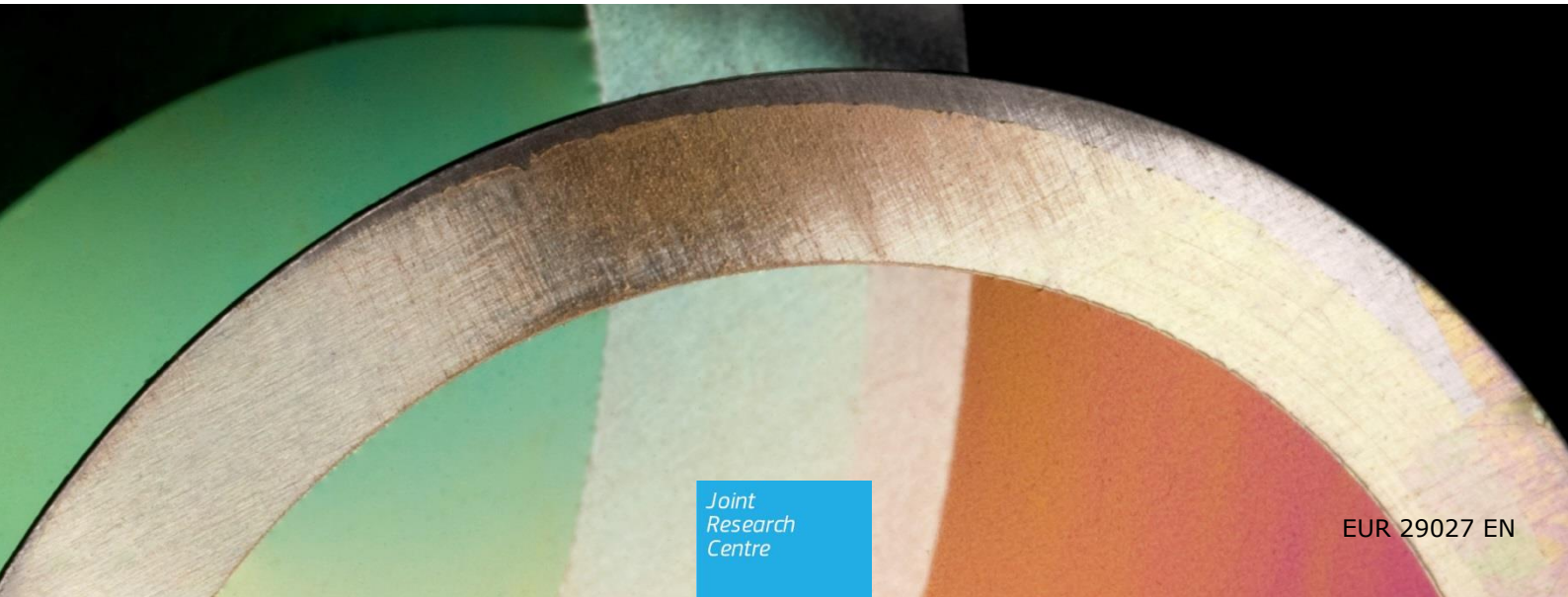
European Commission

JRC TECHNICAL REPORTS

Copernicus Land Services to improve EU statistics

Gallego J.

2017



Joint Research Centre

EUR 29027 EN

Contact information
Name: Javier GALLEGO
Address: JRC, tp. 272
Email: javier.gallego@ec.europa.eu
Tel.: +39.0332.785101

JRC Science Hub
https://ec.europa.eu/jrc

JRC107832

EUR 29027 EN

PDF ISBN 978-92-79-77338-9 ISSN 1831-9424 doi:10.2760/979063

Luxembourg: Publications Office of the European Union, 2017 ©

How to cite this report: Gallego J., *Copernicus Land Services to improve EU statistics*, EUR 29027 EN, Publications Office of the European Union, Luxembourg, 2017, ISBN 978-92-79-77338-9, doi:10.2760/979063, JRC107832

Contents

Abstract

This report analyses the potential use of the Copernicus program as a tool to provide harmonized statistical data on several environmental topics. Some of the Copernicus land services are specifically considered, but the report aims mainly at stating some good practices that can be applied to different topics whenever remote sensing is able to identify the relevant land cover types with a good accuracy. The main message that comes out is that straightforward estimation of land cover area is seldom acceptable. The so-called pixel counting approach should not be used without a previous estimation of the bias coming from the unbalance of commission and omission errors. General statistical rules for the estimation and correction of the bias are reviewed.

The LUCAS survey (Land Use/Cover Area-frame Survey) is run by Eurostat every 3 years on a two-phase sample of points in the European Union (EU). Initially conceived to provide independent agricultural estimates, it has switched to agro-environmental purposes aiming at providing comparable information for the different countries of the EU. In the last LUCAS survey (2015), a sample of around 274,000 has been selected for field visits, with a complementary sample of nearly 60,000 photo-interpreted points to cover areas of difficult access.

In this report we focus on the observation of linear landscape features by counting the number of intersections with 250 m transects associated to each of the visited points. The survey gives valuable observations for geographic comparison and spatial analysis, but still needs some polishing to provide credible estimates of the changes between two reference dates. Simultaneous photo-interpretation of images of different years seems to be a key element to limit the number of fake changes identified.

Automatic identification of linear elements on Very High Resolution images should become an efficient covariate for the estimates (both spatial and temporal), but the attempts carried out in the framework of the Copernicus program still need some improvement.

Keywords: Land cover area estimation, satellite images, Copernicus, Linear landscape elements, Area Frame Survey, Transects.

1 Introduction: The Copernicus land services

The Copernicus Land Monitoring Service of the Copernicus programme (land.copernicus.eu) includes Global, European and local products. Here we focus on the potential use of Pan-European and local products to derive homogeneous and comparable statistical information across different European countries.

Several topics are targeted in this program. They can be classified depending on the type of geographic coverage referring to the 39 countries for which the European Environment Agency (EEA) is providing systematic information (EEA39).

1.1 Pan-European Copernicus land services.

This group refers to products that should provide an approximately complete coverage of EEA39: 33 Member States and 6 associated West-Balkan countries representing a total of 6 million km².

