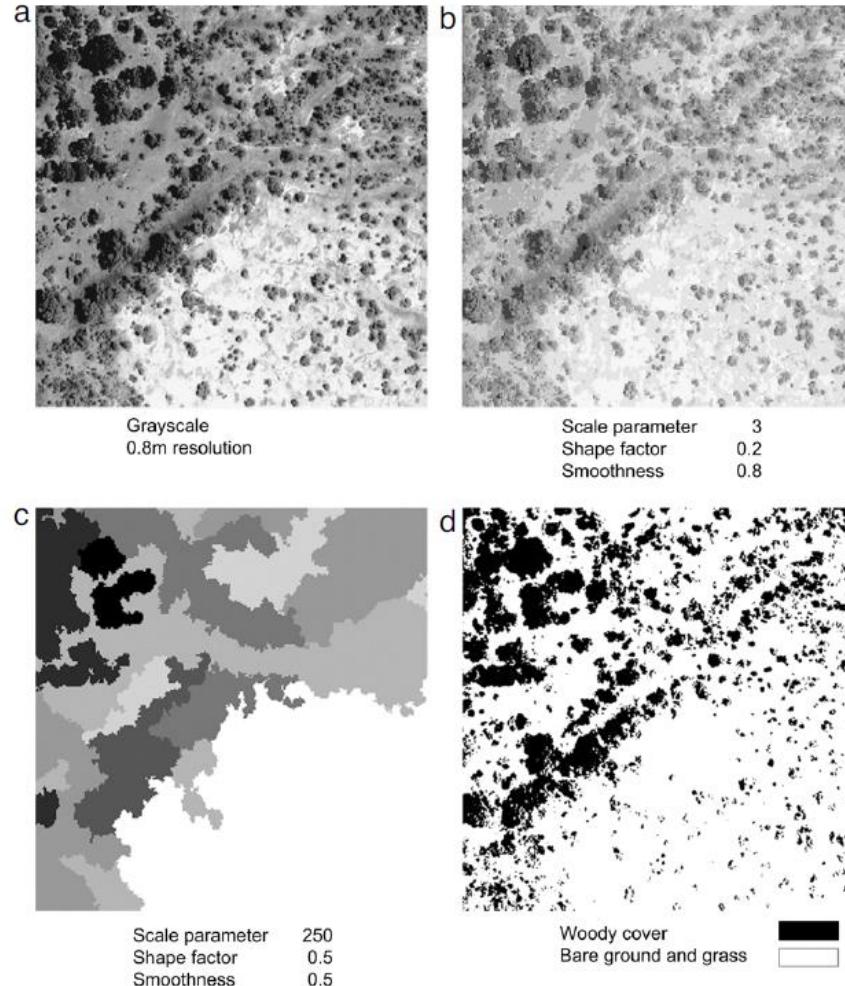


Fig. 2. (a) Aerial photograph of heterogeneous landscape (b) fine scale segmentation (c) coarse scale segmentation (d) object based classification of woody cover, resulting in 97% accuracy (from: Levick and Rogers, 2008, with permission).

Evaluación de la exactitud

Table 10.5 A typical error matrix for assessing classification accuracy. In this case each of the $n = 121$ test pixels was classified into one of four vegetation classes by means of ground observation to produce ground reference data. These assignments were compared on a pixel-by-pixel basis with the results of the automatic classifier being tested. Shaded cells along the diagonal are the number of correctly classified reference samples.

		Ground reference data							
		Class	Evergreen	Deciduous	Grass	Scrub	Total	User accuracy	Commission error
Classification	Evergreen	25	1	6	0	32	25/32 = 0.69	7/32 = 0.22	
	Deciduous	2	35	8	4	47	33/47 = 0.70	14/47 = 0.30	
	Grass	1	4	17	2	24	17/24 = 0.71	7/24 = 0.51	
	Scrub	2	0	1	5	8	5/8 = 0.625	3/8 = 0.38	
	30	38	32	11		$n = 121$			
Producer's accuracy		25/30 = 0.833	33/38 = 0.87	17/32 = 0.53	5/11 = 0.45		Overall accuracy: 80/121 = 0.66		
Omission error		5/30 = 0.167	5/38 = 0.13	15/32 = 0.47	6/11 = 0.55				

