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Land Cover Change and Conversions

METHODOLOGY AND RESULTS FOR OECD AND G20 COUNTRIES

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Foreword

In 2012, the OECD Working Party on Environmental Information (WPEI) requested the Secretariat, namely the Environment Directorate in co-operation with the Economics Department and the Statistics Directorate, to further elaborate the OECD green growth headline indicators.[1] Indicators on changes in land use and land cover were proposed for inclusion in the set of *headline* indicators, and are also included in the OECD Core Set of Environmental Indicators. They are to be used in the country reviews carried out by the OECD, in policy analyses at national and at territorial level, and in public communication by the OECD.

OECD Green Growth *headline* indicators

Environmental and resource productivity	
Carbon and energy productivity	1. CO_2 productivity
Resource productivity	2. Non-energy material productivity
Multifactor productivity	3. Environmentally adjusted multifactor productivity
Natural asset base	
Renewable and non-renewable stocks	4. Natural resource index
Biodiversity and ecosystems	5. Changes in land cover
Environmental quality of life	
Environmental health and risks	6. Population exposure to air pollution ($PM_{2.5}$)
Economic opportunities and policy responses	
Technology and innovation Environmental goods and services Prices and transfers Regulations and management approaches	*Placeholder: no indicator specified*

Source: OECD (2017a) *Green Growth Indicators 2017*

At its meetings in 2014, 2015 and 2016, the WPEI recognised that geospatial data provide opportunities for developing the headline indicator on land cover changes without adding to the response burden of countries, reviewed available datasets for OECD and G20 countries (Diogo and Koomen, 2016), and noted progress in the availability of global land cover datasets but observed their lack of suitability for tracking conversions over time between relevant land cover classes.

[1] The green growth (GG) headline indicators is a small set of indicators selected to track central elements of GG and to facilitate communication with policy makers, the media and citizens. The set has been proposed following the decisions of three OECD bodies – the Committee on Statistics and Statistical Policy (CSSP), the Working Party on Environmental Information of the Environment Policy Committee (EPOC/WPEI), and Working Party 1 on Macroeconomic and Structural Policy Analysis of the Economic Policy Committee (EPC/WP1).

Against this background, the Secretariat has engaged with data providers (space agencies, researchers and the GEO) articulating the needs of the OECD in this domain to help guide future developmental work. It has consulted with international partners (UNSD, FAO, UNCCD and EEA) in an effort to stay abreast of relevant developments. With the recent development and availability of several novel global datasets in 2016-2017, that could be suitable for tracking changes in land cover, the Secretariat prepared a revised proposal on how these datasets could support the calculation of the headline indicator.

This paper presents an updated methodology which includes results based on the most recent global datasets available. It will be integrated into OECD's work and will further evolve when superior datasets become available in the future.

Acknowledgments

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The paper was reviewed by the OECD Environmental Policy Committee and its Working Party on Environmental Information (EPOC/WPEI). It also benefited from the comments received from country Delegates to the Committee on Statistics and Statistical Policy (CSSP) and the Working Party No. 1 on Macroeconomic and Structural Policy Analysis of the Economic Policy Committee (EPC/WP1). These included Australia, Austria, Canada, Chile, Colombia, France, Germany, Hungary, Italy, Korea, Lithuania, Mexico, New Zealand, Norway, Poland, Sweden, the United States, Eurostat of the European Union, and others.

Expert feedback was provided by Olivier Arino (ESA), Giulia Conchedda (FAO), Martin Herold (Wageningen University and GOFC-GOLD), Sara Minelli (UNCCD) and Martino Pesaresi (JRC) at the WPEI Special Session on land cover in November 2017. The authors would also like to thank Sasha Alexander (UNCCD), Renato Cumani (UNCCD), Katia Karousakis (OECD), Johns Muleso Kharika (UNCCD), Tomasz Koźluk (OECD), Myriam Linster (OECD), Barron Joseph Orr (UNCCD), Jean-François Pekel (JRC), Abel Schumann (OECD), Francesco Tubiello (FAO) and the Université catholique de Louvain Geomatics team for helpful comments and suggestions.

Abstract

Changes in the biophysical characteristics of natural habitats – that can be measured with data on land cover – are the best proxy to monitor pressures on ecosystems and biodiversity. This paper presents a suite of indicators that track land cover change over time in a globally consistent manner. The indicators, including an OECD Green Growth headline indicator, represent the Organisation's most recent effort to monitor pressures on ecosystems and biodiversity, using state-of-the-art data and techniques. Results are presented for OECD and G20 countries over 1992-2015 using global multi-period datasets.

The main results show that since 1992, for the OECD area, 1.4% of natural and semi-natural vegetated land has been lost to other land cover types, with variation across OECD countries ranging from 0% to 16%. Globally, the loss intensity doubles, with as much as 2.7% of (semi-)natural vegetated land lost since 1992, equivalent to an area twice the size of Spain. More than half of this global loss occurs in OECD and G20 countries, primarily in Brazil, China, Russia, the United States and Indonesia.

Conversions from (semi-)natural land to cropland and from cropland to artificial surfaces are the most prominent land cover changes observed in the OECD area and globally. Around 1% of (semi-)natural land was converted to cropland in OECD countries since 1992, with variation across countries ranging from 0% to 15%. Globally, it rose to 2.2%. During the same period, 1.5% of cropland in OECD countries was converted to artificial surfaces, with national variation ranging from 0% to 11%.

Supplementary results show that built-up area growth and surface water change remain challenges. Globally, an area the size of the United Kingdom has been covered by buildings since 1990, and a rapid expansion of built-up areas is continuing in some already highly urbanised countries.

Concerning surface water, globally 180 000 km^2 of land was inundated since 1984, mainly through dam-building. During the same period 90 000 km^2 (approximately the area of Portugal) of surface water was lost through drought and unsustainable abstraction for irrigation, mainly in the Middle East, Central and South Asia.

Keywords: land cover, ecosystems, biodiversity, habitat loss, remote sensing, satellite data, Earth observation

JEL codes: Q2, Q24, Q28, Q57, Q58, R11, R14, R52

Résumé

Les modifications des caractéristiques biophysiques des habitats naturels – que l'on peut mesurer au moyen de données sur la couverture des sols – constituent le meilleur indicateur indirect pour mesurer les pressions exercées sur les écosystèmes et la biodiversité. Ce rapport présente une série d'indicateurs qui assurent le suivi des changements de couverture des sols d'une manière cohérente au niveau international. Ces indicateurs, parmi lesquels figure un indicateur phare de la croissance verte de l'OCDE, représentent ce que l'OCDE a produit de plus récent pour suivre les pressions pesant sur les écosystèmes et la biodiversité, en utilisant les données et les techniques d'état de l'art. Les résultats sont présentés pour les pays de l'OCDE et du G20 au moyen d'ensembles de données mondiaux portant sur plusieurs périodes entre 1992 et 2015.

Il ressort des principaux résultats que, depuis 1992, la zone OCDE a perdu 1.4 % des sols naturels et semi naturels végétalisés au profit d'autres types de couverture des sols, avec cependant des disparités entre les pays, les pourcentages nationaux variant de 0 % à 16 %. À l'échelle mondiale, le taux de perte est deux fois plus élevé, puisque 2.7 % des sols (semi-)naturels végétalisés ont disparu depuis 1992, soit l'équivalent de deux fois la superficie de l'Espagne. Plus de la moitié de cette perte est intervenue dans les pays de l'OCDE et du G20, principalement au Brésil, en Chine, en Russie, aux États-Unis et en Indonésie.

La conversion de sols (semi-)naturels en sols cultivés et celle de sols cultivés en sols artificialisés constituent les principaux changements de couverture des sols dans la zone OCDE et à l'échelle mondiale. Depuis 1992, environ 1 % des sols (semi-)naturels ont été convertis en sols cultivés dans les pays de l'OCDE, avec des pourcentages nationaux s'échelonnant entre 0 % et 15 %. Au niveau mondial, ce taux a progressé pour atteindre 2.2 %. Parallèlement, 1.5 % des sols cultivés ont été convertis en sols artificialisés dans la zone OCDE, la proportion variant de 0 % à 11 % selon les pays.

Les résultats complémentaires montrent que l'extension de l'espace bâti et la modification des eaux de surface demeurent problématiques. À l'échelle mondiale, une superficie de la taille du Royaume-Uni a été bâtie depuis 1990, et les espaces bâtis continuent de s'étendre rapidement dans certains pays déjà fortement urbanisés.

S'agissant des eaux de surface, environ 180 000 km^2 de sols ont été inondés dans le monde depuis 1984, principalement du fait de la construction de barrages. Parallèlement, 90 000 km^2 d'eaux de surface (soit à peu près la superficie du Portugal) ont été perdues en raison des sécheresses et des prélèvements d'eau d'irrigation, principalement au Moyen-Orient, en Asie centrale et en Asie du Sud.

Mots clés : couverture des sols, écosystèmes, biodiversité, perte d'habitat, télédétection, données satellitaires, observation de la Terre

Codes JEL : Q2, Q24, Q28, Q57, Q58, R11, R14, R52

Glossary

Land cover: The observed physical and biological cover of the Earth's surface, including natural vegetation, abiotic (non-living) surfaces and inland waters (UN et al., 2014a). Note that *land cover* is different from *land use* which refers to the economic activities or institutional arrangements in a given area (e.g. wild prairie, pasture, golf course are different uses of grassland areas).

Land cover change: Here used to describe changes over time within a *single* land cover class (e.g. change in built-up area extent).

Land cover conversions: Here used to describe changes over time from one land cover class to another (e.g. conversions from tree cover to cropland).

Natural and semi-natural land: Here used to designate land covered by natural or semi-natural vegetation with limited anthropogenic footprint as a proxy for land which is important for maintaining biodiversity and provides higher-value ecosystem services at the global scale.

Artificial surfaces defined by the EEA (2018): Continuous and discontinuous urban fabric (housing areas), industrial, commercial and transport units, road and rail networks, dump sites and extraction sites, but also green urban areas. Defined by the SEEA Central Framework (UN et al., 2014a): Any urban or related feature, including urban parks, and industrial areas, waste dump deposit and extraction sites.

Built-up area: Presence of buildings, where a building is defined as any roofed built-up structure. Note that this definition excludes other parts of urban environments such as paved surfaces (roads, parking lots), parts of commercial and industrial sites (ports, landfills, quarries, runways) and parts of urban green spaces (parks, gardens).

Surface water: Presence of water bodies (rivers, lakes or dams).

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1. Overview

Loss of biodiversity and pressures on ecosystem services are among the most pressing global environmental challenges.[2] Global biodiversity loss is so intense that it has recently been described as 'biological annihilation' (Ceballos et al. 2017).

Land cover and land use change are the leading contributors to terrestrial biodiversity loss (CBD 2010). Detrimental changes in land cover lead to habitat fragmentation and loss and are associated with a decline in the populations of many species and with reduced biodiversity.

Against this background, in 2012 changes in land cover have been proposed as an OECD Green Growth headline indicator. Deleterious changes in land cover due to human activities such as conversions of land from a more natural state to a more artificial state, typically reflect more intense uses of land, degrade natural habitats and ecosystems, affect biodiversity, and erode natural capital. While changes in land cover generally occur at a very slow rate, they have potentially large implications for ecosystems and biodiversity. This indicator is a proxy and does not directly measure biodiversity; but changes in the spatial structure of natural habitats – that can be measured using data on land cover – are considered the best measure currently available to broadly monitor pressures on terrestrial ecosystems and biodiversity.[3] Land cover and land use indicators are also included in the OECD Core Set of environmental indicators under the headings of "biological diversity" and "land and soil resources", and have been identified as requiring further work and research by the OECD since the early 1990s.

Changes in land use and cover are also an important component of the UN Agenda for 2030 with the SDG goals 15, 11 and 6 (Box 1.1). Land is equally an essential element of UN Conventions including the CBD, UNCCD, UNFCCC, Ramsar and the CMS.

It is an opportune moment for the OECD to revisit the feasibility of constructing land cover change indicators to inform its policy work. Recent advances in development of globally consistent multi-period datasets, suitable for measuring *changes* in land cover, relax previous data availability constraints. Early attempts at measuring the conversions between artificial surfaces and agricultural, tree-covered and other vegetated land were constrained by the availability of global datasets. Consequently, they had to rely on a combination of national and regional datasets – posing comparability challenges – and limiting the analysis to European countries, Japan and the United States.[4] The recent availability of novel data products allow for some analysis of changes in land cover consistently over time and at a global scale. Related indicators of land cover dynamics

[2] See e.g. UN Convention on Biological Diversity (CBD); OECD Environmental Outlook to 2050; Rockström et al. 2009; the Millennium Ecosystem Assessment.

[3] For further details, see ENV/EPOC/WPEI(2012)2 and ENV/EPOC/WPEI(2016)1.

[4] See e.g. OECD 2011; Piacentini and Rosina 2012; Silva et al. 2012; Silva and Brown 2013; Brown et al. 2015.

with broad geographic coverage have been first used to describe land resources in a report on green growth indicators (OECD 2017a).

Box 1.1. Selected international targets and indicators related to land cover change

Aichi target 5: By 2020, the rate of loss of all natural habitats, including forests, is at least halved and where feasible brought close to zero, and degradation and fragmentation is significantly reduced.

Aichi target 15: By 2020, ecosystem resilience and the contribution of biodiversity to carbon stocks has been enhanced, through conservation and restoration, including restoration of at least 15 per cent of degraded ecosystems, thereby contributing to climate change mitigation and adaptation and to combating desertification.

SDG target 15.1: By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements

Indicator 15.1.1: Forest area as a proportion of total land area

SDG target 15.3: By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world

Indicator 15.3.1: Proportion of land that is degraded over total land area

SDG target 15.4: By 2030, ensure the conservation of mountain ecosystems, including their biodiversity, in order to enhance their capacity to provide benefits that are essential for sustainable development

Indicator 15.4.2: Mountain Green Cover Index indicator

SDG target 11.3: By 2030, enhance inclusive and sustainable urbanization and capacity for participatory, integrated and sustainable human settlement planning and management in all countries

Indicator 11.3.1: Ratio of land consumption rate to population growth rate

SDG target 6.6: By 2020, protect and restore water-related ecosystems, including mountains, forests, wetlands, rivers, aquifers and lakes

Indicator 6.6.1: Change in the extent of water-related ecosystems

Source: CBD (2011), UN (2017)

Land cover and land use issues have been an increasing focus of OECD's work, including by the Regional Development Policy Committee, the Environmental Policy Committee, the Committee on Agriculture and to some extent the Committee on Science and Technology Policy.[5] Protection of land resources, challenges associated with economic, environmental and social objectives in land use planning, provide an essential underpinning for *Environmental Performance Reviews* and *Economic Surveys*. There is equally an interest to discuss land-related issues in *Going for Growth* to develop holistic

[5] See e.g. OECD 2017b; OECD 2017c; OECD 2016a; OECD 2016b.

policy advice. However, quantitative information on the natural asset base is relatively poor, and a lack of up-to-date and commensurable indicators is a major obstacle to such efforts. It is striking that land cover change is one of the most widely demanded but least available environmental indicators.

In line with the OECD's indicator selection criteria (measurability using quality data, analytical soundness and policy relevance), the following requirements were considered when developing the indicators:

- Achieve the broadest possible **geographic coverage**, including all OECD and G20 countries, and possibly beyond;[6]
- An essential methodological objective is achieving **coherence** across countries;
- Availability of historic **time series** to allow observing trends over an extended period of time which is particularly important for (slow-moving) environmental variables;
- Availability of future updates at regular intervals (**timeliness**);
- Provide more **fine-grained** information at the regional and local levels, in addition to national-level aggregates.[7]
- Ensure that calculation of the indicators is transparent, replicable over time and at the least cost.

This paper presents a suite of indicators on land cover changes to fill information gaps in the OECD sets of green growth indicators and environmental indicators. Results are presented for 46 countries (OECD and G20).[8]

1.1. Summary

Two indicators of land cover conversions are developed as headline indicators for the green growth indicators database:

- ***Loss of natural and semi-natural vegetated land***, defined as the diminution of vegetated land in natural and semi-natural state expressed as percentage of the 'stock' in the previous time period (i.e. intensity of loss). The indicator is currently measured as the percentage of tree-covered area, grassland, wetland, shrubland and sparse vegetation converted to any other land cover type.[9]

[6] There are growing demands to provide information to support the Organisation's *regional programmes and initiatives*, including in Southeast Asia, Latin America and the Caribbean, South East Europe, Eurasia (Central and Eastern Europe, the Caucasus and Central Asia) and the Middle East and North Africa. This requires using data sources with a global coverage.

[7] Incorporating the sub-national dimension into the Organisation's work to enhance its policy advice is one of the strategic orientations of the Secretary-General [C/MIN(2017)1]. This is important, for example, for country reviews where such information allows for a more comprehensive and nuanced assessment of environmental performance and better targeted policy advice. Moreover, the indicators must be suitable for work on regional analysis, on spatial planning instruments and the environment, and on ecosystem services in agriculture.

[8] Including 35 OECD members, 3 accession candidates and 8 non-OECD G20 economies.

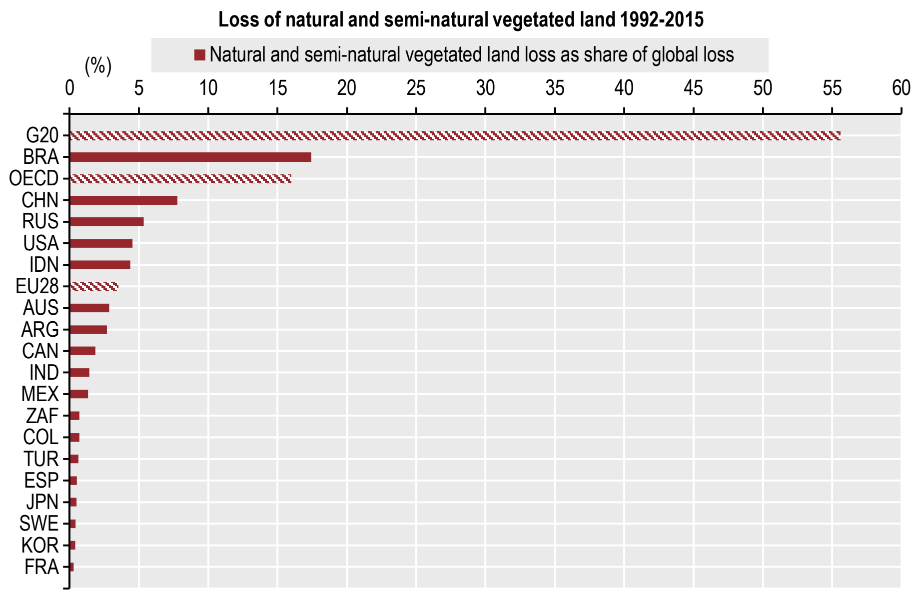
[9] This definition includes "semi-natural" vegetation due to the difficulty of reliably identifying the degree of 'naturalness' of some land cover types. The ecological value of these lands may vary with their use (e.g. natural forests vs planted forests; grasslands as wild meadows versus those used as pasture) however this use is sometimes very difficult to discern via remote sensing.

