Metrology for Earth Observation and Climate

EMPIR EURAMET
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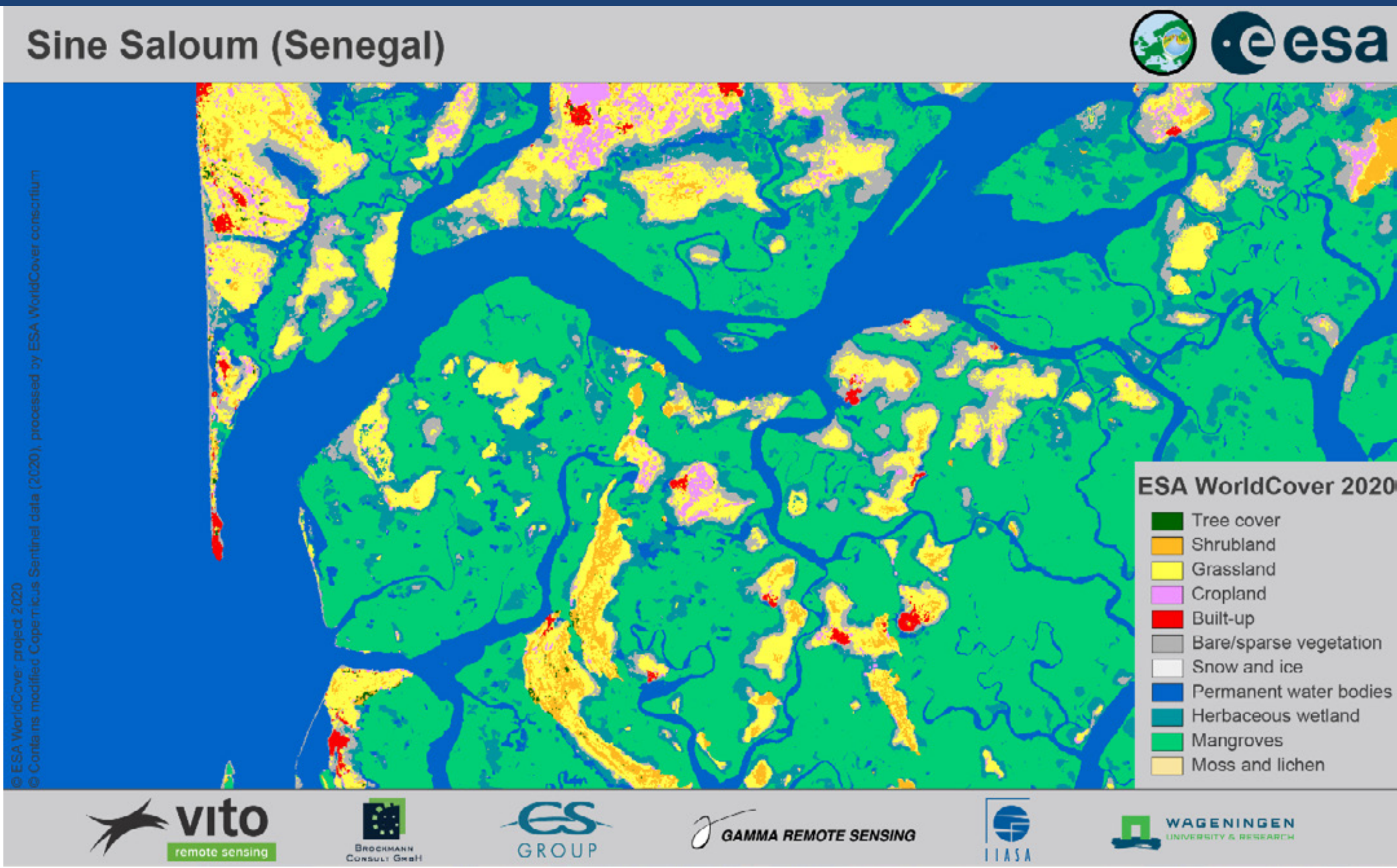
Bringing metrology to land cover mapping



