Università degli Studi Firenze

School of Forestry

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AgriDigit

Stima spazialmente esplicita di variabili forestali inventariali tramite telerilevamento

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Laboratory of Forest Geomatics

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Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria

Dr. Daniel Goodman Horvitz
1921 - 2008

Dr. Donovan J. Thompson
1919 - 1991

A GENERALIZATION OF SAMPLING WITHOUT REPLACEMENT FROM A FINITE UNIVERSE*

D. G. Horvitz† and D. J. Thompson
Iowa State College

This paper presents a general technique for the treatment of samples drawn without replacement from finite universes when unequal selection probabilities are used. Two sampling schemes are discussed in connection with the problem of determining optimum selection probabilities according to the information available in a supplementary variable. Admittedly, these two schemes have limited application. They

with the development of more efficient sampling systems, the system including both the sample design and the method of estimation. One sampling system is said to be more efficient than another if the variance or mean square error of the estimate with the first system is less than that of the second, provided the cost of obtaining the data and results is the same for both. The development of stratified, multi-stage, multiphase, cluster, systematic, and other sample designs beyond

throughout.

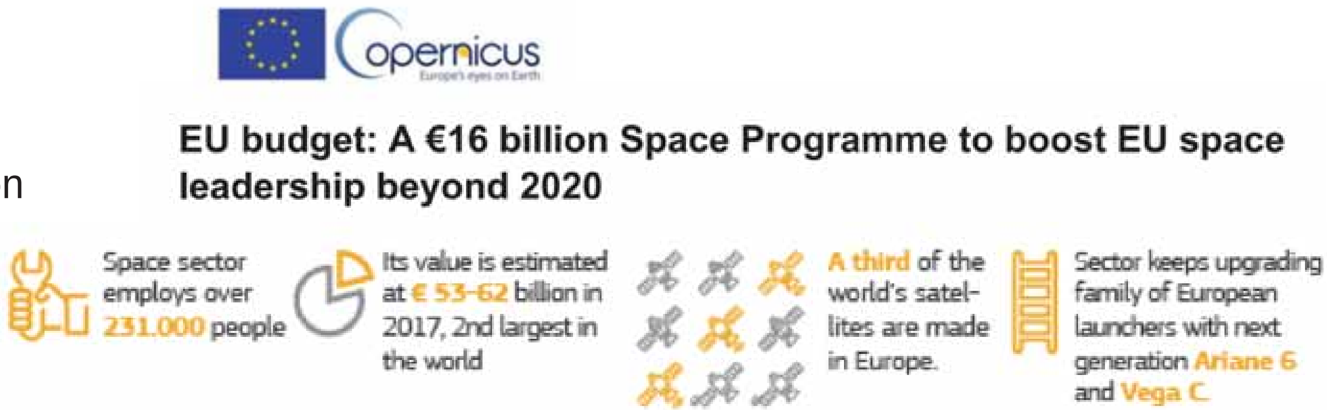
The possibility of using unequal probabilities for selecting the sample elements from the universe as a means of increasing precision perhaps received its first impetus for applied sampling from Hansen and Hurwitz [2] in 1943. They introduced the selection of primary units (in a subsampling scheme) with probabilities proportionate to some measure of their size and presented the appropriate theory. Their sampling scheme was confined (when sampling without replacement) to samples of one primary unit per stratum, however, the theory not having been extended beyond this point. More recently, Midzuno [6] has generalized the Hansen and Hurwitz approach to sampling a combination of n elements of the universe with probability proportionate to some measure of size of the combination. Madow [5] has made some contributions to the theory of the systematic selection of several clusters with probability proportionate to a measure of size.

* Journal Paper No. J2139 of the Iowa Agricultural Experiment Station, Ames, Iowa, Project 1005. Presented to the Institute of Mathematical Statistics, March 17, 1951.
† Now at the University of Pittsburgh.