- CORINE Land Cover (CLC) produced for 1990, 2000, 2006 and 2012. This vector-based dataset includes 44 land cover and land use classes. The product also includes a land-change layer, highlighting changes in land cover and land-use
- High Resolution Layers (HRL) that provide information on specific land cover characteristics produced from 20 m resolution satellite imagery. The main themes covered are:
  - Imperviousness, (sealed soil).
  - Tree cover density and forest type
  - Permanent grasslands
  - Wetlands
  - Water bodies.

HRL Pixels of 20 by 20 m are aggregated into 100 by 100 m grid cells for final products. The same resolution of 100 m is used for the validations by photo-interpretation of a sample on Very High Resolution (VHR) layers.

The imperviousness layer was the first one to be produced in 2006-2008. New imperviousness layers have been produced for 2009 and 2012.

1.2 The local component

The local component aims to provide specific and more detailed information on different *hotspots*. It is mainly based on very high resolution imagery (2,5 m) in combination with other high and medium resolution images. At the moment the three local components are:

- Urban Atlas. It provides detailed land cover and land use information over major EU city areas. The Urban Atlas provides pan-European comparable land use and land cover data covering a number of Functional Urban Areas (FUA). In 2012, an additional layer (Street Tree Layer - STL) was produced for a selection of FUAs.
- Riparian Zones. Land cover and land use in areas along rivers, particularly important for biodiversity in Europe.
- Natura 2000. The Natura 2000 (N2K). It is important to assess whether critical habitat types in N2K sites are effectively preserved. Natural and semi-natural grassland are particularly important.

This report explores how Copernicus can be used to produce sound land cover statistics. We shall look more in depth at the estimation of artificial and impervious areas with the help of different Copernicus data.

2 Estimating and correcting the bias of pixel counting.

Before reporting the specific tests carried out with Copernicus data, it may be good to give a reminder of general principles of area estimation based on remote sensing products (image classification or photo-interpretation) when the area of interest is fully covered, with the exception of a limited amount of missing areas due to persisting cloud cover or other reasons. Below we use the expression "pixel counting", which is more adapted to automatic pixelwise image classification, but the remarks are directly applicable to classifications by object (possibly defined by a segmentation algorithm) or by visual photo-interpretation.

A naïf approach for area estimation using classified satellite images is pixel counting or equivalent. If we have a soft classification, in which each pixel i is estimated to contain a proportion m_i of the current class of interest the pixel counting estimator becomes:

$$\tilde{A} = \sum_i m_i \qquad (1)$$

The main source of error in the pixel counting estimator is the unbalance between commission and omission errors. Additional challenges come from the location or co-registration inaccuracy between the classified images and the reference data used to validate them. Location inaccuracy issues are very important if presence of mixed pixels is significant. However the bias of pixel counting can be strong even if we consider only the misclassification of pure pixels not affected by location inaccuracy. Sampling error is absent if the region of interest is fully covered.

The confusion matrix A for the whole population of pixels is unknown and needs to be estimated. Each cell A_{gc} is the area of class g (ground) classified as c or the proportion compared with the total area of the region. A_{cc} is the area correctly classified into class c. A_{+c} is the total area classified as c, A_{c+} is the unknown total area actually belonging to class c. The pixel counting estimator uses A_{+c} to estimate A_{c+}. It has no variance, unless it is computed on a sample of images. Its bias is the difference between the commission and the omission error.

$$B = A_{+c} - A_{c+} = \sum_{c' \neq c} A_{c'c} - \sum_{c' \neq c} A_{cc'} = \Phi_c - \Psi_c \qquad (2)$$

Additional details can be found in many works, for example papers by Foody, (2002), Gallego (2004), Stehman (2009), McRoberts and Walters(2012) and Olofsson (2014). Rome rules to respect are:

- The validation data used to compute the confusion matrix must be selected with a probabilistic method. Purposive or quota sampling should be avoided.
- The validation sample should not include the data used to train the classification algorithm. The cost of field data collection often pushes practitioners
- The validation sample and the training set should not be spatially correlated (Zhen et al., 2013).
- If confusion matrices are used to correct the bias of pixel counting, boundary pixels should not be excluded.

Several techniques correct the bias of pixel counting without an explicit computation of the omission and commission errors.

2.1 Calibration estimators

Calibration estimators are probably the most frequently used methods to correct the bias of pixel counting. They can use the confusion matrix in different ways.

Direct calibration: $\hat{T}_{dir} = e_g R$ (3)

The matrix e_g contains estimates of the conditional probabilities $p(g/c)$ of each ground class g given the class c in the classification and R is a column vector with $R_c = A_{+c}$ total area of pixels classified into each class c. The computation of its variance is relatively easy and is equivalent to a situation in which the image classification is considered as a post-stratification (Cochran, 1977, page 135).

Inverse calibration: $\hat{T}_{inv} = e_c^{-1} R$ (4)

The matrix e_c contains estimates of the conditional probabilities $p(c/g)$ of each image class c given the class g in the ground. The computation of the variance is more complicated.

The expressions above refer to the application of direct and inverse calibration estimators using extrapolated confusion matrices, assuming that the matrix has been built on the basis of a sample with known sampling probabilities p_i and extrapolated with weights $1/p_i$.

In the remote sensing literature confusion matrices are often expressed in terms of a_{gc}, number of pixels belonging to ground class g that have been classified into class c. The situation depends on the sampling plan used to select the field sample.

If the sampling probability is uniform in the whole region, the confusion matrix a becomes an unbiased estimator of A by just applying a constant extrapolation factor and can be used both for direct and inverse calibration. This is usually the situation if the sample is selected before the images are acquired and classified. With this sampling strategy, the confusion matrix a expressed in number of points can be used both for direct and inverse calibration.

If the sample of points for field observation is selected after the classification of images, the classes c can be used as strata to sample points for field observation. This approach is generally recommended when the field sample is used to validate land cover maps obtained from images and at the same time building area estimations that combine field observations with classified images (Stehman, 2009). The sample size n_c is determined by applying some allocation system (Wagner and Stehman, 2015), or simply by rules of thumb of the type "at least 50 points per stratum". With this sampling strategy the direct calibration estimator can be used with a without extrapolating to A. Commission errors will be correct because the sampling probability is homogeneous in each classification class c, but omission errors may be strongly biased when the sampling probability strongly changes from class to class (Gallego et al., 2016). Inverse calibration cannot be used without a correct extrapolation to A.

