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**Article — Published Version**

## Hotspots of land use change in Europe

Environmental Research Letters

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*Suggested Citation:* Kuemmerle, Tobias et al. (2016) : Hotspots of land use change in Europe, Environmental Research Letters, ISSN 1748-9326, IOP Publishing, Bristol, Vol. 11, Iss. 6, pp. 1-14, <https://doi.org/10.1088/1748-9326/11/6/064020> , <http://stacks.iop.org/1748-9326/11/i=6/a=064020>

This Version is available at:

<https://hdl.handle.net/10419/177224>

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# Hotspots of land use change in Europe

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Environmental Research Letters - <http://dx.doi.org/10.1088/1748-9326/0/0/000000>

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# 1 Study region

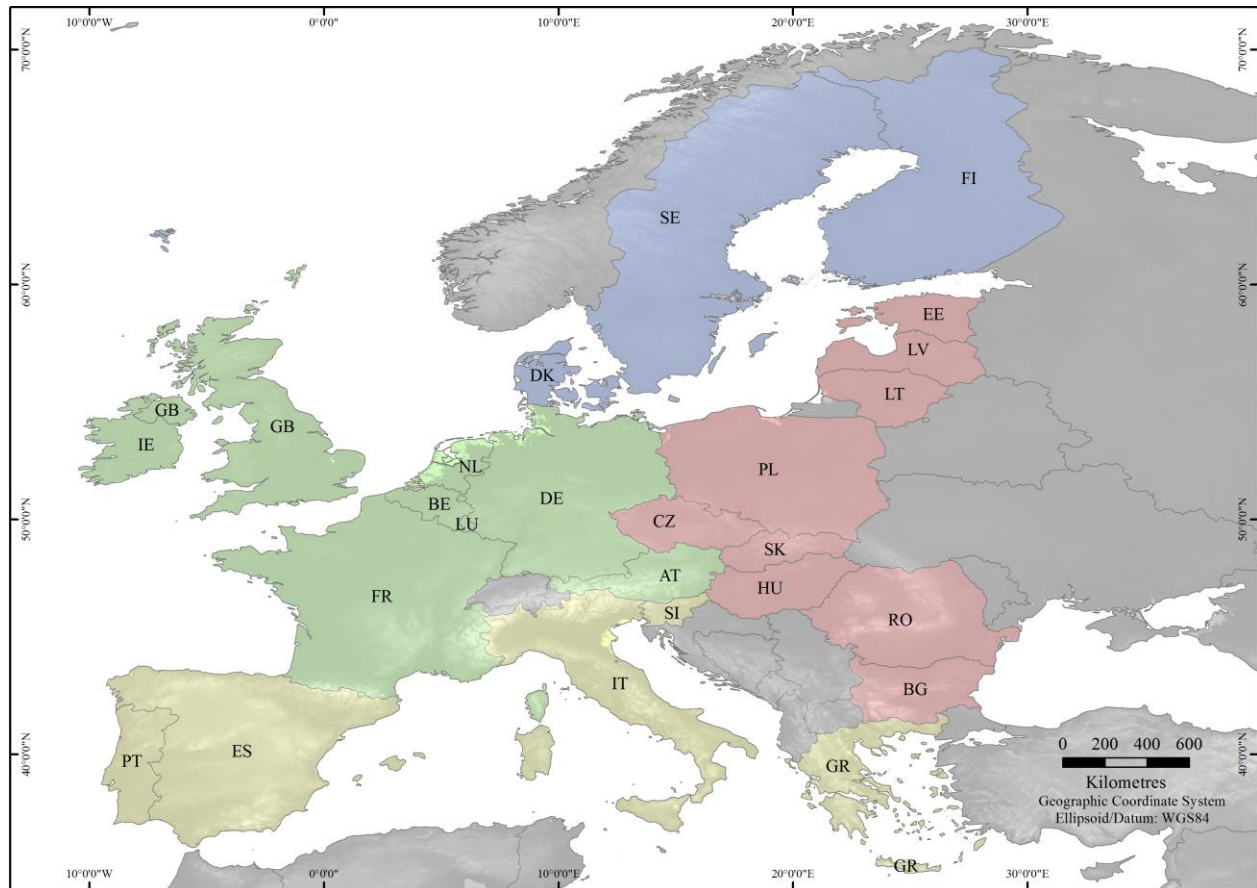


Figure S1: Overview of the study area. Blue coloring indicates, for the purpose of this manuscript, Northern Europe, green Western Europe, red Eastern Europe, and yellow Southern Europe. Abbreviations: BE = Belgium, BG= Bulgaria, CZ= Czech Republic, DK= Denmark, DE= Germany, EE= Estonia, IE= Ireland, EL= Greece, ES= Spain, FR= France, IT= Italy, LV= Latvia, LT= Lithuania, LU= Luxembourg, HU= Hungary, NL= Netherlands, AT= Austria, PL= Poland, PT= Portugal, RO= Romania, SI= Slovenia, SK= Slovakia, FI= Finland, SE= Sweden, UK= United Kingdom

## 2 Description of land-use change indicators

### 2.1 *Data on changes in the extent of broad land-use categories*

We used cropland, permanent crops, and pasture area from the Common Agricultural Policy Regionalized Impact (CAPRI) database (Britz and Witzke 2012) for the years 1990 and 2006 (i.e., corresponding with the CORINE time cuts). CAPRI provides data at the NUTS-2 level) and cropland in this database included all arable land including fodder crops, as well as permanent crops, included fruit and olive orchards, vineyards, and berries. To disaggregate CAPRI cropland to the grid level, we used two datasets: the CORINE layers (100-m gridcells) and the CAPRI-Dynaspat database (1-km gridcells). CAPRI-Dynaspat discerns 13 cropland commodity groups (cereals, rice, wine, oilseeds, olives, roots & tubers, fibers, fodder crops, pulses, sugar beet, vegetables & others, and fallow).