Tabella 1.3.1 - Valori totali e per unità di superficie del volume del fusto e dei rami grossi per le categorie inventariali Boschi alti, Impianti di arboricoltura da legno e Aree temporaneamente prive di soprassuolo e per la macrocategoria Bosco

Distretto territoriale	Boschi alti				Impianti di arboricoltura da legno				Aree temp. prive di soprassuolo				Totale Bosco			
	Volume (m^3)	ES (%)	Volume (m^3 ha^{-1})	ES (%)	Volume (m^3)	ES (%)	Volume (m^3 ha^{-1})	ES (%)	Volume (m^3)	ES (%)	Volume (m^3 ha^{-1})	ES (%)	Volume (m^3)	ES (%)	Volume (m^3 ha^{-1})	ES (%)
Piemonte	126 821 547	3.1	151.0	2.9	2 947 269	15.7	103.2	12.7	7 613	60.2	3.3	45.9	129 776 430	3.0	149.1	2.8
Valle d'Aosta	15 334 302	7.6	156.0	6.9	0	-	0	-	0	-	0	-	15 334 302	7.6	155.8	6.9
Lombardia	105 423 629	4.2	182.4	3.9	2 613 095	19.6	97.4	17.8	0	-	0	-	108 036 723	4.1	178.3	3.9
Alto Adige	104 721 523	4.6	315.0	4.3	0	-	0	-	467 004	31.4	109.6	14.7	105 188 527	4.6	312.4	4.3
Trentino	105 715 538	4.8	283.5	4.6	0	-	0	-	61 011	97.3	24.2	89.8	105 776 549	4.7	281.8	4.6
Veneto	80 931 420	4.6	204.7	4.2	260 012	45.4	124.4	25.6	4 529	100.0	13.4	-	81 195 960	4.6	204.1	4.2
Friuli V.G.	67 066 949	5.4	212.1	5.1	763 052	26.8	100.3	18.7	0	-	0	-	67 830 001	5.3	209.5	5.0
Liguria	49 379 829	4.5	147.3	4.3	39 233	100.0	107.1	-	19 730	56.8	5.7	49.0	49 438 791	4.5	145.8	4.3
Emilia Romagna	71 063 339	3.9	128.7	3.7	1 274 428	20.6	130.8	13.1	356	72.6	0.3	53.7	72 338 122	3.9	128.4	3.6
Toscana	130 873 621	3.1	129.9	3.0	1 042 114	43.2	189.7	34.7	40 250	66.0	15.6	60.5	131 955 985	3.1	129.9	2.9
Umbria	29 142 004	4.8	79.2	4.6	112 665	55.0	33.3	44.6	0	-	0	-	29 254 669	4.8	78.7	4.6
Marche	24 231 008	6.6	83.5	6.3	62 614	66.5	51.6	41.1	0	-	0	-	24 293 622	6.6	83.4	6.3
Lazio	57 249 600	4.7	107.0	4.4	180 483	66.2	105.9	46.5	80 552	46.9	11.1	41.4	57 510 635	4.6	105.7	4.4
Abruzzo	50 404 587	4.6	129.5	4.4	87 051	71.8	77.5	42.2	1 193	100.0	1.0	-	50 492 831	4.6	129.0	4.4
Molise	14 523 394	9.0	110.5	8.5	106 992	93.1	120.0	54.1	5 598	100.0	22.4	-	14 635 984	8.9	110.4	8.4
Campania	42 353 904	6.0	111.5	5.7	112 595	48.3	97.4	42.7	36 194	59.6	11.2	49.3	42 502 693	6.0	110.6	5.7
Puglia	12 046 337	11.0	84.2	10.5	108 303	95.5	123.5	66.4	5 844	100.0	3.0	-	12 160 485	10.9	83.4	10.4
Basilicata	27 415 389	6.9	106.3	6.5	230 731	46.0	123.8	11.1	15 086	73.0	4.6	64.8	27 661 206	6.9	105.1	6.4
Calabria	86 990 394	4.7	190.0	4.3	706 558	54.8	267.7	39.2	270 501	57.0	35.5	53.1	87 967 454	4.7	187.9	4.3
Sicilia	23 125 002	6.7	91.2	6.1	56 190	95.7	49.4	76.4	1 605	86.9	1.1	70.6	23 182 797	6.7	90.5	6.1
Sardegna	31 286 179	5.8	57.1	5.4	1 543 109	22.2	60.4	20.0	53 445	56.1	5.6	53.1	32 882 733	5.6	56.4	5.2
Italia	1 256 099 493	1.1	146.4	1.0	12 246 493	8.7	100.2	7.4	1 070 512	21.4	19.8	20.0	1 269 416 499	1.1	144.9	1.0