- ***Gain of natural and semi-natural vegetated land***, defined similarly as above. It represents the new additions to the 'stock' of such land. This indicator complements the above one.

The two indicators above are supplemented with information on:

- Full land cover conversion matrixes to allow more detailed analyses of land cover dynamics. For example ***conversions to and from cropland*** and ***conversion to artificial surfaces*** help better understand the dynamics of land markets and their outcomes, and thus complement the ecosystem angle (the headline indicator) with a more economic perspective.
- Variables measuring distinct aspects of land cover changes, currently including ***built-up area growth*** and ***surface water change***, with a greater level of harmonised spatial and temporal detail about the distribution of such changes worldwide.

Figure 1.1. OECD and G20 countries account for more than half of global (semi-)natural land loss



The initial results suggest that for the OECD area 1.4% of natural and semi-natural vegetated land has been lost to other land cover types since 1992. This result hides large variations across countries, with national averages ranging from 0% to over 16%. Worldwide, 2.7% of (semi-)natural land has been lost since 1992 – equivalent to an area twice the size of Spain; OECD and G20 countries account for over half (56%) of this loss, which occurs primarily in Brazil, the People's Republic of China (hereafter 'China'), the Russian Federation (hereafter 'Russia'), the United States and Indonesia (Figure 1.1). This indicator measures the land cover changes, which are most likely to have negative impacts on ecosystems and biodiversity, such as urban expansion, deforestation and desertification.

These losses have been accompanied by contemporaneous gains of (semi-) natural land, to a greater extent in OECD countries than elsewhere. Globally, 1.5% of (semi-)natural land has been gained since 1992 equivalent to only about half of the losses. Observed conversions of this sort might reflect afforestation programmes or abandonment of agricultural land. However, such gains are unlikely to compensate the biodiversity damage incurred as a result of (semi-)natural land losses. Consequently, the net loss or gain in (semi-)natural land should be interpreted carefully.

The imbalance between (semi-)natural land loss and gain suggests that some countries have been drawing on their natural resource base to such an extent (i.e. are failing to conserve and sustainably use their land resources) that they may not be able to sustain people's well-being in the long-run.

This paper is organised as follows: Section 2 motivates the overall measurement approach. Section 3 presents the underlying data, indicator definitions and calculation methodology. Section 4 presents the key results. Section 5 discusses their interpretation and limitations. The last Section concludes and outlines next steps.

2. Conceptual approach

2.1. Land cover change as a measure of pressures on biodiversity and ecosystems

Changes in the biophysical characteristics of natural habitats – that can be measured using data on land cover – are considered as the best proxy to monitor pressures on ecosystems and biodiversity. Prominent examples of the use of land cover measures to assess pressures on biodiversity and ecosystem services can be found in the work of the EEA (2015a; 2010), the US EPA (2017), the Millenium Ecosystem Assessment, as well as by Venter et al. (2016) and Lawler et al. (2014). Data on land cover are also of use for the implementation of environmental-economic accounting (UN et al. 2014a; 2014b). Monitoring landscape-scale effects is a useful complement to species-level indicators such as extinction risk because biodiversity loss is so intense that assessing the health of all potentially at-risk species (or species groups) is not feasible (Rodríguez et al. 2007).

The approach adopted here focuses on conversions between more natural vegetated land cover types to less natural land cover types (or with a greater anthropogenic footprint) such as cropland and artificial surfaces. This is motivated by the fact that at the global scale natural vegetated land areas are the most important in terms of their relevance for ecosystems and biodiversity (and pressures thereon). This is supported by evidence suggesting that, for example, the less intense land use associated with the more natural land cover are richer in biodiversity, measured as species richness (Newbold et al. 2015); conversions to cropland and artificial surfaces are the most deleterious for biodiversity (Chaudhary et al. 2015, de Baan et al. 2013); the more natural land cover types provide higher-value ecosystem services and conversions from natural to less natural land cover diminish or eliminate many of the ecosystem services they previously provided (Costanza et al. 2014; de Groot et al. 2012)[10]. In sum, there is a body of evidence suggesting that "ecological value" is higher for some land cover categories than for other categories.

The aggregation of land cover types into the "*natural and semi-natural vegetated land*" category ensures the indicator is relevant to a maximum number of countries because most OECD countries have a large area of at least one of the constituent sub-classes. The inclusion of “semi-natural” vegetation in the definition helps to explicitly communicate the notion of 'naturalness' (which is difficult to measure) as a continuum rather than as a dichotomy. The exact composition of the land cover types deemed to constitute this aggregated *natural and semi-natural vegetated land* category should remain flexible. As methods are refined, it may become possible to discriminate between higher and lower value examples of the same broad land cover categories, for example, to identify pasture,

[10] The value of these lost ecosystem functions has been estimated to be in the range of trillions or even tens of trillions of dollars per year (Costanza et al. 2014).

hay crops and natural grasslands separately or plantation and old-growth forests separately (they are currently all included as 'grassland' or 'tree cover').[11]

The conversion matrix in Table 2.1 formalises the dynamics in land cover structure over time. Each cell of the matrix (A^{ij}) represents the total area of a geographical output area (country, administrative region, metropolitan area) that was converted from land cover class i in period t-1 to land cover class j in period t. For example, A^{12} is the area of (semi-)natural land that was converted to more anthropogenic land cover types between period t-1 and period t.

Table 2.1. Conversion matrix between land cover categories

		Land cover in period t		
		1. Natural and semi-natural vegetated land (of globally higher ecological value)	2. Other land (of globally lower ecological value)	Total
Land cover in period t-1	1. Natural and semi-natural vegetated land (of globally higher ecological value)	A^{11}	A^{12}	$\sum A^{1j}$
	2. Other land (of globally lower ecological value)	A^{21}	A^{22}	$\sum A^{2j}$
	Total	$\sum A^{i1}$	$\sum A^{i2}$	$\sum A^{ij}$

2.2. Availability of data from global land monitoring

A review of data availability [ENV/EPOC/WPEI(2015)4/FINAL; Diogo and Koomen 2016] identified a handful of global land cover datasets that are suitable for measuring land cover consistently at the global scale. The review recommended that reliance on global datasets would be the most practicable approach to meet OECD needs. However, back in 2015 none of the available global land cover products met all the criteria for constructing the OECD indicator. Most importantly, none of the global datasets available in 2015 was suitable for measuring *change* across a range of multiple land cover classes [ENV/EPOC/WPEI(2015)3]. Further progress in development of the OECD indicator was thus dependent on availability of more suitable datasets.

Several global datasets have become available and allow measuring land cover *changes* consistently across countries (Box 2.1). They include a **multi-class** dataset (ESA/UCL Geomatics, 2017a) and an emerging series of **single-class** datasets focusing on a specific attribute of land cover – incl. buildings, surface water, trees (Pesaresi et al. 2015; Pekel et al. 2016; Hansen et al 2013). The single-class datasets, are available (or will soon be available) at high spatial (decametric) and temporal (monthly to yearly) resolutions. These developments allow the measurement of change even at relatively local scales and short time periods. Furthermore the two single-class datasets presented here (the Global

[11] Some datasets identify a single type of very high-value ecosystem and monitor its status. For example, the Intact Forest Landscapes (Potapov et al. 2008) focusses on identifying and monitoring the extent of remaining large tracts of forests with no detected signs of human activity. However, as fewer than half of OECD member countries have any intact forest remaining, changes to this ecosystem would not be representative of the land cover pressures. Given the global relevance of intact forest ecosystem loss, it could be a candidate for future inclusion into the suite of complementary indicators. Indicators reflecting changes in other sensitive ecosystems (e.g. mangroves, wetlands) could be added. This could be addressed as part of follow-up work.

Human Settlement Layer and the Global Surface Water change dataset) are constructed using fully-automated data processing techniques that means they can be routinely updated and improved when new or ancillary data sources become available. Global multi-class datasets are more challenging, the CCI-LC dataset used here is an annual medium-resolution (300m) dataset running from 1992-2015 however due to the sensor differences in the datasets used over this period it does not reliably record changes with the annual frequency implied. Here we present results from 1992-2015 as a single period.

Box 2.1. From land cover mapping to change detection

Land cover datasets typically use observations from satellite-mounted sensors (e.g. from the Landsat, MERIS, MODIS, SPOT or Sentinel missions). The sensor data are collections of large images that record the intensity of reflectance of different wavelengths of the electromagnetic spectrum from the surface of the Earth. The sensor data are processed (corrected, cleaned, georeferenced, composited) into a suite of analysis-ready intermediate datasets. For land cover detection, algorithms are typically 'trained' with these prepared datasets using training datasets where the land cover type is already known for a large number of locations, this lets algorithms subsequently automatically classify the (possibly trillions) of unknown pixels into thematic land cover categories. Doing this at global scales is computationally intensive and requires infrastructure capable of accommodating the massive archives of sensor data. Consequently global land cover datasets are a major undertaking.

There has been a shift in interest from (snapshot) land cover mapping to (continuous) change detection. Change detection is additionally challenging because a 'snapshot' land cover dataset produced for a year based on all scenes available that year might, in the following year classify pixels that have not substantively changed cover differently from the previous year because of (for example) seasonal or short-term climatic and meteorological conditions or different acquisition conditions (e.g. sun angle). In order to reduce this sensitivity to the particular moment of observation, robust change detection requires the analysis of long time series of observations for a specific pixel, and this in turn requires harmonisation across sensors with different characteristics and other technical challenges. This has only recently been attempted at global scales.

3. Empirical implementation

3.1. Underlying data

Three research outputs have been identified as candidates for supplying datasets for OECD's land cover indicators. The datasets used to support the indicators about land cover change *between* classes are products of the Climate Change Initiative Land Cover project (ESA/UCL 2017a). The datasets that provide richer information for a single land-cover type are both outputs from the Joint Research Centre: The Global Human Settlement Layer (Pesaresi et al. 2015) and Global Surface Water (Pekel et al. 2016).

These datasets are outputs of decades of Earth observation missions by different national and supranational space organisations. Their production typically requires the analysis of petabytes of archived sensor data. The datasets are methodologically varied, and may use the outputs of other products as intermediate data sources (as is the case of the CCI-LC datasets which include JRC GHSL data on built-up areas, among other datasets, as a source). Furthermore, the datasets can evolve as methodological improvements are implemented or new data become available[12].

3.1.1. Climate Change Initiative Land Cover (CCI-LC)

The CCI-LC datasets are the only available global datasets that can provide some acceptably harmonised indication of the type and intensity of change *between* different land cover types. The different data products have been produced by the European Space Agency (ESA) to support climate modelling on a global scale. The CCI-LC datasets contribute to the Global Climate Observing System (GCOS) of the World Meteorological Organization (WMO).

In this paper we are most interested in the datasets of land cover *state.*[13] The goal of the land cover state datasets are to provide a stable and consistent account of long-term land cover status and changes that is 'immune' to short-term seasonal and temporary changes (e.g. snow cover in winter, crop rotation, forest burn scars).

The land cover state products are available as annual global datasets from 1992 to 2015 inclusive. They distinguish between (up to) 37 land cover classes[14] using the FAO Land

[12] For example, since the time of drafting, the first GHSL layer derived from ESA's *Sentinel* missions has been produced, updating the series to 2016 at around four times the resolution of that available for previous years. Only a brief introduction of the underlying datasets is provided here. More exhaustive information is available in each of the dataset user guides, metadata and project pages.

[13] There is also a *seasonality* component characterising vegetation greenness, fire and snow.

[14] There are 22 global classes and 15 region-specific subclasses (e.g. there is a specific subclass for African savannahs).

Cover Classification System (Di Gregorio, 2005). For change detection, these classes are mapped (by the data producers) to a smaller number of broader land cover classes that approximate the IPCC land categories. These are artificial surfaces, tree cover, grassland, cropland, wetland and 'other' (comprising shrubland, sparse vegetation, bare land and water).[15] These IPCC-inspired land cover categories are used because this dataset was designed to support climate research[16]. The aggregation of more specific classes into broader classes is necessary because classification accuracy is lower between more similar classes (e.g. different mosaic vegetation types or different types of forest); accurate detection of *change* between these classes is consequently more challenging. Changes are recorded in the CCI-LC datasets at ostensibly yearly intervals; however because of the heterogeneous data input (satellite missions end and new ones come online – see Table 3.1), the accuracy of change detection is not constant over time.

A range of sensor archives are used for different time periods (Table 3.1). Several other sensor archives are used by other land cover products that are also used as inputs to CCI-LC. While the datasets are published at a 300 m resolution, changes are detected at a minimum resolution of 1 km.

Table 3.1. Satellite data sources for CCI-LC maps

LC Dataset	Reference Period	Satellite data source
Baseline 10-year global LC map	2003-2012	MERIS FR/RR global SR composites between 2003 and 2012
Global annual LC maps	1992-1999	Baseline 10-year global LC map; AVHRR global SR composites between 1992 and 1999 for back-dating the baseline;
	1999-2013	Baseline 10-year global LC map; SPOT-VGT global SR composites between 1999 and 2013 for up and back-dating the baseline; MERIS FR global SR composites between 2003 and 2012 to delineate the identified changes at 300 m spatial resolution; PROBA-V global SR composites at 300 m for year 2013 to delineate the identified changes at 300 m spatial resolution;
	2014-2015	Baseline 10-year global LC map; PROBA-V global SR composites at 1 km for years 2014 and 2015 for up-dating the baseline; PROBA-V time series at 300 m for 2014 and 2015 to delineate the identified changes at the LC map spatial resolution;

Source: Reproduced from Table 2-3 in CCI-LC supporting documentation for CCI-LC PUG v2 (ESA/UCL-Geomatics, 2017b).

Figure 3.1 shows a land cover 'snapshot' of the world for 2015. Figure 3.2 shows some of the land cover changes that can be discriminated, using an example from Argentina showing conversion of tree cover to cropland and shrubland (used for cattle grazing). These sorts of changes have been viewable in composited Landsat images for several

[15] In CCI-LC "urban" is somewhat similar to "built-up" areas because it is partly constrained by the GHSL (Section 3.1.2). However, the CCI-LC uses additional data sources to generate an annual time series.

[16] Future iterations of these or other datasets may provide alternative aggregated classes between which changes can be detected, for example, categories approximating the 14 SEEA land cover classes.

years[17], but they have never been available in a *classified* dataset which can begin to support quantitative analysis, until recently.

These datasets are new and their use to report areal statistics of land cover and land cover change is serendipitous to their intended purpose. It is important to note that the suitability of the CCI-LC for purposes of generating land cover statistics has not yet been formally validated, however the UNCCD and the FAO already use CCI-LC data to support statistical and indicator work (Box 3.1).

Box 3.1. Global land monitoring data used by international organisations

Land cover information to support compilation of SEEA land cover accounts (FAO)

The FAO is testing the use of the CCI-LC to populate land cover area and share of total area for 12 of the 14 SEEA land cover categories at country level. The FAO is working with countries to explore the usefulness of its new land cover statistics, mainly through capacity development activities. For further information, see the FAOSTAT Land Cover domain (www.fao.org/faostat/en/#data/LC).

The calculation methodologies used in this paper and by the FAO differ in two ways: (i) FAO re-scale areal statistics to keep countries' total land areas consistent across FAOSTAT; (ii) FAO uses the CCI-LC to generate statistics for 12 land cover categories (12 out of 14 SEEA categories) while this paper (which is concerned with the estimation of land cover *conversions*) uses the 9 categories previously listed between which conversions can currently be measured. The above may explain differences between FAOSTAT results and those shown here in Annex Table A.2. Future datasets might allow measuring such conversions at a more disaggregated level, or using a different aggregation such as the SEEA classes, which would provide the opportunity for greater alignment.

Land cover information to support monitoring of land degradation (UNCCD)

The UNCCD is testing the CCI-LC datasets for supporting countries in setting Land Degradation Neutrality (LDN) targets and report on the SDG target 15.3. LDN is defined as "a state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems". Proposed mechanisms for achieving neutrality (i.e. no net loss) include counterbalancing future land degradation (anticipated losses) through planned measures to achieve equivalent gains elsewhere within the same land type. Neutrality is assessed by monitoring the LDN indicators (land cover, land productivity, carbon stocks and locally-relevant indicators) relative to a fixed baseline. For further information, see UNCCD http://www2.unccd.int.

Concerning the calculation methodologies, the UNCCD propose a conversion matrix effectively the same as the one in Table 3.3 in this paper except that bare land, water, shrubland and sparse vegetation are presented together as an 'other' category, they then measure all 30 possible land cover conversions, describing them as being detrimental (or not) to achieving land degradation neutrality. The

[17] e.g. http://time.com/timelapse2016/

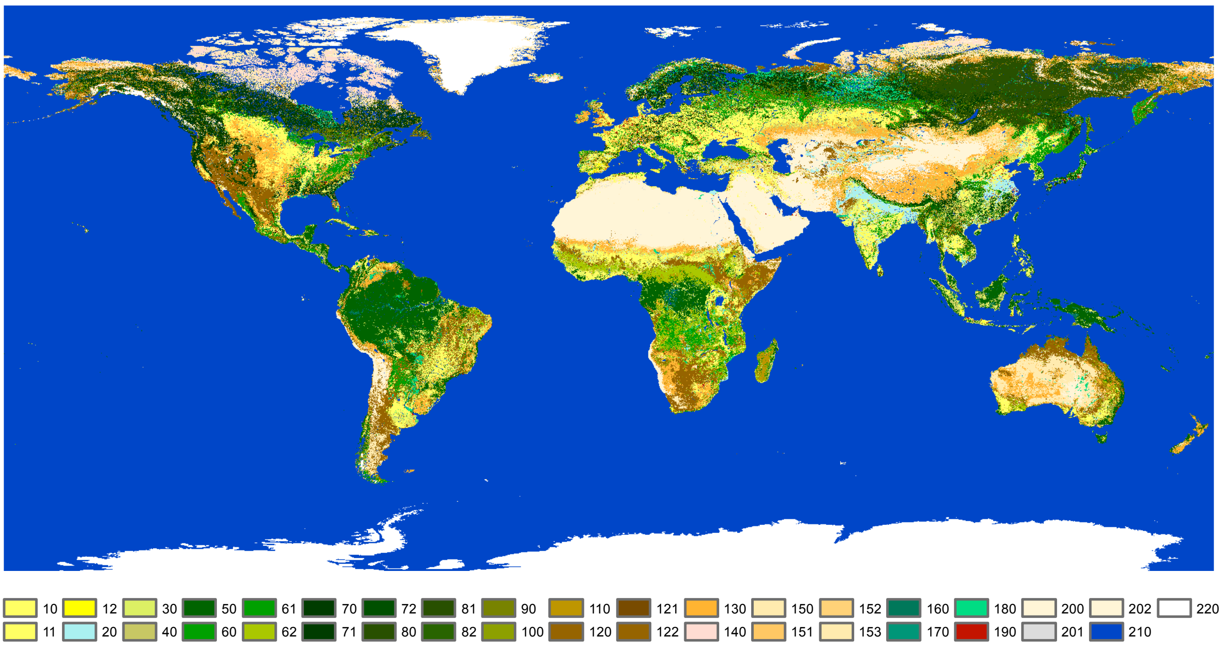
conversion matrices, such as those in Annex Tables A.3 and A.4 in this paper, can be used to not only construct the OECD headline indicator but also to describe land cover conversions according to each country's individual circumstances.