La matriz de confusión

Evaluación de exactitud: índice Kappa

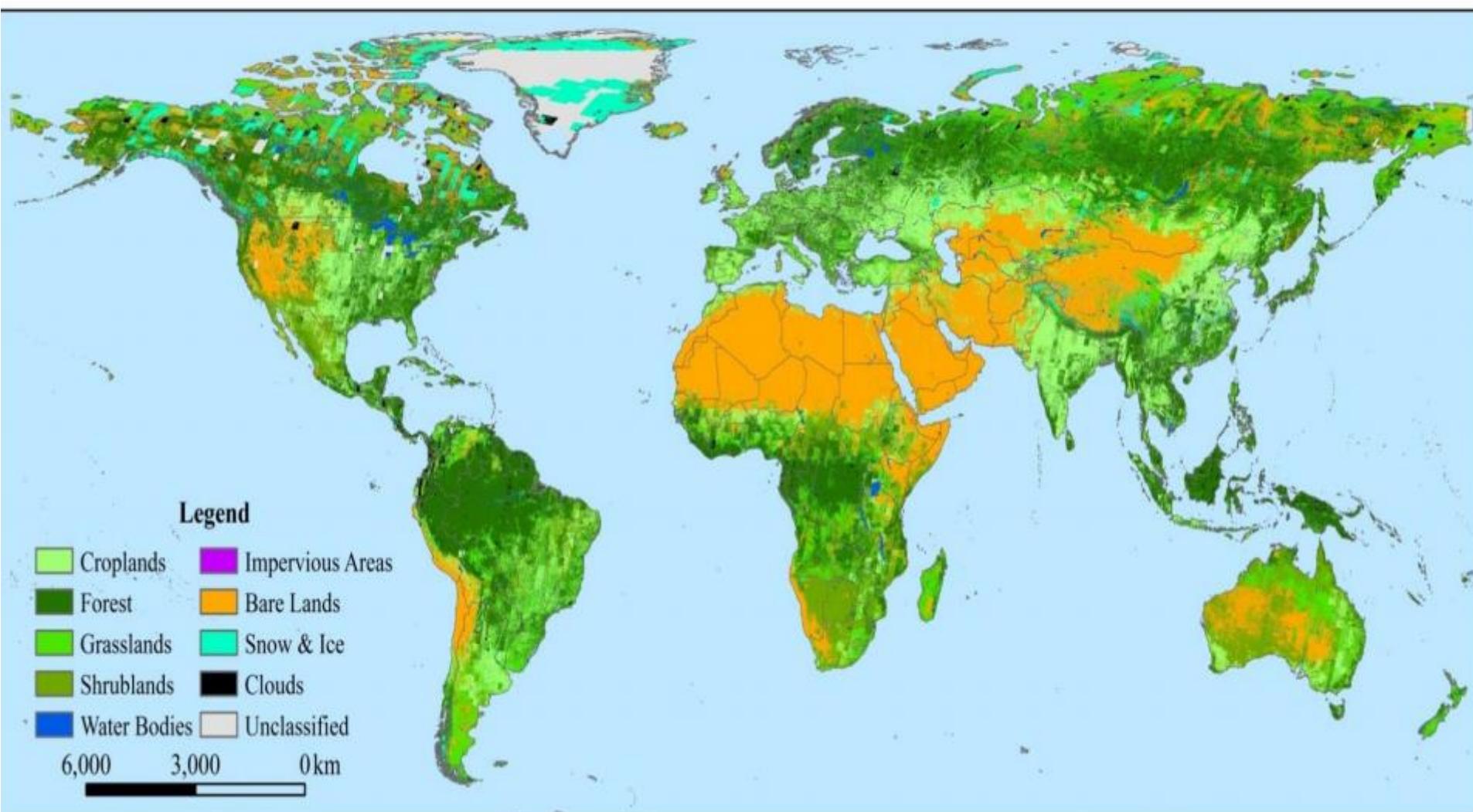
Debe ser Mayor a 0.75

$$\kappa = \frac{n \sum_{i=1}^k x_{ii} - \sum_{i=1}^k (x_{i+} \times x_{+i})}{n^2 - \sum_{i=1}^k (x_{i+} \times x_{+i})}, \quad (10.5)$$

where x_{ii} are the diagonal cells of the matrix, the x_{i+} are the row marginal totals and the x_{+i} are the column marginal totals and n is the total number of elements in the matrix.

Algunos ejemplos

FROM-GLC (Accuracy: 63.72%)