The number of points n_g to be observed in each ground class g is determined a priori. This approach is sometimes applied with a purposive sampling sometimes referred to as quota sampling: field surveyors will be sent around with the aim of collecting a given number of points. For example the target may be recording coordinates of 50 points in maize fields, 50 points in wheat fields and 50 points in other land cover classes. Surveyors travel around and choose points that they consider "representative", often in the middle of large fields. This is a practical way to collect field data at low cost, but the impact on the possible bias of estimators is not well known. Probabilistic sampling methods in which n_g is fixed a priori may be envisaged, but sampling probabilities are likely to be complex. In any case the author of this annex is not aware of any application to agricultural surveys. If we assume that this sampling strategy can be applied with a uniform probability for each ground class g, inverse calibration can be applied on a, omission errors will be correct, but commission errors will be biased. Direct calibration cannot be used without extrapolating to A. If the analyst is confident that the conditional probability $p(c/g)$ computed on a quota sample, the inverse calibration estimator based on the confusion matrix a expressed in number of points or pixels can be a cheap solution. From the quota sample, the extrapolation to A will not be possible and the direct calibration estimator cannot be used. Commission and omission errors computed from a cannot be compared to assess if direct pixel counting on the classified images overestimate or underestimate each class c.

In general probabilistic sampling is recommended both for land cover maps validation and for area estimation combining field data with classified satellite images (Congalton and Green, 1999, Foody, (2002), Stehman et al. (2003, 2005), Wagner and Stehman (2015), Olofsson et al (2014), Li et al (2014). However if a survey based on probabilistic sampling cannot be afforded, it is legitimate to look for cheaper systems. The inverse calibration estimator based on a quota field sampling might be a good approach, although the suitability is likely to be linked to the share of pure and mixed pixels.

2.2 Regression estimator

The regression estimator exploits the link between field proportion of a given land cover class y and the proportion x of a related class. Assuming there is no stratification:

$$\bar{y}_{Reg} = \bar{y} + \hat{b}\,(\bar{X} - \bar{x}) \qquad (8)$$

And an approximation to the the variance is

$$Var(\bar{y}_{Reg}) = Var(\bar{y})\,(1 - r_{xy}^2) \qquad (9)$$

When the sample size is not large enough or there is one or more strongly influential observations, a more complex approximation may be necessary (Gallego et al., 2014). It should be highlighted that a reasonable application of the regression estimator requires approximately continuous distributions of x and y between 0 and 1. This means that the sampling units should not be points (that would concentrate both distributions on 0 and 1), but area segments sufficiently large to contain several crop plots or landscape patches.

2.3 Choosing an estimator.

All calibration estimators have problems dealing with mixed pixels because the sampling unit is a point or a pixel and the location accuracy is usually of the order of magnitude of a pixel. Thus we will be comparing a pixel in the image with field data that correspond to a neighboring pixel. When the plot size is small or crops are mixed, as it generally happens in less developed agriculture, image classification is not very accurate and the efficiency of calibration estimators is further reduced by co-location inaccuracy. For example Ceccarelli et al (2016) found that calibration estimators gave relative efficiencies close to 1 in tests conducted in Senegal and Kenya, in spite of using Rapid Eye images with a resolution around 5 m. This means that, for this particular example, the ex-post use of classified images did not significantly improve the accuracy of field surveys, although the same study gives a more optimistic assessment of the use of images to improve the sampling frame.

If we use an inverse calibration estimator with a quota sampling of points in the middle of relatively large fields, the problem of misregistration (co-location inaccuracy) will be irrelevant. The impact of non-probabilistic sampling on the estimations is not well known, even if it is well known that it introduces an optimistic bias in the confusion matrix (Hammond and Verbyla, 1996)

The problem of mixed pixels can be formally addressed considering sub-pixel land cover proportions, but the behavior of calibration estimators with sub-pixel classifiers is not very well known.

Czaplewski and Catts (1992) and Walsh and Burk (1993) compare $\hat{T}_{dir}$ and $\hat{T}_{inv}$ in different data sets and report a superior performance of the direct estimator with several criteria: feasibility, bias and variance. Yuan (1997) finds that $\hat{T}_{inv}$ gives slightly smaller variance than $\hat{T}_{dir}$; according to his results, $\hat{T}_{dir}$ is still preferable from the point of view of bias if the sample is not very large compared to the number of cells in the confusion matrix.

The regression estimator is generally less sensitive to location inaccuracy. The regression estimator is suitable when the sampling units are segments of clusters of points containing a relatively large number of pixels. It can also be seen as a bias correction method and it does not exclude mixed pixels that are naturally included in the sampling units. If the sampling units are segments with a size at least one order of magnitude larger than the registration inaccuracy, the impact of location uncertainty is minor. For example if we work with images with a resolution of 20 m, the location uncertainty is likely to be of the order of 20 m. If the sampling units are square segments of 300 m x 300 m or 500 m x 500 m, they approximately correspond to the same patch in the field data and the image, including mixed pixels. From this point of view, the regression estimator is probably the safest bias correction for crop area estimation, even if it less frequently applied in the remote sensing literature than calibration estimators.

Kerdiles et al (2013) and Liu et al. (2014) report values between 1.6 and 2.7 for the relative efficiency of the regression estimator in test areas in China with complex landscapes of thin stripes.

Li et al., (2014) compare various estimators in three pilot areas in China and obtain better results for the regression estimators than for calibration estimators. They also observe a stronger degradation of the inverse calibration when the accuracy of the image classification gets weaker.

2.4 Objectivity and subjectivity in area estimators from satellite images.

Pixel counting can generate a dilemma if some *a priori* belief is available from external information on the area of a given crop c. Suppose for example that an area close to 1,000,000 ha is expected. The image analyst will compute a first area estimate with a given setup of the classification. The setup of the classification includes the choice of the algorithm type, the rules to eliminate outliers or fill missing data and the tuning of specific parameters. A simple example of specific parameter is the prior probability in the maximum likelihood classifier.

If the area classified as c is far from the expected figure of 1,000,000 ha, a conscious analyst will probably try to improve the classification reviewing the initial setup until a better agreement is found. There is nothing wrong about this approach to improve the classification, conceived as an answer to the question "where is the crop *c* grown?". However a question mark appears on the objectivity of the estimated area if direct pixel counting is used. This is a major reason to stress the importance of a rigorous bias correction when estimating areas from classified images.

3 The LUCAS survey

LUCAS (Land Use/Cover Area-Frame survey) is an area frame survey based on point observations. It was initially carried out in 2001 and 2003 with a two-stage systematic design in the 15 countries that were member states in 2001 strongly inspired on the French TER-UTI survey (Delincé, 2001).

