Mapping from space

Earth Observation and Machine Learning

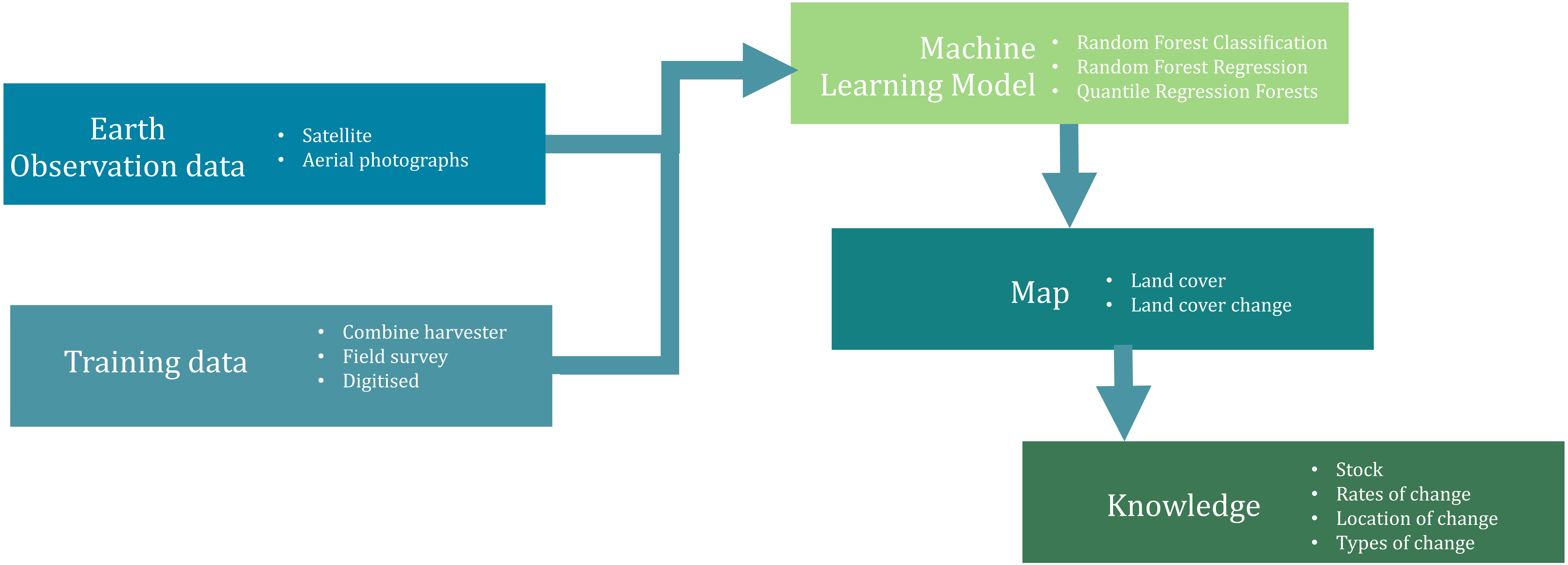
Clare Rowland

With contributions from Dan Morton, Chris Marston,
Nye O’Neil, Paul Scholefield, Luis Carrasco,
Merryn Hunt and Alan Blackburn

UK Centre for
Ecology & Hydrology

Contents

A recipe for EO and ML



Random Forest for image classification (1)

Aim: to develop methods for mapping urban creep

Motivation: get estimates of urban creep for Scotland

Test area: Edinburgh

Data: aerial photography

Map: urban creep, urban expansion, plus new roads and urban decrease/regeneration

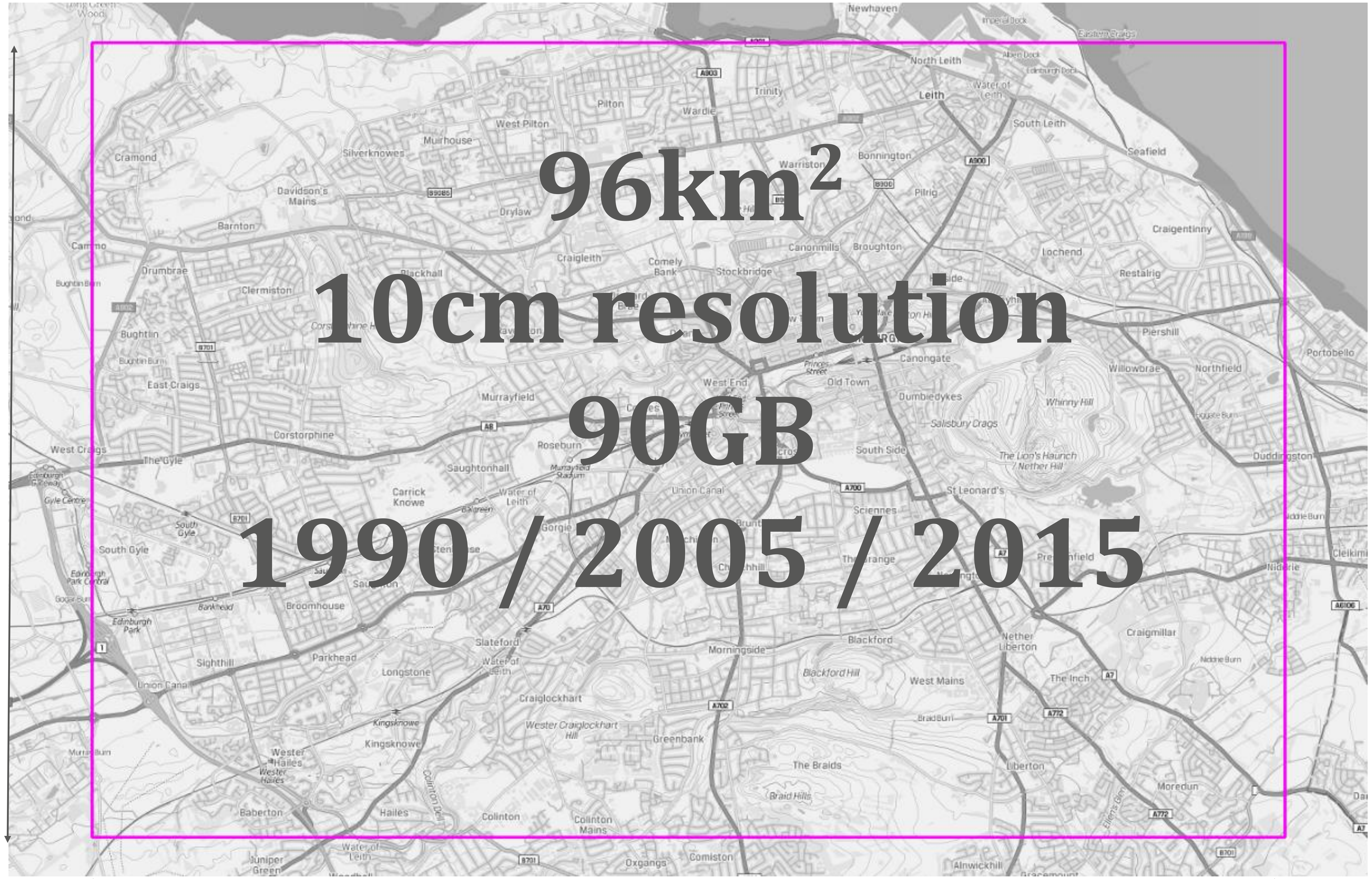
UK Centre for Ecology & Hydrology

CREW CENTRE OF EXPERTISE FOR WATERS

SEPA Scottish Environment Protection Agency

Rowland, C.S., Scholefield, P., O'Neil, A., & Miller, J., (2019) Quantifying rates of urban creep in Scotland: results for Edinburgh between 1990, 2005 and 2015, CREW, Aberdeen, 45pp