Áreas mas frecuentemente estudiadas con enfoques de land-cover

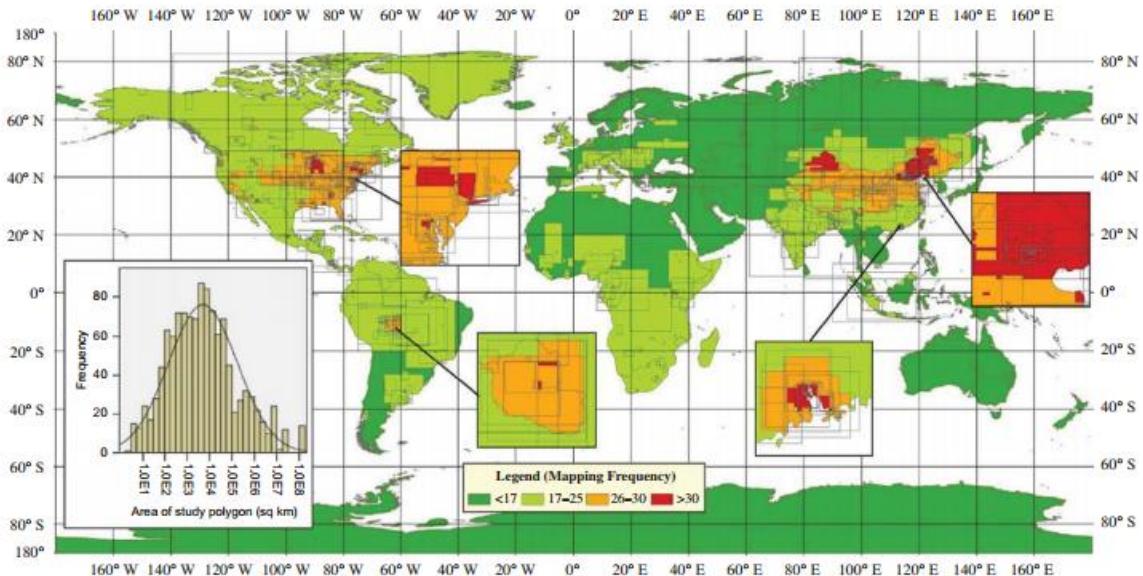


Figure 2. Hotspot areas of land-cover mapping research. Concrete information on areas of study was used to create this map based on 1783 papers that contain sufficient information on the area of study. A histogram of study area size shows that most studies are at a regional scale ($100-100,000 \text{ km}^2$).

Mapa de complejidad de mapeo

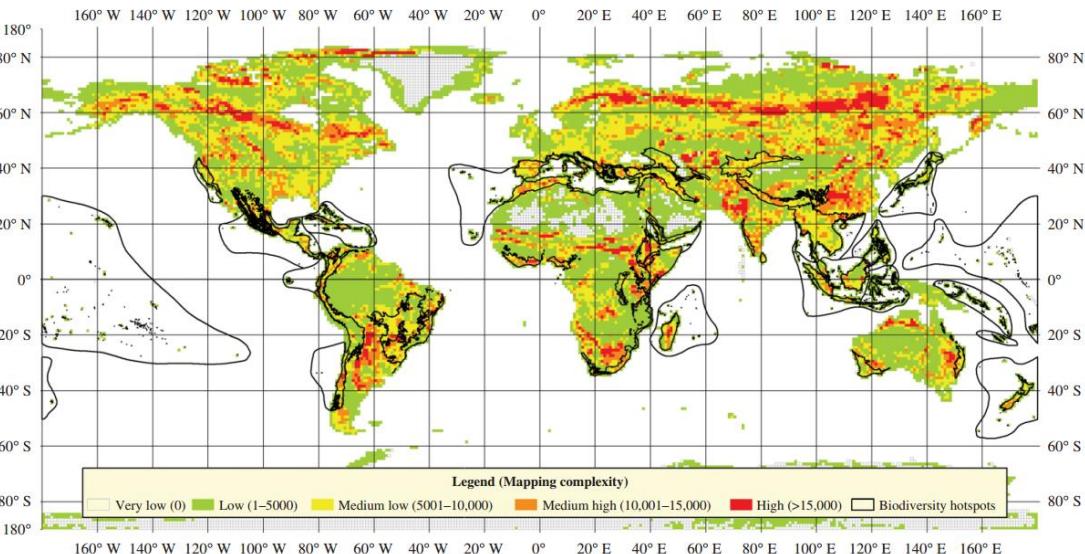
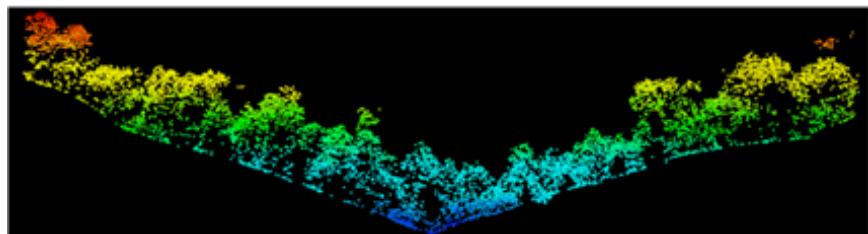


Figure 3. Biodiversity hotspots and the distribution of mapping complexity around the world.