International co-ordination (FAO-UNCCD-OECD)

The three lines of work (FAO, UNCCD and OECD) have related, yet different, objectives: the FAO focuses mainly on assisting the compilation of land accounts to help countries report on international targets relating to food and agriculture, the UNCCD focuses on achieving land degradation neutrality as a means to maintain ecosystem services and food security, and the OECD's headline indicator focuses on measuring land cover conversions with the aim to monitor pressures on biodiversity and ecosystems. Typically, land cover monitoring is used as a proxy measure and reflecting the current scarcity of globally consistent land cover change datasets, the three respective areas of work currently use the same CCI-LC datasets. There are therefore obvious opportunities for peer-learning and coordination.

A major task ahead of these international and inter-governmental bodies is to better communicate the policy demands of their respective constituencies concerning global land monitoring to potential data providers (space agencies and the Earth observation community more broadly). In addition, they should more clearly articulate their (arguably similar) needs concerning the desired dataset specifications and quality characteristics (e.g. deriving globally and temporally consistent measures of land cover change at given spatial, temporal and thematic resolutions, together with confidence bounds or similar uncertainty metrics).

Figure 3.1. CCI-LC 2015 land cover dataset



Note: See Table 3.2 for legend key.

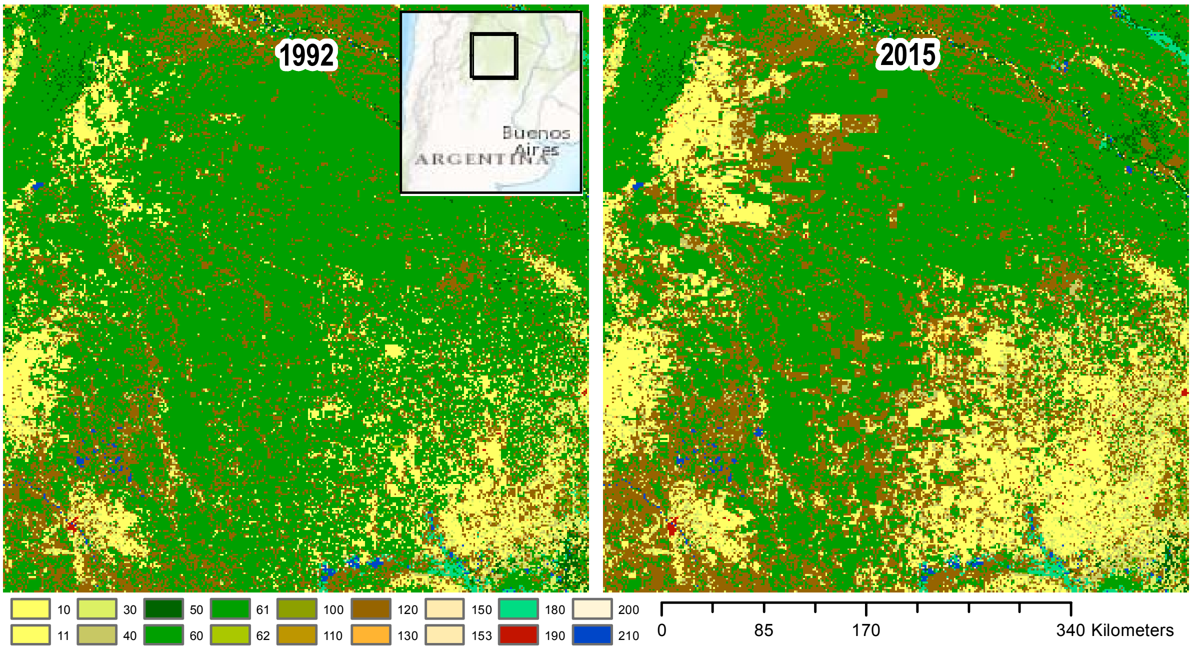
Table 3.2. Mapping between IPCC and CCI-LC classes

(Provided by the data producers)

IPCC classes		LCCS Legend used in CCI-LC and the encoding used in the dataset (some classes include regionally-discriminated subclasses e.g. savannah – see CCI-LC supporting documentation for further details)	
Agriculture (called cropland in this paper)		Rainfed cropland	10, 11, 12
		Irrigated cropland	20
		Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)	30
		Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (< 50%)	40
Forest (called tree cover in this paper)		Tree cover, broadleaved, evergreen, closed to open (>15%)	50
		Tree cover, broadleaved, deciduous, closed to open (> 15%)	60, 61, 62
		Tree cover, needleleaved, evergreen, closed to open (> 15%)	70, 71, 72
		Tree cover, needleleaved, deciduous, closed to open (> 15%)	80, 81, 82
		Tree cover, mixed leaf type (broadleaved and needleleaved)	90
		Mosaic tree and shrub (>50%) / herbaceous cover (< 50%)	100
		Tree cover, flooded, fresh or brackish water	160
		Tree cover, flooded, saline water	170
Grassland		Mosaic herbaceous cover (>50%) / tree and shrub (<50%)	110
		Grassland	130
Wetland		Shrub or herbaceous cover, flooded, fresh-saline or brackish water	180
Settlement (called artificial surfaces in this paper)		Urban	190
Other	Shrubland	Shrubland	120, 121, 122
	Sparse vegetation	Lichens and mosses	140
		Sparse vegetation (tree, shrub, herbaceous cover)	150, 151, 152, 153
	Bare area	Bare areas (changes are not detected in class 220 – permanent snow and ice)	200, 201, 202, 220
	Water	Water	210

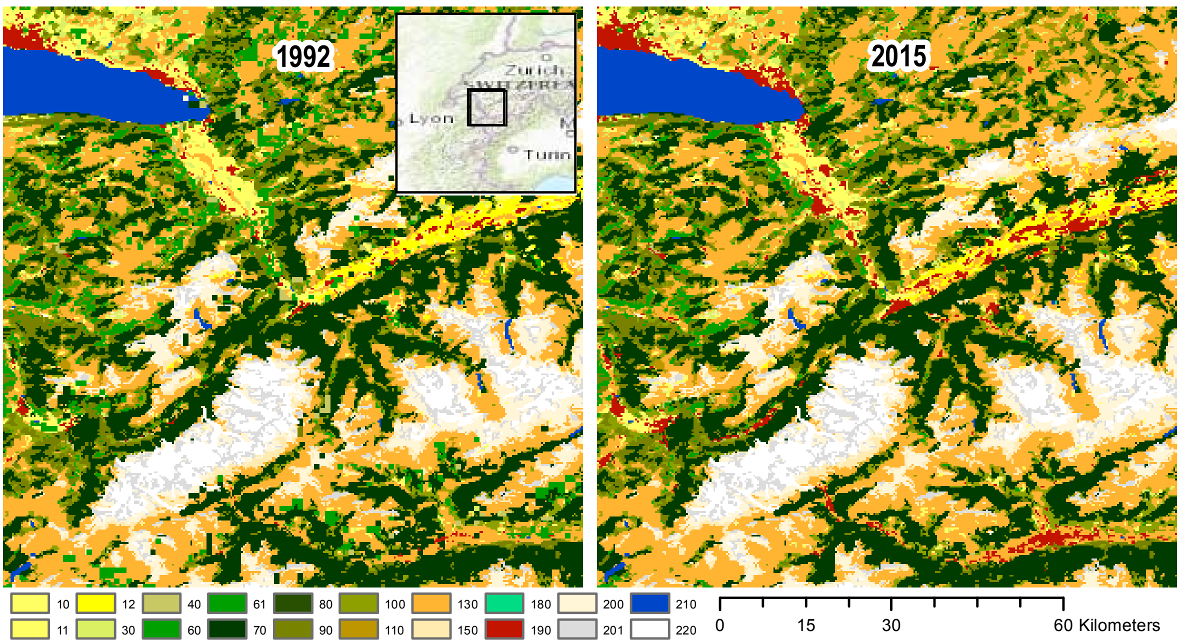
Note: Shaded classes constitute the natural and semi-natural vegetated land category used in the OECD indicator. In this paper different names for the categories (cropland, tree cover and artificial surfaces for agriculture, forest and settlement) are used to explicitly communicate the fact that their definition and use here is exclusively as *land cover* classes and not *land use* classes.
Source: Adapted from Table 3-3 in CCI-LC supporting documentation for CCI-LC PUG v2 (ESA/UCL-Geomatics, 2017b).

Figure 3.2. Clearance of dry forest in the Argentinian Gran Chaco region



Note: The maps are mostly showing Salta, Chaco, and Santiago del Estero provinces. Clearance of broad-leaved forest (green) for cropland (yellow) and cattle grazing (shrubland in brown) has occurred on a large scale. Note that these maps are showing a *vast* area (larger than Great Britain). See Table 3.2 for legend keys.
Source: ESA/UCL-Geomatics (2017a) *Annual land cover state maps*

Figure 3.3. Urban development on cropland and pasture in the Alps



Note: Haute-Savoie (left), Lake Geneva and Valais (upper left, centre and right) and Aosta (lower-right) regions of France, Switzerland and Italy. Urbanisation (red) of cropland and grassland (yellow and orange) is particularly notable in the Alpine valleys. See Table 3.2 for legend keys.
Source: ESA/UCL-Geomatics (2017a) *Annual land cover state maps*

3.1.2. *Global human settlement layer (GHSL)*

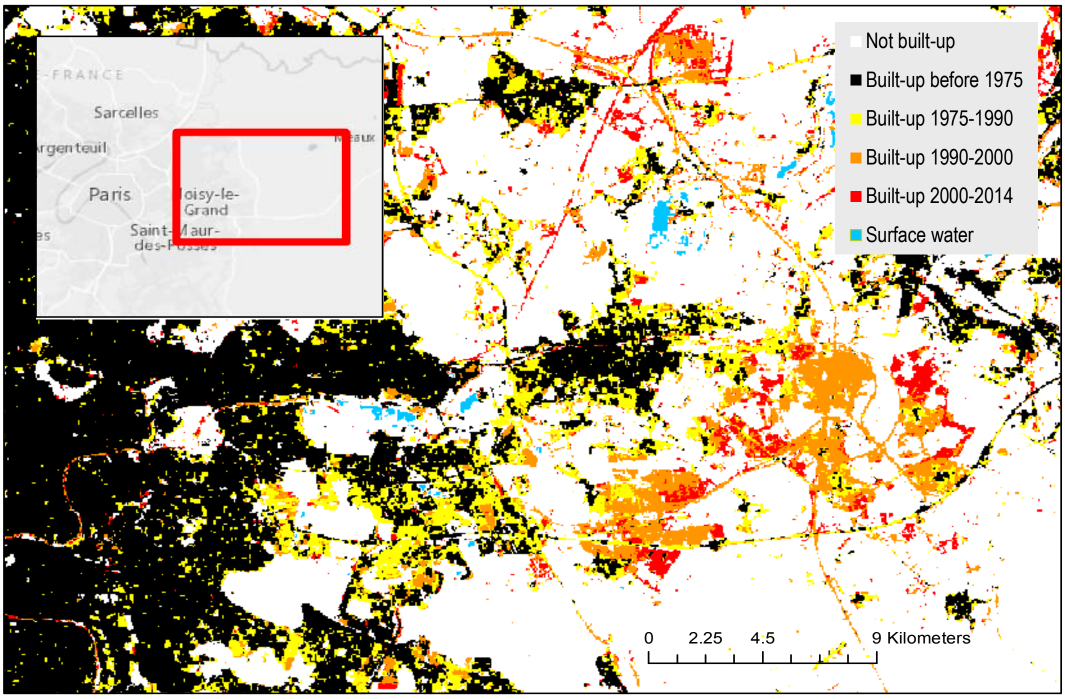
The JRC Global Human Settlement Layers (Pesaresi et al. 2015) map the extent and change over time of built-up areas. It is one product of an ongoing project that produces spatial information about the human presence on the planet. One of the key motivations behind mapping built-up areas is that it allows more accurate mapping of *human populations* (via datasets compiled from census data) which in turn provides the evidence base necessary to evaluate (for example) global population exposure to natural hazards[18]. It provides an unprecedented level of harmonised spatial and temporal detail about the distribution of built-up areas and people worldwide. Figure 3.4 shows a GHSL product for the area around the Marne river to the east of Paris, France. It shows the extent and temporal pattern of considerable urban development. The orange area in the centre-right is Disneyland Paris, built in the early 1990’s, and the surrounding areas in red are housing developments, hotels and shopping centres that developed after 2000.

The historical built-up dataset shown here uses the Landsat archive to achieve a time series at 10-15 year intervals at a minimum of 38 m resolution starting from 1975, however the methodology is designed to be sensor-agnostic; the most recent dataset year (2016) at 20 m resolution uses data from ESA’s Sentinel 1 mission. It is expected that the data from the Sentinel satellites will allow updates at yearly intervals at these high resolutions (as fine as 10 m – sufficient to detect the construction of even small individual dwellings). Fundamentally the built-up dataset is a probabilistic one, with every pixel assessed on a confidence scale of 0% (definitely not built up) to 100% (definitely built up). The dataset used here is a more compact discretely classified dataset derived from the confidence data that uses a 50% certainty cut-off. (For further methodological information, see Pesaresi et al., 2016.)

“Built-up” in the GHSL is defined as *the presence of buildings*. This definition largely excludes other parts of urban environments and the human footprint such as paved surfaces (roads, parking lots), commercial and industrial sites (ports, landfills, quarries, runways) and urban green spaces (parks, gardens). Consequently, such built-up area is likely to be somewhat smaller than some other urban area data where “urban area” is defined in broader *land use* terms or where different types of urban area are more specifically identified (e.g. CORINE).

[18] e.g. JRC Atlas of the Human Planet (2016) and JRC Atlas of the Human Planet: Global Exposure to Natural Hazards (2017).

Figure 3.4. Built-up area dynamics between Paris and Meaux in the Ile-de-France region



Source: Pesaresi et al. (2016), JRC Global Human Settlement Layer (dataset GHS_BUILT_LDSMT_GLOBE_R2015B_3857_38_v1_0). Service Layer Credits (inset map): Esri, HERE, DeLorme, OpenStreetMap contributors, and the GIS user community.

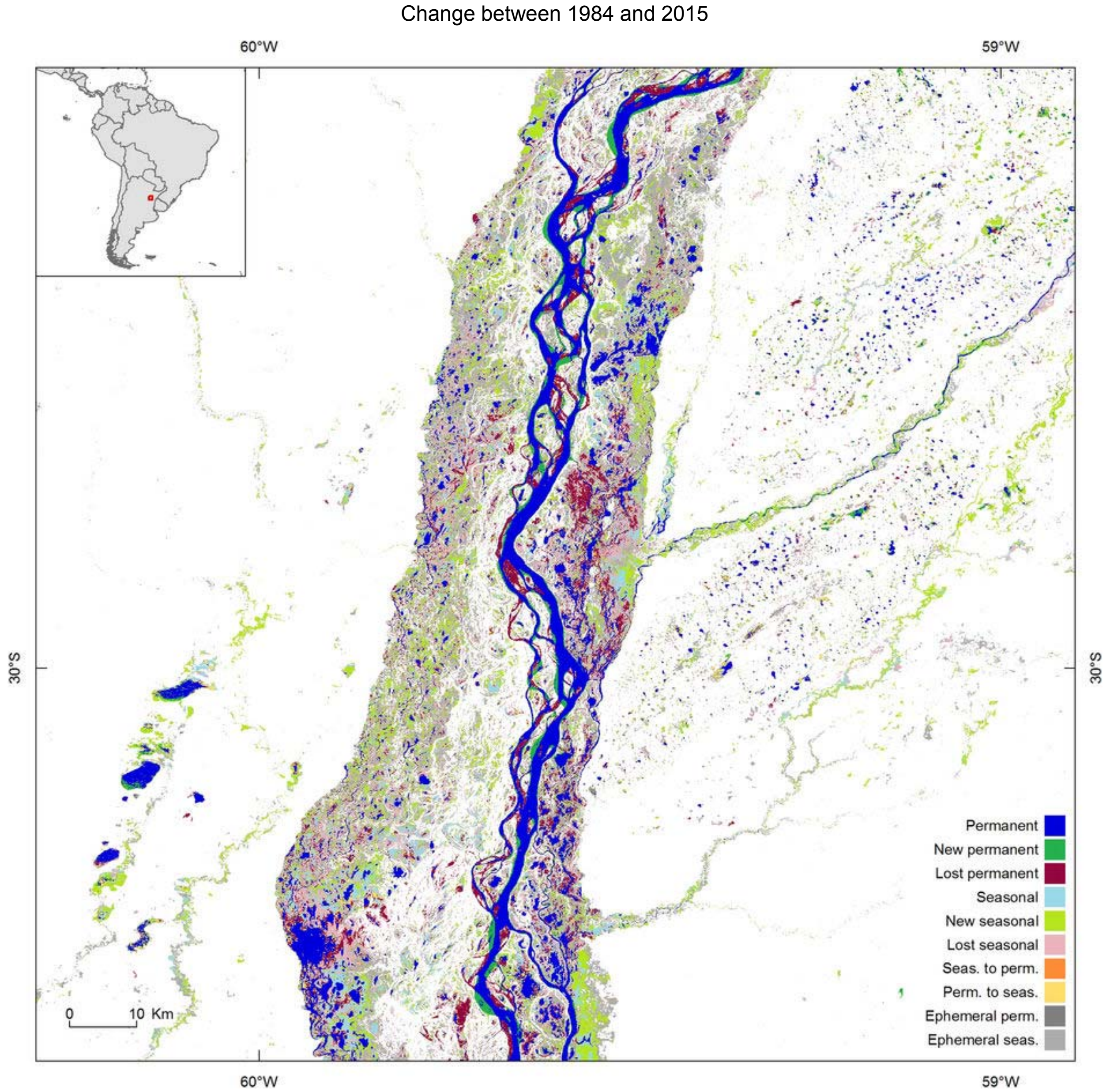
3.1.3. Global surface water (GSW)

The Global Surface Water Change project (Pekel et al. 2016) is a JRC project, in collaboration with Google's Earth Engine[19] that also uses the Landsat archive to characterise surface water changes from 1984 to 2015 at monthly intervals. The result is a suite of products that document different facets of surface water *state* at a 30 m resolution globally. Available information per pixel includes water occurrence, recurrence, seasonality, water change intensity and transitions.

This is an unprecedentedly rich dataset with a notably high spatial and thematic resolution for a global dataset. Its overall accuracy exceeds 95%. Figure 3.5 shows a section of the Parana river in Argentina. It is unusual to get such specific information about a land cover phenomenon in this sort of high-resolution global dataset.