To calculate the cropland share per gridcell in our target grid, we regarded the CORINE layers as authoritative for the spatial extent of cropland areas, while using the CAPRI-Dynaspat (Heckelei and Kempen 2011; Leip et al. 2008) for defining the patterns of fractional cover of cropland commodity groups, for which no information is available in CORINE. CAPRI-Dynaspat is consistent with CAPRI at NUTS2, but shows small deviations with CORINE (for a quantitative comparison between CORINE and CAPRI cropland cover please see [http://agrienv.jrc.ec.europa.eu/publications/pdfs/HNV\\_Final\\_Report.pdf](http://agrienv.jrc.ec.europa.eu/publications/pdfs/HNV_Final_Report.pdf), p29 and Appendix p81-87). CAPRI-Dynaspat areas outside of the extent of the CORINE cropland were masked. To account for these discrepancies, cropland areas in CORINE without CAPRI Dynaspat information (very few grid cells) were allocated to neighboring grid cells by applying Euclidian allocation. In some regions (e.g. Mecklenburg-Vorpommern) CAPRI numbers on cropland areas were unreasonably high, likely representing reporting errors. We truncated the CAPRI-Dynaspat cropland amount in these cases using the CORINE cropland area. The resulting cropland fractions per gridcell were then used as weights for disaggregating the NUTS-2 CAPRI statistics to our 3-km grid-level.

For pasture areas we first allocated the class “meadows & pastures” from CAPRI to the extent of the CORINE pastures class (excluded the class ‘Sparsely vegetated areas’). CAPRI reports significantly larger pasture areas in all NUTS-2 regions than the CORINE pasture class (which is essentially a grassland class). Thus, in a second step, the remaining CAPRI pasture areas were assigned to the CORINE classes ‘heterogeneous agricultural areas’, as well as

‘shrublands and herbaceous vegetation not designated as pastures’. For further details on the allocation procedure for cropland and pastures please see Plutzer et al. (2016).

To map agricultural abandonment and recultivation, we used time series of MODIS Normalized Differenced Vegetation Index (NDVI), using the 16-day composites from both satellites Terra (MOD13Q1, v5), and Aqua (MYD13Q1, v5), thus yielding a time series with images every 8 days) for the time period 2000 to 2012 at a spatial resolution of 232m (Estel et al. 2015). We applied a multi-step pre-processing chain to reduce effects arising from clouds, water, ice, and soil background, and thus to construct a consistent NDVI time-series. We also normalized the NDVI time series to make them more comparable across the broad environmental gradients prevailing in Europe.