A detailed zoom on the Sine Saloum River Delta in Senegal dominated by mangroves https://vito.be/en/news/release-10-m-worldcover-map

Introduction

Land cover is one of 54 Essential Climate Variables (ECVs) selected by the World Meteorological Organization (WMO) [1]. Land cover (LC), specifically land cover change, simultaneously affects climate and is affected by it [2]. Land cover change affects climate biophysically – by altering reflective properties of land surface and evapotranspiration, and biogeochemically – by changing carbon stocks. Past research suggests that, since pre-industrial times, the biophysical mechanism had a net cooling effect on climate; whereas the biogeochemical mechanism had a net warming effect [3]. Climate change, in turn, has amplified land cover changes through intensification of droughts, rainfall, etc. [4]. Land cover can also have a mitigation role: several land-based solutions such as reforestation, and peatland restoration can help reduce GHG emissions or increase terrestrial carbon uptake [5].

Land cover maps provide a means to monitor and manage land cover conditions, and parametrise climate models and other environmental models. The quality of land cover maps is a topic of ongoing research, as widely adopted quality assessment practices are known to have limitations.

Challenge

Quality assessments of land cover maps are performed by comparing land cover maps with reference datasets. Such comparisons are summarised in a form of a confusion matrix (Figure 1). These provide information about overall map quality and the quality of classification of individual land cover classes, but no information about how the quality of the map varies spatially. Yet, the spatial variability of LC maps quality can be large [6]. Proposed methods for obtaining spatially-explicit understandings of map quality rely on interpolation techniques, which allow the prediction of map quality at unseen locations [7]; other methods use the probability output of a classifier used for the production of a LC map [8]. The latter method is gaining a lot of attention, however, this method does not take into account that the input data, which is fed to the classifier, has associated uncertainties. To account for such uncertainties, these should be propagated using the law of propagation of uncertainty [9] through the entire processing chain used to create an LC map. This would represent a metrologically-rigorous approach to obtaining per-pixel uncertainties of an LC map. The framework for applying the law of propagation of uncertainty

Actual land cover classes (reference dataset)

Predicted land cover classes (land cover map)

	A	B	C	D	$\sum$
A	n_{AA}	n_{AB}	n_{AC}	n_{AD}	n_{A+}
B	n_{BA}	n_{BB}	n_{BC}	n_{BD}	n_{B+}
C	n_{CA}	n_{CB}	n_{CC}	n_{CD}	n_{C+}
D	n_{DA}	n_{DB}	n_{DC}	n_{DD}	n_{D+}
$\sum$	n_{+A}	n_{+B}	n_{+C}	n_{+D}	n

Figure 1. An example of confusion matrix. *A, B, C, D* are four land cover classes. Adapted from Strahler et al. [7]

to Earth Observation data has been previously demonstrated in FIDUCEO (Fidelity and uncertainty in climate data records from Earth Observations) project [10].

Solution

Land Cover maps are usually produced by applying a machine learning classification algorithm, such as Random Forest (RF) or Artificial Neural Network (ANN), to surface reflectance measurements—often referred to as Bottom-of-Atmosphere (BOA) reflectance. This is because reflective properties of land surfaces depend on land cover surface type (forest, crop, bare soil, etc.). If a classification algorithm is supervised, which is often the case, it needs to be trained (developed) based on a training dataset (TD). The training dataset consists of a set of pixels (and corresponding reflectance measurements) for which the land cover class is assumed to be known. Once a classifier is trained, it is applied to the entire scene.

BOA reflectance is a derived product, produced by atmospheric correction of Top-of-Atmosphere (TOA) radiance measurements. Atmospheric correction is necessary as Earth's atmosphere and its constituents (e.g. aerosols, water vapour, etc.) significantly affect radiance signals travelling through it. TOA radiance is a derived product as well, produced by radiometric and spectral corrections of raw digital numbers (DN) measured by a space-borne sensor. This full processing chain – from raw digital numbers to land cover map – is shown in Figure 2.

No measurement/model is perfect; at each step of this processing chain there will be various effects with associated uncertainties, which will contribute to the uncertainty of the measurand – the land cover map (LCM). The uncertainty tree diagram shown in Figure 3 offers a visual representation of how these various sources of uncertainty propagate.