Number of satellites	Purpose
3135	Communications
1030	Earth Observation
385	Technology development/demonstration
154	Navigation/positioning
22	Earth science
18	Other purposes



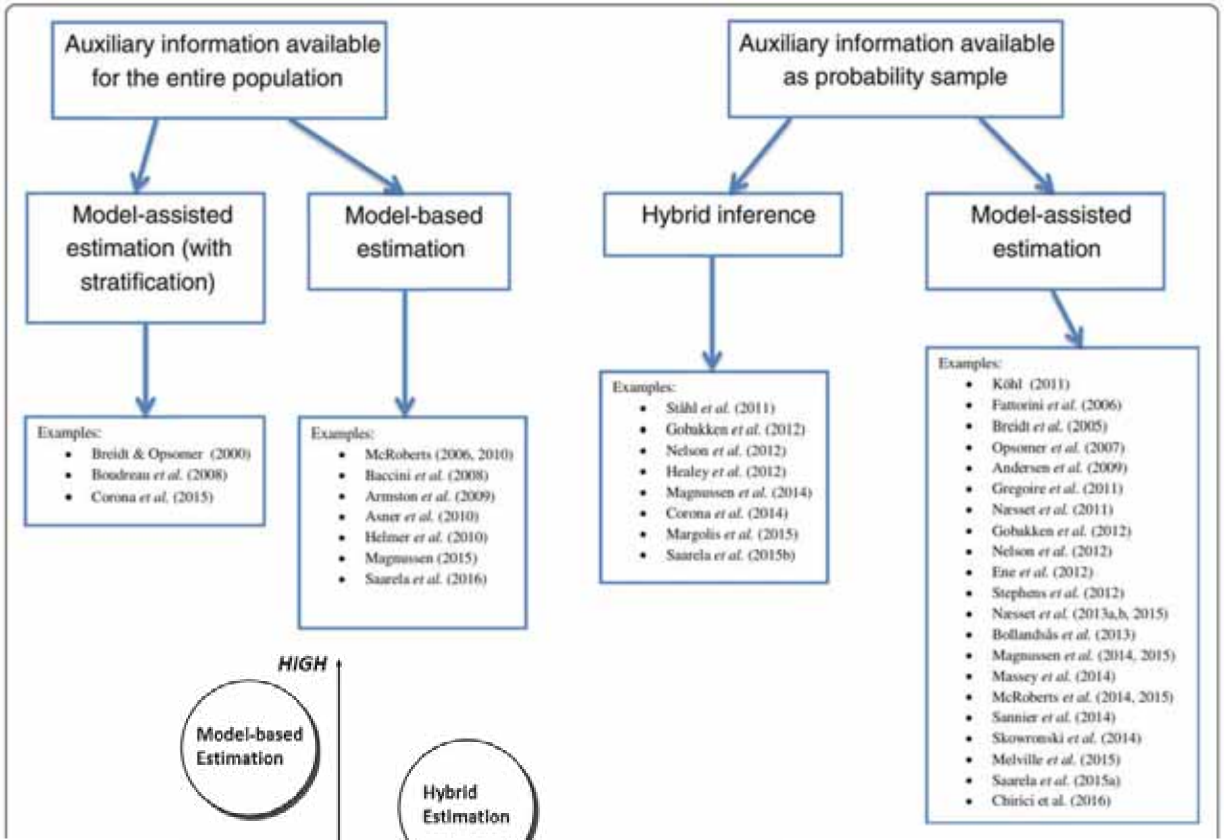
In NFIs Remote sensing contributed:

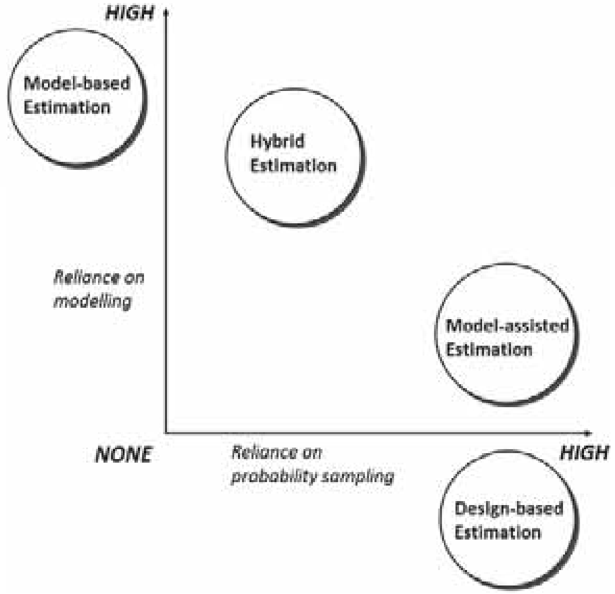
- To the production of more timely, cost efficient, and precise **traditional inventory estimates**

- To derive **new spatial products** (maps, small area estimates)

Technologies that are now on the horizon have the potential to alter radically the ways in which trees are measured,estimates are produced, and products are delivered.

The **lack** of standardized, spatially exhaustive **open access datasets**, as well as community consensus on methods and best practices limits the broader uptake and operationalization of these approaches





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DISCUSSION Open Access

Use of models in large-area forest surveys: comparing model-assisted, model-based and hybrid estimation

Göran Ståhl[1], Svetlana Saarela[1*], Sebastian Schnell[1], Sören Holm[1], Johannes Breidenbach[2], Sean P. Healey[3], Paul L. Patterson[3], Steen Magnussen[4], Erik Næsset[5], Ronald E. McRoberts[3] and Timothy G. Gregoire[6]

Abstract

This paper focuses on the use of models for increasing the precision of estimators in large-area forest surveys. It is motivated by the increasing availability of remotely sensed data, which facilitates the development of models predicting the variables of interest in forest surveys. We present, review and compare three different estimation frameworks where models play a core role: model-assisted, model-based, and hybrid estimation. The first two are well known, whereas the third has only recently been introduced in forest surveys. Hybrid inference mixes design-based and model-based inference, since it relies on a probability sample of auxiliary data and a model predicting the target variable from the auxiliary data. We review studies on large-area forest surveys based on model-assisted, model-based, and hybrid estimation, and discuss advantages and disadvantages of the approaches. We conclude that no general recommendations can be made about whether model-assisted, model-based, or hybrid estimation should be preferred. The choice depends on the objective of the survey and the possibilities to acquire appropriate field and remotely sensed data. We also conclude that modelling approaches can only be successfully applied for estimating target variables such as growing stock volume or biomass, which are adequately related to commonly available remotely sensed data, and thus purely field based surveys remain important for several important forest parameters.