Second, for the years 2001 to 2012, we classified each grid cell as either managed (i.e., active, plowed, mowed or heavily grazed) or fallow (i.e. unmanaged) and finally applied the CORINE agricultural mask (i.e., all classes with non-permanent cropland and pastures). To do so, we used a Random Forests classifier (Cutler et al. 2007; Waske et al. 2012), with training data sampled across Europe using a random-stratified setup. Independent validation data came from the Land Use/Cover Area Frame Statistical Survey (LUCAS, [www.lucas-europa.info](http://www.lucas-europa.info)), field campaigns, and higher-resolution satellite images (e.g. GoogleEarth imagery). LUCAS provides ground information on land cover and land management (Delincé 2001; Gallego and Delincé 2010; van der Zanden et al. 2013), including fallow, abandoned and active farmland. For LUCAS 2009 and 2012, for instance, around 500,000 points were surveyed and photo-documented by field surveyors in 23 (2009) and 27 (2012) EU countries (Eurostat 2014).

Training and validation data were crosschecked to ensure field labels were correct, as class labels may have changed after a plot was surveyed on the ground (e.g., plowing of a fallow field after a site was visited) using the temporal profiles of the MODIS NDVI time series and high-resolution imagery in GoogleEarth. The resulting annual active/fallow maps had an average overall accuracy of 89.8% (standard deviation of 1.1%). Using the annual active/fallow time series, we defined agricultural abandonment as all pixels that had a maximum of two fallow years in 2001-2006 and a maximum of one active in 2007-2012. Recultivation was defined as a maximum of one active year in 2001-2006 and a maximum of two fallow years in 2007-2012. For details, including a sensitivity analysis regarding the abandonment and recultivation definitions, see Estel et al. (2015). We then calculated abandonment, and recultivation rates at the 3-km grid level (relative to total farmland in 2001).

Assessing changes in forestland from satellite-based land cover maps such as CORINE is challenging, because forest cover changes can reflect permanent gains or losses in forest area, but also temporary cover losses due to natural disturbance (e.g., storms or fire) or management (e.g., harvest), which do not reflect land use change. To derive forestland maps, we disaggregated and harmonized regional level forest area statistics for the years 1990 and 2005 to the 3-km grid using CORINE forest area as weights (Plutzer et al. 2016). Forestland extent was taken from the State of European Forests (SoEF) database (Forest Europe 2011) at NUTS-3 to NUTS-1 level, depending on the country (see Levers et al. 2014 and Verkerk et al. 2015 for details).

To calculate the extent of urban area change, we relied on the 1990 and 2006 CORINE maps and calculated percent urban land cover within 1-km grid cells based on the 11 urban or built-up classes, following the protocol by Feranec et al. (Feranec et al. 2012). Further details on the allocation procedure for forestland and urban area are provided in Plutzer et al. (2016).

## ***2.2 Data on changes in the management intensity within broad land use categories***

To measure cropland inputs, we relied on a recently developed 1-km dataset of fertilizer application rates (Overmars et al. 2014; Temme and Verburg 2011). This dataset was generated using statistics on fertilizer use data at the NUTS-2 level from the CAPRI database, which contains both manure and chemical fertilizer input for all major crops for 1990 – 2007 from the Farm Structure Survey (see Britz and Witzke 2012 for details). To summarize the fertilizer data across crop types, cropland area at the NUTS-2 level was stratified into three fertilizer input classes: low (<50 kg/ha), medium (50-150 kg/ha) and high (>150 kg/ha) (Overmars et al. 2014). Next, multinomial regression models were fitted to create probability maps for each class and for each country. As response variable, we used ~150,000 cropland points from LUCAS, to which crop-specific nitrogen application rates had been assigned. As predictors, a set of environmental (i.e., soil, topography, climate) and socio-economic (i.e., population density and accessibility) factors at a resolution of 1 x 1 km<sup>2</sup> was used (Temme and Verburg 2011). For countries without LUCAS coverage, regressions from neighboring countries were applied. Using the resulting probability maps, a hierarchical procedure was then used to allocate the NUTS-2 level areas of the three fertilizer application classes to the grid level (Overmars et al. 2014; Temme and Verburg 2011). For the purpose of this manuscript, we aggregated data to a 3-km target grid for 1990 and 2006 (our target years for which CORINE land cover information was available) by calculating an area-weighted mean, using the values 50, 150, and 250 kg/ha as class values.