The pink branch shows effects that lead to the uncertainties associated with the conversion of digital numbers to TOA radiance; the green branch shows effects that lead to the uncertainties associated with atmospheric correction of TOA radiance to BOA reflectance; the orange branch shows effects that lead to the uncertainties associated with the representation of the scene with a training dataset; and the red branch shows effects associated with independent labelled data used in the training dataset.

A few studies tried to address uncertainties associated with some of the effects highlighted in Figure 3. Radiometric uncertainties were propagated to the Sentinel-2 Scene Classification product (without accounting for uncertainties associated with atmospheric correction and classifier) in [11]; uncertainties associated with training datasets were reviewed in [12]. This shows an increasing attention of researchers to this topic.

Outcome

In June 2023, the importance of developing uncertainty propagation methods for land cover mapping algorithms was highlighted by the Biosphere Monitoring Group at the Metrology for Climate Action workshop organised by the Bureau International des Poids et Mesures (BIPM) and the World Meteorological Organization (WMO) [13]. As shown above, some efforts to estimate uncertainty sources necessary for developing uncertainty propagation frameworks requested by the BIPM and WMO have already been undertaken but further efforts are required to build a comprehensive uncertainty budget. Here we present an uncertainty tree diagram, which helps to visualise different sources of uncertainty and understand the gaps in the current knowledge. This uncertainty tree only identifies uncertainties associated with a map produced based on a single satellite image, more uncertainty sources have to be accounted for when multiple satellite images are used.

It is important to note that land cover maps are usually not a goal in themselves but an important input in several applications – climate and carbon flux models, hydrologic models, biodiversity and food security studies, etc. These downstream applications have been shown quite sensitive to the quality of land cover maps [14], [15], [16]. Improved estimations of uncertainties associated with land cover maps produced in a metrologically-rigorous way would help to enhance the quality of these downstream products.

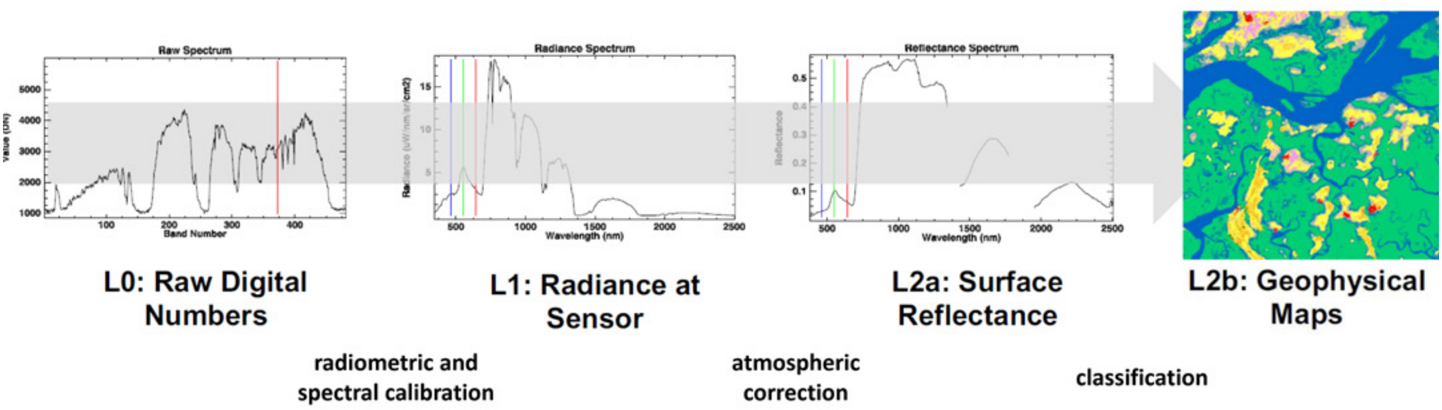


Figure 2. An example of production chain of a land cover map based on Earth Observation data (i.e. *L0* Raw Digital Numbers are measured by a spaceborne sensor).
Adapted from Thompson et al. [17]
(NB: L2b Geophysical Map is replaced by ESA WorldCover map)