Keywords: Design-based inference, Model-assisted estimation, Model-based inference, Hybrid inference, National forest inventory, Remote sensing, Sampling

Introduction

Use of models in large-area surveys of forests is attracting increased interest. The reason is the improved availability of auxiliary data from various remote sensing platforms. Aerial photographs (e.g., Næsset 2002a, Bohlin et al. 2012) and optical satellite data (e.g. Reese et al. 2002) have been available and used operationally for many decades, while data from profiling (e.g., Nelson *et al.* 1984, Nelson et al. 1988) and scanning lasers (e.g., Næsset 1997) and radars (Solberg et al. 2010) have become available for practical applications more recently. Some of the new types of remotely sensed data, such as data from laser scanners, have already become widely applied in forest inventories (e.g., Næsset 2002b). A common application involves the development of models that are applied wall-to-wall over an area of interest (e.g., Næsset 2004), often for providing data for forest management. However, this type of data is increasingly applied also in connection with large-area forest surveys, such as national-level forest inventories (Tomppo et al. 2010, Asner et al. 2012).

Applications of models in large-area forest surveys often use the model-assisted estimation framework (Särndal et al. 1992) where a model is used to support the estimation following probability sampling within the context of design-based inference (Gregoire 1998). Importantly, an inadequately specified model will not make the estimators biased in this case, but only affect the variance of the estimators. Examples of large-area forest inventory applications include Andersen et al. (2011) who applied the technique in Alaska, Gregoire et al. (2011) and Gobakken et al. (2012), who applied it in Hedmark County, Norway, and Saarela et al. (2015a) who used it in Kuortane, Finland.

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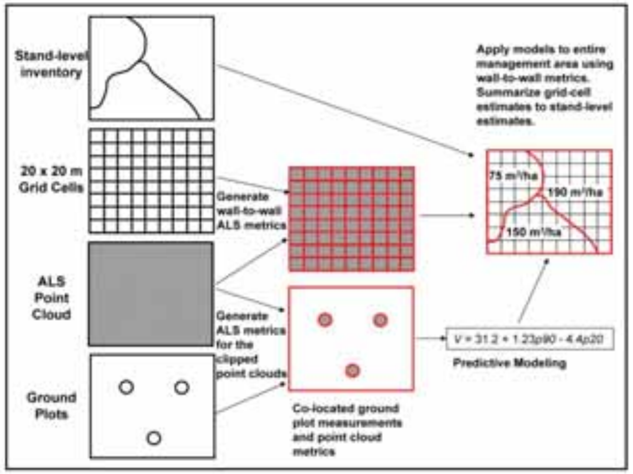
Data assimilation/data integration

How to integrate multiple input data from multiple sources?
We just have to choice!

UAV->LiDAR->SATELLITE->NFI



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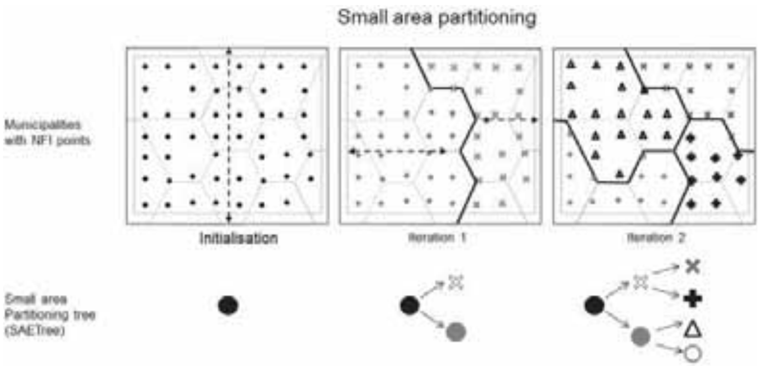