After some tests in Greece in 2004 and the previous experience of the Italian AGRIT program (Martino et al, 2009), Eurostat changed in 2006 to a two-phase sample of unclustered points: In the first phase a systematic sample on a square grid of about 1,100,000 points with a 2 km step was selected. Each point was photo-interpreted for stratification into 7 classes and further subsampling for field visits.

In 2006 the survey was defined with a strong priority on annual crops and consequently the agricultural strata had a much higher sampling rate (Gallego and Delincé, 2010). The orientation became later more environmental. The survey has been run every 3 years: 2009, 2012 and 2015. In 2015 the field sample had 274,000 points. An additional substratification was defined for LUCAS 2015 with the scope of covering areas difficult to reach in practice (Gallego et al, 2015). Points considered difficult to reach are excluded from the second-phase sample for field survey and observed by photo-interpretation. The criteria to consider that a point is difficult to reach have been tuned for each survey using the lessons learnt in the previous occasion. Accessibility criteria include altitude, distance and elevation change to the closest road and land cover type according to the CORINE Land Cover (CLC) map (EEA, 2007).

LUCAS has a double nomenclature: land cover (76 classes in 2015) and land use (33 classes). For many classes the land cover strongly determines the land use (if the land cover is wheat, the land use will be almost certainly agriculture), but other land cover classes may have a variety of land uses: the use of grassland may be have agricultural, sports and leisure, residential, etc. Field surveyors take landscape pictures looking at N, S, W and E, as well as a picture of the sampled point (Eurostat, 2016). Micro data of the field observations can be downloaded from the Eurostat website (http://ec.europa.eu/eurostat/web/lucas/data/primary-data/2015). Landscape pictures can be also seen on an online photo viewer (http://ec.europa.eu/eurostat/statistical-atlas/gis/viewer/?config=LUCAS-2012.json&). For around 10% of the points, a soil sample is collected to provide a harmonized source for soil assessment in the EU.

The surveyor walks along a transect of 250 m eastwards from the point and recording changes of land cover type (with a reduced nomenclature), as well as linear landscape elements crossed by the transect. Information derived from the transects has been used to map landscape richness and fragmentation (Eurostat, 2010, Paracchini, 2013). Here we look at the use of transects to assess linear landscape elements, important to reduce the soil erosion and protect biodiversity.

4 Estimating the length of linear elements from transects.

Estimating the total length of a given type of linear elements is in principle an application of the classical Buffon's needle problem (Wood and Robertson, 1998). An unbiased estimate of the total length is in stratum *h*:

$$\hat{L}_h = \frac{\pi D_h}{2 n_h u} \sum_{j \in h} \theta_j \qquad (1)$$

Where n_h is the number of transects of length *u* (250 m) and θ_j is the number of intersections of transect *j* with the linear elements under estimation and D_h is the area of stratum *h*. The term π/2 comes from the assumption that the angle between the linear element and the transect has a uniform distribution. If we remove the term D_h in equation (1), we obtain the density of linear elements (in km/km^2 for example).

The estimator's variance has been adapted for systematic sampling by substituting the usual estimator of the variance by a local estimator in which each sample element is compared only to the closest elements in the same stratum (Gallego and Delincé, 2010). This estimator is an extension of an estimators proposed by Wolter (1984) for one-dimensional systematic sampling. Both the estimator proposed by Wolter and this two-dimensional extension have been empirically checked to overestimate the variance, but much less than the traditional estimator for random sampling.

Table 1 reports EU-27 (Croatia excluded) length estimates for several types of linear elements. The consistency of the figures is difficult to assess because most countries do not have national statistics to compare with. The main problem is the application of the definition by the surveyors, even if the documentation of the definitions is rather detailed (Eurostat, 2015). The 140 pages of these instructions for surveyors give a lot of information, but it is difficult to assess how well this document, or its translation to more than 20 languages, is understood and applied by more than 700 surveyors who carry out the field work. These figures are probably reasonable, but it is not clear how policy relevant they are. A photo-interpretation of a limited number of transects on Google Earth suggests some heterogeneity in the way surveyors apply the nomenclature.

Table 1. Estimated total length (in thousands of km) of different types of linear elements in the EU

	2012	cv %	2015	cv %	change	cv %
Grass margins	12282	0.4	12879	0.4	597	7.1
Shrub margins	1651	1.3	1858	1.2	207	10.6
Single trees and shrub	966	1.2	935	1.2	-31	36.6
Lines of trees	1666	1.0	1481	1.1	-185	8.2
Conifer hedges	104	3.8	91	4.2	-14	29.4
Managed broad leave hedges	1761	1.0	1686	1.0	-75	18.9
Abandoned broad leave hedges	2557	1.0	2797	0.9	240	9.8
Groves	468	2.1	400	2.3	-68	14.0
Stone walls	2634	1.2	2823	1.2	189	9.4

We get some more interesting information if we estimate the density of linear elements separately by major land cover or land use types. For example we can estimate the total density of hedges for each of the main land cover categories of CLC (EEA, 2007).

Table 2. Estimated density of hedges for different major CLC land cover types

CLC class	n	km/km^2	CV (%)
Artificial	14421	0.95	0.5
Arable land	78835	1.05	0.2
Permanent crops	8241	1.13	0.6
Managed grassland	24673	3.32	0.2
Natural grassland	4420	0.59	1.1
Forest	73238	0.25	0.4
Shrubland	20836	0.29	0.7
Heterogeneous areas	35676	1.52	0.2
Bare land	1548	0.27	2.8

Table 2 illustrates how important managed grassland landscapes are for the richness of linear elements. An additional issue that can raise some interest is whether if the hedges in residential areas have a significant impact on the total length of hedges. The relevant CLC subclass for this purpose is "discontinuous urban", for which the LUCAS transect-CLC exercise gives the surprising estimate of 1.1 km/km^2 of hedges, much lower than expected. The likely reason for this is the coarse resolution of CLC (Minimum Mapping Unit of 25 ha): most residential areas with hedges are smaller and not reported by CLC. The average density of a specific type of linear elements per region gives us a picture of this aspect in the EU landscape. Figure 1 shows the distribution of hedges in the EU.