Frecuencia y exactitud de los satélites utilizados



LiDAR

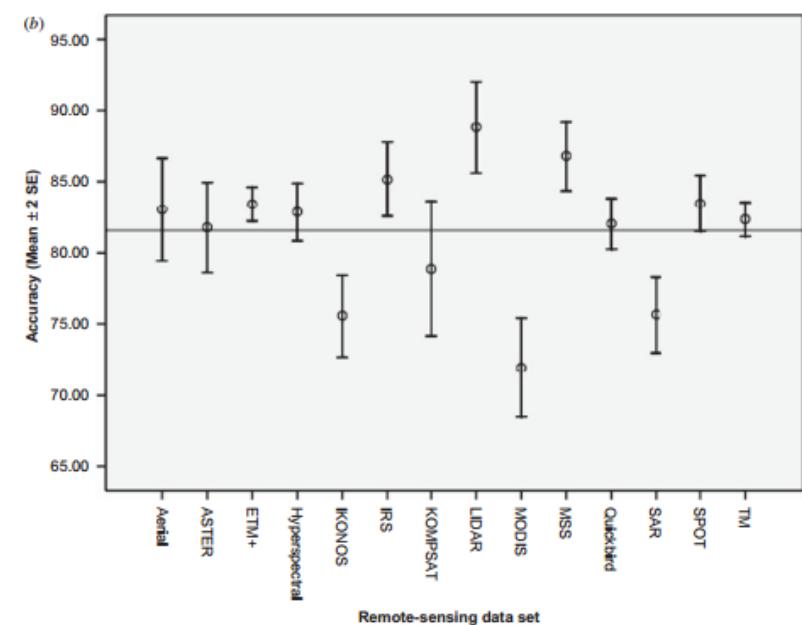
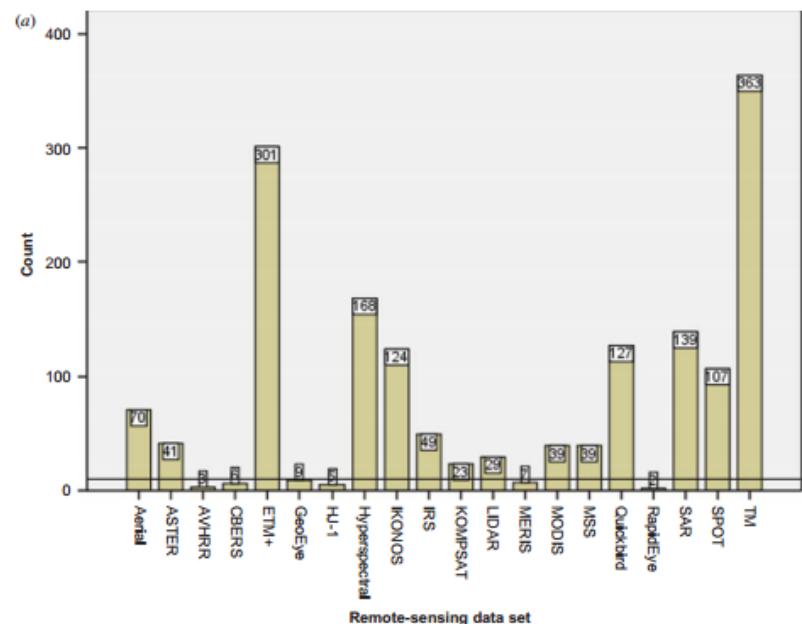


Figure 6. Frequency and accuracy of remotely sensed data types in land-cover mapping. (a) Frequency of data types used in experiments ($N = 1651$); (b) classification accuracy in relation to data type ($N = 1619$; types with <10 experiments are excluded).

Le Yu, Lu Liang, Jie Wang, Yuanyuan Zhao, Qu Cheng, Luanyun Hu, Shuang Liu, Liang Yu, Xiaoyi Wang, Peng Zhu, Xueyan Li, Yue Xu, Congcong Li, Wei Fu, Xuecao Li, Wenyu Li, Caixia Liu, Na Cong, Han Zhang, Fangdi Sun, Xinfang Bi, Qinchuan Xin, Dandan Li, Donghui Yan, Zhiliang Zhu, Michael F. Goodchild & Peng Gong (2014) Meta-discoveries from a synthesis of satellite-based land-cover mapping research, International Journal of Remote Sensing, 35:13, 4573-4588.