[19] https://earthengine.google.com/

Figure 3.5. Surface water change of a section of the Parana river in Argentina



Source: Taken directly from Pekel et al. (2016, extended Data Figure 4.2).

3.1.4. Territorial boundaries

The data and indicators are presented at national and sub-national scales, including:

- *country* – the FAO Global Administrative Unit Layer (GAUL) (2015) level 0 political boundary dataset is used.[20]
- *macro-region* (territorial level 2 or TL2) – based on the OECD territorial classification or, when unavailable, a corresponding level using FAO GAUL.[21]
- *functional urban area* (FUA) – based the OECD definition of FUAs.[22]

[20] www.fao.org/geonetwork/srv/en/metadata.show?id=12691

[21] For OECD countries, see www.oecd.org/gov/regional-policy/43428422.pdf; for other countries, see OECD (2011, Annex A.2).

[22] See www.oecd.org/gov/regional-policy/all.pdf for a list of all FUAs and www.oecd.org/cfe/regional-policy/Definition-of-Functional-Urban-Areas-for-the-OECD-metropolitan-database.pdf for the FUA methodology. FUA boundaries have been defined for 29 OECD member countries. Work is ongoing to update and expand this dataset.

3.2. Indicator definitions

Nine broad land cover types are distinguished for the calculation of the current edition of the headline indicator: tree cover, grassland, wetland, cropland, artificial surfaces, and 'other' (comprising shrubland, sparse vegetation, bare land and water). The choice of these aggregated land cover types is dependent on what it is possible to report from the underlying datasets used and the classification system used by that dataset. In this case, it is CCI-LC's mapping of the CCI-LC legend to IPCC-like categories.

Table 3.3. Conversion matrix between land cover categories

		Land cover in period t									
		1. Tree cover	2. Grassland	3. Wetland	4. Shrubland	5. Sparse veg.	6. Cropland	7. Artificial surfaces	8. Bare land	9. Water	Total
Land cover in period t-1	1. Tree cover	A^{11}	A^{12}	A^{13}	A^{14}	A^{15}	A^{16}	A^{17}	A^{18}	A^{19}	$\sum A^{1j}$
	2. Grassland	A^{21}	A^{22}	A^{23}	A^{24}	A^{25}	A^{26}	A^{27}	A^{28}	A^{29}	$\sum A^{2j}$
	3. Wetland	A^{31}	A^{32}	A^{33}	A^{34}	A^{35}	A^{36}	A^{37}	A^{38}	A^{39}	$\sum A^{3j}$
	4. Shrubland	A^{41}	A^{42}	A^{43}	A^{44}	A^{45}	A^{46}	A^{47}	A^{48}	A^{49}	$\sum A^{4j}$
	5. Sparse vegetation	A^{51}	A^{52}	A^{53}	A^{54}	A^{55}	A^{56}	A^{57}	A^{58}	A^{59}	$\sum A^{5j}$
	6. Cropland	A^{61}	A^{62}	A^{63}	A^{64}	A^{65}	A^{66}	A^{67}	A^{68}	A^{69}	$\sum A^{6j}$
	7. Artificial surfaces	A^{71}	A^{72}	A^{73}	A^{74}	A^{75}	A^{76}	A^{77}	A^{78}	A^{79}	$\sum A^{7j}$
	8. Bare land	A^{81}	A^{82}	A^{83}	A^{84}	A^{85}	A^{86}	A^{87}	A^{88}	A^{89}	$\sum A^{8j}$
	9. Water	A^{91}	A^{92}	A^{93}	A^{94}	A^{95}	A^{96}	A^{97}	A^{98}	A^{99}	$\sum A^{9j}$
	Total	$\sum A^{i1}$	$\sum A^{i2}$	$\sum A^{i3}$	$\sum A^{i4}$	$\sum A^{i5}$	$\sum A^{i6}$	$\sum A^{i7}$	$\sum A^{i8}$	$\sum A^{i9}$	$\sum A^{ij}$

The headline indicator of ***loss of natural and semi-natural vegetated land*** is defined as the percentage of the tree cover, grassland, wetland, shrubland and sparse vegetation classes from CCI-LC converted into any other land cover type. It is the sum of the red-shaded cells in the top-right of the matrix in Table 3.3, expressed as a percentage of the sum of the blue-shaded cells in the rightmost column, or more formally:

$$\textit{Loss of (semi-)natural vegetated land} = \frac{\sum_{i=1,2,3,4,5}(A^{i6} + A^{i7} + A^{i8} + A^{i9})}{\sum(A^{1j} + A^{2j} + A^{3j} + A^{4j} + A^{5j})} * 100 \qquad [1]$$

This indicator measures the land cover changes which are most likely to have negative impacts on ecosystems and biodiversity such as urban expansion, deforestation and desertification.[23]

A complementary indicator of ***gain of natural and semi-natural vegetated land*** is defined similarly, as new additions to land covered by natural and semi-natural vegetation converted from any other land cover type.[24] It is the sum of the green-shaded cells in the lower-left of the matrix expressed as a percentage of the sum of the blue-shaded cells in the rightmost column:

$$Gain\ of\ (semi\text{-})natural\ vegetated\ land = \frac{\sum_{j=1,2,3,4,5}(A^{6j} + A^{7j} + A^{8j} + A^{9j})}{\sum(A^{1j} + A^{2j} + A^{3j} + A^{4j} + A^{5j})} * 100 \qquad [2]$$

This indicator thus measures the land cover changes with potentially positive impacts on ecosystems and biodiversity. Observed conversions of this sort might reflect afforestation programmes or abandonment of agricultural land (e.g. due to developments in local or global markets with agricultural commodities). Both, the losses [1] and the gains [2] are expressed in relation to the same denominator, measuring the inflows and outflows from the same *stock* of (semi-)natural land.

In addition to the indicators, the constituent values of the matrix will be published to allow further analysis[25]. This includes the conversions between the IPCC categories as well as the row and column sums, expressed as percentage of total area[26]. This will provide the necessary context to the headline indicator. See Annex Tables A.1-A.4 for aggregated summaries and Figure 4.8 for examples with more detail.

[23] The premise that the correlation between land cover and its "ecological value" is higher for these land cover categories than for other categories is a useful generalisation that will however not hold in all situations. (See Section 5 for further discussion.)

[24] The inclusion of artificial surfaces in this definition is for completeness; in practice, observations of conversions from artificial surfaces are unlikely due to high cost.

[25] For example, when characterising the land cover change in the area of Argentina shown in Figure 3.2 it is necessary to look at the conversions from forest to grassland, shrubland and sparse vegetation separately (evidence of clearance for cattle ranching) as well as conversions to cropland in order to quantify the drivers of forest loss in this region. The headline indicator alone is not sufficient as the aggregation into semi-natural land conceals much of the land cover change.

[26] In the CCI-LC, 'water' is one of the possible 'land cover' types (and changes occur to and from water-covered areas) therefore the denominator 'total area' includes water. This is not always an appropriate denominator, e.g. the denominator used for built-up area share presented here (Section 4.2.1) does not include water which is typically not subjected to urban development.

3.3. Technical implementation

The technical methodology is straightforward. Pixels, and the way they change, are counted from the underlying data for each of the output areas. Geographic data management and analysis is performed using GIS software.

Data preparation of CCI-LC results

The input land cover datasets are reprojected to the Mollweide equal-area projection with a 273 m cell size. The boundary datasets are also reprojected to the same projection and appropriately rasterized with a matching cell size.

An intermediate 'difference raster' is produced using datasets from two different years. In the results presented here these are the 1992 and 2015 CCI-LC datasets. Each of the (in this case 835) different states of conversion and non-conversion that occur between these years is given a unique code in the intermediate raster using the *raster analysis* tools.

The areas of each conversion (or non-conversion) type in the intermediate raster are calculated using the *tabulate area* tool for each of the features in the reprojected rasterised boundary datasets (the Country, TL2 and FUA boundaries). The 'snapshot' values, aggregated class totals, conversions to and from the aggregated class totals, and the other indicators are calculated in statistical software using the tabulated areas of different conversion states.

Data preparation of Global human settlement layer results

The multi-temporal built-up presence dataset[27] is appropriately reprojected to the Mollweide equal-area projection with a 38 m cell size. The area of built-up land per epoch is calculated for each of the features in the reprojected rasterised boundary datasets using the *tabulate area* tool (the Country, TL2 and FUA boundaries treated as detailed above with an appropriate cell size etc.).

Data preparation of Global surface water results

The country and continent-level results from the project data (Pekel et al., 2016) are used. No custom analysis has been performed however it is also possible to calculate results for smaller output areas (regions, cities) as has been done for the other indicators presented in this paper.

[27] *GHS_BUILT_LDSMT_GLOBE_R2015B_3857_38_v1_0* downloaded November 2016 from http://cidportal.jrc.ec.europa.eu/ftp/jrc-opendata/GHSL/GHS_BUILT_LDSMT_GLOBE_R2015B/

4. Results

4.1. (Multi-class) land cover conversions

The proposed headline and complementary indicators represent an advance compared to data previously available at the global scale. A simple descriptive analysis is presented below.

First the magnitude, intensity, geographical distribution and immediate drivers of *(semi-)natural land loss* are presented, followed by two more specific indicators: *conversion of (semi-)natural vegetated land to cropland* (as the main immediate driver of (semi-)natural land loss) and *conversion of cropland to artificial surfaces*.

4.1.1. Loss of (semi-)natural land

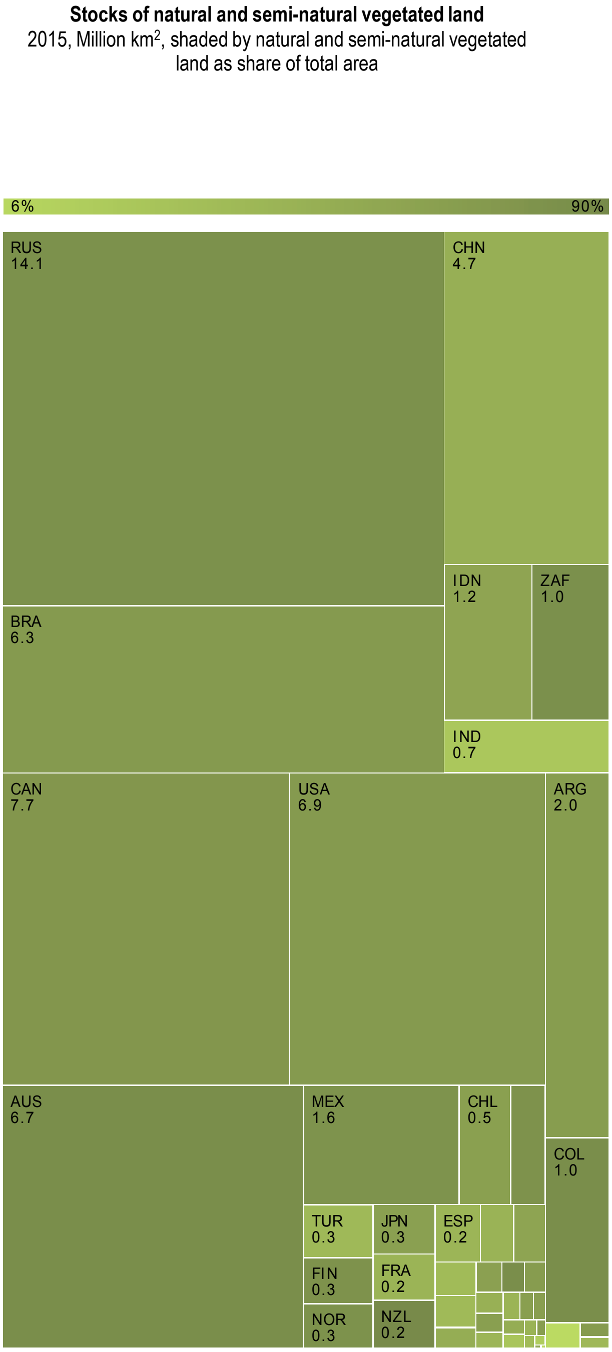
Among OECD countries, from 1992 to 2015, the most intense losses of (semi-)natural land have occurred in Korea and Israel. Indonesia and Brazil have seen intense losses driven by deforestation (Figure 4.1). In absolute terms Brazil, China, Russia and Indonesia have seen the greatest losses – although in Russia there have also been similarly large gains of (semi-)natural land (Figure 4.2). Globally, Central and South America, Sub-Saharan Africa, Rift-valley Africa, The Mediterranean, The Middle East, Bangladesh, Eastern China and Southeast Asia have seen the most intense loss of (semi-)natural vegetated land (Figure 4.3). Annex Table A.1 provides additional detail. The imbalance between (semi-)natural land loss and gain suggests that some countries have been drawing on their (semi-)natural resource base to such an extent (i.e. are failing to conserve and sustainably use their land resources) that they may not be able to sustain well-being in the long-run.

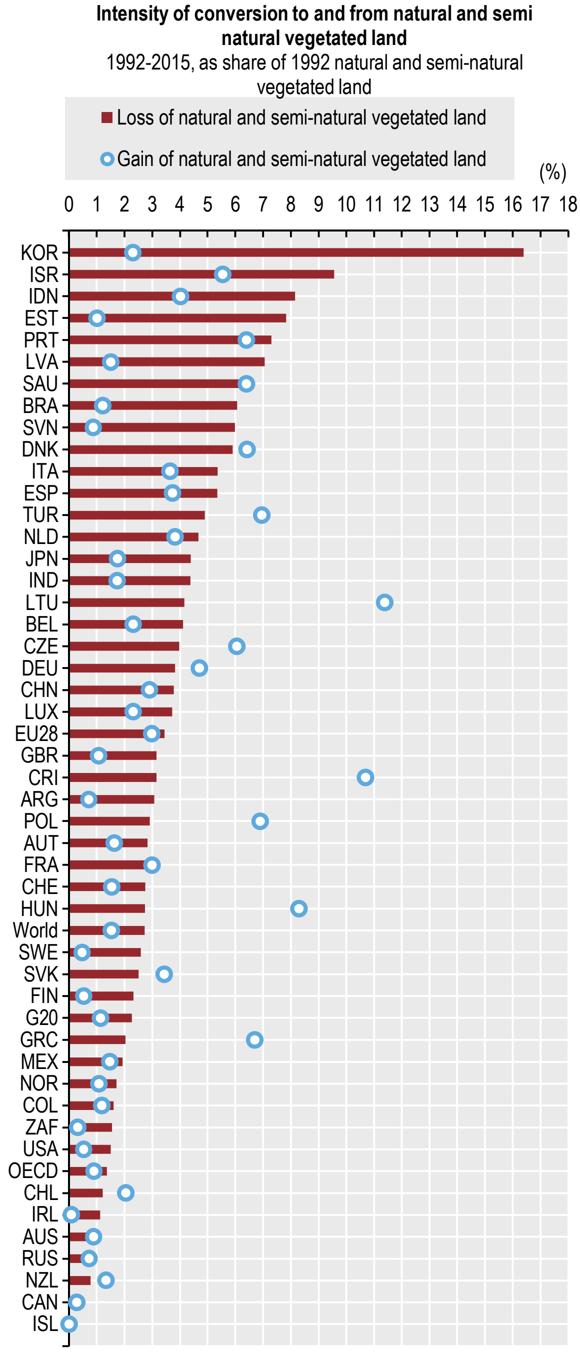
At the sub-national level, Riau in Indonesia (for oil palm and pulpwood[28]) and Mato Grosso and Rondonia in Brazil (due to population growth, logging, smallholder farming and ranching[29]) are the areas that have seen both very intense loss of (semi-)natural land as well as very large overall losses (Figure 4.4). In the case of Mato Grosso alone, an area more than a thousand times larger than Paris intra-muros has been lost since 1992. This is 14% of the 'opening stock', of which almost none has been replaced and is itself a conservative estimate that does not include forest cleared for grazing that would be classified as grassland or shrubland. Regions in China, Russia and Argentina have also seen large and intense losses of (semi-)natural land. The areas with the least intense loss of (semi-)natural land are those with lower population densities or very large stocks of (semi-)natural land such as the Arctic, Western United States, parts of Canada, Patagonia, parts of Botswana and Namibia, parts of Equatorial Africa, and much of Australia and New Zealand.