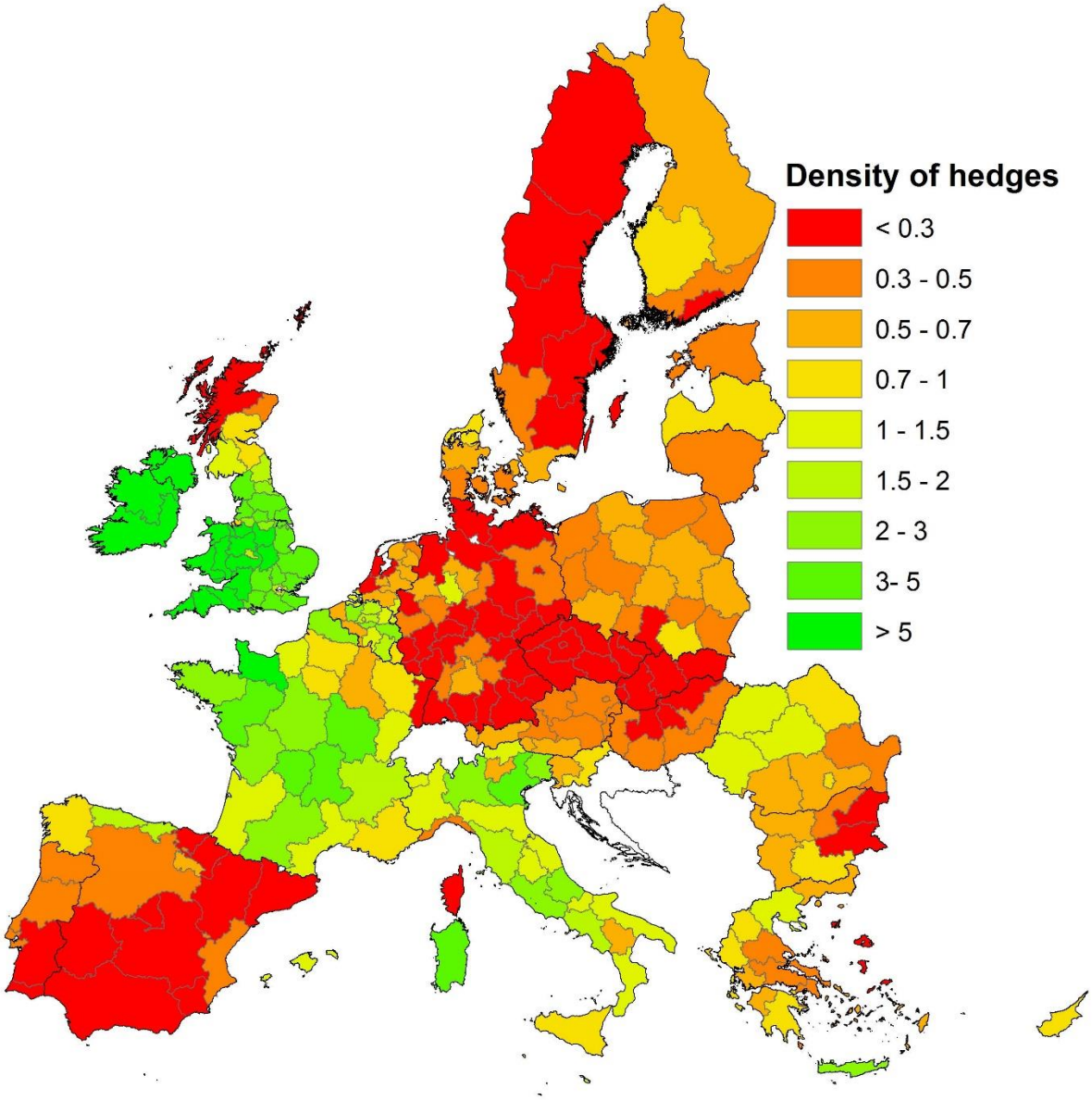


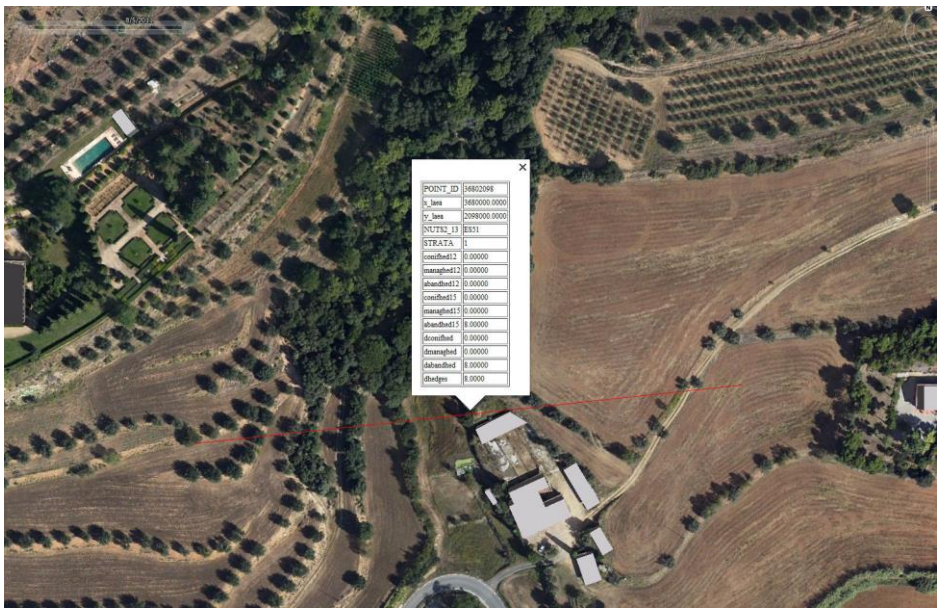
Figure 1. Estimated density of hedges per region in the EU in km/km^2.