Frecuencia y exactitud de los métodos de clasificación

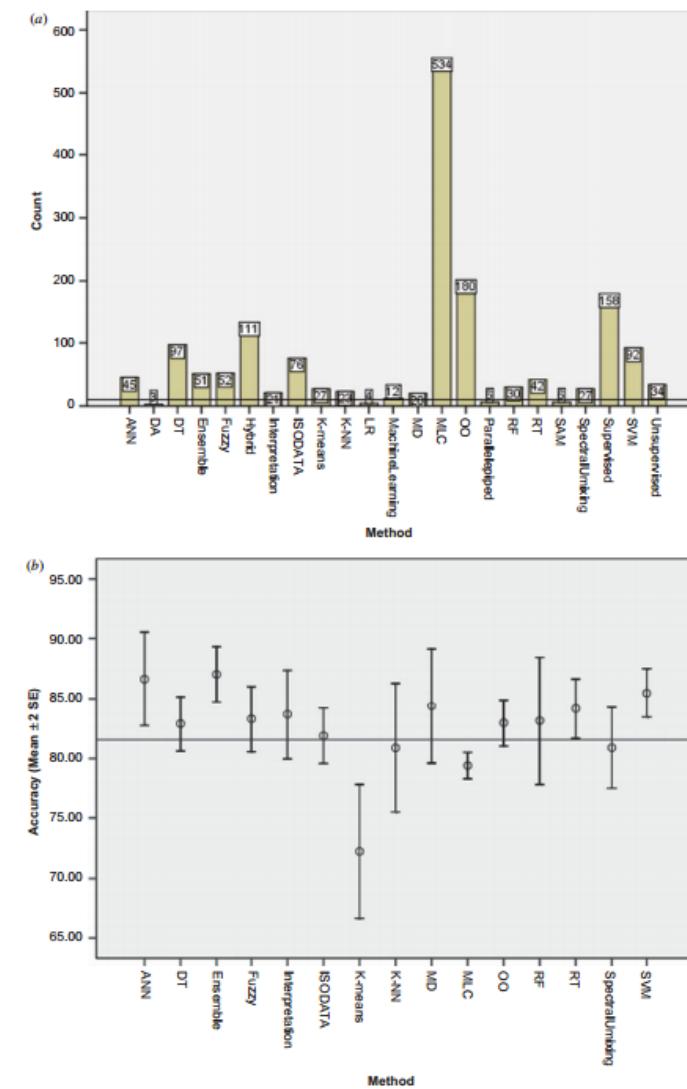


Figure 7. Frequency and accuracy of classification methods in land-cover mapping. (a) Frequency of classification methods used in experiments ($N = 1361$); (b) classification accuracy versus classification method ($N = 1317$; <10 experiments and general-type methods (i.e. supervised, unsupervised, machine learning, hybrid) are excluded). ANN: Artificial Neural Network, DA: Discriminant Analysis, DT: Decision Tree, Ensemble: Ensemble classifiers (i.e. AdaBoost, Bagging), Hybrid: unsupervised and supervised hybrid classifiers (e.g. the most common examples are ISODATA and MLC hybrid), Machine Learning: advanced machine learning (i.e. Active Learning, Particle Swarm Optimization), ISODATA: Iterative Self-organizing Data Analysis Techniques Algorithm, K-NN: K-Nearest Neighbour, MD: Minimum Distance, MLC: Maximum Likelihood Classifier, OO: Object Based, RF: Random Forest, RT: Regression Tree, SAM: Spectral Angle Mapping, SVM: Support Vector Machine.