Vega et al., 2021
A new small area estimation algorithm to balance between statistical precision and scale
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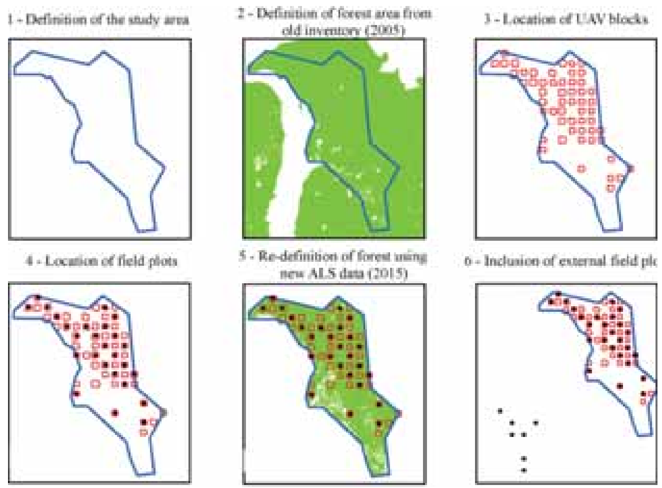

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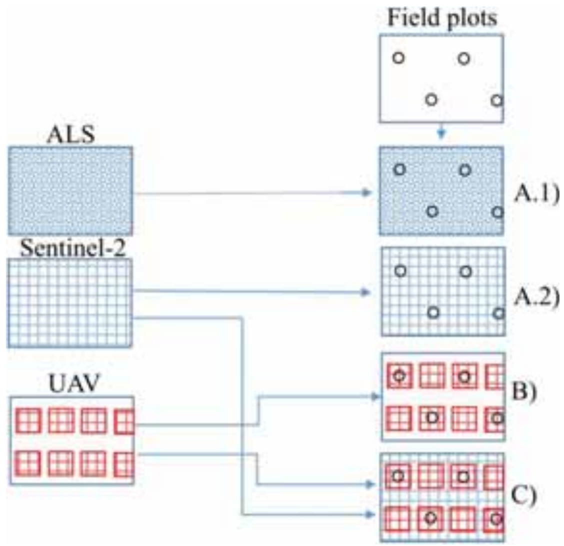

Puliti S, Saarela S, et al., 2018
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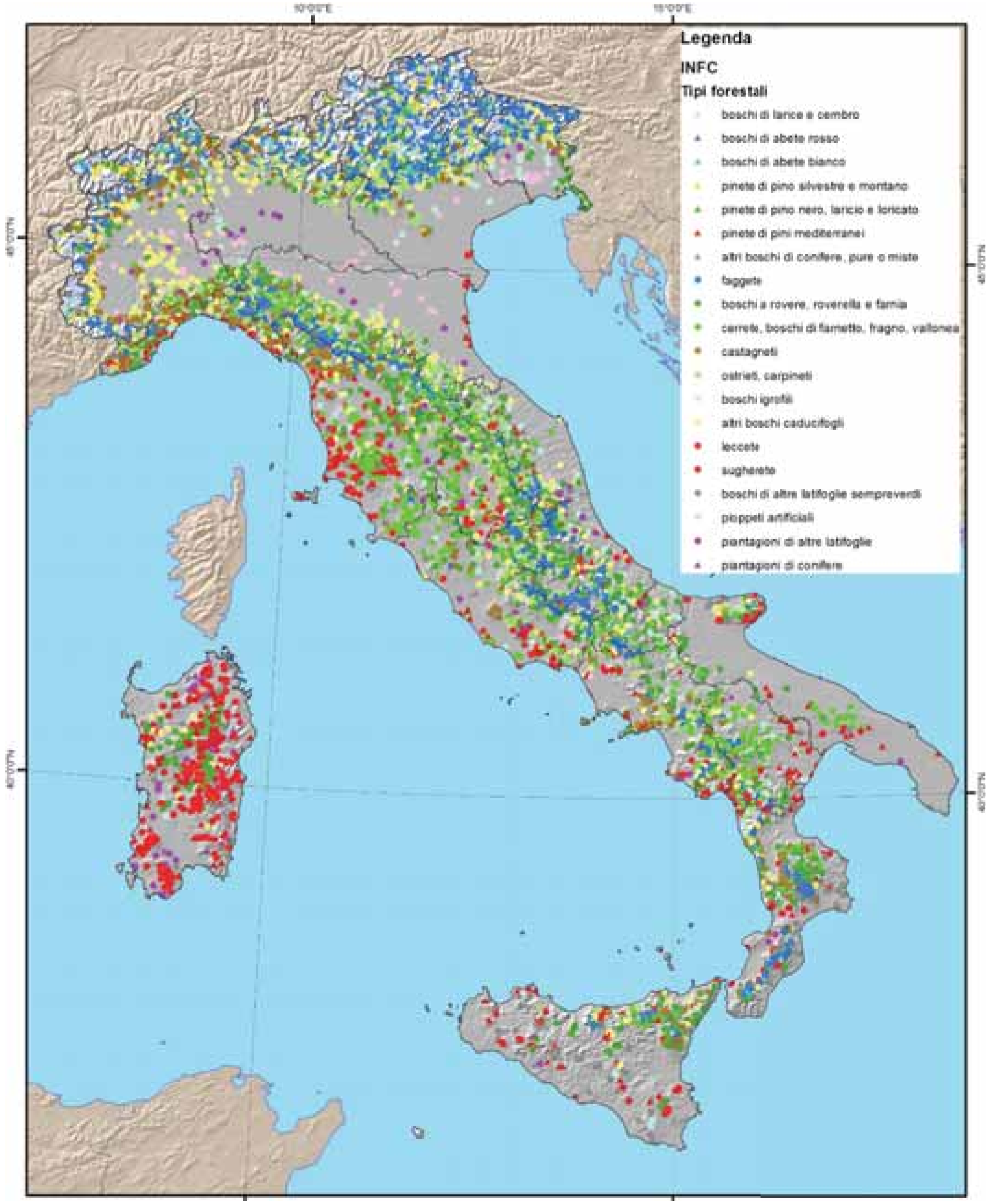
https://doi.org/10.1016/j.rse.2017.10.007