8km



12km

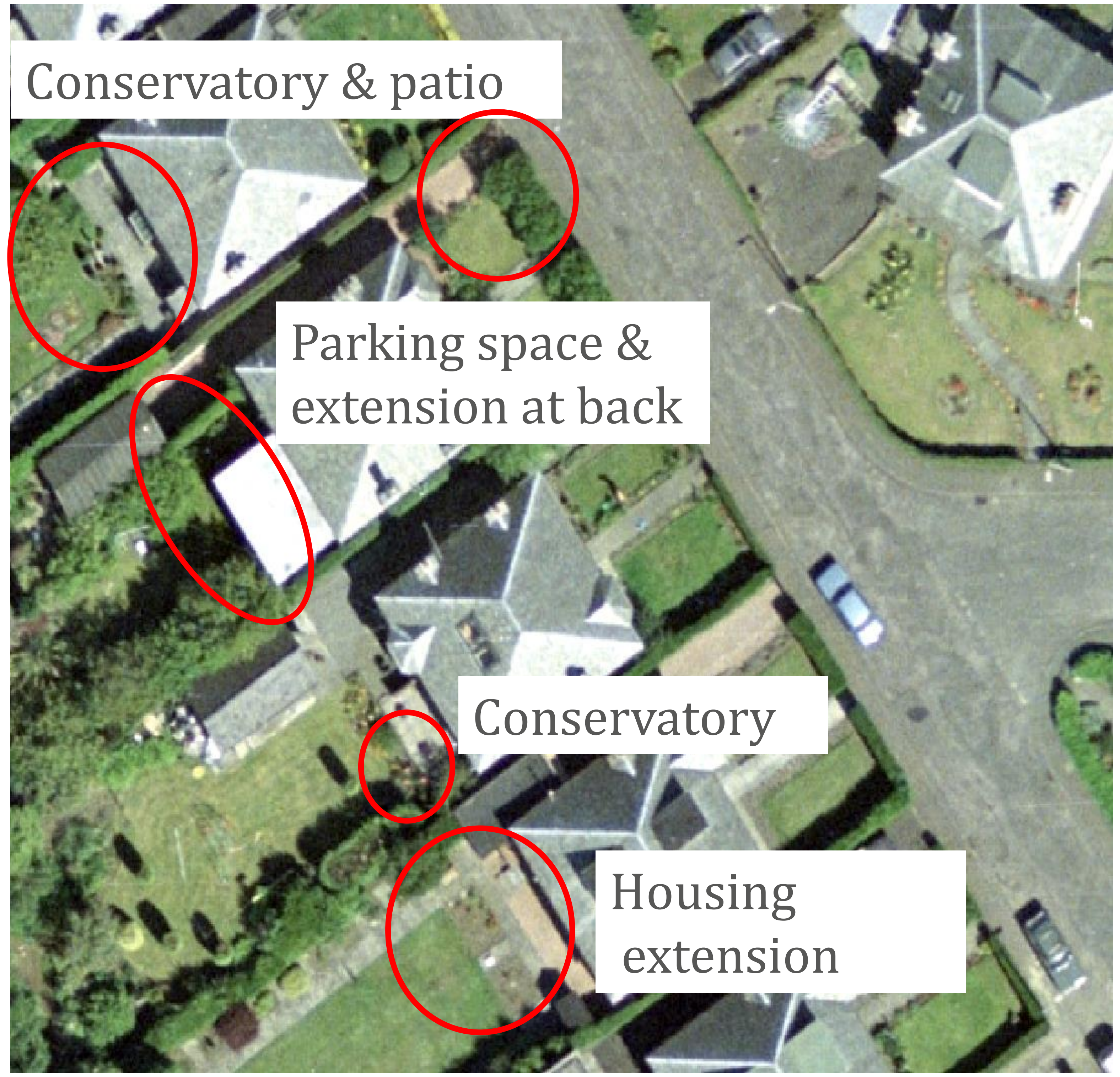
UK Centre for Ecology & Hydrology

CREW CENTRE OF EXPERTISE FOR WATERS

SEPA Scottish Environment Protection Agency

Urban Creep in Edinburgh

1990



2015

Hydrological Impact of urban creep - potentially high :

- large numbers of small changes
- unplanned, unmanaged
- large cumulative effect