[28] http://lcluc.umd.edu/hotspot/deforestation-riaus-forests-two-global-pulp-and-paper-companies-will-decide-their-fate-0

[29] http://lcluc.umd.edu/hotspot/rond%C3%B4nia%E2%80%99s-deforestation-caused-clearing-along-roads

Figure 4.1. Countries continue to convert natural and semi-natural vegetated land, including in some of the most biodiverse regions

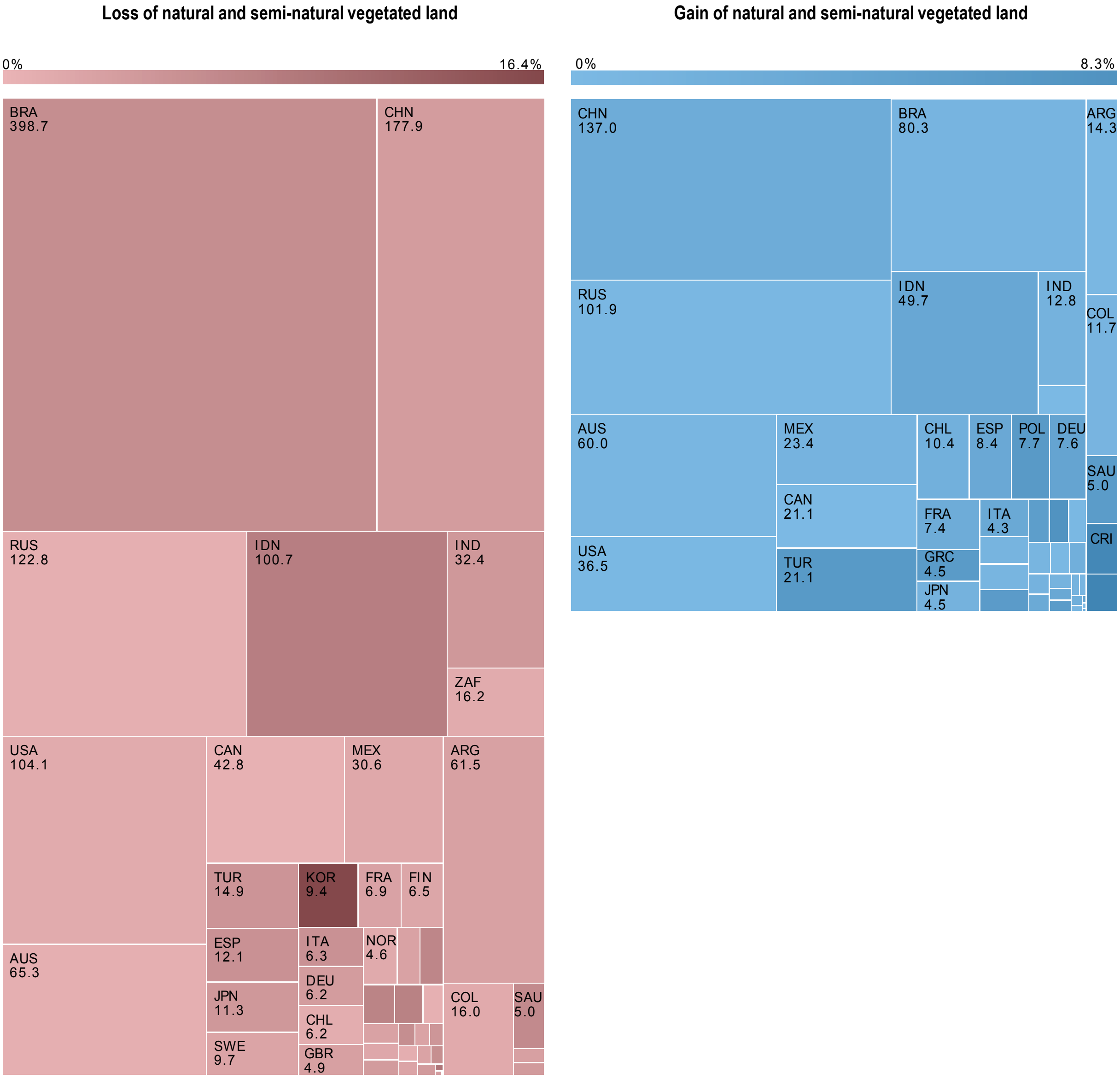




Note: World figures refer to the area within political boundaries (excluding seas, oceans and Antarctica) here and in subsequent tables and figures (i.e. it is the sum of all countries).
Source: OECD calculations using data from ESA/UCL-Geomatics (2017a) *Annual land cover state maps*

Figure 4.2. Losses of natural and semi-natural vegetated land exceed gains

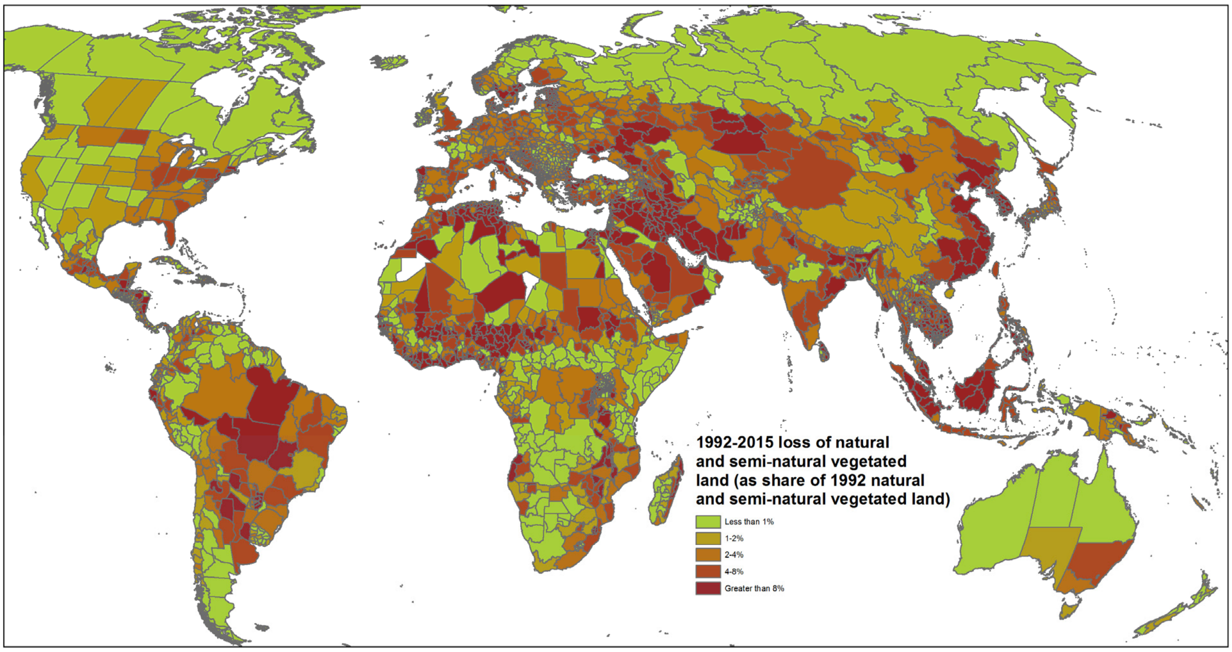
1992-2015, thousand km2, shaded by the intensity of loss or gain (as % of 1992 (semi-)natural vegetated land)



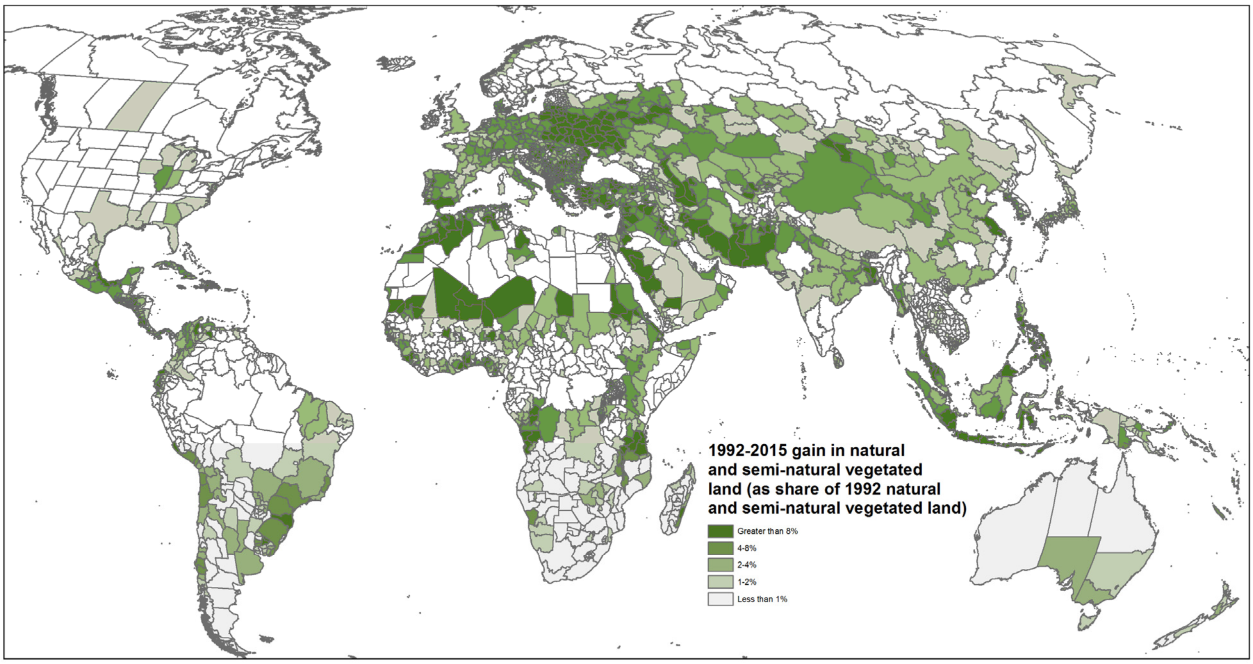
Note: The "gap" (636 000 km^2) between (semi-)natural land gain and loss for OECD & G20 countries shown here is approximately the area of France.
Source: OECD calculations using data from ESA/UCL-Geomatics (2017a) *Annual land cover state maps*

Figure 4.3. Natural and semi-natural vegetated land loss and gain intensity is heterogeneously distributed across all continents

Loss

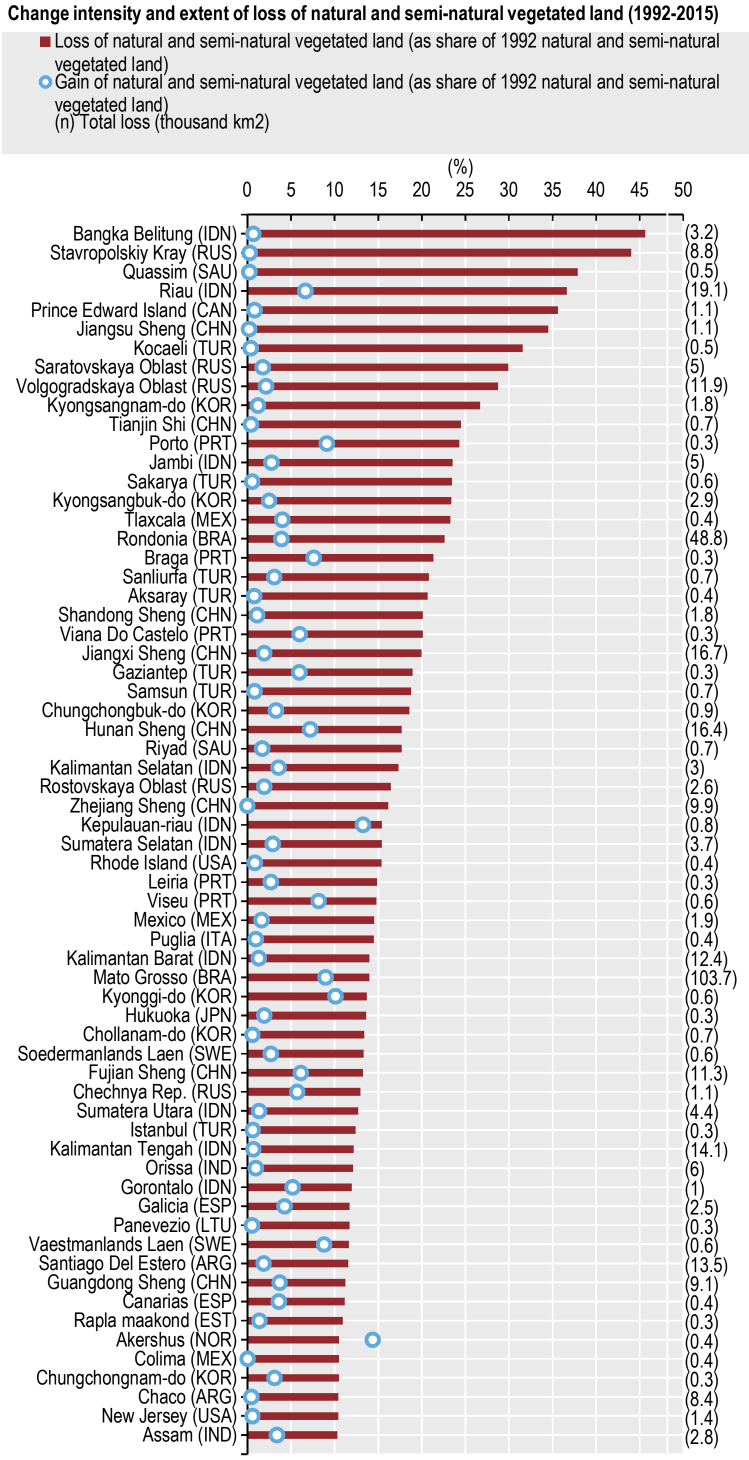


Gain



Note: These maps are susceptible to both the modifiable areal unit problem, a common issue in maps where redrawing a boundary can radically change the overall message, and to the small denominator problem, where a small change in a large area where the denominator is very small can have a disproportionate impact on the visual "story" (there can also be a ‘large denominator’ problem where a large change can be disguised by very large denominator). Care should therefore be taken in drawing conclusions from these choropleth maps.
Source: OECD calculations using data from ESA/UCL-Geomatics (2017a) *Annual land cover state maps*

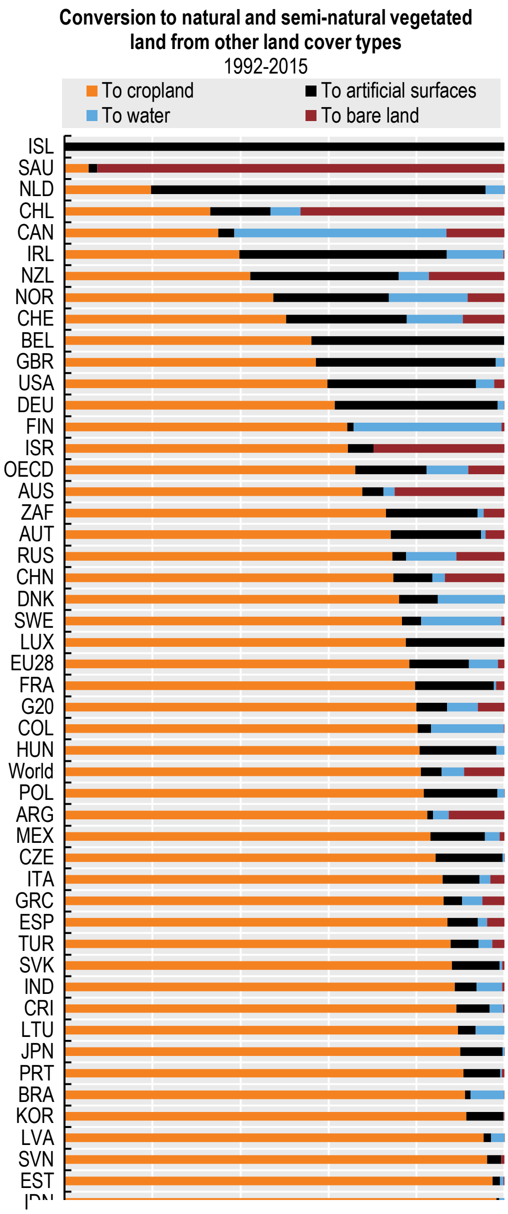
Figure 4.4. Some regions have seen intense losses of natural and semi-natural vegetated land



Note: The Figure shows second-order administrative subdivisions with the greatest rate of (semi-)natural land cover loss and loss greater than 250 km² (2.5 times greater than the area of Paris intra-muros). Larger regions are therefore more likely to be shown here. Loss in regions in Northern Europe (North of approx. 55°) are overestimated because of a classification error between cropland and tree cover in mosaic agricultural areas.

Source: OECD calculations using data from ESA/UCL-Geomatics (2017a) *Annual land cover state maps*

Figure 4.5. The greatest share of natural and semi-natural vegetated land is converted to cropland



Source: OECD calculations using data from ESA/UCL-Geomatics (2017a) *Annual land cover state maps*

In most countries the greatest share of (semi-)natural land is converted to *cropland* (Figure 4.5). In some countries, high proportions of (semi-)natural land to cropland conversion might be partly explained by long-term conversions of arable cropland from pasture, or planting of arable crops following commercial forestry or orchard-type crops. The second greatest driver of (semi-)natural land loss is *urbanisation*. Again in some countries some of this (semi-)natural land loss has probably replaced pasture-like land uses. Notable shares of conversions to bare land, possibly an indication of long-term drought, are observed in Saudi Arabia, Chile, Israel and Australia. Further work is needed to understand the factors driving the observed changes – for instance, conversions to water account for a large share in some countries.

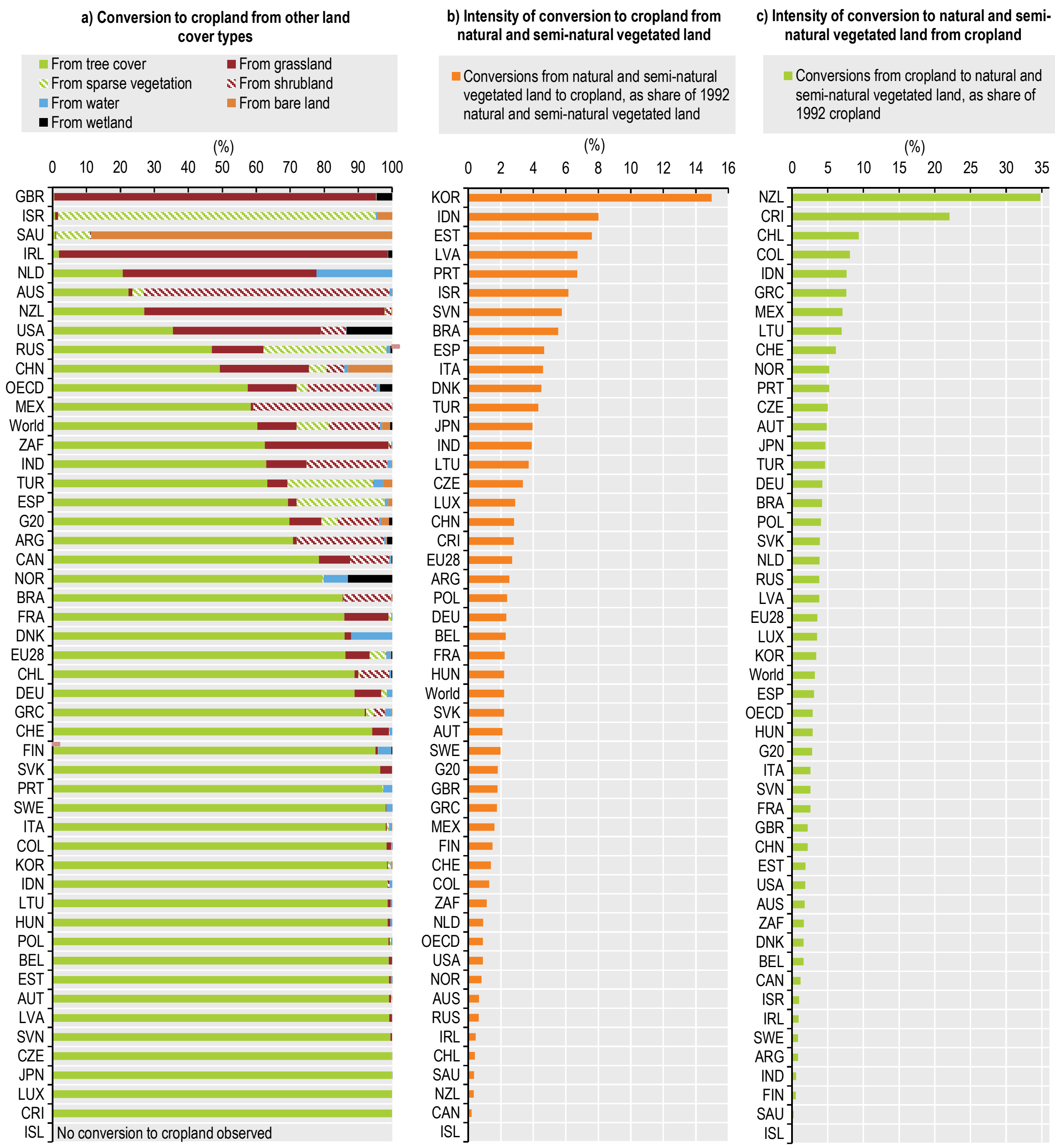
Because the greatest share of (semi-)natural land is converted to cropland, it is relevant to examine transitions to cropland in more detail.