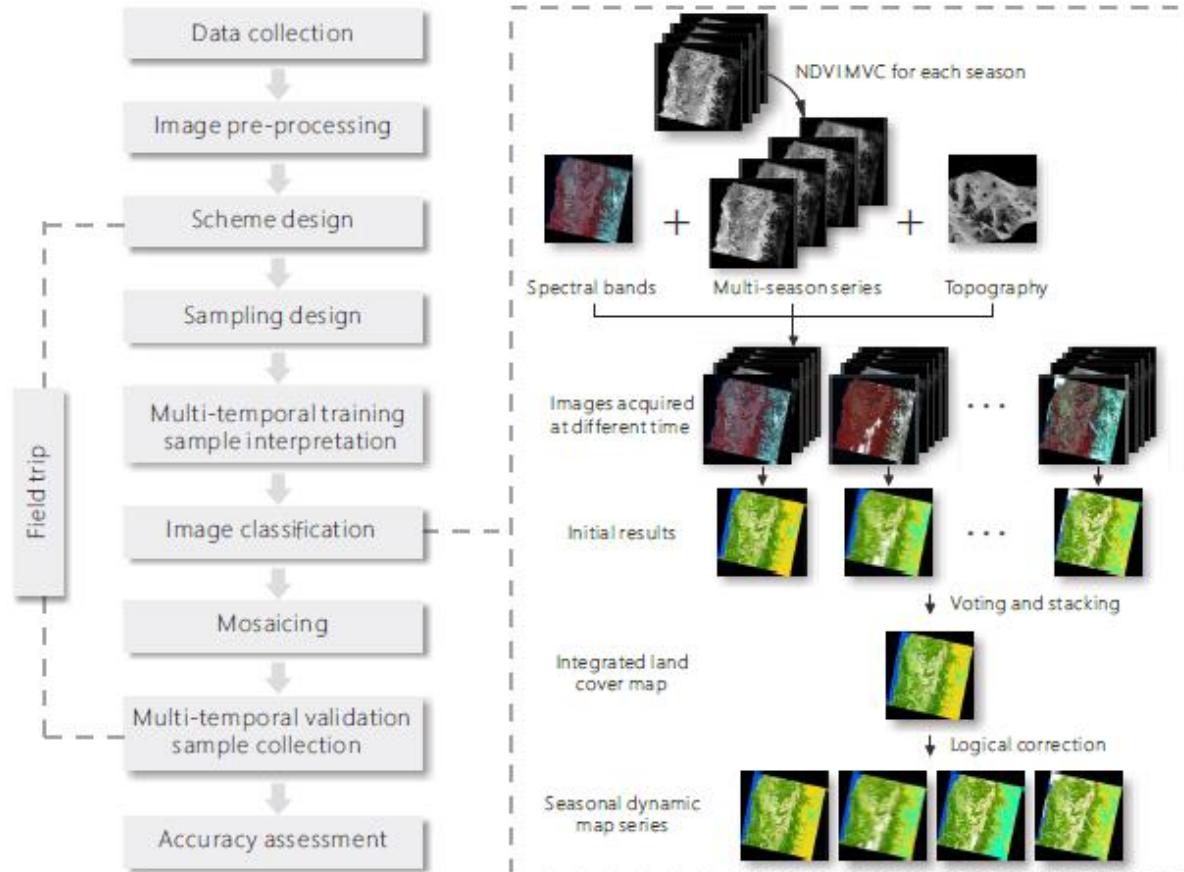


Y en
Chile ...

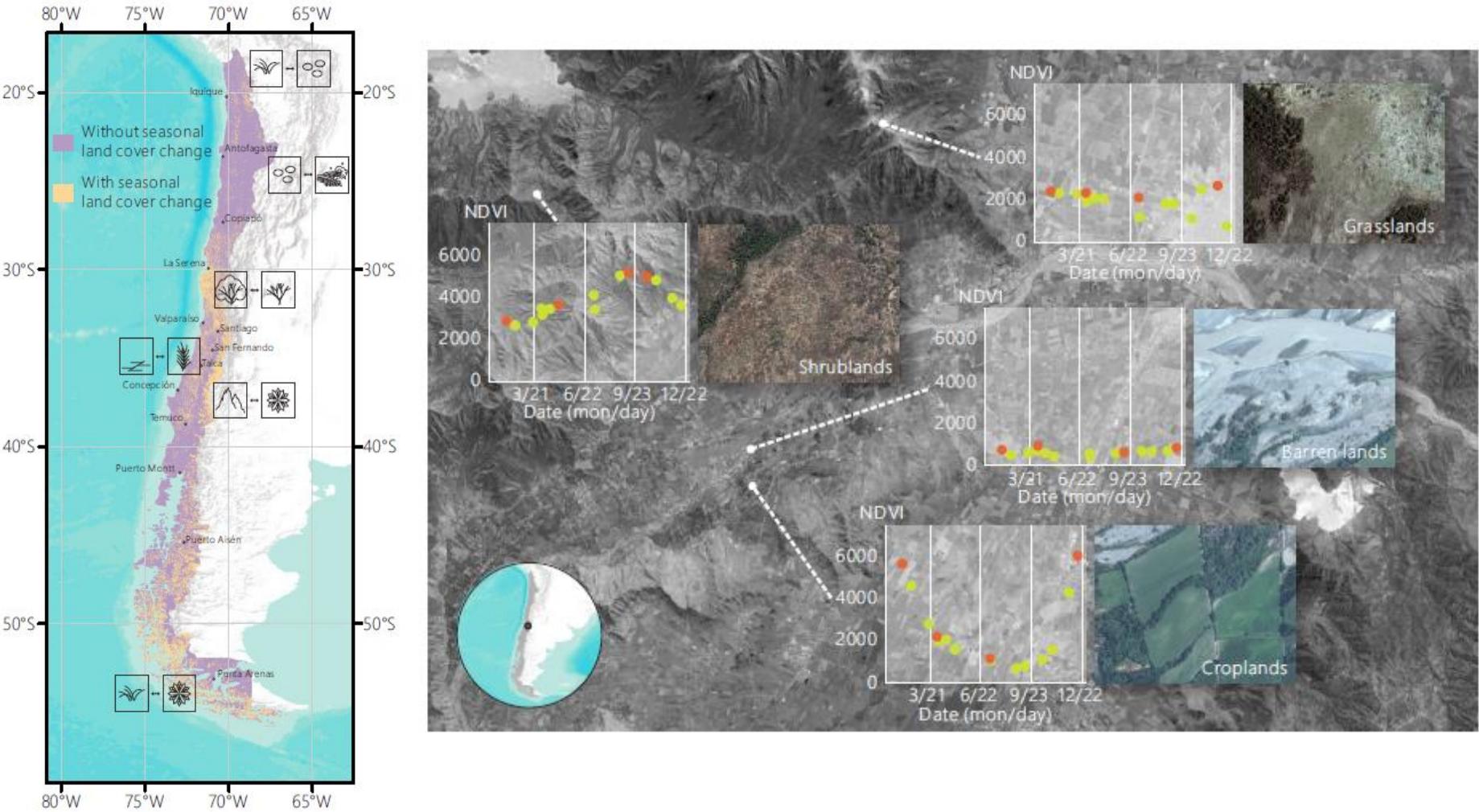
Detailed dynamic land cover mapping of Chile: Accuracy improvement by integrating multi-temporal data