UK Centre for Ecology & Hydrology

CREW CENTRE OF EXPERTISE FOR WATERS

SEPA Scottish Environment Protection Agency

Random Forest Classification

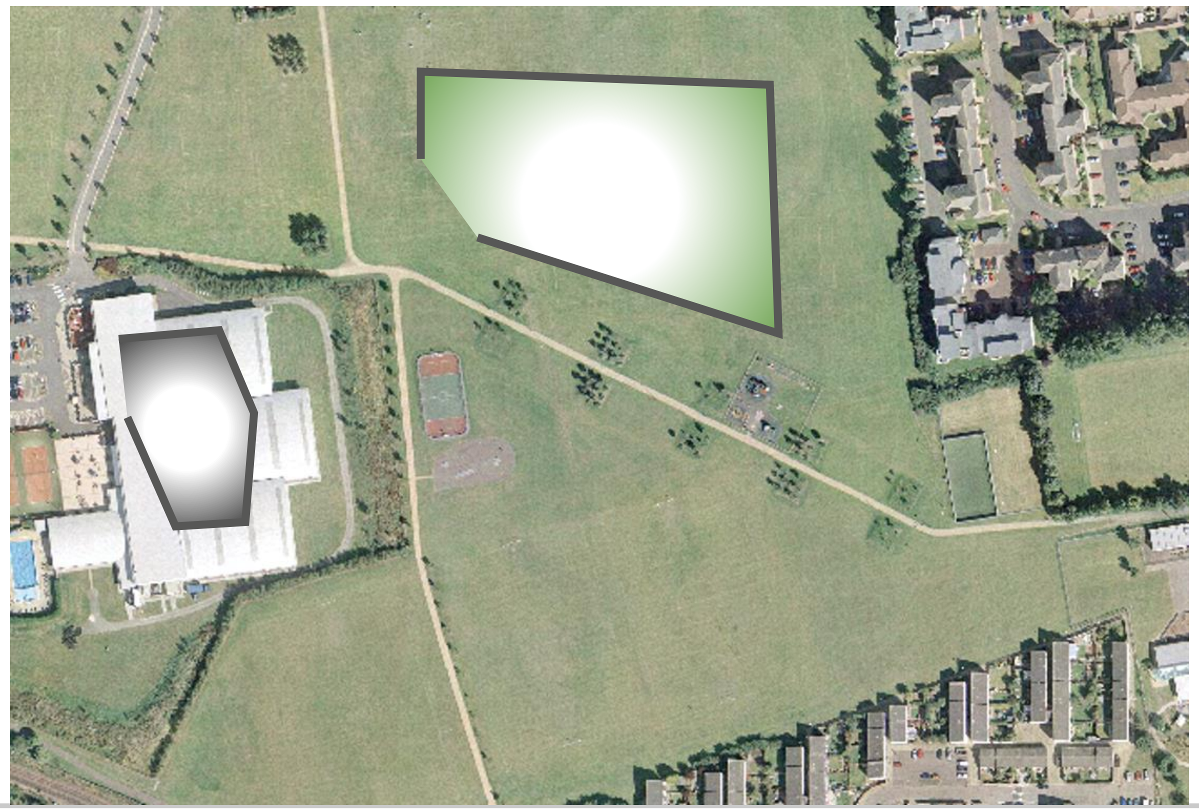
Aerial photography

Segmented photography

Random Forest Classification

Vegetation
Urban
Shadow

Manually digitised Training areas



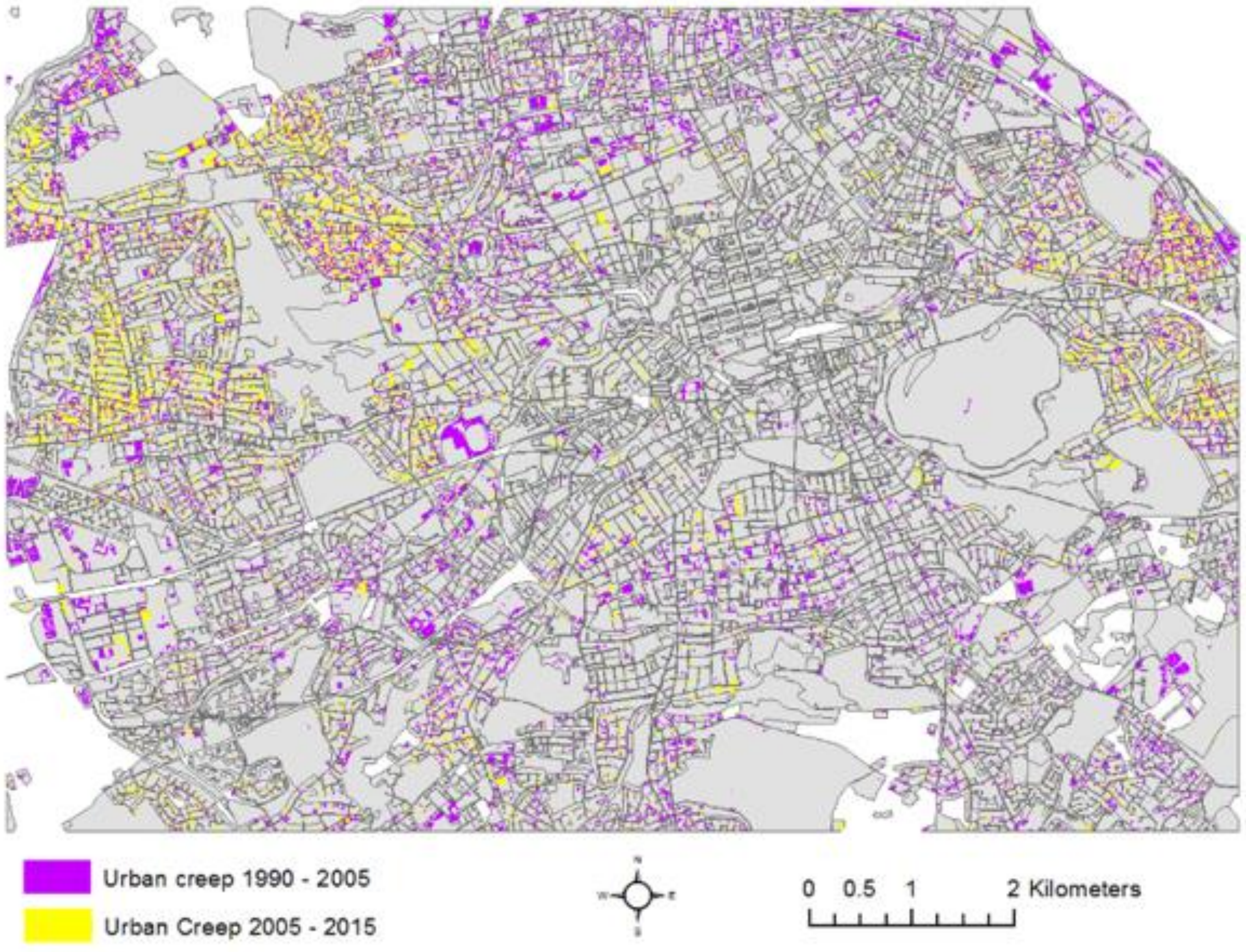
UK Centre for Ecology & Hydrology

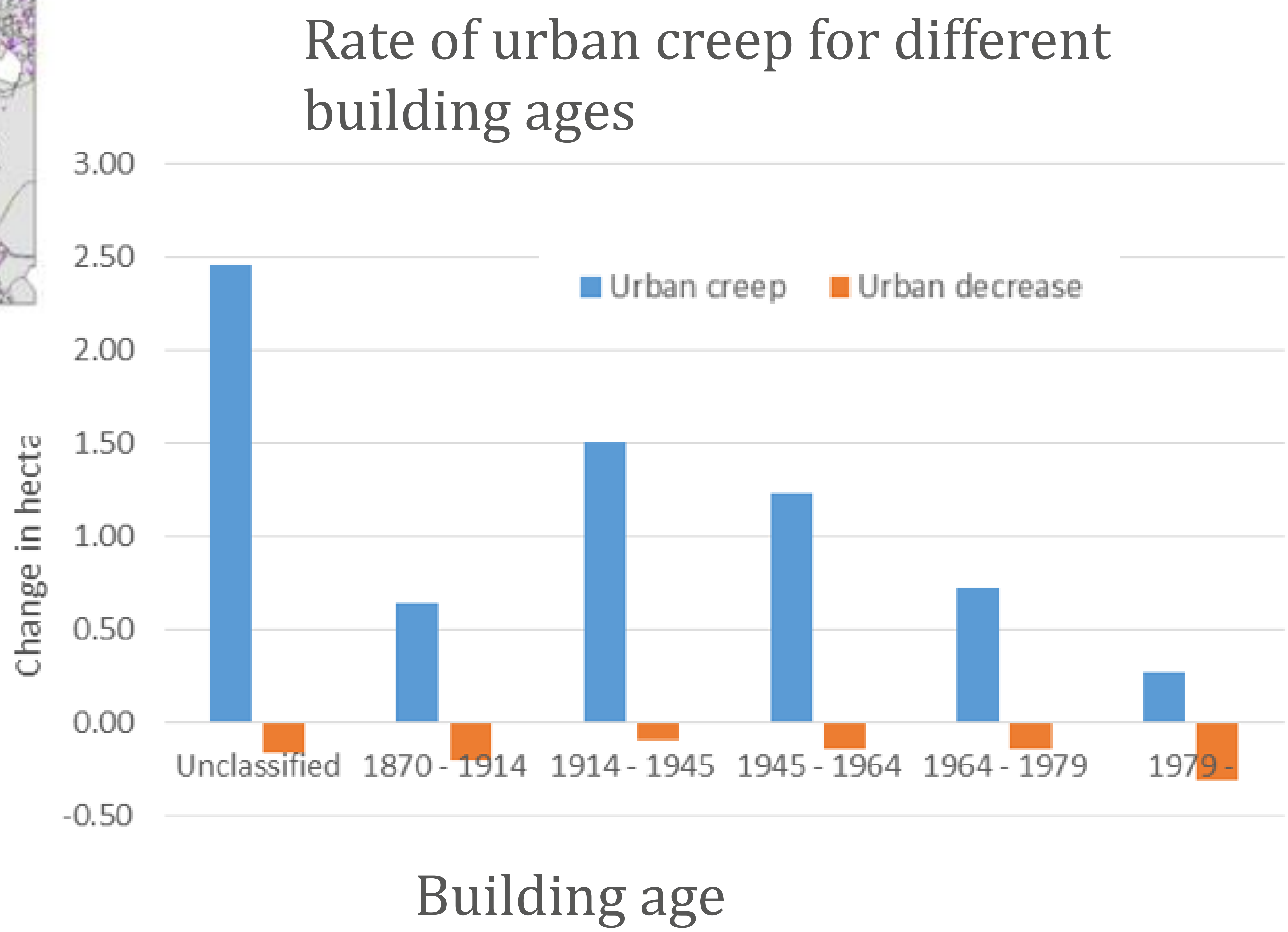
CREW CENTRE OF EXPERTISE FOR WATERS

SEPA Scottish Environment Protection Agency

Rowland, C.S., Scholefield, P., O'Neil, A., & Miller, J., (2019) Quantifying rates of urban creep in Scotland: results for Edinburgh between 1990, 2005 and 2015, CREW, Aberdeen, 45pp

Urban creep in Edinburgh 1990 - 2015



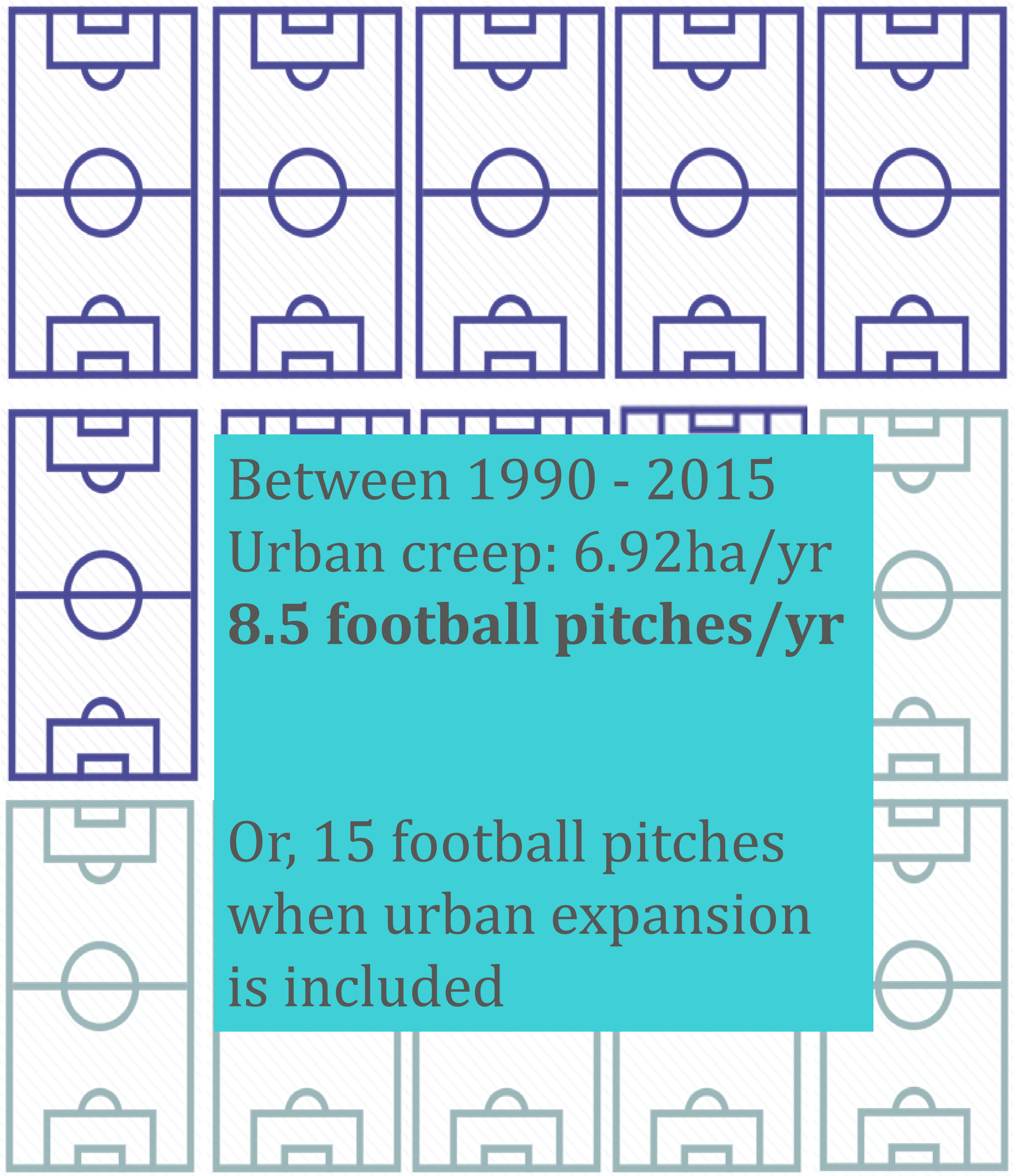


UK Centre for Ecology & Hydrology

SEPA Scottish Environment Protection Agency
Buidheann Dìon Àrainneachd na h-Alba

Knowledge…

- Urban creep is spatially and temporally variable
- Urban creep rates vary with property age and structure
- Urban creep can be mapped from aerial photography



