Assessing ecosystem service delivery and interactions: methodology to integrate Remote sensing data into ecosystem services mapping

RESAS1.4.1 NATURAL ASSET INVENTORY AND NATURAL CAPITAL ACCOUNTS

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Suggested citation: Poggio L and Gimona A (2017) Assessing ecosystem service delivery and interactions: methodology to integrate Remote sensing data into ecosystem services mapping, Technical Report, James Hutton Institute, 6 pp.

Use of remote sensing images for Ecosystem services mapping

This report illustrates the contribution of remote sensing data to a national scale (Scotland) assessment of key ecosystem services (ESS). We explored methods to combine and assimilate multiple data sources with remote sensing data, in particular spatial-statistical approaches to assimilate image time series. We also assessed the role of images in upscaling input data sets for ESS models and in understanding biodiversity patterns at the national scale.

Remote sensing images tested

MODIS

A set of indices was derived from the Terra Moderate Resolution Imaging Spectro-radiometer (MODIS) 8 and 16 day composite products. The data were acquired from the NASA ftp website (ftp://e4ftl01u.ecs.nasa.gov/MOLT/) for 12 years between 2000 and 2012. The indices were selected for their capability to differentiate spectral responses from different bare soils, vegetation cover and mixed situations:

1) Enhanced Vegetation Index (EVI; Huete et al., 2002)
2) Normalised Difference Water Index (NDWI; Gao, 1996) with NIR and SWIR (Short Wave In-fraRed) band: SWIR = 2130 (Gu et al., 2008)
3) Leaf Area Index (LAI; Knyazikhin et al., 1999) is defined as the one-sided green leaf area per unit ground area in broadleaf canopies and as half the total needle surface area per unit ground area in coniferous canopies.
4) Land Surface Temperature (LST; Wan, 1999)
5) primary productivity (Running et al., 1999, 2004).
6) Phenology information (Jönsson and Eklundh, 2004). The parameters calculated are:
    a. length of the season (LOS); time from the start to the end of the season.
    b. seasonal amplitude; difference between the maximum value and the base level, given as the average of the left and right minimum values.
7) snow indices: snow indices were derived from the Snow Cover and its quality assurance (QA) products (MOD10A2, v005) of Terra MODIS (Riggs et al., 2006). The data on the presence/absence of snow were considered as binary sequence and processed to obtain indices taking into account the temporal pattern of snow presence (Poggio and Gimona, 2015).

The medians over 12 years (2000-2011) were used as covariates. The resulting raster data were further downscaled to a resolution of 100x100m using the method described in Poggio and Gimona (2015a).

Landsat

Landsat provides high spatial resolution images with a minimum revisit cycle of 16 days, that can be greatly extended due to cloud contamination or duty cycle limitations (Ju and Roy, 2008). Cloud free (cloud cover < 10%) scene of Landsat 8 were acquired for July 2013 as standard level 1 terrain corrected (L1T) product. The images were atmospherically corrected and then mosaicked to provide cover for most of Scotland. The temperature for the thermal bands was processed from digital numbers (DN) to Kelvin (Chander et al., 2009). The clouds were detected using the Automated Cloud-Cover Assessment (ACCA) algorithm from Irish (2000) with the constant values for pass filter one from Irish et al. (2006) using Landsat bands numbers already been processed from DN into reflectance and temperature. Cloud pixels were discarded.

Sentinel-1

The Sentinel-1 (S1) mission provides data from a dual-polarization C-band Synthetic Aperture Radar (SAR) instrument. This includes the S1 Ground Range Detected (GRD) scenes, processed using the Sentinel-1 Toolbox to generate a calibrated, ortho-corrected product. Each scene was pre-processed with Sentinel-1 Toolbox using the following steps: Thermal noise removal, Radiometric calibration Terrain correction using SRTM 30. The final terrain corrected values were converted to decibels via log scaling log value = log10 (value) and quantized to 16-bits. The data were pre-processed, prepared, mosaicked and downloaded from Google Earth Engine (Google Earth Engine Team, 2015). The median of the images available between June 2015 and May 2016 was calculated for VV and VH polarisation. No further transformations were applied.

Sentinel-2

Sentinel-2 (S2) is a wide-swath, high-resolution, multi-spectral imaging mission supporting Copernicus Land Monitoring studies, including the monitoring of vegetation, soil and water cover, as well as observation of inland waterways and coastal areas. Each band represents TOA reflectance scaled by 10000. The data were mosaicked and downloaded from Google Earth Engine (Google Earth Engine Team, 2015). The obtained mosaicked image (June to September 2016) showed some areas with snow and other smaller areas with some remaining clouds.