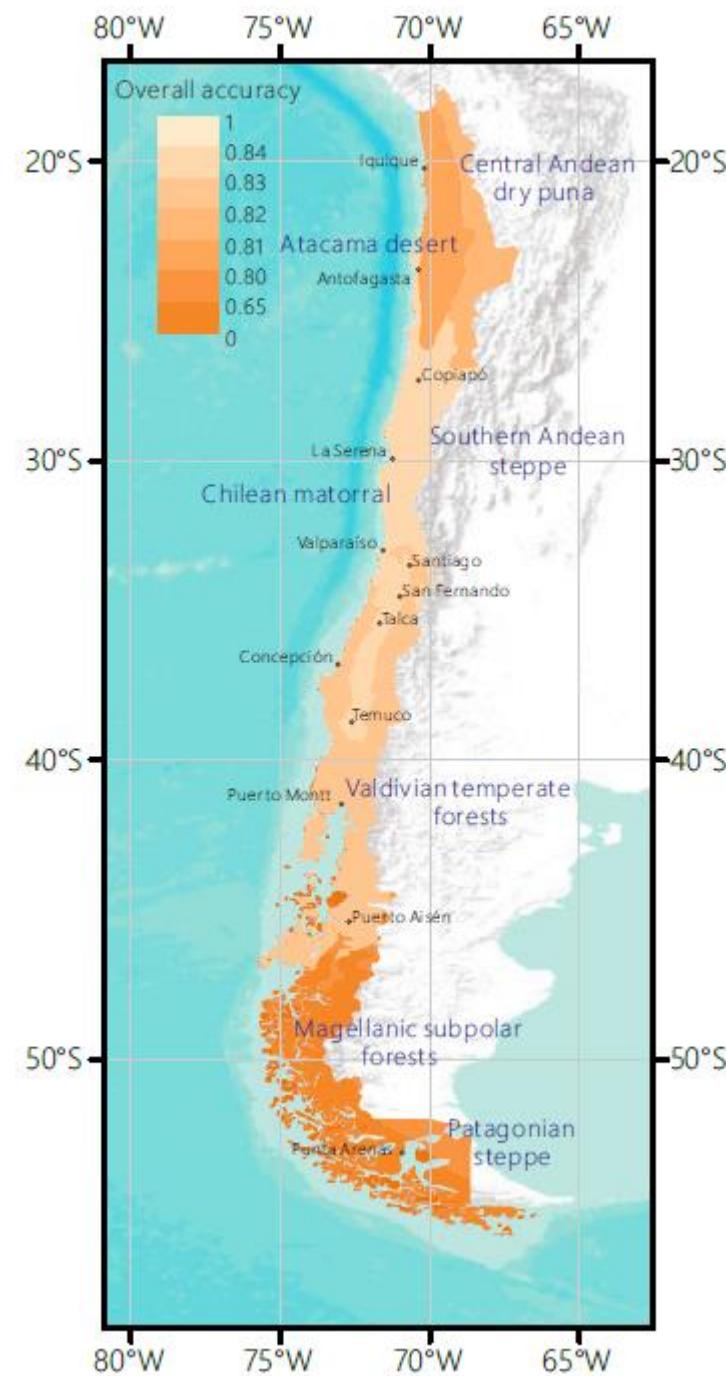
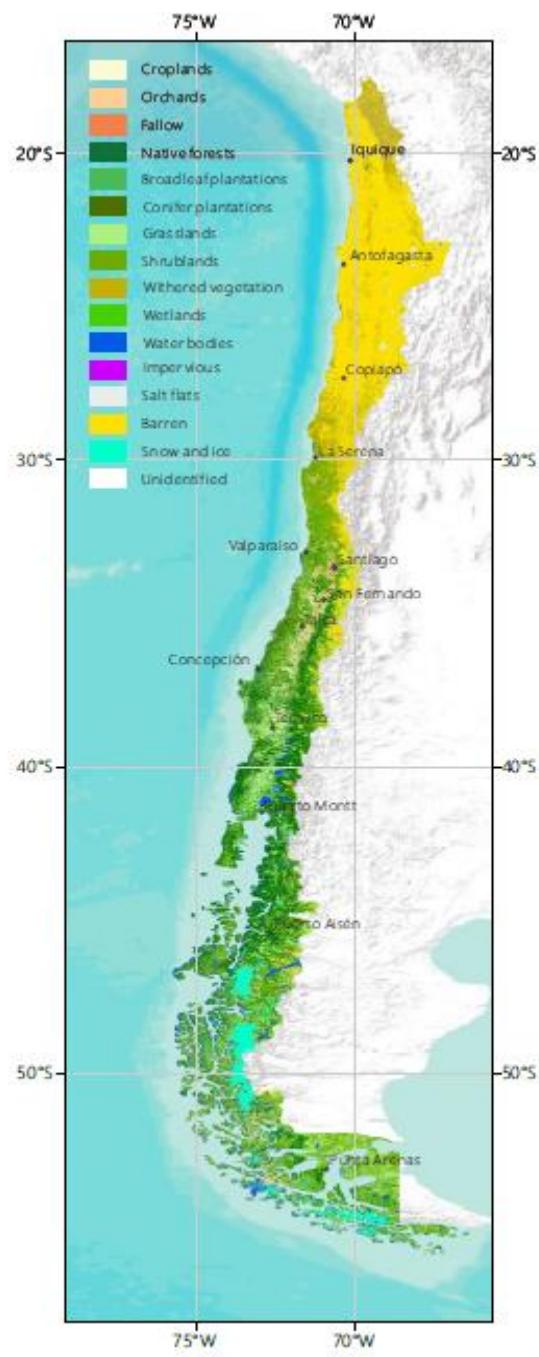