4.1.2. Conversions to cropland

New cropland is converted primarily from tree-covered areas in most countries (Figure 4.6a). Grassland and bare land also play a significant role in some countries. Korea, Estonia, Latvia, Portugal and Israel have converted the greatest share of (semi-)natural land to cropland in OECD countries (Figure 4.6b) although in some cases this may have been re-cultivation of previously abandoned agricultural land. In Estonia, Latvia and other countries in Northern Europe, conversions from (semi-)natural land to cropland are overestimated because of a classification error between cropland and tree cover in mosaic agricultural areas.

Figure 4.6. Most cropland is converted from tree-covered areas

1992-2015



Note: Wetland transitions observed in USA, GBR and NOR in panel A are likely classification errors. See Section 4.1.4 for discussion. The intense conversions from cropland to (semi-)natural land in New Zealand shown in panel c are considerably overestimated because of an error where non-cropland pixels were incorrectly classified as cropland in 1992. Conversions from (semi-)natural land to cropland in Northern Europe (North of approx. 55°) are overestimated because of a classification error between cropland and tree cover in mosaic agricultural areas.

Source: OECD calculations using data from ESA/UCL-Geomatics (2017a) *Annual land cover state maps*

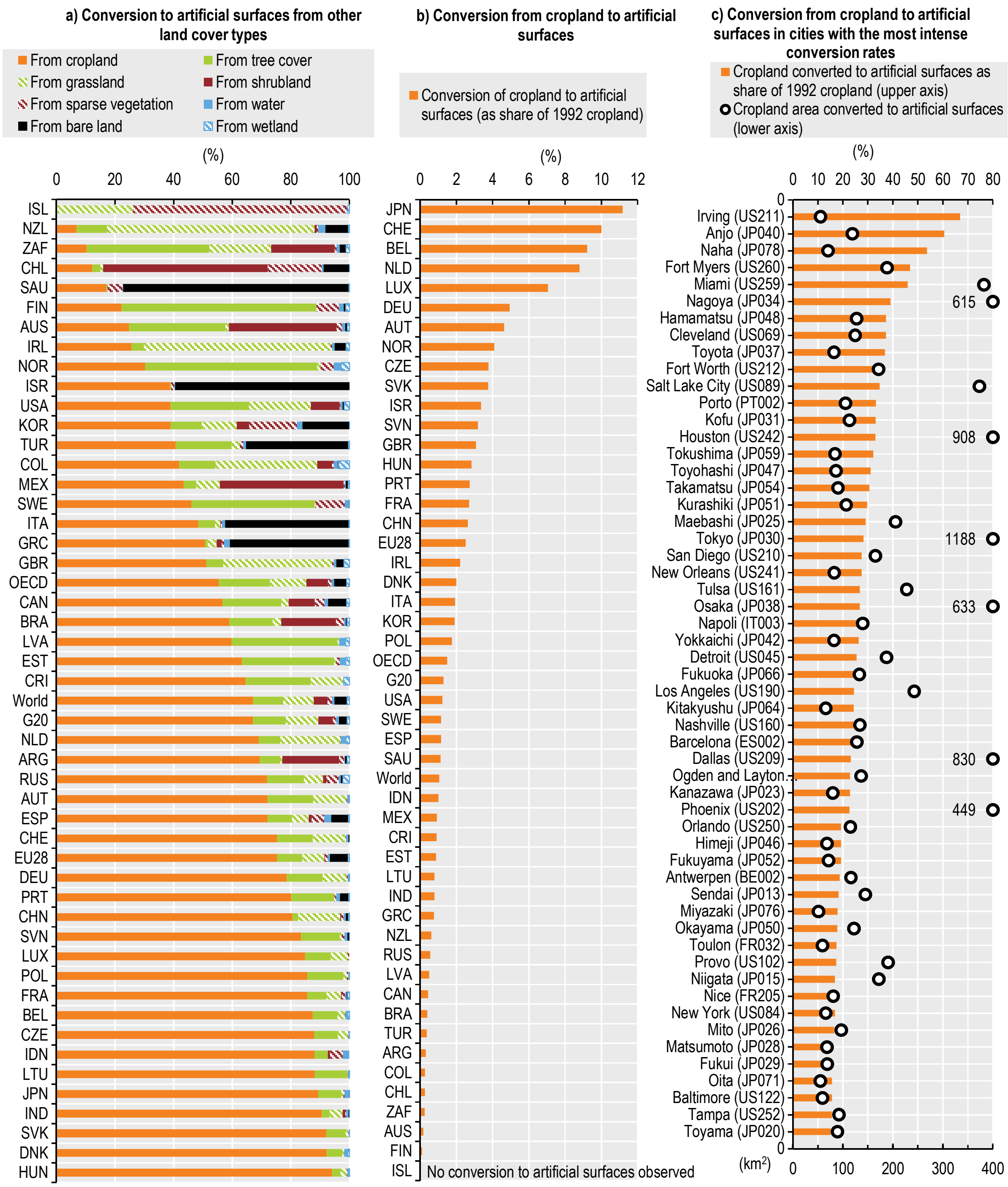
4.1.3. Conversions to artificial surfaces

Most new artificial surfaces are built on cropland with the exception of a handful of countries where development mostly takes place on tree-covered areas, grasslands or shrubland (Figure 4.7a). It is therefore particularly useful to look more specifically at cropland to artificial surface conversions. In addition to the pressures on biodiversity caused by the loss of farmland and natural habitats, conversions to artificial surfaces involve soil sealing, which often irreversibly degrades soil and leads to the cumulative loss of productive agricultural land. Increases in the area of impermeable land also have local climatic and hydrological consequences such as increased flood risk. Urban expansion further affects quality of life via air, noise and light pollution and decreasing access to extra-urban green space.[30] It is important to note that the nature of urbanisation (e.g. housing density, polycentricity, and other aspects of urban spatial structure) also plays a role and might have implications for the societal benefits and costs of urbanisation (e.g. decreased resource use due to reduced transportation needs in dense cities, agglomeration benefits, economies of scale, and greater innovation; see e.g. OECD 2017c).

Among OECD countries, Japan, Switzerland, Belgium, the Netherlands and Luxembourg saw relatively large conversions from cropland to artificial surfaces since 1992 (Figure 4.7b). Among OECD functional urban areas, cities in the United States and Japan have experienced the most intense conversions of cropland to artificial surfaces (Figure 4.7c) – Nagoya, Houston, Tokyo, Osaka, Dallas and Phoenix have all seen extensive (in terms of total area converted) and intensive (as a proportion of total cropland) conversions. Further analysis is necessary to draw stronger conclusions by accounting for the characteristics of FUAs.

[30] See EEA (2016) *Urban Sprawl in Europe* (p. 26) for a summary of studies on the effects of urban sprawl.

Figure 4.7. Most urban development occurs on cropland, 1992-2015



Note: Panel C shows functional urban areas (FUA) with the greatest share of cropland to artificial surface conversion and greater than 50 km^2 (half the area of Paris intra-muros) cropland to artificial surface conversion. Larger cities are therefore more likely to be shown here. These results are very sensitive to how the city is defined and the geography of the administrative units used when designating FUAs. Cropland does not include pasture land so the total 'lost' agricultural land may be larger.

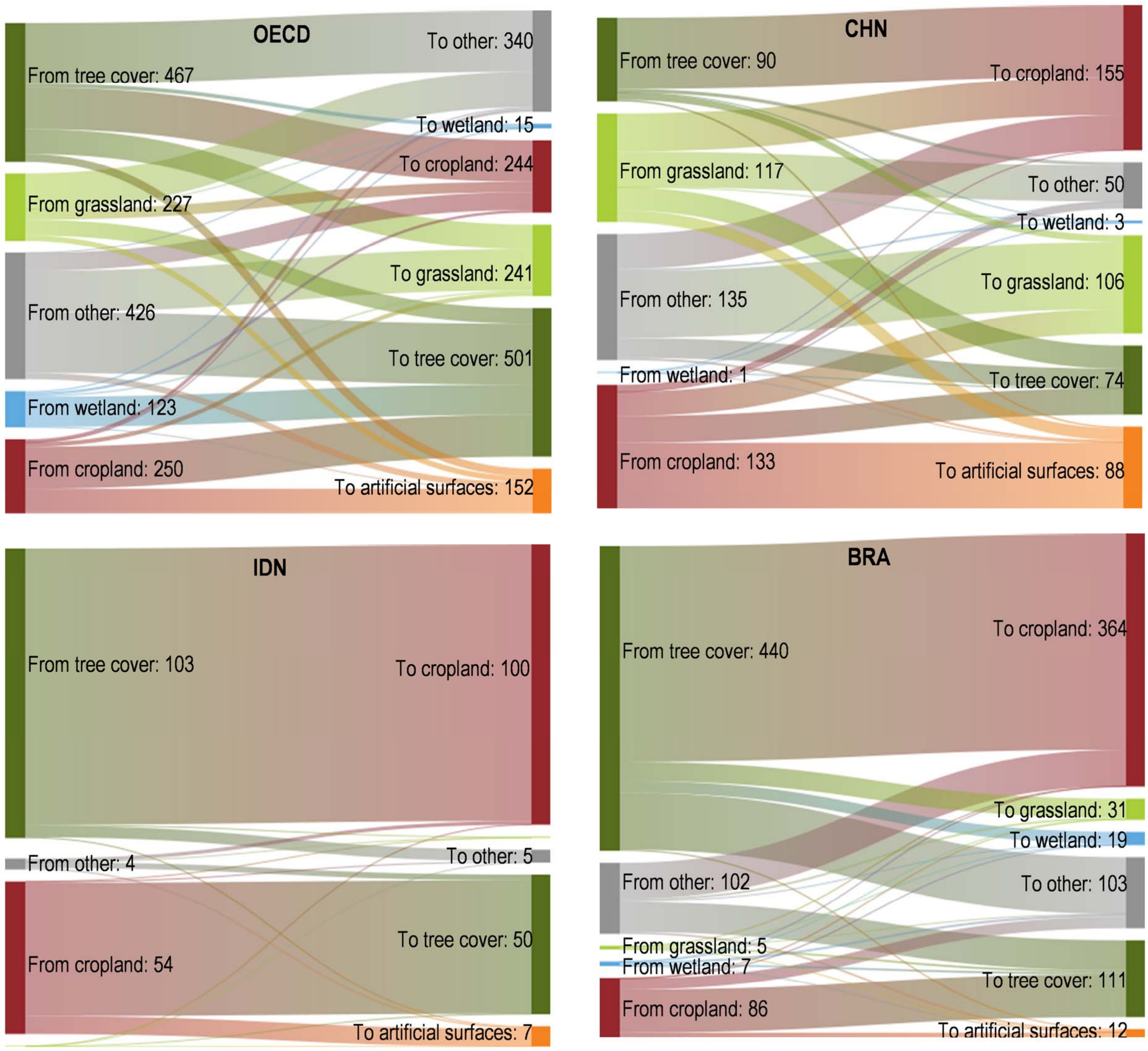
Source: OECD calculations using data from ESA/UCL-Geomatics (2017a) *Annual land cover state maps*

4.1.4. Land cover conversion patterns

A more comprehensive account of land cover changes is presented below. Some countries have seen vast changes from tree cover and other land (shrub land, sparse vegetation, bare land and water) to cropland. In Brazil, more tree-covered area was converted to cropland from 1992-2015 than in all OECD countries combined (Figure 4.8). In China, conversions to artificial surfaces are notable. Further analysis is needed to understand the factors driving the observed changes.

Figure 4.8. Conversion of tree cover to cropland in Indonesia and Brazil is high compared to conversions across OECD countries and China

1992-2015, thousand km^2



Note: "Other" consists of water, bare land, shrub land, and sparse vegetation. See Annex Tables A.3 and A.4 for further details.
Source: OECD calculations using data from ESA/UCL-Geomatics (2017a) *Annual land cover state maps*

Conversion results between some individual IPCC categories should be treated with caution. Misclassification is more likely between different vegetated land types as these classes are often similar and are more difficult to reliably distinguish. For example, the observed conversions from wetlands to tree-cover seen in Figure 4.8a is partly an ambiguous classification issue: the observable biophysical difference between the wetland definition (*Shrub or herbaceous cover, flooded, fresh-saline or brackish water*)[31] and the flooded forest classes (*Tree cover, flooded, fresh or brackish water, Tree cover, flooded, saline water*) is small and difficult to distinguish reliably via remote sensing.

4.2. (Single-class) land cover change

A growing number of datasets provide more detailed information about changes in a specific type of land cover. Here we present two, built-up-area and surface water, that meet many of the indicator criteria listed in the Introduction. These datasets are more specialised, which means they can typically provide more thematic detail, higher resolution, a longer time series, and likely greater accuracy than a multi-class dataset. The use of these datasets is preferred when only one specific land cover type is of interest as they are typically better at characterising these specific phenomena. While there are substantial differences between some of the following results and those from CCI-LC presented above (stemming from differences in resolution, methodology, and, in some cases, denominator used) they usefully complement the information derived from the CCI-LC and provide greater local insight into specific changes.

4.2.1. Built-up area

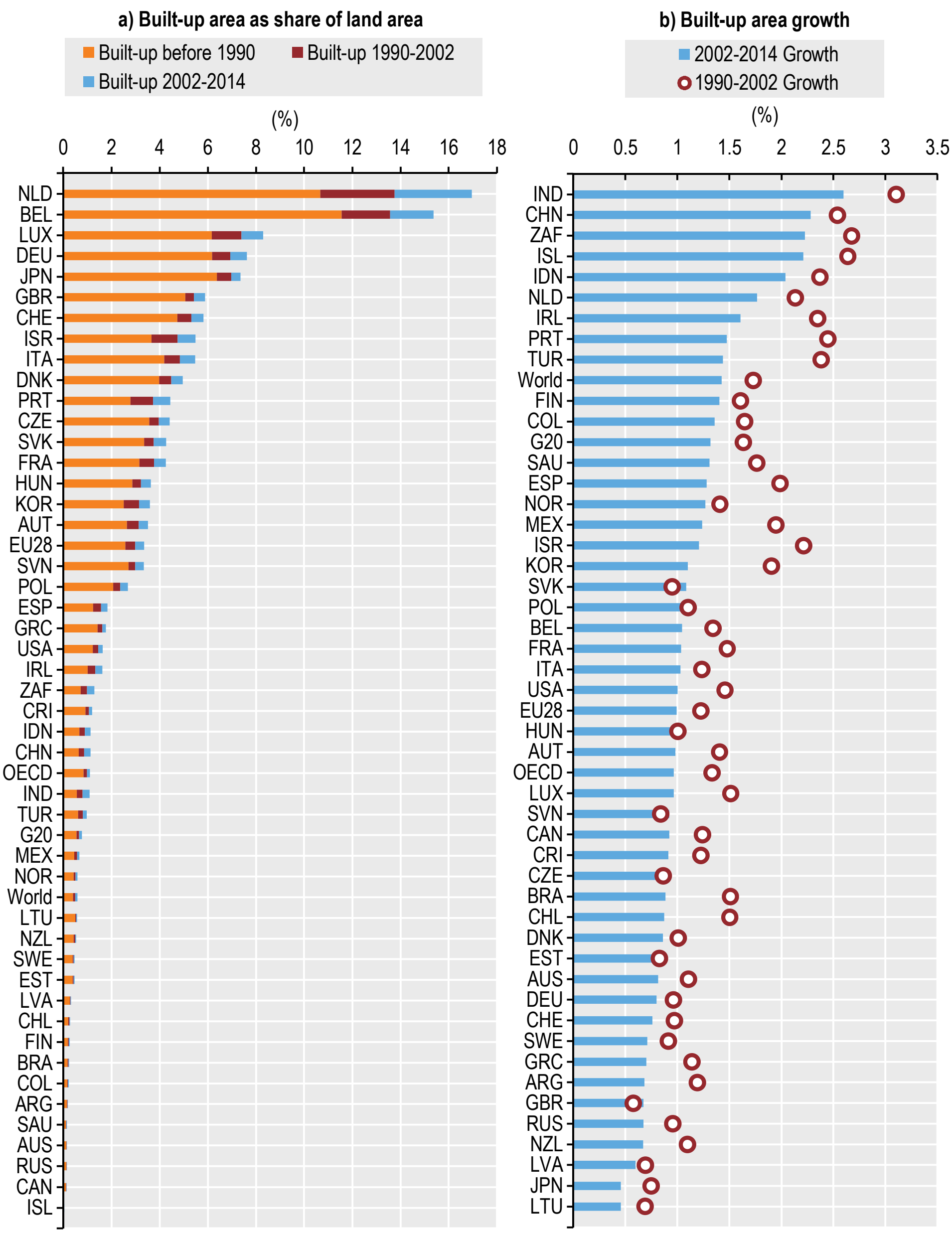
GHSL provides some advantages over CCI-LC for information on built-up area and urban expansion. It has a longer time series for some areas (from 1975)[32] and a higher resolution (38 m with 20 m or better from 2016) which makes it more suitable for studying changes in smaller areas like cities and for studying the changing urban structure. The results shown here suggest that some countries that are already highly urbanised and have less available space such as the Netherlands and Belgium have also seen high levels of urban growth (Figure 4.9a). Some large and previously relatively un-urbanised countries like India, China and South Africa have urbanised rapidly in the last 25 years (Figure 4.9b). OECD countries accounted for almost half the global built-up area in 2014, however, they represent a much smaller share of newly built-up area. Globally, an area the size of the United Kingdom has been converted to built-up areas since 1990 (244 000 km^2) (Figure 4.10). See Annex Table A.5 for more details on built-up area share and change.

[31] This narrow definition of wetland as *land cover* is not comparable to those used elsewhere, e.g. the Ramsar convention definition of wetlands include *marshes, peatlands, floodplains, rivers and lakes, and coastal areas such as saltmarshes, mangroves, intertidal mudflats and seagrass beds, and also coral reefs and other marine areas no deeper than six metres at low tide, as well as human-made wetlands such as dams, reservoirs, rice paddies and wastewater treatment ponds and lagoons* (Ramsar Convention Secretariat (2016), An Introduction to the Ramsar Convention on Wetlands).

[32] Data from the 1975-1990 epoch underestimates the built-up areas as detected in the successive epochs because the earlier satellite-borne sensors were inferior to later sensors and geographic coverage was less comprehensive.