4.1 Changes of linear elements.

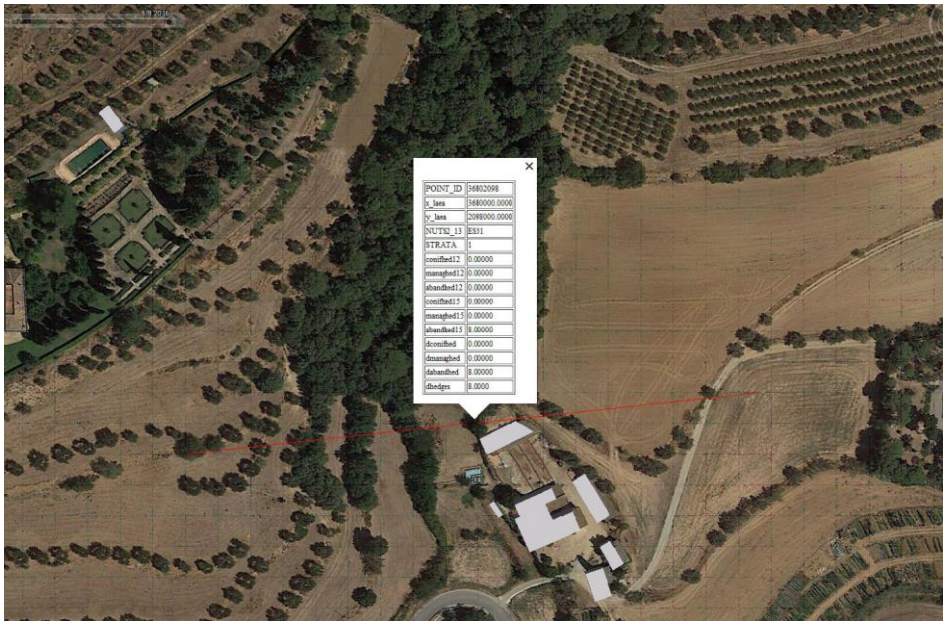
A more important issue for policy makers is the estimation of changes between two reference dates in order to understand the environmental efficiency of the agricultural policy. The last columns of table 1 report the estimated changes between 2012 and 2015. They raise serious doubts on the time consistency. Although the sampling errors reported are good at EU level, the estimated changes are too strong to be realistic.

We have explored outliers on the change estimates of the "hedges" category (grouping the three types of hedges in the nomenclature. 102 transects reported a difference of 5 or more crosses of the transects with hedges between 2012 and 2015 (46 with a decrease and 56 with an increase). The photo-interpretation on publicly online available Very High Resolution (VHR) images highlights the weakness of the estimates: Images close to 2012 and close to 2015 were not always available and possible changes could not be assessed in 29 cases because of insufficient images. For the other 73 transects there were 2 cases in which the reported strong change matched with photo-interpretation, 5 cases had with

a minor change (one new hedge or one hedge disappeared) and 67 in which no change could be appreciated. Figure 2 shows an example of transect for which 8 hedges are reported in 2015 and none in 2012. Images acquired in 2011 and 2016 strongly suggest that there has been no major change. We are clearly in front of a problem of non-sampling errors: the criterion of the surveyor to label the same landscape elements has been different. The instructions to surveyors clearly stressed that major changes compared to the previous surveys should be checked in view of the field documents of the previous survey, but they have been probably lost in the bunch of a complex set of observation rules. This issue needs to be tackled, possibly with a simultaneous photo-interpretation of images of a large sample of transects.



2011



2016

Figure 2. Example of transect with two images corresponding to 2011 and 2016.

5 The Copernicus layer of green linear elements in riparian zones.

It is interesting to cross LUCAS information on linear elements with information produced by automatic analysis of satellite images. If the correlation is good, a regression estimator combining both might be pertinent.

There does not seem to be any image classification of linear elements at EU scale, but an interesting attempt is being produced in the framework of the EU-EEA Copernicus program (www.copernicus.eu) that includes the production of a several high resolution information layers (Maes et al., 2012, Sannier et al, 2016). One of the products targeted in the Copernicus Land Services is a layer of Green Linear Elements (GLE), at the moment limited to riparian zones, covering approximately 500,000 km2 in EEA-39, the 39 countries covered by the European Environment Agency (Geoville, 2016). When downloading the data, the user is asked to acknowledge that these products have not been validated. Our observations confirm that this prudent warning is justified and suggest that improvements are still needed.

The GLE product provides information on linear vegetation features such as hedgerows, scrub and tree rows with a minimum length of 100m and a width of up to 10m. Isolated patches of trees and scrub with a size between 500 m² and 0.5 ha. Green linear elements including trees and hedgerows with 100m minimum length and 500m² Minimum Mapping Unit (MMU). These thresholds make a significant difference with LUCAS observation rules that do not put any minimum length to the targeted linear elements.

We have explored the behaviour of this map produced by automatic classification compared with the LUCAS transect intersections for the GLE set of riparian zones in the Po valley in Italy. A total of 874 transects has been found to be inside these riparian zones for more than 80% of the transect length. The green linear elements identified by LUCAS transects data have been regrouped including the three categories of hedges, lines of trees and groves. This grouped category seems to correspond to the GLE targeted by Copernicus, except for the length threshold. Table 4 reports the frequency of the number of intersections illustrates the low level of consistency between both sources. The meaning of a linear correlation between both sources is debatable, with one of the variables having values 0 or 1, but still can be computed (r=0.05), showing a low level of consistency. Figure 3 shows an example of area with several GLE that meet the requirements of the image classification product and have been missed. In exchange commission errors seem to be low.

		LUCAS GLE intersections								
Copernicus GLE intersections		0	1	2	3	4	5	6	11	Total
	0	637	117	46	12	4	0	1	1	818
	1	42	8	3	0	1	1	1	0	56
	Total	679	125	49	12	5	1	2	1	874

Table 3. Frequency of intersections of transects observed in the field (LUCAS) and in the Copernicus image classification in the riparian zones of the Po valley.