Colocated Data + Computation + APIs

I risultati del progetto AGRIDIGIT

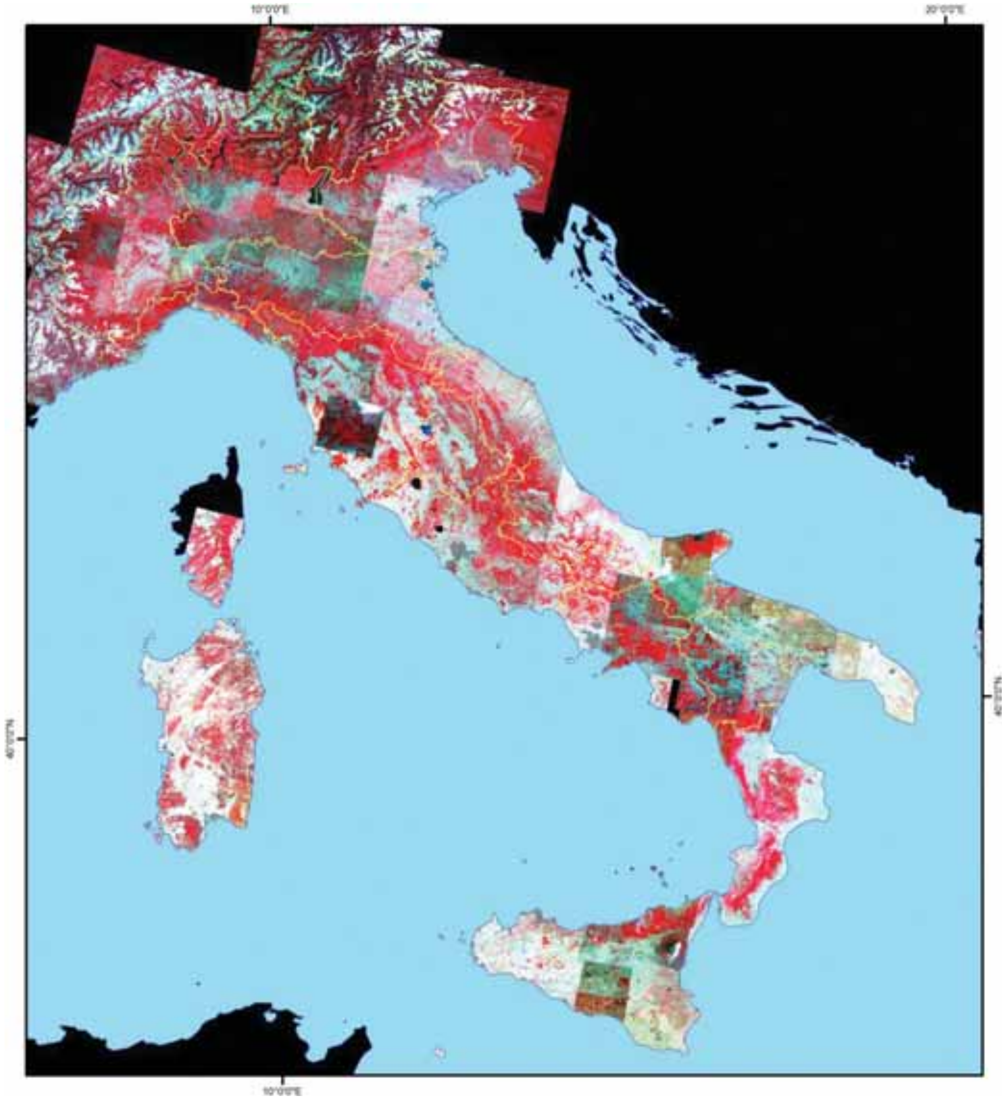
dalla ricerca all’applicazione

stima spazialmente esplicita di variabili forestali



Il problema dei dati di input

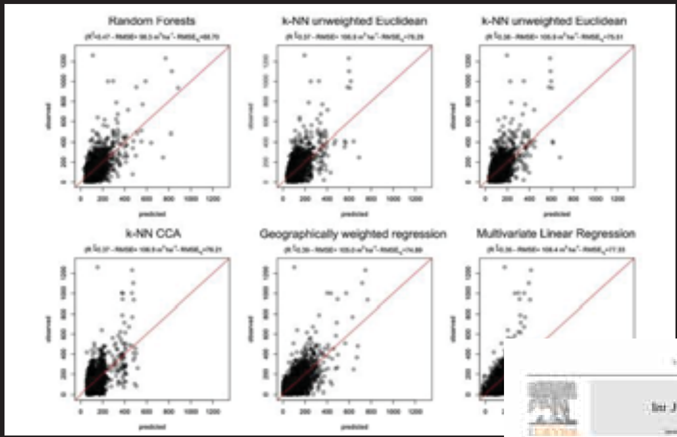
Con algoritmi di intelligenza artificiale è possibile spazializzare con immagini telerilevate e altri strati informativi geografici il dato osservato nelle aree di saggio a terra INFC

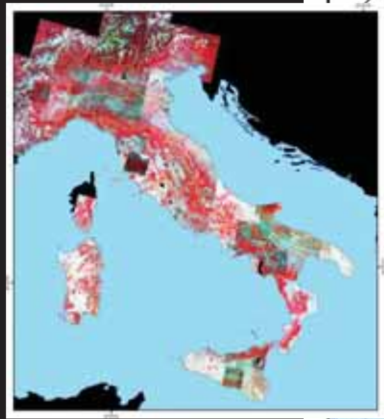


Esempio di applicazione sul dato INFC2005

National application

LOO $R^2 = 0.61$ and RMSE $\cong 52\ m^3ha^{-1}$





Int J Appl Earth Obs Geoinformation

Wall-to-wall spatial prediction of growing stock volume based on Italian National Forest Inventory plots and remotely sensed data