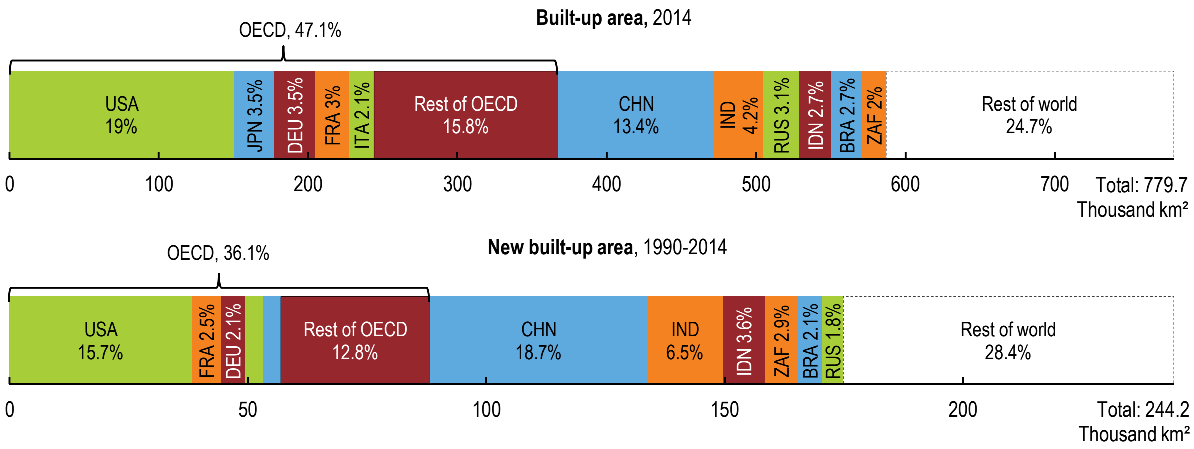
There are many applications of these data. Analyses using this dataset to more accurately map human populations have better indicated the location and number of people exposed to natural hazards (floods, earthquake, hurricanes etc.) and also that the global exposure to natural hazards have increased over the last 40 years (i.e. urban areas and cities are increasingly located in high-risk zones) (Pesaresi et al., 2017). Other analysis has also shown that at the country level, built-up area per capita is generally increasing, and that in some countries built-up area has *also* grown faster than GDP (i.e. land consumption for built-up development has exceeded both population growth and economic growth, see OECD 2017a). In analyses at the city level, trends of generally increasing built-up area per capita (de-densification) have been observed across OECD functional urban areas. However, richer analyses made possible by the time series and resolution of GHSL can reveal examples where despite *overall* densification (for example by considerable densification in the urban core), an increasing proportion of low-density development (sprawl) can be observed elsewhere in the city (see OECD 2017c). This ability to go beyond relatively simple indicators like built-up area per capita and towards a more comprehensive characterisation of urban structure is a good example of the application of these kinds of spatial datasets.

Figure 4.9. Urban growth continues in many highly urbanised countries



Note: "Built-up" refers only to buildings, excluding all other types of urban land such as paved surfaces (roads, parking lots), parts of commercial and industrial sites (ports, landfills) and parts of urban green spaces (parks, gardens). The land area denominator used here is total land area (excluding inland water).
Source: OECD calculations using data from JRC Global Human Settlement Layer (dataset GHS_BUILT_LDSMT_GLOBE_R2015B_3857_38_v1_0).

Figure 4.10. OECD countries account for half of the global built-up area but only a third of the new built-up area



Note: "Built-up" refers only to buildings, excluding all other types of urban land such as paved surfaces (roads, parking lots), parts of commercial and industrial sites (ports, landfills) and parts of urban green spaces (parks, gardens).

Source: OECD Calculations using data from JRC Global Human Settlement Layer (dataset GHS_BUILT_LDSMT_GLOBE_R2015B_3857_38_v1_0).

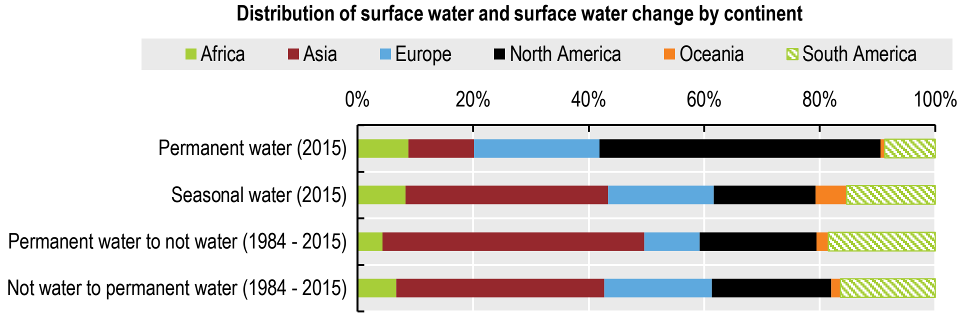
4.2.2. Surface water

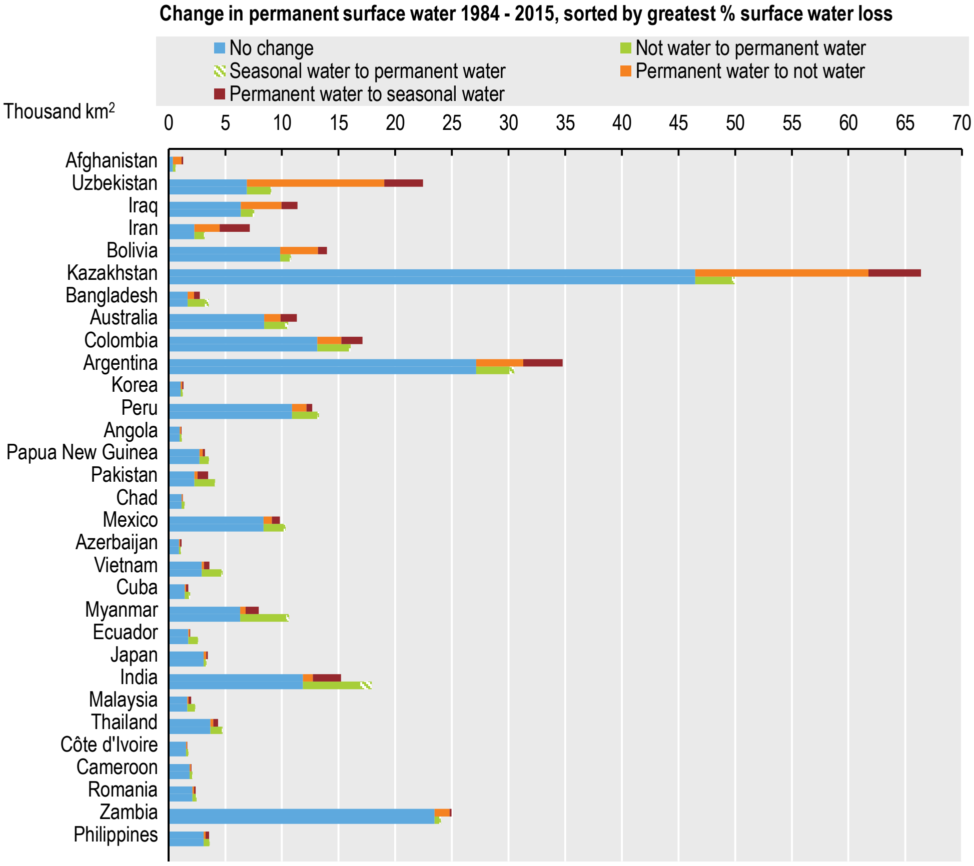
Globally, surface water loss has been most extensive (by total area) and most intense (as a proportion of 1984 permanent surface water) in Central Asia (Figure 4.11) where it was (and continues to be) driven by droughts, river diversion and abstraction. Elsewhere, losses are often caused by long-term droughts. From 1984 to 2015, twice as much land was converted to surface water, principally by dam building, than vice-versa (90 000 km^2 permanent water lost, 184 000 km^2 gained). This extraordinary area of new surface water is more than twice the area of Portugal, while the global loss is around half the area of all the lakes in Europe. Among OECD and G20 countries, inundation was the most extensive in Canada, however surface water gain was both extensive *and* intense in India, China and Brazil (Figure 4.12). (See Annex Table A.6 for more details.)

These changes impact in different ways on biodiversity and climate. Both surface water gains and losses have biodiversity costs and impacts on ecosystem service provision. Damming is known to be one of the most important anthropogenic impacts on freshwater ecosystems. Dams fragment river systems and potentially block migration routes, leading to the loss of megafauna as well as changing the downstream flooding patterns and sediment deposition leading to the loss of floodplains, riparian zones and wetlands (Rosenberg et al., 2000). This is particularly relevant because global dam building is currently booming with thousands of major projects planned, including a large number in biodiverse locations like the Amazon basin (Zarfl et al., 2015).

It should be noted that these data refer only to water surface area, they do not estimate the volume of water gained or lost.

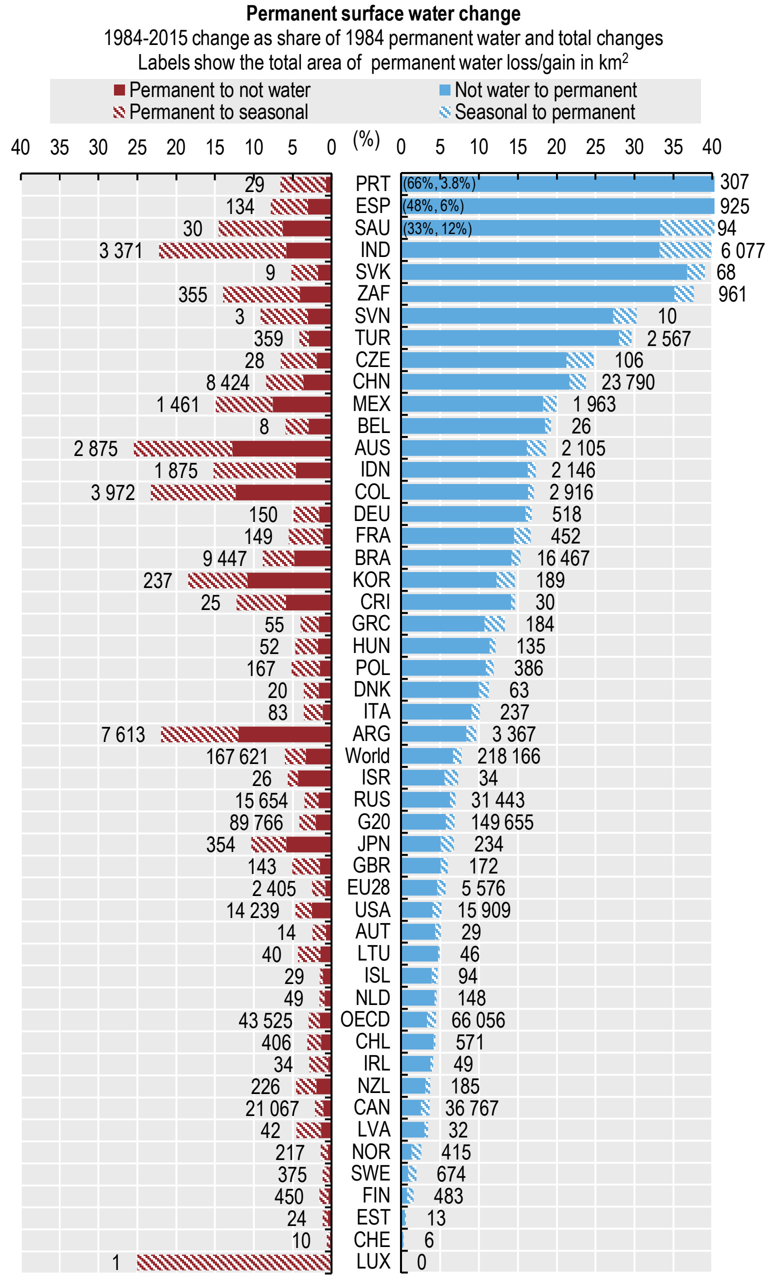
Figure 4.11. Large surface water losses and gains indicate damaging biodiversity impacts





Note: Countries have been selected based on loss intensity. Only countries which saw the most intense surface water loss and which had more than 1 000 km^2 of permanent surface water in 1984 are shown in the lower chart. All countries presented saw greater than 5% surface water loss (disregarding concomitant gains). Permanent surface water is defined as areas that were water for every month of the reference year. Seasonal surface water is defined as areas that were water for 1 to 11 months of the reference year.
Data source: Pekel et al. (2016) *Global Surface Water*

Figure 4.12. Permanent surface water gain was more extensive than loss



Note: Permanent surface water is defined at areas that were water for every month of the reference year. Seasonal surface water is defined as areas that were water for 1 to 11 months of the reference year.
Data source: Pekel et al. (2016) *Global Surface Water*

5. Limitations and caveats

The underlying assumption of the headline indicator, that natural and semi-natural vegetated land cover better promotes and conserves biodiversity and provides higher-value ecosystem services is generally reasonable. However, the indicator is a high-level proxy which comes with several caveats:

- Certain types of conversion, such as permanent deforestation for agricultural land and urbanisation are typically detrimental and therefore broadly fair proxies for pressures on biodiversity and ecosystem services. However, there are examples where the opposite is true. For example, some types of traditional farmland provide essential habitats for farmland birds in Europe and may have higher biodiversity (or be more rare or more difficult to replace) than tree-covered areas. Conversely, orchard crops like olive trees planted on cropland may be recorded as a gain in (semi-)natural land (conversion to tree cover), but the biodiversity value of the land may remain largely unchanged.
- This indicator measures *quantity* (the area or share of land cover converted to another type) without characterising *value* or *quality*. Therefore it cannot distinguish between the loss of habitats with high biodiversity value (e.g. rare habitats with high levels of endemism, primary tropical forests) and areas of the same land cover category but of lower value (e.g. some commercial forestry or plantations).
- The aggregation of tree cover, grasslands, wetland, shrubland and sparse vegetation into the *natural and semi-natural vegetated land* category can conceal important land cover conversions between these categories. These may be very significant (like forest clearing for grazing mentioned earlier). Value judgements about particular transitions are contestable and should be evaluated and adjusted according to the local context in order to better understand land cover change dynamics in an area.
- *Degradation* within (semi-)natural vegetated land cover, where the productivity, biodiversity or other ecosystem services provided by the land are reduced, but where the land cover does not transition from one class to another, is not captured at all.
- Related to all of the above, the ability to reliably identify changes between or degradation within more richly described land cover classes (e.g. wooded wetlands) would provide a better proxy for biodiversity or ecosystem services value in many cases.

An absence of detrimental land cover change in an area does not mean that there are few pressures on biodiversity in that area. Invasive species, pollution, climate change etc. might have negative effects that do not include remotely observable changes in land cover.

The indicator may capture some medium-term land use/land cover ‘cycling’ such as some types of crop rotation between pasture land and arable crops as well as potentially large seasonal effects caused, for example, by drought linked to cyclical phenomena like El Niño. These may not be permanent changes and should be interpreted with care.

Care should be taken when comparing countries with each other because they may be very different in ways that are not evident from looking at these datasets alone. For example, the rate and type of tree cover change in tropical forests is naturally different from that which occurs in xeric or boreal forests.

In general, this sort of indicator may not be appropriate for smaller output areas (smaller regions and cities). The minimum suitable size of the output area is difficult to specify, however, it depends on the resolution and accuracy of the dataset. Furthermore, large output areas can conceal considerable local variation.

Dataset limitations

The underlying datasets are relatively new, and some geographic areas and some dimensions of the datasets, most importantly the accuracy with which they characterise changes, have not all received detailed scrutiny among the user community. The main limitations are the following:

- All Earth observation-derived information is scale-dependent. The areal statistics produced from land cover datasets are very sensitive to the resolution used. Results can disagree simply because a different resolution has been used.
- Relatedly, the pixels of land cover datasets are rarely homogenous even when they purport to be so. In reality they may contain a mix of (for example) built-up land, grassland and tree cover. Therefore calculating *areas* based on these datasets is inherently only approximate. This is particularly relevant when aggregating broader classes like *tree cover* from datasets like CCI-LC where many of the constituent land cover classes are explicitly mosaic landscapes.
- As noted in Section 4.2, users should generally not expect results from different land cover datasets to agree. This includes results calculated from national and regional datasets not mentioned here. This can be partly because of the resolution issue discussed above, and also because although different datasets might share ostensibly similar land cover classes (e.g. urban land), the definitions actually pursued are often rather different. Similarly, seemingly minor differences in how ambiguous classes like mosaic tree cover are defined (for example to customise the classification for a specific location or context) could have a significant impact on the final product.
- The three datasets use data from multiple satellite missions in order to achieve the long (23-40 year) time series necessary to observe relatively slow-moving land cover change phenomenon (as shown in Table 3.1 for example). In all cases, sensor characteristics differ between the beginning and the end of the time series because new and improved satellites are commissioned and old ones obsolete. For example, there is a considerable difference in quality between the lower resolution pre-2000 data from the AVHRR sensor compared to data from later sensors used as inputs in the CCI-LC project. Data producers make efforts to mitigate this effect; however the quality and completeness of these datasets vary over time, and in some cases observed land cover phenomena *may* be a result of these changing inputs.
- Some 'land' cover like mangroves, some islands, tidal islands/reefs and some estuarine water bodies lie outside of the political and administrative boundaries used in this paper to calculate results at national and sub-national scales so

changes in these environments (and their ‘snapshot’ shares) will not be reflected in the indicator.

- CCI-LC mosaic classes of natural vegetation (class values 100, 110), lichens and mosses (class value 140), sparse vegetation (class value 150) and flooded forest with fresh water (class value 160) are notably inaccurate as in other datasets as these are ambiguous classes. Regional accuracy is poorer in the western part of the Amazon basin, Chile, southern Argentina, the western Congo basin, the Gulf of Guinea, eastern Russia, the eastern coast of China and Indonesia due to poorer MERIS coverage in these areas. Cloudier areas are likely to be less accurate than dryer areas. Abrupt changes are better detected than gradual ones because slower changes generally transition through several more ambiguous mosaic land cover classes that are not easily discriminated and detected (ESA/UCL Geomatics, 2017b). The CCI-LC dataset does not show features with a minimum dimension smaller than approximately 150 m (e.g. linear features like road and rail networks) and changes smaller than approximately 500 m^2 because of its land cover and land cover change detection resolutions. Because of this limitation, some types of land cover change may be completely missed: for example, routine forestry operations where modestly sized forest stands (hectares to tens of hectares) are clear-cut.

Towards understanding the uncertainty associated with the indicators

The accuracy of change detection, spatial variation in accuracy, and the level and type of bias in the datasets, and consequently in the derived *indicators,* is mostly unknown. Although different forms of uncertainty or data quality information exist for all of the datasets presented (some datasets include the per-pixel confidence in the land cover classification; others include an approximate relative indication of uncertainty via the number of satellite observations available for each pixel); in general, translating the pixel-level confidence of a particular land cover classification into meaningful uncertainty estimates for output areas is challenging (particularly so in the presence of asymmetric classification errors in land cover datasets like CCI-LC). In an ideal scenario one would be able to calculate the upper and lower bounds of each estimate for each output area; however this type of information is not currently available. It would be useful if future research could better characterise these different types of uncertainty (particularly the accuracy with which changes are detected) and provide guidance to those users who may be interested in using these types of datasets to produce areal statistics.

6. Concluding remarks and next steps

Internationally comparable data on land cover change were requested in the 1990s by OECD's work on environmental indicators, and more recently by the 2011 OECD Green Growth Strategy. Now is an opportune moment to develop indicators on land cover change. For the first time, new datasets with adequate accuracy have become available and provide a broadly comparable indication of the types and intensities of land cover change phenomena with wide geographic coverage.