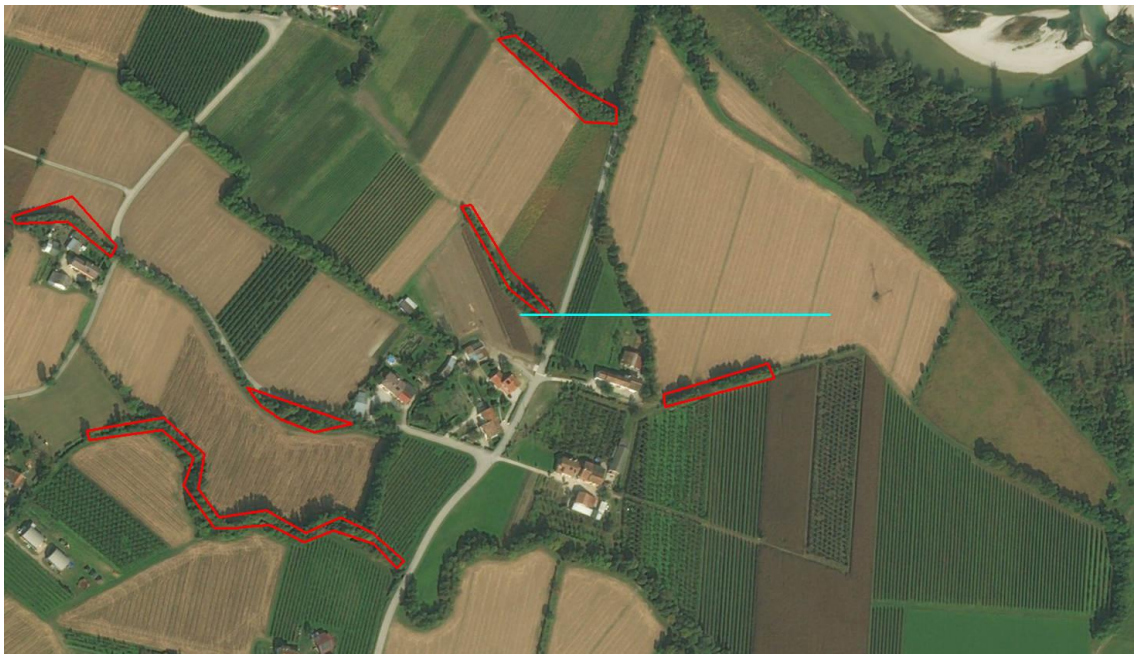


Figure 3. Example of linear green elements identified by automatic classification (in red) in the Po valley. In blue a LUCAS transect.

6 Discussion and Conclusions

The direct area estimation by pixel counting in a classified image, or equivalent approaches, is known to have a bias because commission and omission errors. We have illustrated with the example of the estimation of impervious areas in Europe that a simple correction of bias using a confusion matrix gives acceptable results if the confusion matrix has been properly weighted with the inverse of sampling probabilities. In exchange if these weights are ignored, the correction can be completely wrong and even "correct" the estimates in the wrong direction. In our example the bias of the naïf (direct) estimation of impervious area from classified satellite images is above 20%, even if the overall accuracy of the classification is above 98%. This observation has an implication on the use of remote sensing for area estimation that is not new, but is worth reminding:

- the risk of bias in direct area estimation from classified images is particularly strong if the targeted classes occupy a small proportion of the geographic area.
- Bias correction with a sample of more accurate and approximately unbiased data requires applying the correct weights from the sampling plan.

We have illustrated the observations on linear landscape elements carried out by the Eurostat LUCAS survey. We have highlighted the elements that need to be improved and this may give a rather negative sensation to the reader. The large majority of transects that we have photo-interpreted suggest that the geographic picture that the survey gives of the richness of linear elements across EU regions and major land cover types (CLC) is essentially correct, although a more structured sample-based photo-interpretation exercise is needed.

The consistency of observations of the same transect from one survey to the next one (e.g. 2012 to 2015) still contains a number of fake changes. This happens only for a low proportion of transects, but this is enough to disturb the estimation of changes for a feature that is essentially stable in the EU. The efforts Eurostat has made on the observation rules to avoid fake changes seems to be still insufficient: the surveyor is asked ask to check with the help of images (e.g. the field documents or the landscape pictures of the previous survey) when an apparent change results from the comparison of both observations, but this remark might get lost in the transmission chain headquarters-contractor-national coordinator-trainers-surveyors. The complexity of the instructions to enumerators probably gives a hand to the loss of the message.

Location errors of the graphic documents used for the field work and GPS inaccuracy can be an additional reason for the inconsistency. However the location accuracy of both tools has greatly improved since the beginning of LUCAS and should not be a major source of errors anymore.

Automatic identification of Green Linear Elements (GLE) on Very High Resolution (VHR) images has a strong potential as a covariable for the geographic and temporal estimates of linear elements and its changes, but the products currently available in the Copernicus Program still need some improvement to be efficient.

Simultaneous photo-interpretation of pairs of VHR images (satellite or aerial ortho-photos) should be a key tool for the estimation of changes. However strong limitations appear on the availability of images of the reference years for which the change is wished. There is probably room for an adaptation of the censored data techniques used for survival analysis in biometrics and technometrics. For example if we can see a change between two images dated 2010 and 2016, we can derive some incomplete information on a possible change between the reference years 2012 and 2015. This remains for the moment a track to explore.

References

Ceccarelli T., Downie M., Remotti D., 2016, Role of Earth Observations for Crop Area Estimates in Africa. Experiences from the AGRICAB Project, ICAS VII, Rome, October 26-28 2016.

Congalton R.G., Green K. 1999, *Assessing the accuracy of remotely sensed data: principles and practices*, Lewis publishers, Boca Raton. 137 pp.

Czaplewski R.L. 1992, Misclassification bias in areal estimates. *Photogrammetric Engineering and Remote Sensing*. 58 (2): 189-192.

Czaplewski R.L. Catts G.P., 1992, Calibration of remotely sensed proportion or area estimates for misclassification error. *Remote sensing of Environment*. n. 39, pp 29-43.

Delincé J. 2001, A European approach to area frame survey. Proceedings of the *Conference on Agricultural and Environmental Statistical Applications in Rome* (CAESAR), June 5-7, Vol. 2 pp. 463-472. http://www.ec-gis.org:/

EEA 2007, *CLC2006 technical guidelines*, Technical report No 17/2007. European Environemnt Agency, Copenhagen. http://www.eea.europa.eu/publications/technical_report_2007_17

Eurostat 2010, *Landscape structure indicators from LUCAS*. http://ec.europa.eu/eurostat/statistics-explained/index.php/Landscape_structure_indicators_from_LUCAS

Eurostat 2015, *LUCAS 2015. Technical reference document C1. Instructions for surveyors*. http://ec.europa.eu/eurostat/documents/205002/6786255/LUCAS2015-C1-Instructions-20150227.pdf

Eurostat 2016, LUCAS : Land Use and Land Cover Survey. http://ec.europa.eu/eurostat/statistics-explained/index.php/LUCAS_-_Land_use_and_land_cover_survey

Foody, G. M. 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment, 80*(1), 185-201. doi:10.1016/S0034-4257(01)00295-4

Gallego F, Palmieri A, Ramos H. 2015, Sampling system for LUCAS 2015. EUR 27596. Luxembourg (Luxembourg): Publications Office of the European Union; EUR 27596 EN

Gallego F.J. , Kussul N., Skakun S., Kravchenko O., Shelestov A., Kussul O., 2014, Efficiency assessment of using satellite data for crop area estimation in Ukraine. *Internatinal Journal of Applied Earth Observation and Geoinformation*, 29, pp. 22-30.