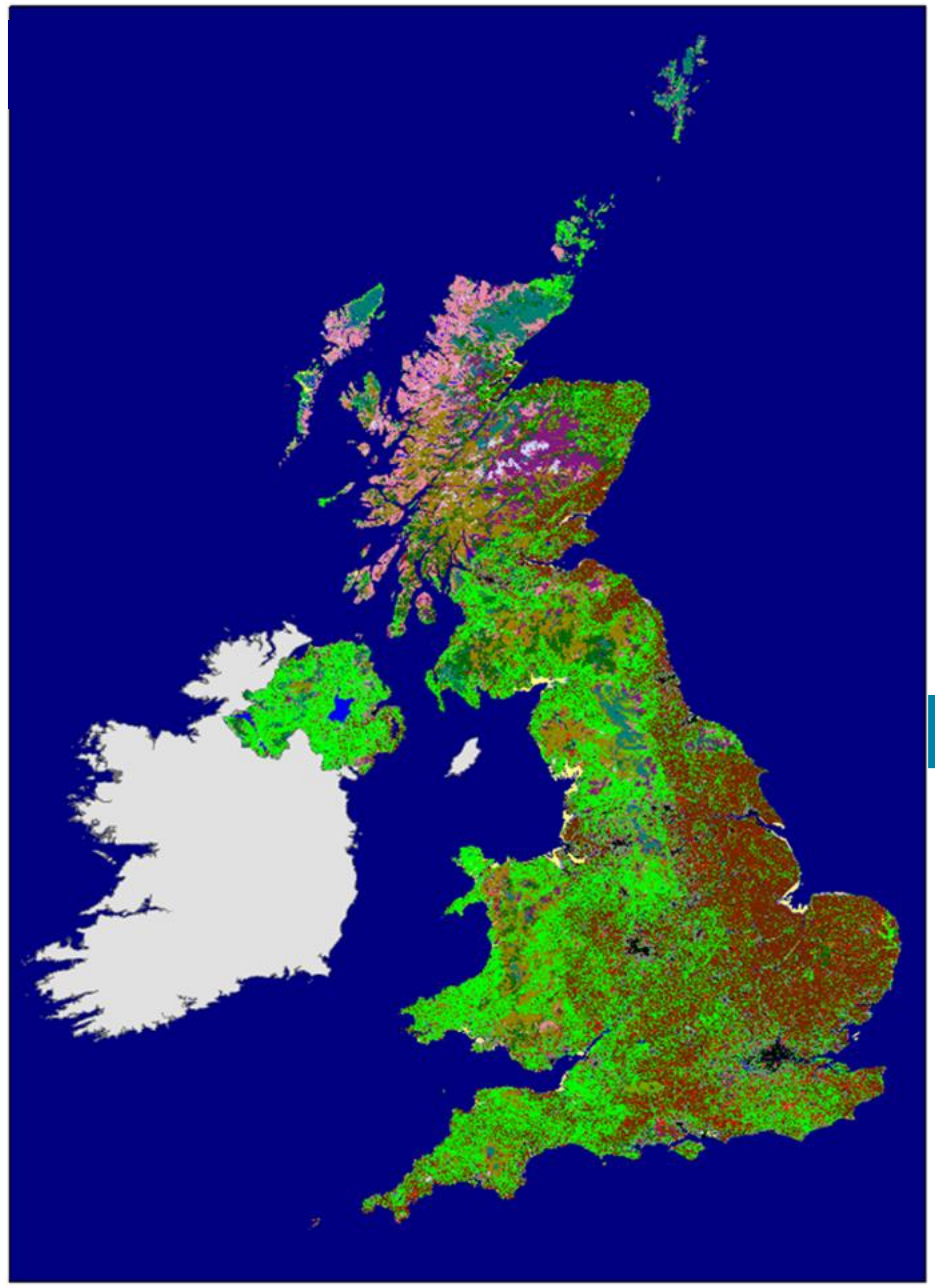
UK Centre for Ecology & Hydrology

CREW CENTRE OF EXPERTISE FOR WATERS

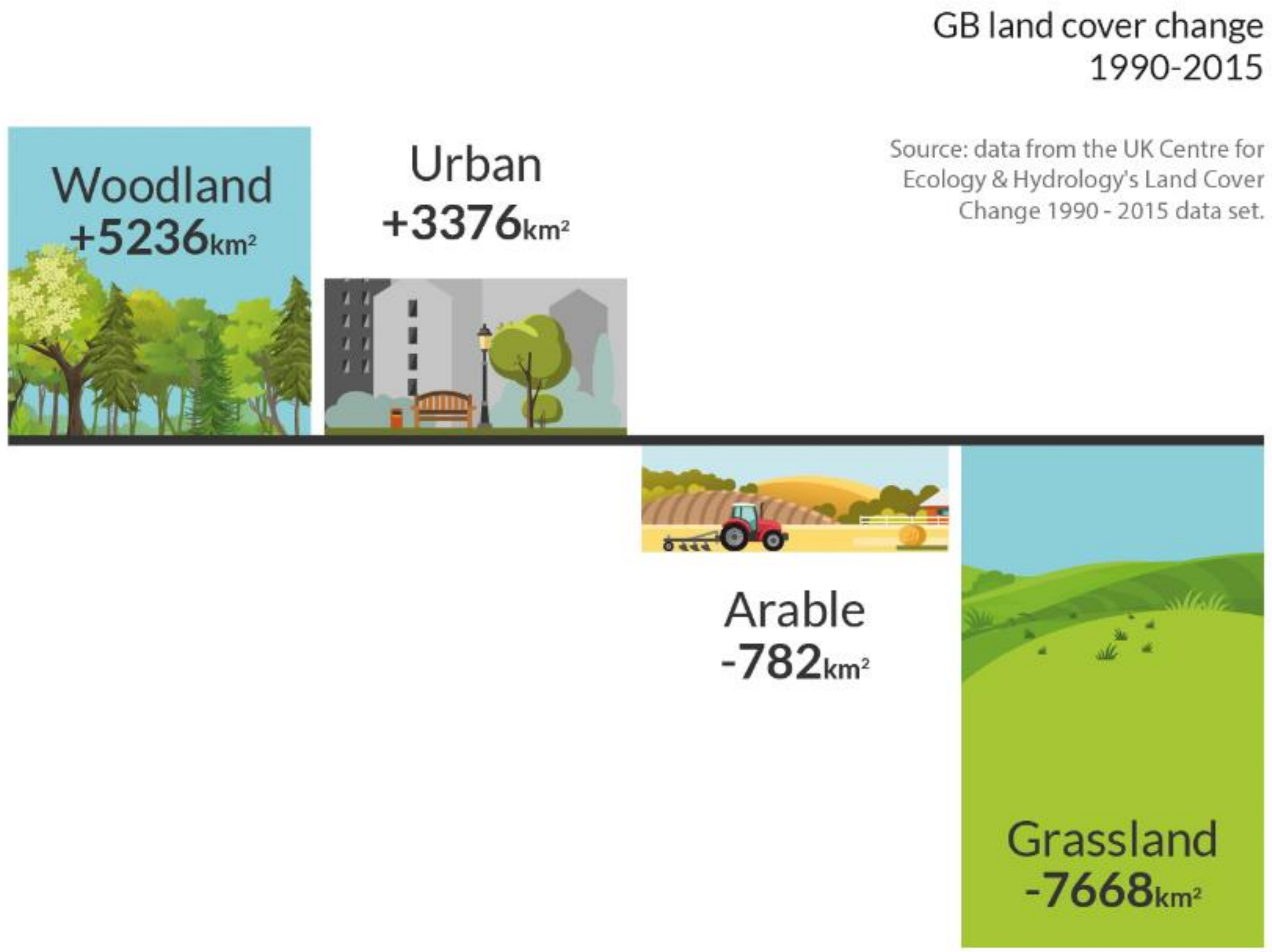
SEPA Scottish Environment Protection Agency

Rowland, C.S., Scholefield, P., O'Neil, A., & Miller, J., (2019) Quantifying rates of urban creep in Scotland: results for Edinburgh between 1990, 2005 and 2015, CREW, Aberdeen, 45pp

Random Forest for Image Classification (2)