Results confirm that OECD and G20 countries continue to convert land from its more natural state to more anthropogenic systems, with potentially harmful impacts on biodiversity and ecosystems. Forest loss, particularly in the tropics, is a serious concern, clearance of forest for agricultural use is extensive. Urbanisation is intense in some countries, and globally vast areas continue to be irreversibly built-up. In a handful of countries there has been a considerable loss of permanent surface water, however, most countries have inundated a greater surface area through dams than has been lost through other processes.

The OECD Working Party on Environmental Information (WPEI) has requested a continued monitoring of developments in global land cover data availability, with a view to updating and improving indicators. Land cover change indicators will be improved as new datasets become available in the future. For example, continuous updating of land cover products based on change-detection could yield alternative multi-class land cover change datasets in the future (e.g. the US LCMAP, the EU Copernicus global land service, and China's GlobLand). New global single-class datasets are also forthcoming, e.g. wetlands, tree cover and impervious cover. Work is on-going as part of efforts to develop a Global Biodiversity Observing System to measure a set of Essential Biodiversity Variables (EBV). It is likely that the EBVs will include remotely-sensed biophysical variables about land cover and ecosystem structure. These are promising developments because the variables may be more explicitly linked to biodiversity value (e.g. Pereira et al., 2013; Petorelli et al., 2016; Paganini et al., 2016; see also the GEOBON initiative).

Land, and consequently habitat, fragmentation by transport infrastructure, urban development and intensive agriculture is an equally important and closely related land cover change phenomenon that threatens biodiversity in many countries. Insights into the extent and changes in land fragmentation could be developed. Established methodologies to measure fragmentation exist (see e.g., EEA 2015b) but it is not clear whether available data could support a global fragmentation indicator.

There is also potential to use these data to examine the effectiveness of land-protection policies such as designated protected areas, local land use regulations or other land management measures. Drawing on land- and biodiversity-relevant policy instruments covered by the OECD's PINE database (oe.cd/pine), such efforts could help assess the broader public policy framework directed at conservation and sustainable use of biodiversity and ecosystems.

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Annex A.

Table A.1. Loss of natural and semi-natural vegetated land, 1992-2015

(As percentage of 1992 natural and semi-natural vegetated land, using ESA's CCI-LC)

	Loss of (semi-) natural land	Gain of (semi-) natural land	Converted to cropland	Converted to artificial surfaces	Converted to water	Converted to bare land
KOR	16.4	2.3	15.0	1.4	0.0	0.0
ISR	9.6	5.5	6.2	0.6	0.0	2.8
IDN	8.2	4.0	8.0	0.1	0.1	0.0
EST	7.8	1.0	7.6	0.1	0.1	0.0
PRT	7.3	6.4	6.7	0.6	0.0	0.0
LVA	7.1	1.5	6.7	0.1	0.2	0.0
SAU	6.5	6.4	0.4	0.1	0.0	6.0
BRA	6.1	1.2	5.5	0.1	0.5	0.0
SVN	6.0	0.9	5.7	0.2	0.0	0.0
DNK	5.9	6.4	4.5	0.5	0.9	0.0
ESP	5.4	3.7	4.7	0.4	0.1	0.2
ITA	5.4	3.6	4.6	0.4	0.1	0.2
TUR	4.9	6.9	4.3	0.3	0.2	0.1
NLD	4.7	3.8	0.9	3.5	0.2	0.0
IND	4.4	1.7	3.9	0.2	0.3	0.0
JPN	4.4	1.7	4.0	0.4	0.0	0.0
LTU	4.2	11.4	3.7	0.2	0.3	0.0
BEL	4.1	2.3	2.3	1.8	0.0	0.0
CZE	4.0	6.0	3.3	0.6	0.0	0.0
CHN	3.8	2.9	2.8	0.3	0.1	0.5
DEU	3.8	4.7	2.3	1.4	0.1	0.0
LUX	3.7	2.3	2.9	0.8	0.0	0.0
EU28	3.4	3.0	2.7	0.5	0.2	0.1
GBR	3.2	1.1	1.8	1.3	0.1	0.0
ARG	3.1	0.7	2.5	0.0	0.1	0.4
CRI	3.1	10.7	2.8	0.2	0.1	0.0
POL	2.9	6.9	2.4	0.5	0.0	0.0
AUT	2.8	1.6	2.1	0.6	0.0	0.1
CHE	2.8	1.6	1.4	0.8	0.4	0.3
FRA	2.8	3.0	2.2	0.5	0.0	0.1
HUN	2.7	8.3	2.2	0.5	0.0	0.0
World	2.7	1.5	2.2	0.1	0.1	0.2
SWE	2.6	0.5	2.0	0.1	0.5	0.0
SVK	2.5	3.4	2.2	0.3	0.0	0.0
FIN	2.3	0.5	1.5	0.0	0.8	0.0
G20	2.3	1.1	1.8	0.2	0.2	0.1
GRC	2.0	6.7	1.8	0.1	0.1	0.1
MEX	1.9	1.5	1.6	0.2	0.1	0.0
NOR	1.7	1.1	0.8	0.4	0.3	0.1
COL	1.6	1.2	1.3	0.0	0.3	0.0
USA	1.5	0.5	0.9	0.5	0.1	0.0
ZAF	1.5	0.3	1.1	0.3	0.0	0.1
OECD	1.4	0.9	0.9	0.2	0.1	0.1
CHL	1.2	2.0	0.4	0.2	0.1	0.6
IRL	1.1	0.1	0.4	0.5	0.1	0.0
AUS	1.0	0.9	0.7	0.0	0.0	0.2
RUS	0.9	0.7	0.6	0.0	0.1	0.1
NZL	0.8	1.3	0.3	0.3	0.1	0.1
CAN	0.6	0.3	0.2	0.0	0.3	0.1
ISL	0.0	0.0	0.0	0.0	0.0	0.0

Table A.2. Land cover shares, 2015

(As percentage of total area, using ESA's CCI-LC)

	(Semi-)natural vegetated land					Other land cover types			
	1. Tree cover	2. Grassland	3. Wetland	4. Shrubland	5. Sparse vegetation	6. Cropland	7. Artificial surfaces	8. Bare land	9. Water
ARG	13.1	3.0	3.3	33.7	16.9	23.4	0.2	4.8	1.5
AUS	11.6	15.8	1.3	21.7	36.6	8.2	0.2	4.4	0.3
AUT	53.8	15.2	0.2	0.0	1.4	23.0	2.8	2.8	0.8
BEL	22.3	14.8	0.3	0.0	0.0	50.8	11.2	0.0	0.6
BRA	51.2	5.2	1.6	15.1	0.0	24.8	0.3	0.0	1.6
CAN	47.0	2.4	0.8	3.9	23.2	5.7	0.1	5.9	10.9
CHE	37.5	28.2	0.0	0.0	2.8	15.0	4.4	8.6	3.5
CHL	30.8	4.4	0.0	15.8	15.6	6.3	0.3	21.5	5.1
CHN	18.8	28.0	0.4	0.4	2.4	29.1	1.3	18.3	1.4
COL	65.6	13.3	2.2	4.8	0.5	12.2	0.2	0.0	1.2
CRI	70.9	0.4	0.1	0.0	0.0	26.6	0.8	0.0	1.2
CZE	37.0	7.6	0.1	0.0	0.1	50.0	4.4	0.0	0.8
DEU	32.0	13.5	0.3	0.0	0.1	45.9	6.8	0.0	1.4
DNK	11.6	6.3	1.4	0.0	0.0	69.7	3.8	0.1	7.1
ESP	30.9	6.5	0.1	4.4	1.9	52.8	1.4	1.0	1.0
EST	58.2	5.2	4.4	0.0	0.0	25.4	0.7	0.0	6.1
EU28	37.2	10.9	2.1	1.4	1.0	41.0	2.9	0.6	3.0
FIN	71.9	0.6	7.1	0.1	1.4	8.6	0.2	0.1	10.1
FRA	26.9	16.5	0.3	0.6	0.5	50.6	3.2	0.5	0.9
G20	36.7	10.6	1.8	10.8	9.5	20.1	0.7	6.6	3.1
GBR	8.6	46.3	5.3	0.0	2.1	29.6	5.4	0.3	2.5
GRC	27.9	5.4	0.2	18.4	0.5	40.6	1.5	1.9	3.7
HUN	18.5	7.1	0.6	0.0	0.0	68.2	4.1	0.0	1.4
IDN	60.5	0.3	0.0	0.1	1.0	34.8	0.9	0.0	2.5
IND	17.4	2.4	0.3	3.9	0.2	72.5	0.9	0.7	1.8
IRL	7.8	66.5	12.3	0.0	0.3	7.9	1.3	0.4	3.6
ISL	0.0	23.3	7.0	0.2	35.3	0.0	0.0	30.2	3.9
ISR	2.8	0.1	0.0	0.1	3.6	29.8	4.4	56.7	2.4
ITA	29.0	6.4	0.1	2.0	0.8	53.4	4.4	2.3	1.6
JPN	65.9	0.1	0.2	0.0	0.0	24.2	6.4	0.0	3.2
KOR	47.1	0.4	0.1	0.9	0.5	44.1	3.3	0.2	3.4
LTU	34.8	4.7	0.5	0.0	0.0	56.9	1.2	0.0	1.9
LUX	33.3	24.2	0.0	0.0	0.0	36.3	5.9	0.0	0.3
LVA	57.7	7.5	2.2	0.0	0.0	30.0	0.6	0.0	2.0
MEX	37.0	7.8	0.0	35.5	0.0	16.5	0.7	1.4	1.0
NLD	10.1	33.7	1.9	0.0	0.1	39.1	11.1	0.2	3.9
NOR	42.9	12.0	7.8	1.0	18.0	4.4	1.1	6.2	6.6
NZL	30.3	52.0	0.5	6.0	0.8	2.3	1.0	4.0	3.1
OECD	32.7	11.5	1.1	13.5	15.9	15.7	0.9	4.2	4.4
POL	32.0	5.2	0.3	0.0	0.0	58.6	2.4	0.0	1.5
PRT	41.0	0.9	0.2	1.5	0.1	51.6	2.9	0.4	1.4
RUS	57.9	6.9	4.8	5.6	7.7	11.0	0.2	2.2	3.6
SAU	0.0	0.0	0.0	0.2	3.8	1.4	0.2	94.3	0.1
SVK	47.8	4.1	0.1	0.0	0.0	43.2	4.0	0.1	0.7
SVN	65.9	3.6	0.1	0.0	0.1	27.7	2.0	0.4	0.2
SWE	67.1	4.1	7.1	0.1	3.0	8.6	0.4	0.7	8.8
TUR	24.5	9.9	0.3	0.8	4.1	55.7	1.0	1.9	1.9
USA	31.8	18.3	0.8	19.8	2.8	20.1	1.5	2.7	2.3
World	29.7	9.3	1.3	9.1	7.0	17.6	0.5	22.9	2.7
ZAF	7.8	18.0	0.2	50.9	7.5	14.0	0.6	0.6	0.5

Table A.3. Conversion matrix for OECD countries, 1992-2015

(1000 km^2, using ESA's CCI-LC)

OECD		To									
		1. Tree cover	2. Grassland	3. Wetland	4. Shrubland	5. Sparse veg	6. Cropland	7. Artificial surfaces	8. Bare land	9. Water	Total *from*
From	1. Tree cover		83.37	13.13	123.54	44.45	140.27	26.54	8.35	27.33	466.97
	2. Grassland	52.55		0.41	9.82	108.48	35.17	18.70	0.99	0.60	226.73
	3. Wetland	102.63	4.91		1.44	1.20	8.88	1.39	0.27	2.12	122.82
	4. Shrubland	116.19	20.25	0.17		9.38	49.23	11.45	0.94	1.28	208.88
	5. Sparse vegetation	69.19	115.41	0.11	3.58		8.09	1.66	19.37	3.36	220.76
	6. Cropland	140.64	14.20	0.06	5.00	2.04		84.04	0.68	3.25	249.90
	7. Artificial surfaces	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
	8. Bare land	1.07	1.96	0.01	0.39	51.95	0.57	6.44		1.28	63.67
	9. Water	19.00	0.96	1.16	1.21	1.60	1.84	1.34	1.23		28.35
	Total *to*	501.26	241.06	15.04	144.98	219.10	244.05	151.55	31.83	39.22	

Table A.4. Conversion matrix for the world, 1992-2015

(1000 km^2, using ESA's CCI-LC)

World		To									
		1. Tree cover	2. Grassland	3. Wetland	4. Shrubland	5. Sparse veg	6. Cropland	7. Artificial surfaces	8. Bare land	9. Water	Total *from*
From	1. Tree cover		236.28	112.99	455.63	79.33	1154.58	40.30	21.36	84.26	2184.72
	2. Grassland	152.21		2.74	13.26	179.64	220.64	40.71	57.16	8.59	674.94
	3. Wetland	232.73	6.20		4.03	2.64	10.86	2.73	0.35	12.20	271.73
	4. Shrubland	454.28	34.82	0.98		12.03	287.91	18.31	4.95	4.67	817.96
	5. Sparse vegetation	123.16	241.94	3.22	5.60		182.51	5.96	125.82	6.24	694.45
	6. Cropland	671.80	79.87	1.12	33.25	15.62		263.21	11.01	16.47	1092.35
	7. Artificial surfaces	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00
	8. Bare land	2.81	176.32	0.04	0.83	224.57	44.01	17.16		8.44	474.17
	9. Water	40.78	6.98	19.99	4.67	6.05	12.38	3.29	44.49		138.63
	Total *to*	1677.77	782.40	141.08	517.27	519.87	1912.88	391.67	265.15	140.87	

Table A.5. Built-up area change (%)

(As percentage of land area, using JRC's GHSL)

	Built-up before 1975*	Built-up before 1990	Built-up before 2000	Built-up before 2014
NLD	6.0	10.7	13.1	17.0
BEL	7.1	11.6	13.2	15.4
LUX	3.7	6.2	7.2	8.3
DEU	4.1	6.2	6.8	7.6
JPN	4.6	6.4	6.9	7.4
GBR	4.1	5.1	5.3	5.9
CHE	3.0	4.7	5.2	5.8
ISR	1.0	3.7	4.6	5.5
ITA	2.3	4.2	4.7	5.5
DNK	2.3	4.0	4.4	5.0
CZE	2.2	3.6	3.9	4.4
PRT	1.4	2.8	3.6	4.4
FRA	1.9	3.1	3.7	4.3
SVK	1.9	3.3	3.6	4.3
HUN	1.7	2.9	3.1	3.6
KOR	1.3	2.5	3.1	3.6
AUT	1.7	2.6	3.0	3.5
EU28	1.6	2.6	2.9	3.4
SVN	1.8	2.7	2.9	3.3
POL	1.1	2.1	2.3	2.7
ESP	0.7	1.2	1.5	1.8
GRC	0.9	1.4	1.6	1.8
IRL	0.6	1.0	1.3	1.6
USA	0.8	1.2	1.4	1.6
ZAF	0.3	0.7	0.9	1.3
CRI	0.6	0.9	1.0	1.2
CHN	0.3	0.6	0.8	1.1
IDN	0.4	0.7	0.8	1.1
IND	0.3	0.6	0.7	1.1
OECD	0.5	0.8	1.0	1.1
TUR	0.2	0.6	0.8	1.0
G20	0.3	0.5	0.6	0.8
MEX	0.2	0.5	0.6	0.7
LTU	0.3	0.5	0.5	0.6
NOR	0.3	0.4	0.5	0.6
World	0.2	0.4	0.5	0.6
EST	0.3	0.4	0.4	0.5
NZL	0.4	0.4	0.5	0.5
SWE	0.3	0.4	0.4	0.5
CHL	0.1	0.2	0.2	0.3
FIN	0.1	0.2	0.2	0.3
LVA	0.2	0.3	0.3	0.3
ARG	0.1	0.2	0.2	0.2
AUS	0.1	0.1	0.1	0.2
BRA	0.1	0.2	0.2	0.2
COL	0.2	0.2	0.2	0.2
SAU	0.0	0.1	0.1	0.2
CAN	0.1	0.1	0.1	0.1
RUS	0.1	0.1	0.1	0.1
ISL	0.0	0.0	0.0	0.0

Note: *Data for 1975 is incomplete as built-up detection from this period is limited by inferior sensor coverage and characteristics. The denominator used here is all *land* area (excluding water). It is not the same as used in Table A.2 for CCI-LC-based share of artificial surfaces.

Table A.6. Surface water change, 1984-2015 (%)

(As percentage of permanent water in 1984, using JRC's GSW)

	Change from not-water to permanent	Change from permanent to not-water	Change from permanent to seasonal	Change from seasonal to permanent
PRT	65.5	0.7	5.9	3.8
ESP	47.8	3.0	4.8	6.2
SVK	36.8	1.7	3.4	2.3
ZAF	35.1	4.1	9.8	2.5
SAU	33.3	6.3	8.2	12.1
IND	33.2	5.8	16.4	6.7
TUR	28.0	2.9	1.2	1.6
SVN	27.3	3.0	6.1	3.0
CHN	21.7	3.6	4.8	2.1
CZE	21.3	1.9	4.7	3.5
BEL	18.5	3.0	3.0	0.7
MEX	18.3	7.6	7.3	1.7
COL	16.3	12.3	10.9	0.7
IDN	16.3	4.6	10.5	1.0
AUS	16.2	12.7	12.7	2.5
DEU	16.0	1.6	3.3	0.8
FRA	14.5	1.1	4.4	2.1
BRA	14.2	4.8	4.0	1.2
CRI	14.1	5.9	6.3	0.5
KOR	12.3	10.8	7.6	2.4
HUN	11.4	1.7	3.0	0.7
POL	10.9	1.5	3.7	1.0
GRC	10.7	1.6	2.4	2.6
DNK	10.0	1.6	2.0	1.3
ITA	9.1	1.1	2.4	1.1
ARG	8.4	11.9	10.0	1.3
World	6.7	3.3	2.6	1.1
RUS	6.3	1.6	1.9	0.7
G20	5.8	2.0	2.1	1.1
ISR	5.6	4.3	1.3	1.7
GBR	5.1	1.5	3.6	1.0
JPN	5.1	5.8	4.5	1.7
LTU	4.7	1.4	2.9	0.2
EU28	4.7	0.8	1.7	1.1
AUT	4.4	0.7	1.8	0.7
NLD	4.3	0.9	0.6	0.2
CHL	4.2	1.3	1.8	0.2
USA	4.0	2.5	2.1	1.1
ISL	3.9	1.0	0.4	0.7
IRL	3.8	0.4	2.4	0.3
OECD	3.3	1.5	1.5	1.1
NZL	3.1	1.9	2.6	0.6
LVA	3.0	1.3	3.2	0.4
CAN	2.5	1.0	1.1	1.1
NOR	1.4	0.4	0.9	1.2
SWE	0.9	0.3	0.8	1.0
FIN	0.8	0.4	1.1	0.8
EST	0.5	0.5	0.6	0.1
CHE	0.3	0.2	0.4	0.1
LUX	0.0	0.0	25.0	0.0

Note: *Permanent* surface water is defined as areas that were water for every month of the reference year. *Seasonal* surface water is defined as areas that were water for 1 to 11 months of the reference year.

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