Example of use of remote sensing images for ESS mapping: soil organic carbon and risk of erosion

The figures show two examples of ESS mapping with the input of remote sensing images. Figure 1 shows the distribution of soil organic carbon concentrations in Scotland (Poggio and Gimona,2017). Figure 2 show the map of the soil erosion risk based on the integration of RUSLE with expert opinion rules (Lilly et al, 2002). The remote sensing images were used for upscaling (Poggio et al, unpublished) of soil, weather and land cover data.

The combination of different optical and radar sensors gave the best models and most accurate predictions results. The use of radar Sentinel-1 data proved useful for numerous models, soil properties in particular (Poggio and Gimona,2017). Further investigations are needed to assess the results when accounting for the seasonality within Sentinel-1 data.

Combining optical with radar sensors has a great potential to overcome issues, especially in regions with high cloud cover. Sensors with more frequent overpass, but coarser resolution can provide the seasonality element to sensors with less frequent overpass but more detailed resolution. Sensors with higher spatial resolution can provide information of the shorter range variability. Readily available radar bands can add information without the issue of the cloud cover (Poggio and Gimona,2017).

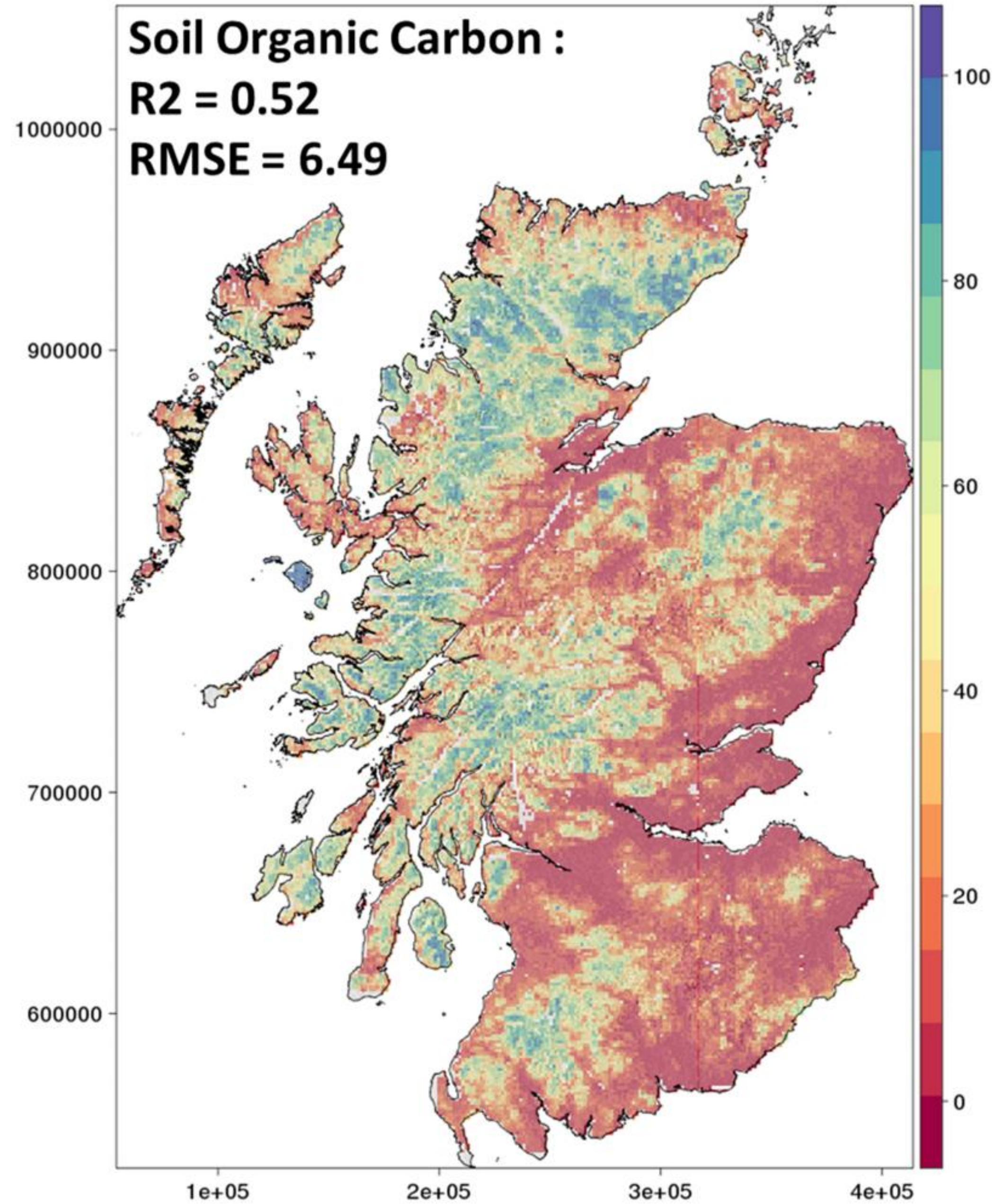

Figure 1. Soil organic carbon at 100m resolution obtained with integration of different remote sensing sensors (Poggio, Gimona, 2017).