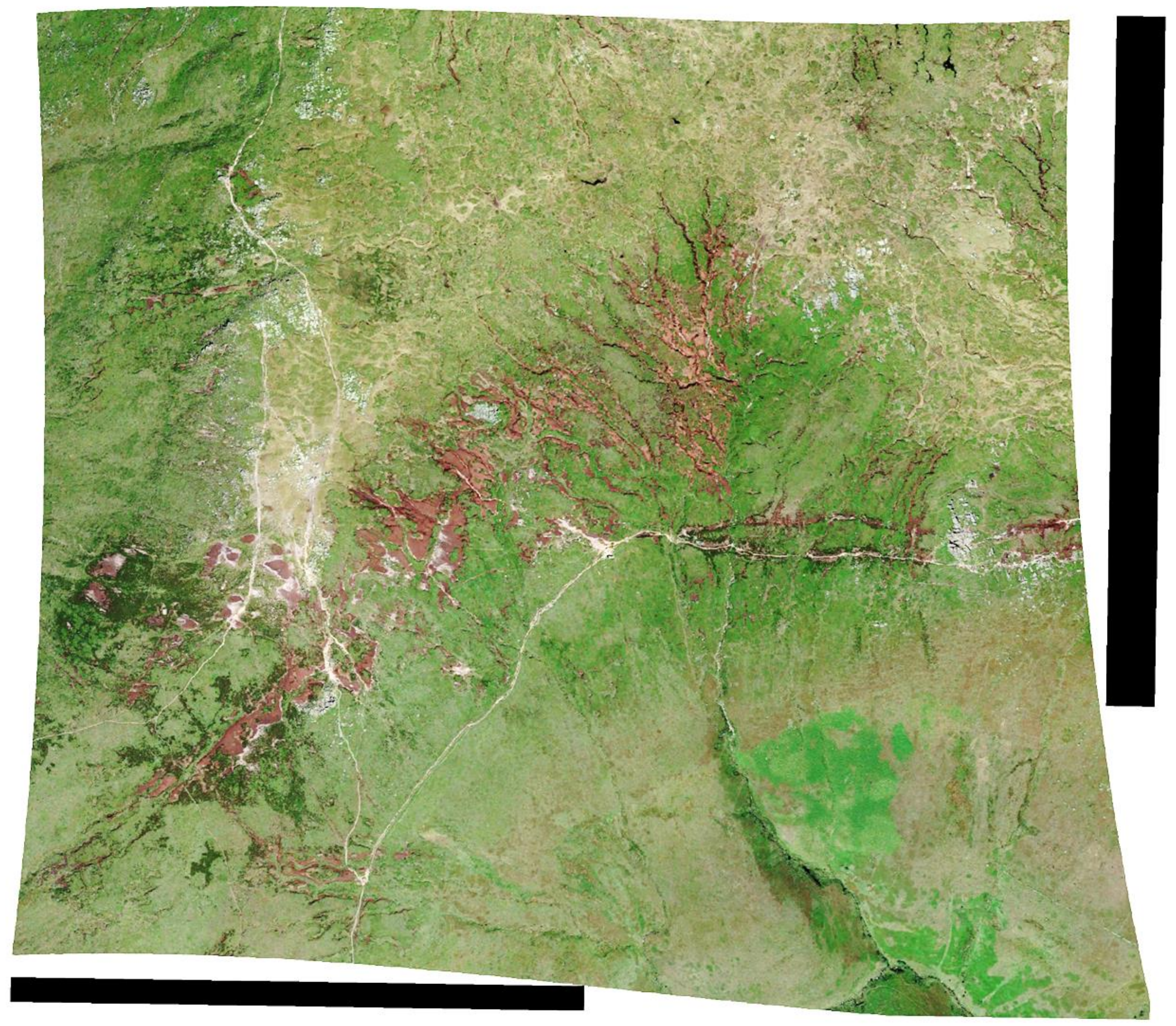
Land Cover Map (1990, 2000, 2007, 2015, 2017, 2018, 2019)



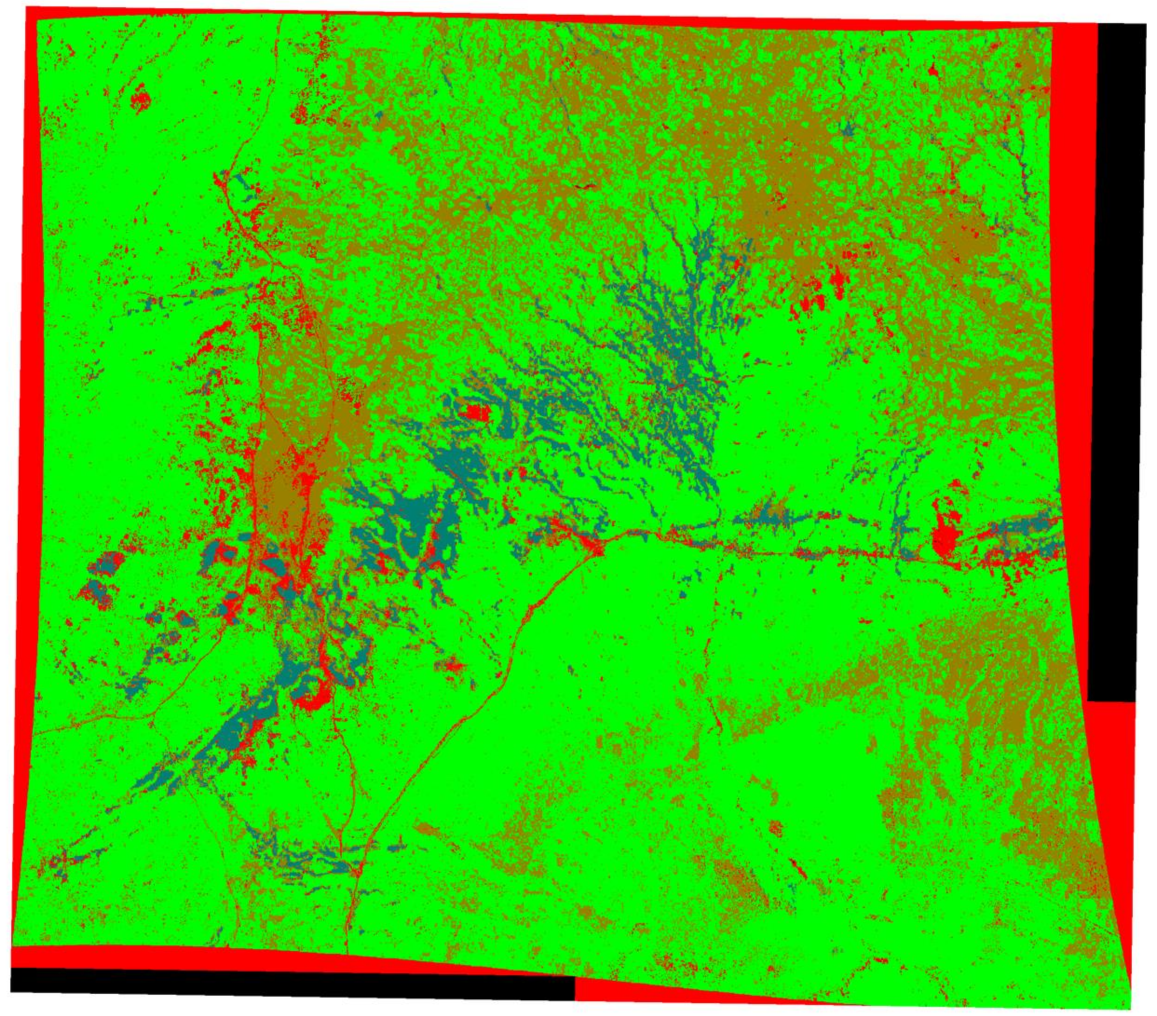
Land Cover Change 1990 - 2015

Carrasco, L., O'Neil, A.W., Morton, R.D. and Rowland, C.S., (2019) Evaluating Combinations of Temporally Aggregated Sentinel-1, Sentinel-2, And Landsat 8 For Land Cover Mapping with Google Earth Engine, *Remote Sensing*, 11(3), 288, https://doi.org/10.3390/rs11030288

Random Forest Regression (1)