In terms of cropland outputs, we used yields for the 13 most prevalent crops types defined by CAPRI-DynaSpat in the EU (i.e., cereals, oilseeds, pulses, roots & tubers, sugar beet, olives, flax & hemp, wine & grapes, fruits, rice and vegetables) from the CAPRI database at the NUTS-2 level for 1990 and 2006. Yields were expressed as the amount of biomass harvested per crop. To disaggregate yields to the 3-km target grid, we derived crop suitability maps using environmental niche modelling, in our case based on a maximum entropy algorithm (Phillips et al. 2006; You and Wood 2006). Niche models require data on the occurrence of a particular species (in our case a specific crop), which we took from the LUCAS database. Maxent then describes the niche of a crop based on environmental factors by contrasting the distribution of values of an environmental factor at the occurrence locations with the overall distribution of this factor. As environmental factors (i.e., predictors), we used bioclimatic, soil, and topographic variables. The resulting crop suitability maps were combined with the cropland area maps described above by calculating the product of cropland share and suitability. These layers then served as weights for the disaggregation of harvest yields (see Plutzer et al. (2016) for details), resulting in a map of the amount of biomass harvested on cropland area per grid cell [ $\text{tC km}^2 \text{ yr}^{-1}$ ].

Regarding grazing systems, we used one input and one output metric. Regarding inputs, we derived grazing intensity on pastures by downscaling NUTS-2 level livestock numbers to the 1-km grid level following Neumann et al. (2009). The NUTS-2 level statistics do not distinguish between grazing and stall feeding, and we assumed that all dairy cattle, beef cattle, heifers, sheep and goats were dominantly grazing. We converted all livestock numbers to equivalent livestock units using region-dependent conversion factors. We then used a grazing potential map, using grassland productivity, terrain and accessibility as main determinants (see Neumann et al. (2009)), to spatially allocate these livestock units. Areas with very low grazing potential were not allocated any livestock. Based on the resulting livestock densities, four grazing intensity categories were distinguished (1:  $<25 \text{ LSU/km}^2$ ; 2:  $25\text{-}50 \text{ LSU/km}^2$ ; 3:  $50\text{-}100 \text{ LSU/km}^2$ ; 4:  $>100 \text{ LSU/km}^2$ ). We then calculated an area-weighted mean at the 3-km target grid using class means ( $100 \text{ LSU/km}^2$  for the fourth class).

In terms of output metrics, we used biomass yields and calculated biomass removed from pastures (in  $\text{tC km}^2 \text{ yr}^{-1}$ ) from CAPRI at the NUTS-2 level and disaggregated these to the 3-km target grid. We did so following the approach by Neumann et al. (2009), using a combination of actual Net Primary Productivity (NPP) and slope as weights, assuming a linear decrease of pasture suitability between 6% and 24% slope. Actual NPP was taken from Plutzer et al. (2016),

slope was calculated on the basis of the SRTM-90m digital elevation model ([www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1](http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1)). No metrics regarding changes in the input intensity of grazing systems were available to use.

To assess forestry management intensity, we compiled and harmonized annual roundwood removal maps based on regional harvest statistics from 2000 to 2005 at the level of administrative units (Levers et al. 2014). In this study, we disaggregated these regional harvesting statistics using the forest cover map developed in section 1.1, which was combined with a pixel-level harvest likelihood map to produce wood removal maps at the target resolution of 3x3km<sup>2</sup>. This likelihood map was derived using linear regression modelling to link harvesting statistics with productivity, tree species composition and terrain ruggedness as the most important location factors (see Verkerk et al. (2015) for details on the harvest likelihood maps and disaggregation approach). To extend the time period covered, we disaggregated national-level harvesting data from Forest Europe et al. (2011) for 1990, assuming constant harvesting ratios among regions within a country, which is supported by the very stable harvesting patterns found by Levers et al. (2014). We assigned wood removal volumes only to grid cells that were forests already in 1990. New forests either established or deforested after 1990 were assumed not to supply wood in 2005, due to long production cycles in forestry.