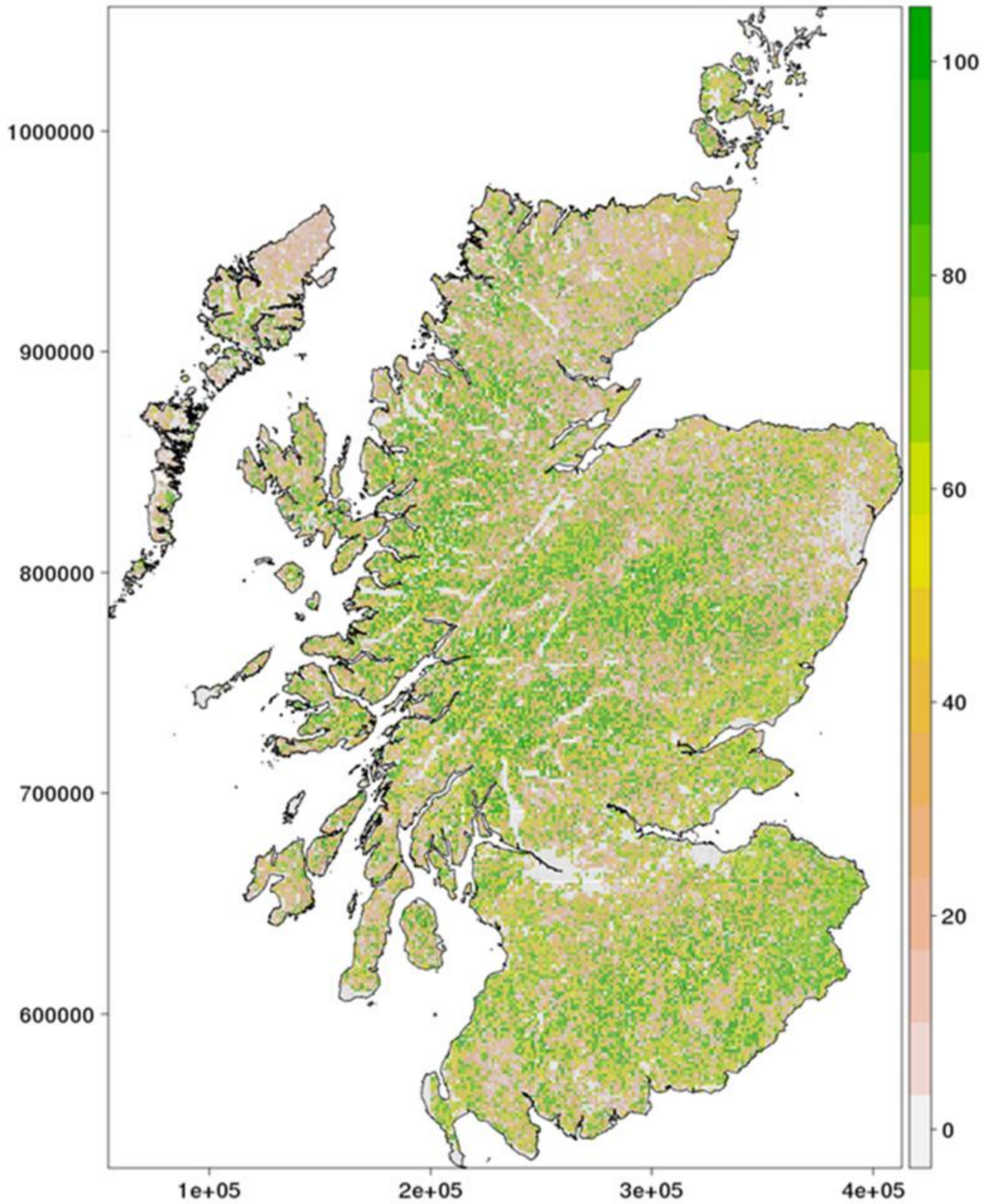

Figure 2. Soil erosion risk: integration of RUSLE with expert opinion and using remote sensing images for upscaling (Poggio et al, unpublished).

The combination of all these information is powerful for further predictions in Ecosystem services modelling .

Acknowledgements

This report was funded by the Rural & Environment Science & Analytical Services Division of the Scottish Government.

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