Aerial photo



High resolution classification

Bare peat
Blue/green

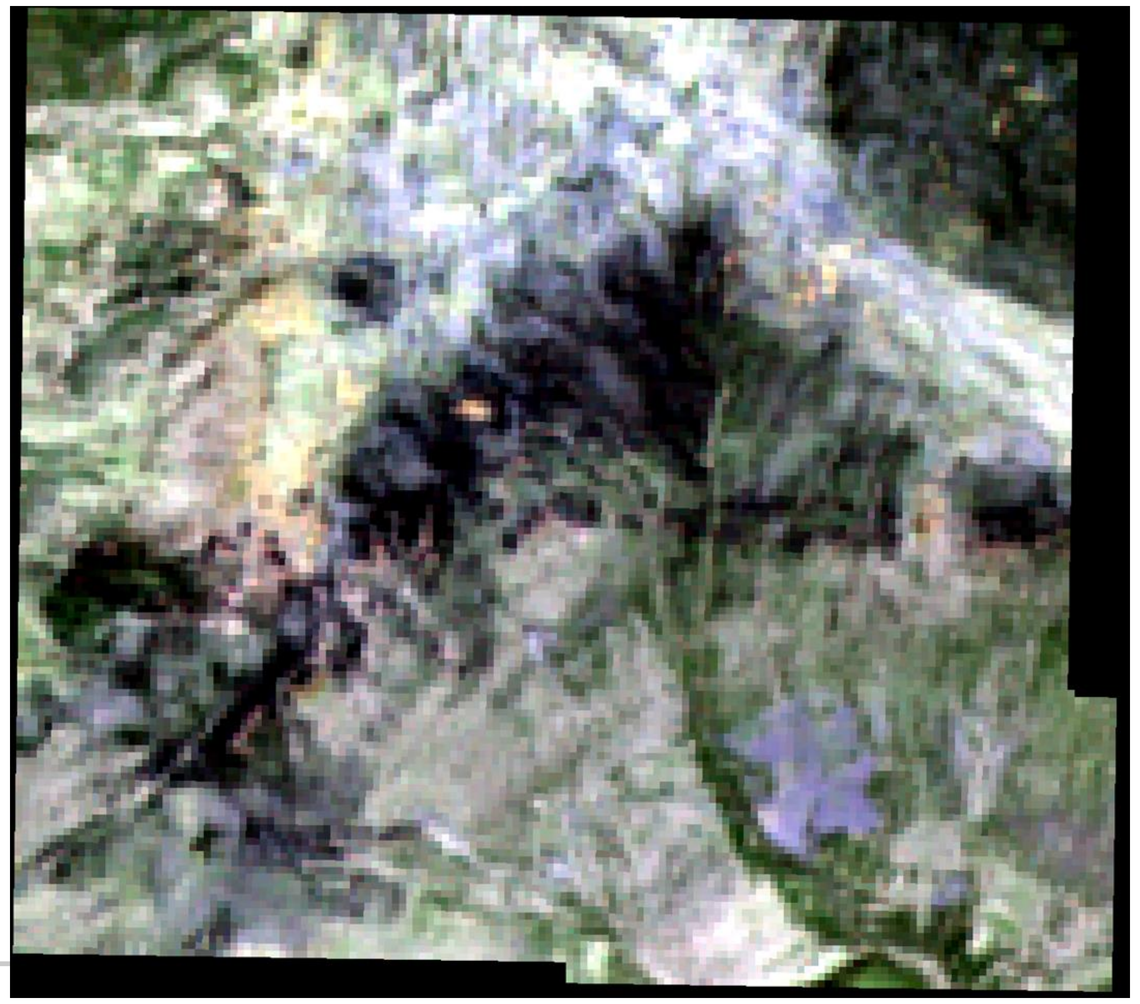
Recovering peat
Off brown

Exposed rock
Red

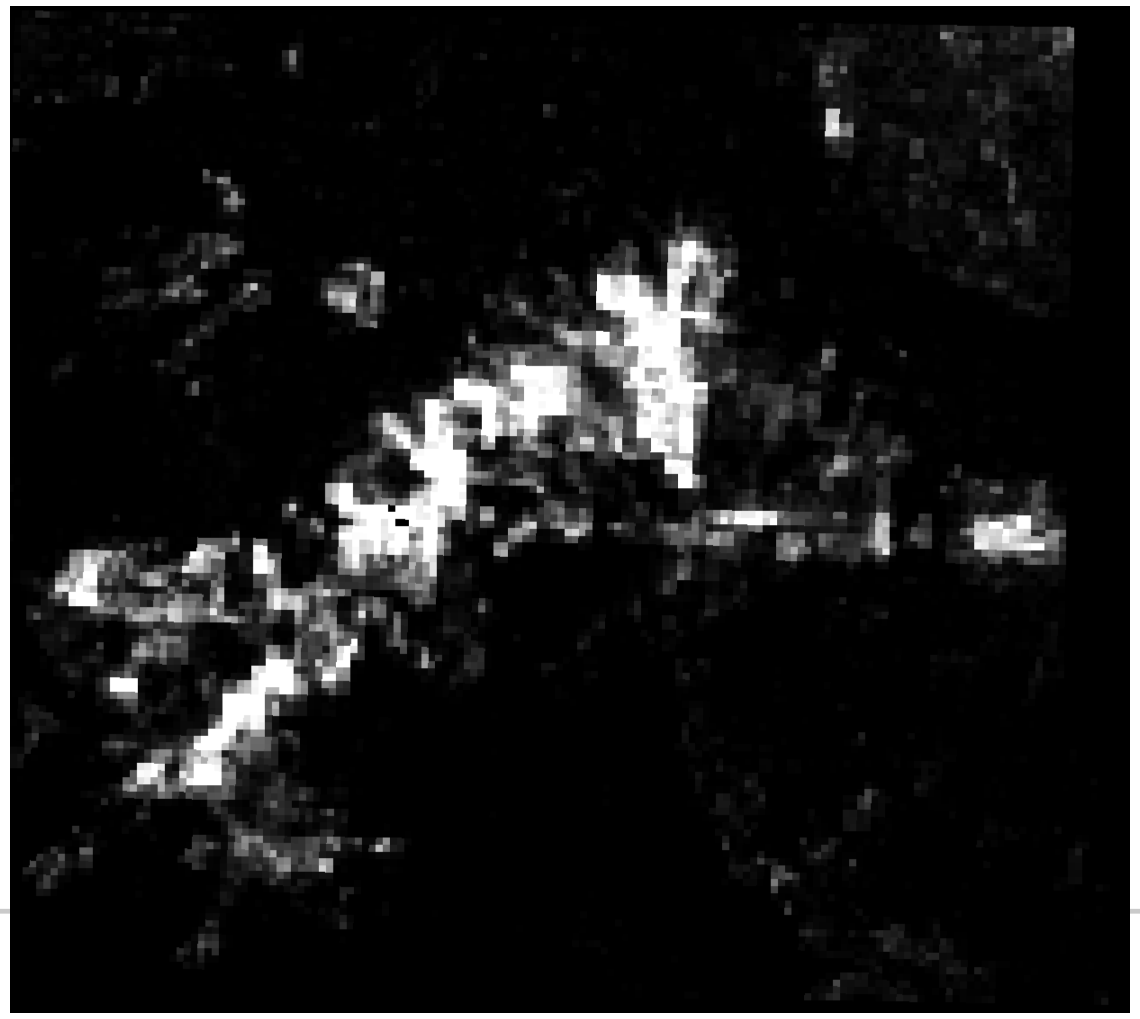
Vegetation
Green

Training data and Random Forest Regression

+



Sentinel-2 image



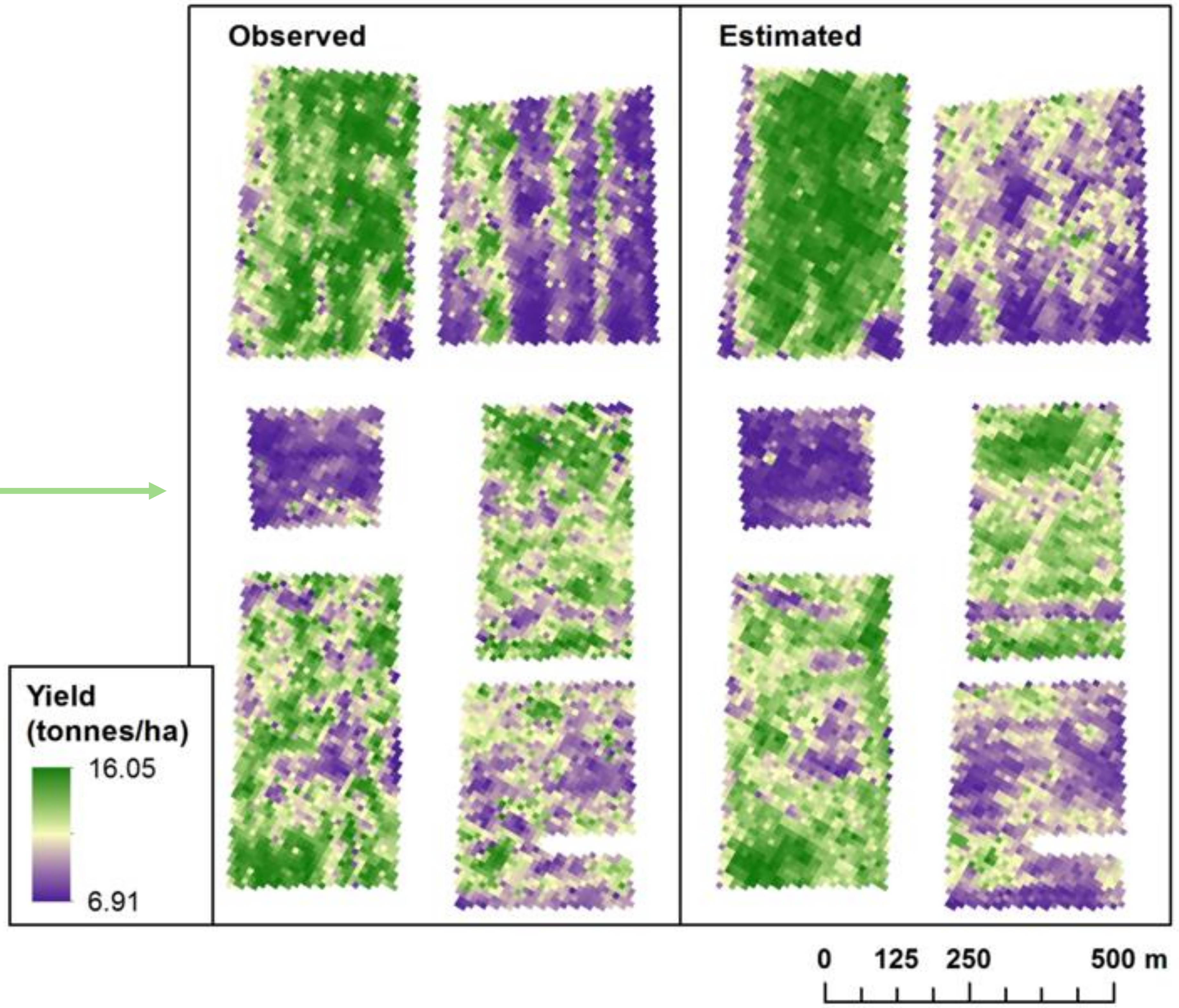
Estimated % bare peat

Random Forest Regression (2)

Data from:

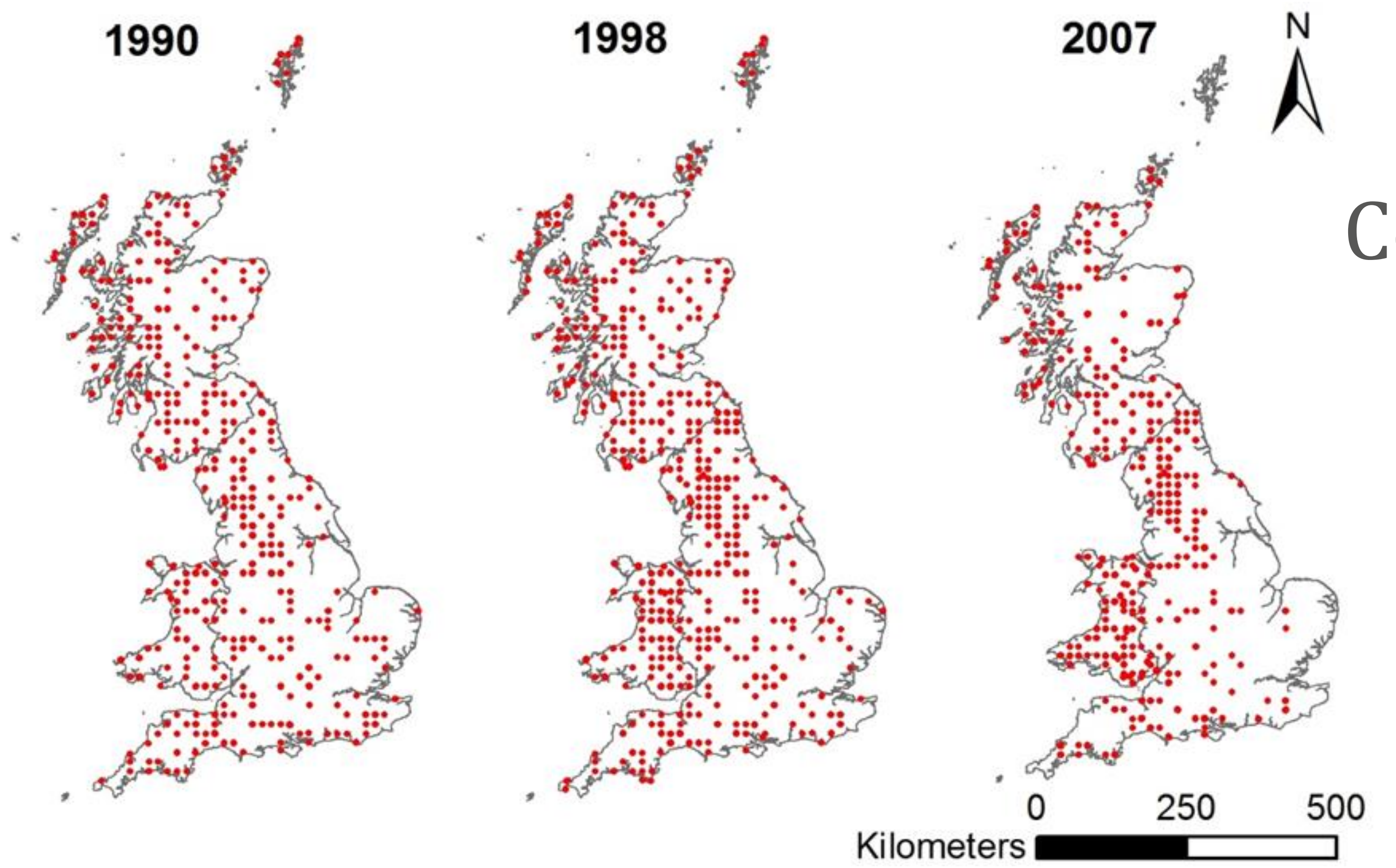
And from:

Random Forest Regression



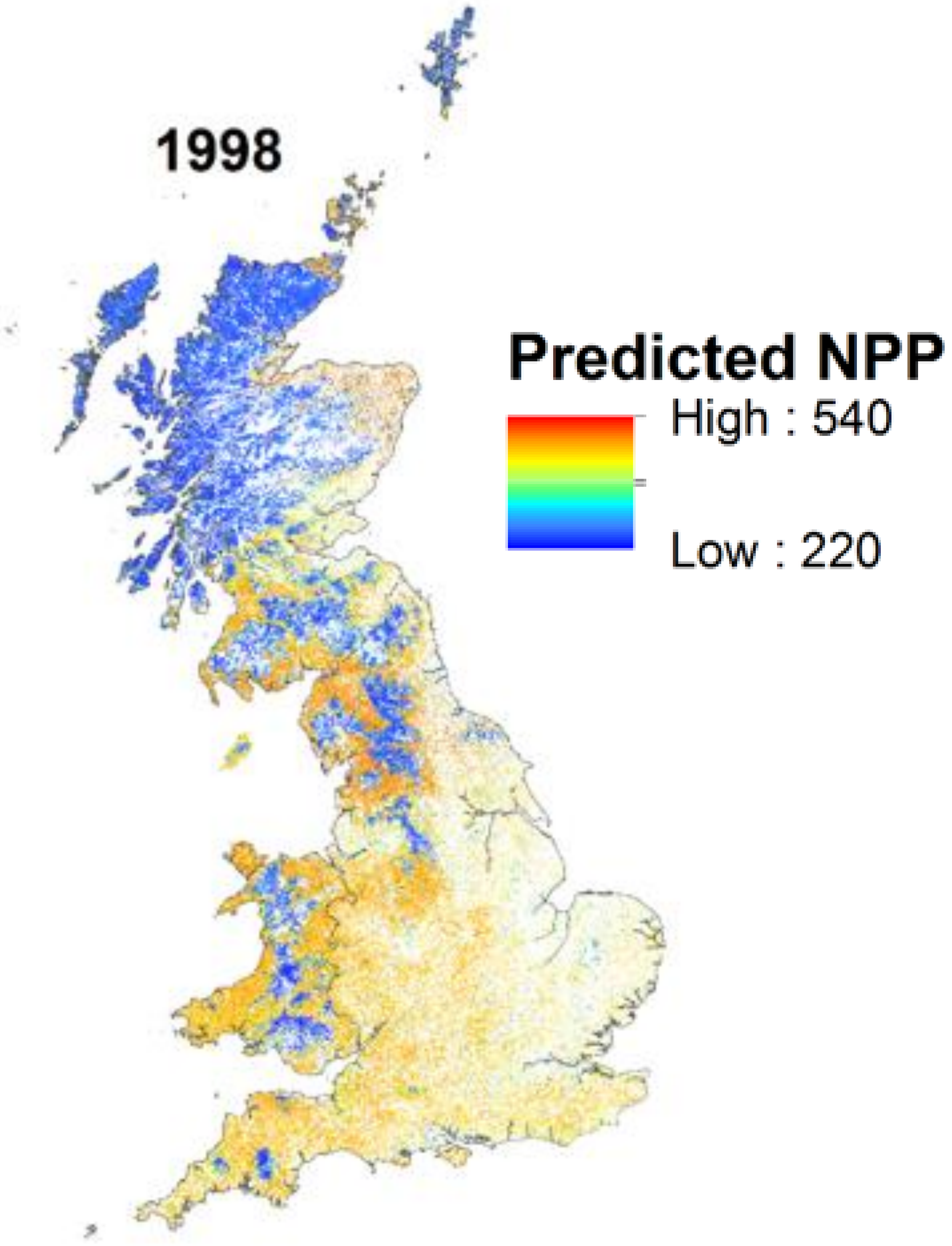
Hunt, M.L., Blackburn, G.A., Carrasco, L., Redhead, J.W., Rowland, C.S., (2019) High resolution wheat yield mapping using Sentinel-2, *Remote Sensing of Environment*, **233**, 111410