### 3 Calculation of Moran's I

The bivariate Moran's I quantifies the association of a given variable (x) at a location and a different variable (y) at surrounding locations and is calculated as:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_i (Y_i - \bar{Y})^2}$$

where  $N$  is the number of observations (i.e., gridcells),  $X_i$  is variable 1 at a particular location  $i$ ,  $Y_j$  is variable 2 at another location  $j$ , and  $w_{ij}$  is a weight indexing location  $i$  relative to  $j$ . For details, please see Anselin (1995) and Anselin (2001).



## 4 Distribution of land use categories

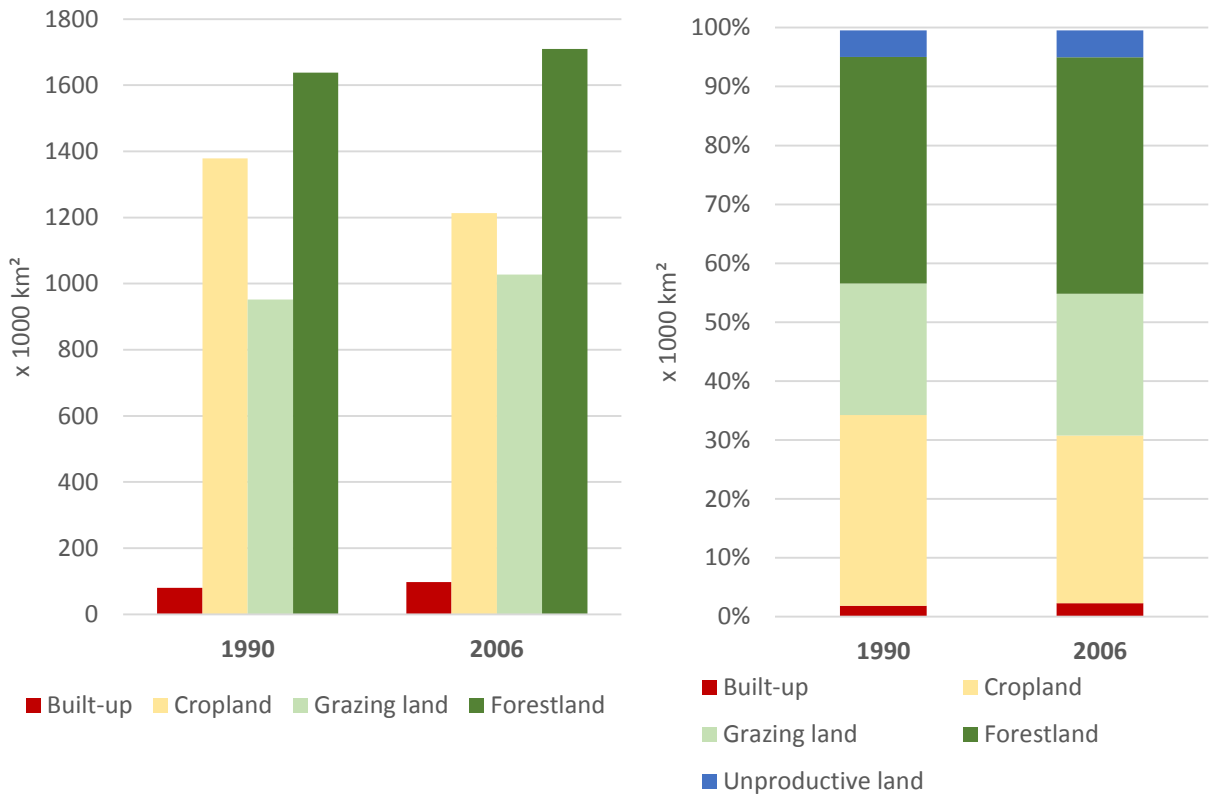


Figure S2: Distribution of major land-use categories in the two target years 1990 and 2006. Left: area per land use category and year. Right: relative shares of land-use category per year.