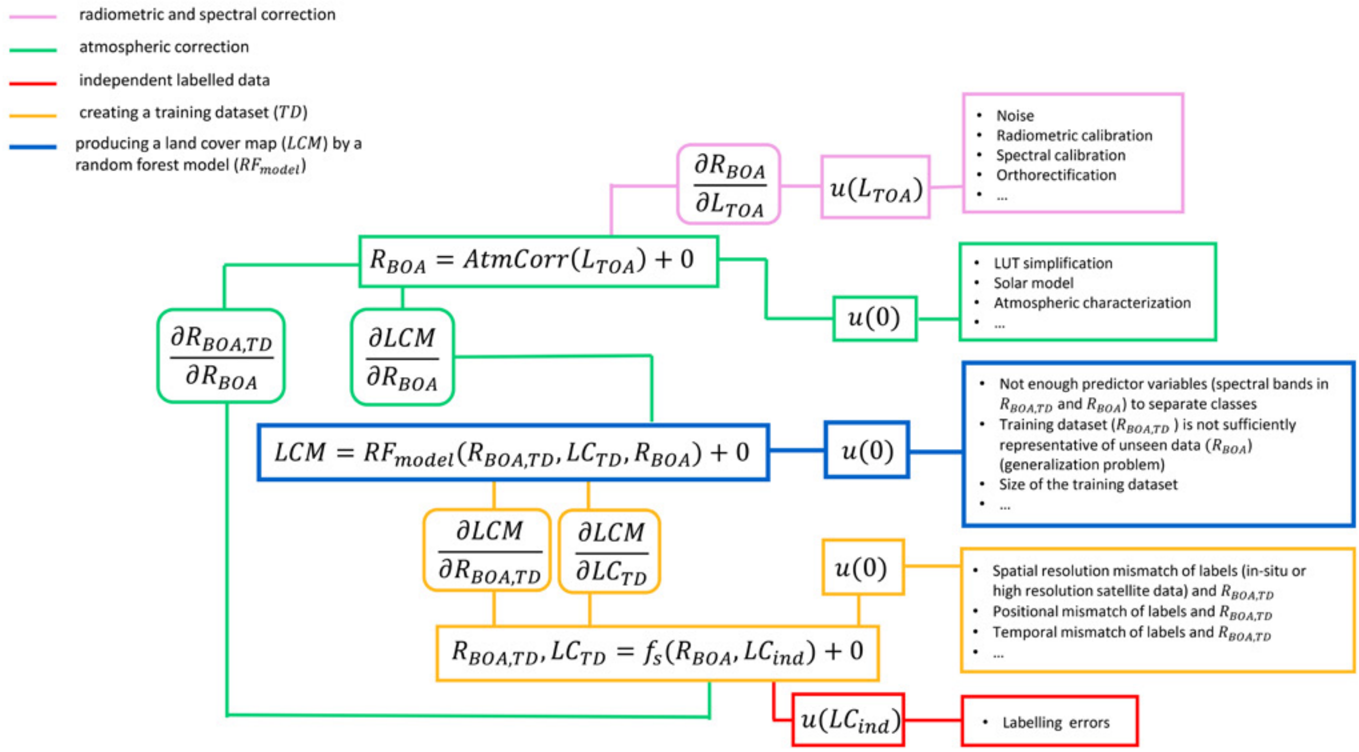


Figure 3. Uncertainty tree diagram for land cover classification (assuming that LC map is produced based on a satellite image and Random Forest as a classifier)
(L_{TOA} – Top-of-Atmosphere radiance, *AtmCarr* – atmospheric correction algorithm, R_{BOA} – Bottom-of-Atmosphere reflectance, $R_{BOA,TD}$ – Bottom-of-Atmosphere reflectance used in training dataset (*TD*), f_s – *TD* sampling, LC_{TD} – land cover labels of *TD*, RF_{model} – Random Forest (*RF*) model, LC_{ind} – independent labelled data, *LCM* – final Land Cover map

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