Quantile Regression Forest: Grassland Condition

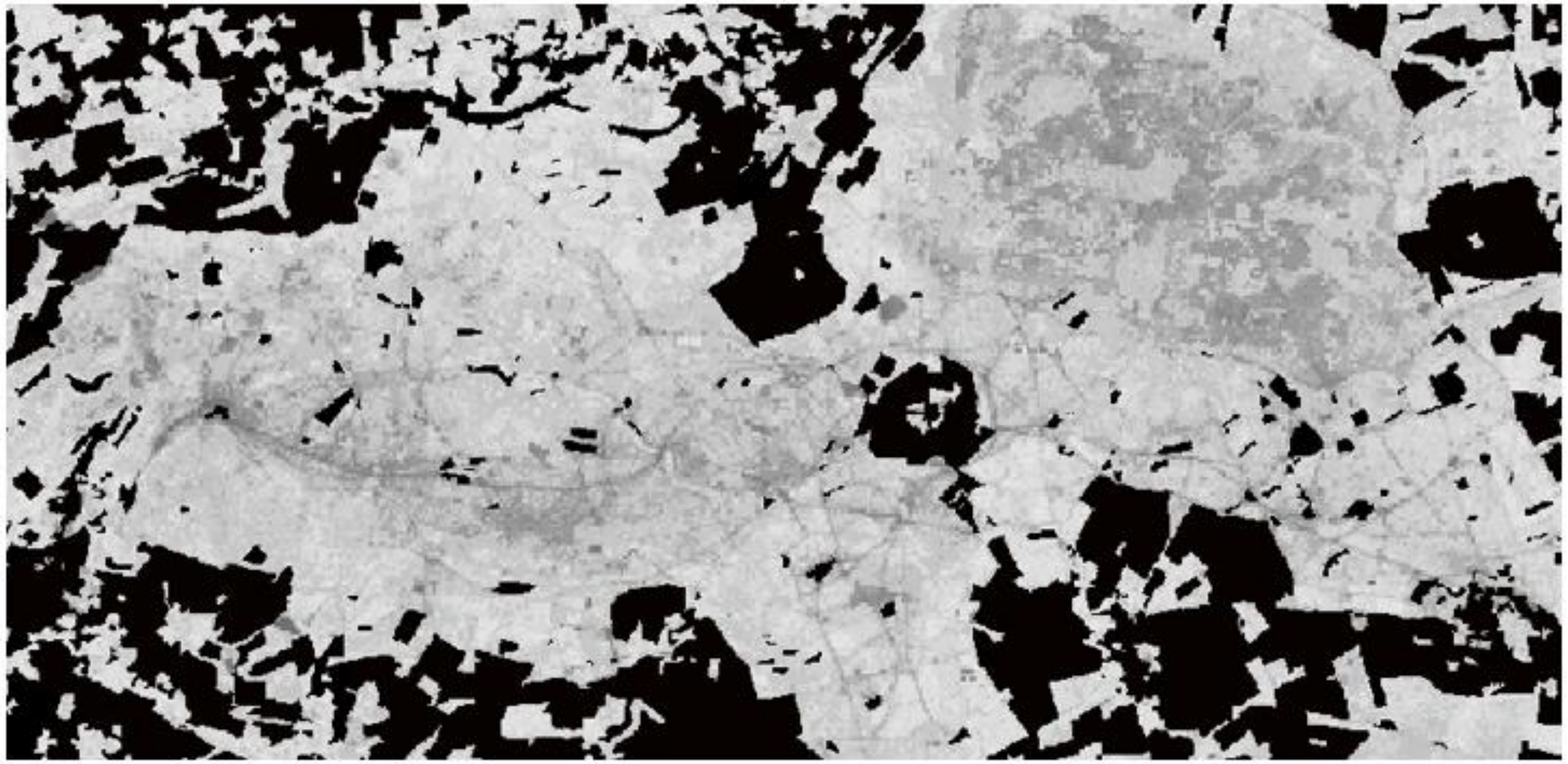


Countryside Survey data

Satellite data

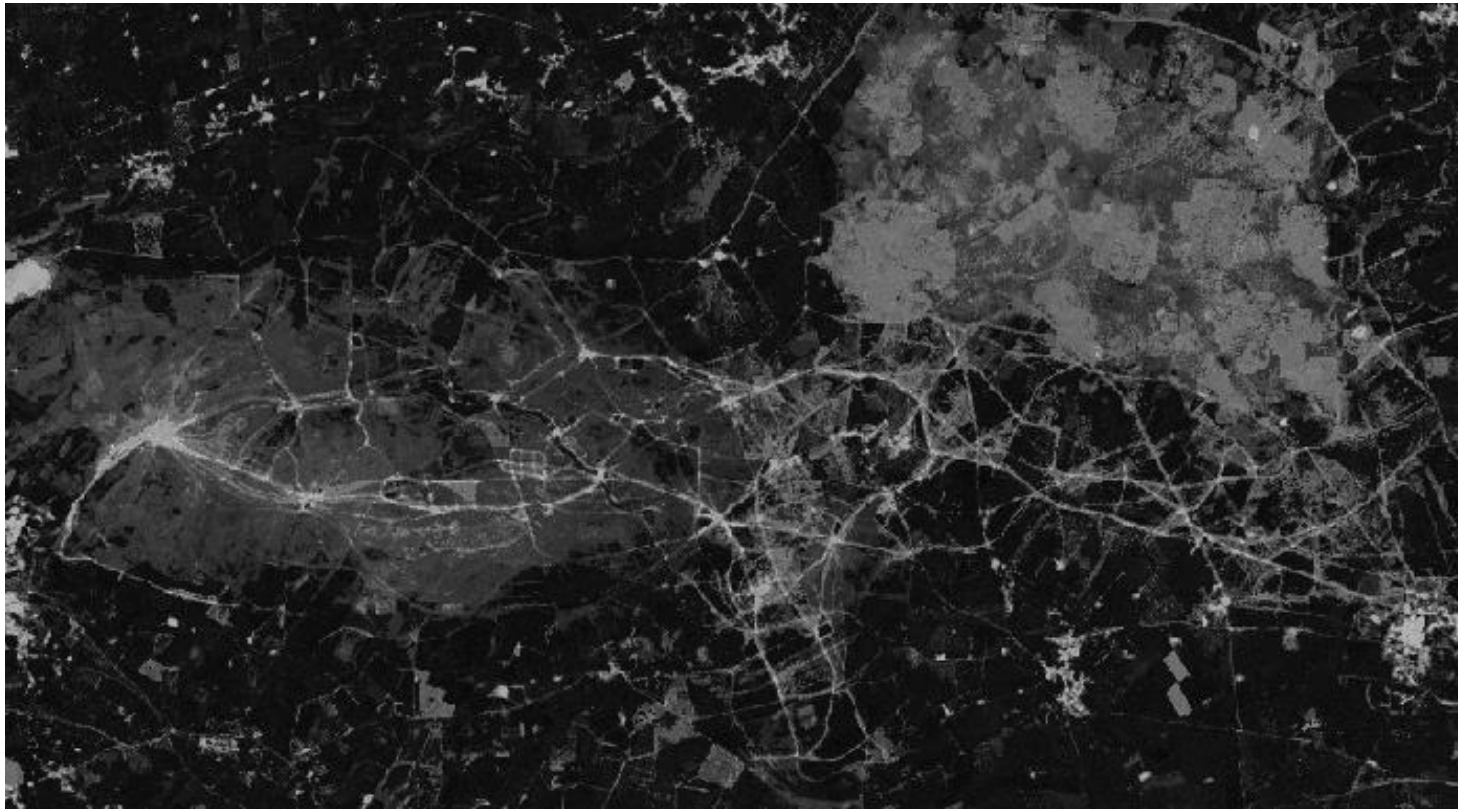


Grassland condition

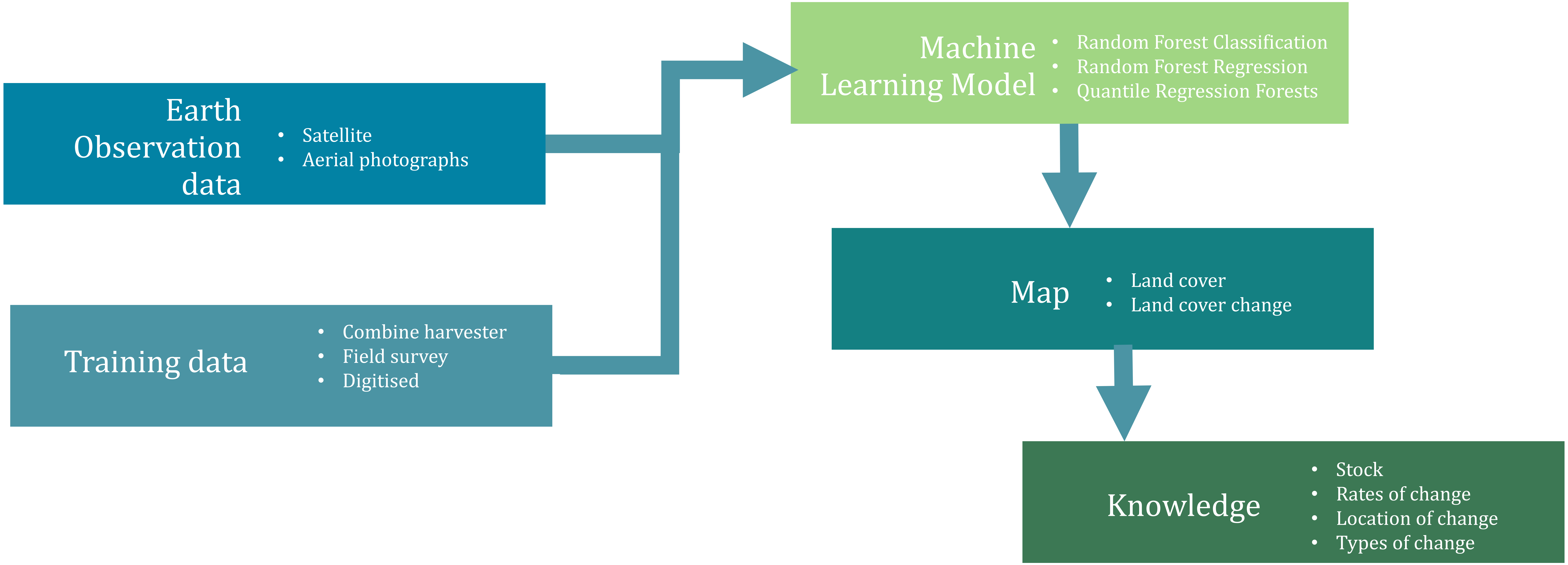


Black – no grass
Dark grey – low NPP values
Light grey – high NPP values

Uncertainty information



A recipe for EO and ML



Summary

1. Random Forest classification and regression are useful tools for deriving EO data sets
2. Success depends on the quality (and relevance) of the EO data & the quality of the training data (accuracy + distribution of the training sample)
3. The spatial distribution of the training data is a key issue when dealing with large spatial data sets e.g. EO data
4. Need better techniques for understanding when satellite data is within/beyond the bounds of the training data