## 5 Sensitivity analyses of hotspot/coldspot mapping

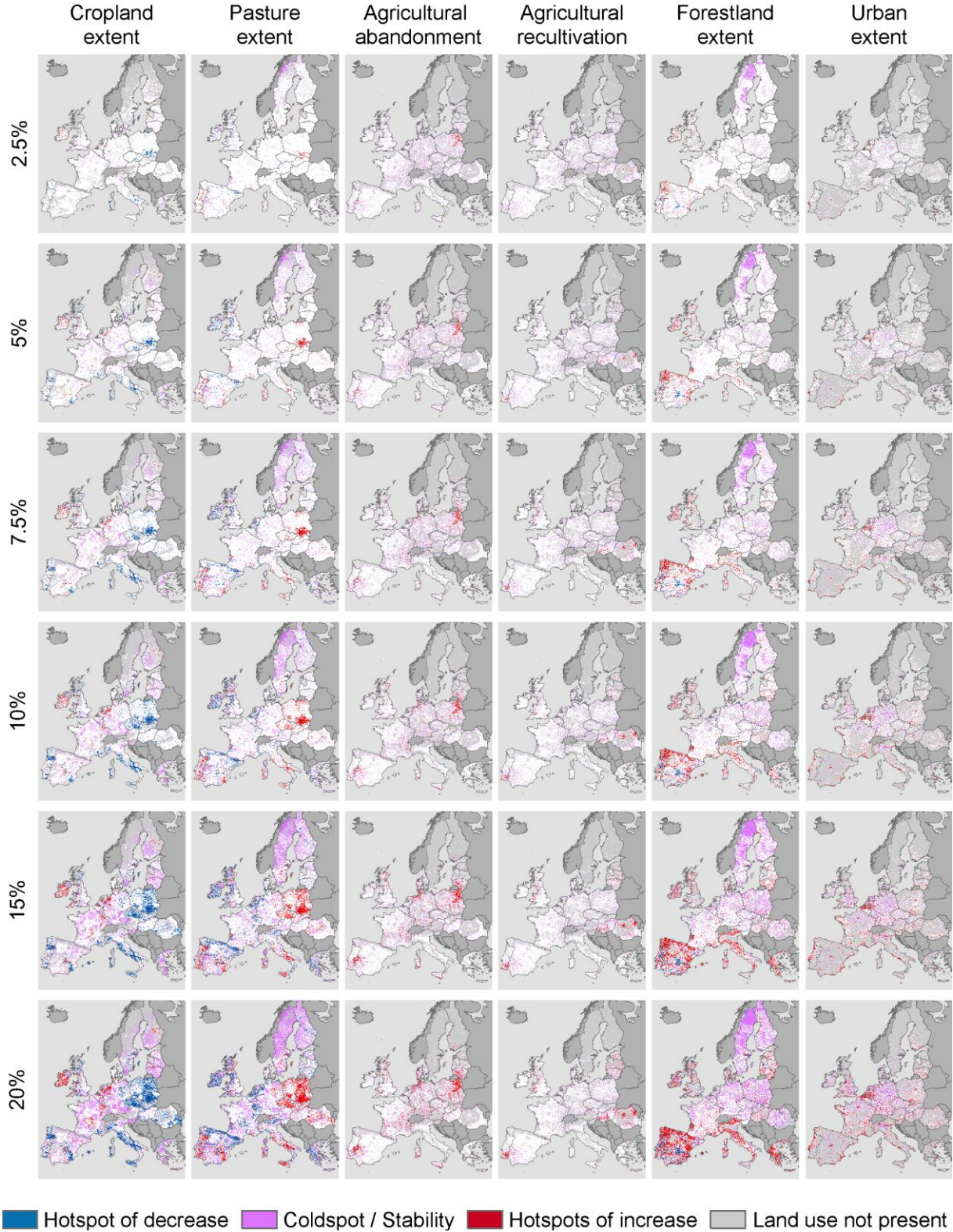
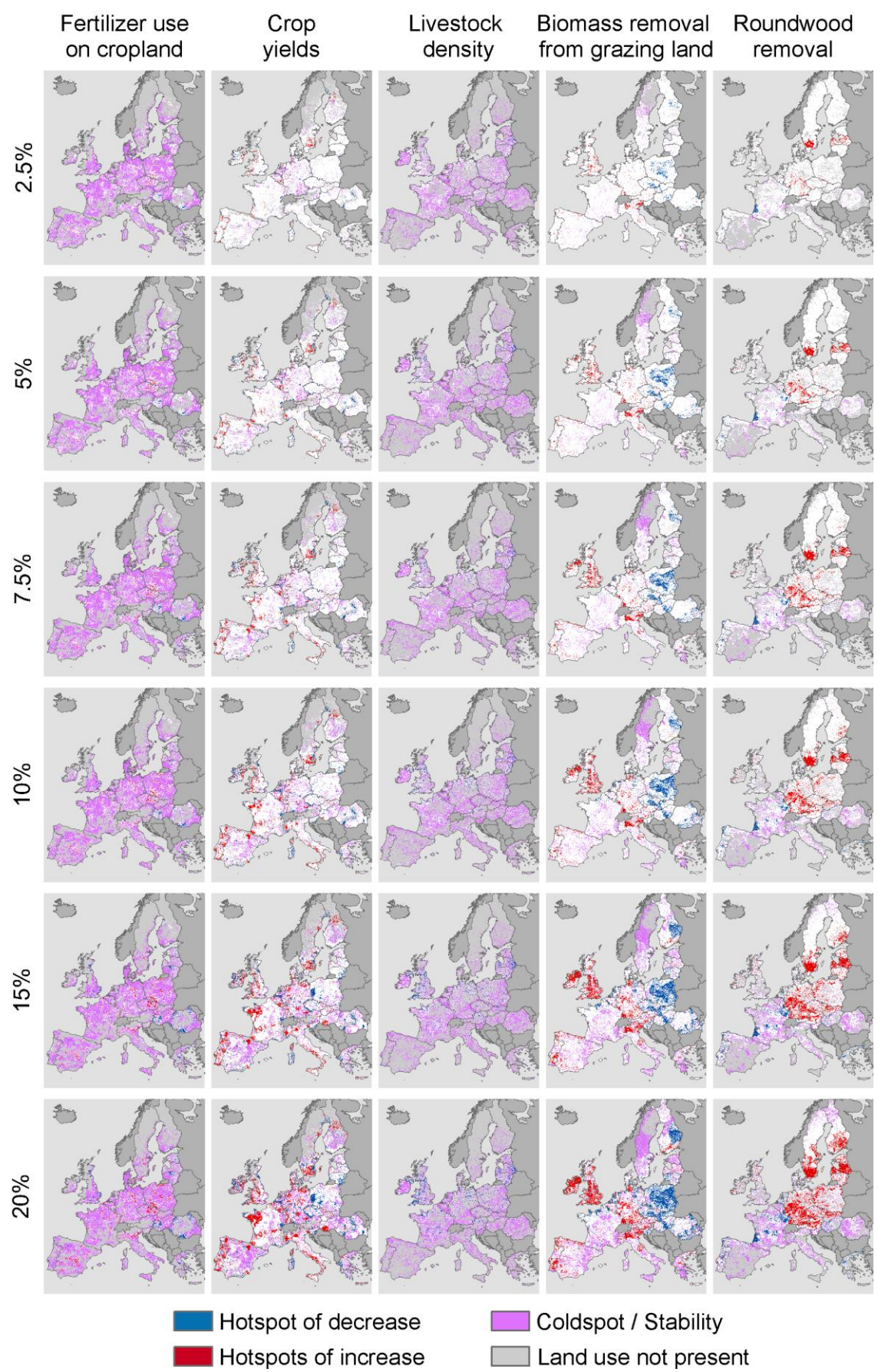


Figure S3: Sensitivity of hotspots of area changes in broad land use classes to varying the quantile threshold chosen to define hotspots (thresholds considered: top/bottom 2.5%, 5%, 7.5%, 10%, 15%, and 20% of the change distribution).





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