Gallego F.J., 2004, Remote sensing and land cover area estimation . *International Journal of Remote Sensing*. Vol. 25, n. 15, pp. 3019-3047 .

Gallego J., Sannier Ch., Pennec A., 2016, Validation of Copernicus Land Monitoring Services and Area Estimation. *ICAS VII*, Rome, October 26-28 2016.

Gallego, F.J. Delincé, J. 2010, The European Land Use and Cover Area-frame statistical Survey (LUCAS). In *Agricultural Survey Methods*, R. Benedetti, M. Bee, G. Espa, F. Piersimoni. (Ed.), pp. 151-168 (New York: John Wiley & sons).

Geoville 2016 *Development of EO derived information services for EEA*. D7 – Project Technical Summary Report. http://land.copernicus.eu/user-corner/technical-library/esa-geoville-study.

Hammond T.O., Verbyla D.L., 1996, Optimistic bias in classification accuracy assessment, *International Journal of Remote Sensing,* Vol. 17 No 6 pp.1261-1266.

Kerdiles, H, Dong, Q., Spyratos, S., Gallego F.J., 2013: Use of high resolution imagery and ground survey data for estimating crop areas in Mengcheng county, China. In *Proceedings of 35th International Symposium on Remote Sensing of Environment (ISRSE35).*

Li, Y., Zhu, X., Pan, Y., Gu, J., Zhao, A., & Liu, X. 2014. A comparison of model-assisted estimators to infer land cover/use class area using satellite imagery. *Remote Sensing, 6*(9), 8904-8922.

Liu, J., Chen, Z., Wang, L., Wang, X., Dong, Q., & Gallego, J. F. 2014. Assessing the crop acreage at county level on the north china plain using an adapted regession estimator method. *3rd International Conference on Agro-Geoinformatics, Agro-Geoinformatics 2014,*

Maes, J. et al, 2012. Mapping ecosystem services for policy support and decision making in the European union. *Ecosystem Services, 1*(1), 31-39.

Martino, L., Palmieri A., Gallego J., 2009, *Use of auxiliary information in the sampling strategy of a European area frame agro-environmental survey*. Eurostat technical document, http://ec.europa.eu/eurostat/documents/205002/769457/LUCAS2009_S2-Sampling_20090000.pdf.

McRoberts, R. E., & Walters, B. F. 2012. Statistical inference for remote sensing-based estimates of net deforestation. *Remote Sensing of Environment, 124*, 394-401.

Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E., Wulder, M.A., 2014, Good practices for estimating area and assessing accuracy of land change Remote Sensing of Environment 148, 42 - 57

Paracchini M.L. 2013, LUCAS: *Landscape structure and Linear elements*. http://ec.europa.eu/eurostat/documents/205002/274769/LUCAS_UseCase-AEI28.pdf.

Sannier, C. et al. 2016 A Validation of Copernicus high resolution layer on imperviousness degree for 2006, 2009 and 2012. *Spatial Accuracy Assessment*, Montpellier, 5–8 July 2016. http://www.spatial-accuracy.org/system/files/Accuracy%202016%20Proceedings.pdf

Stehman, S. V. 2009. Sampling designs for accuracy assessment of land cover. *International Journal of Remote Sensing, 30*(20), 5243-5272. doi:10.1080/01431160903131000

Stehman, S. V., T. L. Sohl, and T. R. Loveland. 2005. An evaluation of sampling strategies to improve precision of estimates of gross change in land use and land cover. *International Journal of Remote Sensing* 26, (22): 4941-4957.

Stehman, S.V., Wickham J.D., Smith J.H., Yang L., 2003, Thematic accuracy of the 1992 national land-cover data for the Eastern United States: statistical methodology and regional results. *Remote sensing of Environment* 86, 500-516.

Wagner, J. E., & Stehman, S. V. 2015. Optimizing sample size allocation to strata for estimating area and map accuracy. *Remote Sensing of Environment, 168*, 126-133..

Walsh T.A., Burk T.E., 1993, Calibration of satellite classification of land area. *Remote sensing of the environment* 46: 281-290.

Wolter K.M. 1984, An investigation of some estimators of variance for systematic sampling. *Journal of the American Statistical Association*, Vol. 79 No 388, pp. 781-790.

Wood G. R., Robertson J. M. 1998, Buffon got it straight. *Statistics and Probability Letters, 37*(4), 415-421.

Yuan D 1997, A simulation comparison of three marginal area estimators for image classification, *Photogrammetric engineering and remote sensing*, 63 (4): 385-392

Zhen, Z., Quackenbush, L. J., Stehman, S. V., & Zhang, L. 2013. Impact of training and validation sample selection on classification accuracy and accuracy assessment when using reference polygons in object-based classification. *International Journal of Remote Sensing, 34*(19), 6914-6930.

GETTING IN TOUCH WITH THE EU

In person

All over the European Union there are hundreds of Europe Direct information centres. You can find the address of the centre nearest you at: http://europea.eu/contact

On the phone or by email

Europe Direct is a service that answers your questions about the European Union. You can contact this service:

- by freephone: 00 800 6 7 8 9 10 11 (certain operators may charge for these calls),

- at the following standard number: +32 22999696, or

- by electronic mail via: http://europa.eu/contact

FINDING INFORMATION ABOUT THE EU

Online

Information about the European Union in all the official languages of the EU is available on the Europa website at: http://europa.eu

EU publications
You can download or order free and priced EU publications from EU Bookshop at: http://bookshop.europa.eu. Multiple copies of free publications may be obtained by contacting Europe Direct or your local information centre (see http://europa.eu/contact).

KJ-NA-29027-EN-N

JRC Mission

As the science and knowledge service of the European Commission, the Joint Research Centre's mission is to support EU policies with independent evidence throughout the whole policy cycle.

EU Science Hub
ec.europa.eu/jrc

@EU_ScienceHub

EU Science Hub - Joint Research Centre

Joint Research Centre

EU Science Hub

Publications Office

doi:10.2760/979063

ISBN 978-92-79-77338-9