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Enfoque multi-temporal

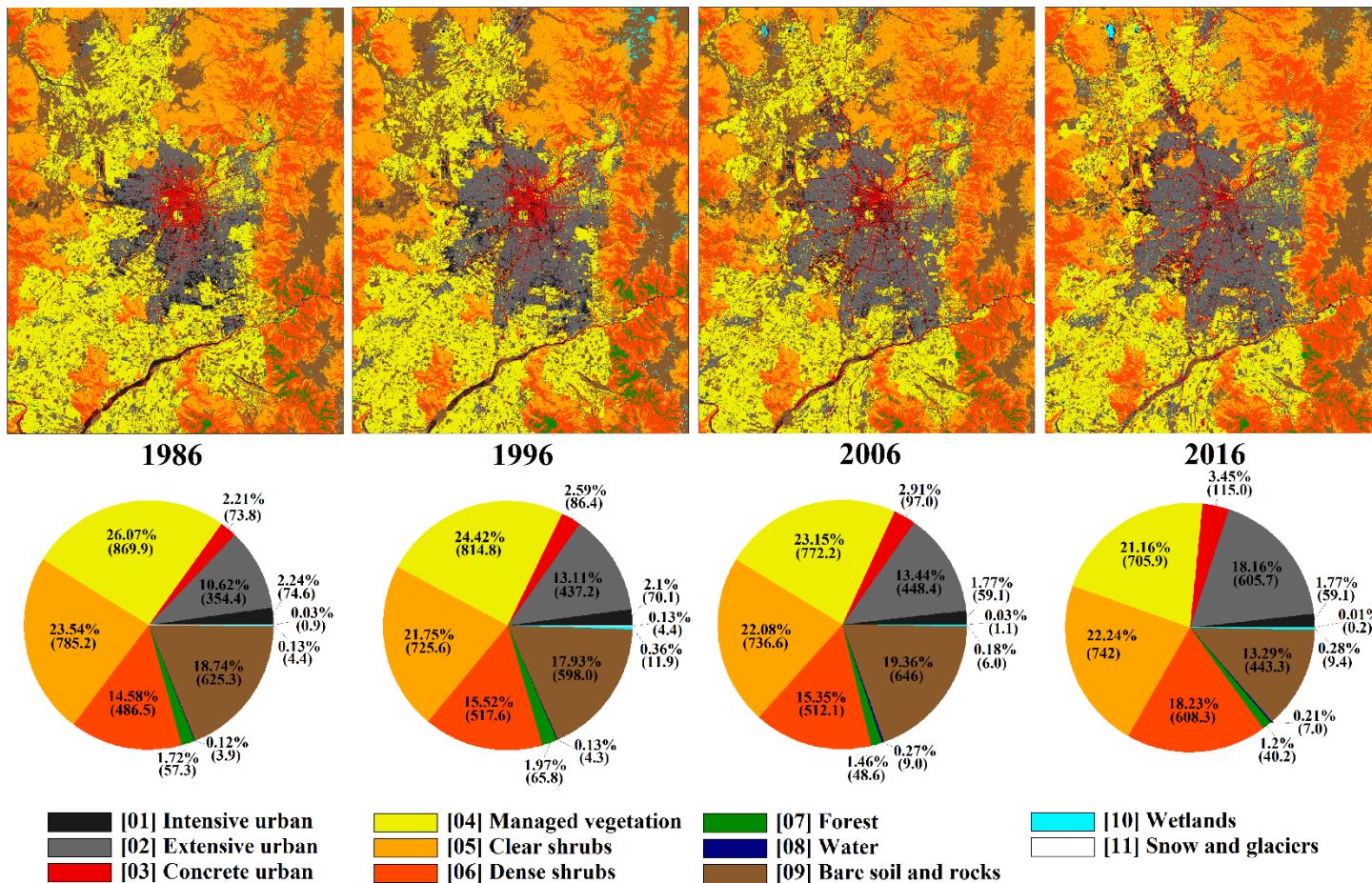




RESEARCH ARTICLE

Evolution of air quality in Santiago: The role of mobility and lessons from the science-policy interface

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Gracias