NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs)

*G*lobal *Lan*d *C*over *E*stimation (GLanCE) Product User Guide

Version 1.0

August 2022

Science Team

Principal Investigator: Mark Friedl
Co-Principal Investigator: Curtis Woodcock
Co-Investigator: Pontus Olofsson
Co-Investigator: Thomas Loveland
Co-Investigator: Chris Barber
Collaborator: Zhe Zhu

Document History

Version 1.0: August 2022

Table of Contents

List of Tables

1. **Dataset Overview**

1.1. General Description

To address the need for high-quality long-term records of land cover and land cover change, the data set described herein uses a long time series of Landsat imagery to create a global record of annual land cover and land cover change. Specifically, the ***G***lobal ***Lan***d ***C***over ***E***stimation (GLanCE) data record covers all land areas outside of Antarctica, includes the period from 2001-2019 at annual time steps, and is generated at 30 m spatial resolution. The science data sets (SDSs) included in the GLanCE data record provide annual information related to land cover, land cover change, and associated dynamics in surface ecological conditions. The core mapping algorithm used in this project is the Continuous Change Detection and Classification (CCDC) algorithm (Zhu and Woodcock 2014). CCDC assumes that noise is ephemeral, that land cover change is persistent, and uses all available Landsat observations to map land cover and identify the timing of land cover change at each pixel.

The GlanCE product includes 10 Science Data Sets (SDSs), all of which are described and defined in detail in Section 2. Broadly speaking, the GLAnCE SDSs are designed to characterize three broad landscape attributes:

1. Land Cover and Land Cover Change. Four SDSs provide information related to: (1) the land cover class; (2) the estimated quality associated with the land cover class[1]; (3) the previous land cover class for those pixels where change occured; and (4) the approximate day of year (DOY) of change.

2. Magnitude, Seasonality, and Changes in Greenness. Four SDSs are included that characterize annual greenness at each pixel via the Enhanced Vegetation Index (EVI2; Huete et al., 2002): (1) median; (2) amplitude; (3) rate of change (if present); and (4) magnitude of change in EVI2 median for those pixels where change occurred.

3. Leaf Type and Phenology. Two SDSs are included that indicate the inferred leaf type and phenology for pixels classified as tree cover[1].

1.2. Science Context and Background

Land cover plays a key role in the Earth's climate, ecological, and socio-economic systems (Bonan, 2008; Foley et al., 2011), and maps of land cover provide the single most important basis for characterizing the ecological state and biophysical properties of the Earth's land areas (Feddema et al., 2005; Foley et al., 2005). Land cover and land surface properties influence biosphere-atmosphere interactions and the role of land cover and land use in the global carbon cycle is both well-documented and profound (Houghton, 2020). Accurate information related to the global distribution of global land cover is therefore required to

[1]Note, this set of SDSs is not included in V1.0 but will be included in future versions of the data set.

parameterize land processes in regional-to-global scale Earth system models (Bonan et al., 2002; Fuchs et al., 2018). In addition, as the Earth's population has surged over the last several decades, the global area of land dominated by humans has rapidly expanded, ecologically important regions have been degraded, the area available for new land use (*e.g*., cities, croplands) has decreased, and land resources have become increasingly scarce (Ellis & Ramankutty, 2008; Foley et al., 2005; Goldewijk, 2001; Sanderson et al., 2002). Hence, accurate and timely information related to land cover and land cover change is essential for managing natural resources and for understanding the ecological, biogeographic, and resource management footprint of society (Song et al., 2018).

Remote sensing has been used to map land cover for over four decades (Loveland et al., 1991; Strahler, 1980; Townshend et al., 1991). Until relatively recently global land cover and land use data were only available at coarse spatial resolution from data sets such as the Global Land Cover Type product (Friedl et al., 2010; Sulla-Menashe et al., 2019) produced by NASA, and the GlobCover (Arino et al., 2008) and Climate Change Initiative Land Cover data sets (Plummer et al., 2017) produced by the European Space Agency (ESA). Because these products are based on coarse spatial resolution imagery (nominally at 500 or 300 meters), the representation of land cover they provide is highly generalized. Further, because spatio-temporal variation in most land cover occurs at spatial scales well below the resolution provided by coarse spatial resolution remote sensing, these products do not meet the needs of the large, diverse, and growing community of scientists and applied stakeholders who require high quality and high spatial resolution information related to land cover, and ultimately land cover change, over large areas.

To address this need, global land cover products at medium spatial resolution based on imagery from Landsat and other sensors such as Sentinel 1 and 2 have started to become available. The most widely used of these products tend to be focused on specific themes including urban land use or impervious surface mapping (Gong et al., 2020; Liu et al., 2021; Liu et al., 2018), forest cover (Feng et al., 2016; Hansen et al., 2013; Kim et al., 2014), or surface water (Pekel et al., 2016), and therefore support a focused community of end-users. In parallel, several general-purpose land cover maps that depict a finite set of discrete classes (generally ~10) have also been created. The GlobeLand30 data set provides maps of global land cover at 30 m for 10 classes for 2000, 2010, and 2020 (Chen et al., 2015). The iMap World data set provides land cover data and maps at 30 m for the period 1985-2020 based on Landsat imagery (Liu et al., 2021). The GLC_FCS30 product provides maps of global land cover for 2015 in three different land cover schemes with 9, 16 and 24 classes (Zhang et al., 2021) and, most recently, ESA created the WorldCover data set for 2020, which includes 11 land cover classes and is produced at 10 m spatial resolution using data from Sentinel 1 and 2 (Zanada et al. 2021). Significantly, these two latter products do not provide information related to land cover change, which is required for many applications and is essential for characterizing and modeling changes in global land cover that have occurred over the last several decades. The GLanCE data record is designed to build upon and extend the existing legacy of global land cover maps to provide high-quality long-term records of land cover and land cover change at medium spatial resolution.

2. Dataset Characteristics

The 10 Science Data Sets (SDSs) included in the GlanCE product are described in Table 1. For all datasets, "current year" is defined as starting on July 2nd and ending on July 1st. Annual SDSs are calculated based on this time period and land cover SDS is reported for July 1st. Following this convention, a change that occurs in the current calendar (January 1st -July 1st) is assigned a change DOY less than or equal to 180, and a change that occurs in the previous calendar year (July 2nd to December 31st) is assigned a DOY greater than 180. Note that the V1.0 GLanCE data set is derived from Landsat Collection 1. Future versions of the data set will use Landsat Collection 2, which should improve the quality of the data set because of the improved geolocation and data density (in some regions) provided by Collection 2 data.

2.1. Data Formats and Projection

The GlanCE data are provided as tiles with dimensions of 150 x 150 km. The pixel size is 30 m and each tile has 5000 rows x 5000 columns. Tiles are provided in GeoTIFF format and with a custom Lambert Azimuthal Equal Area projection. More information related to the custom continental projections can be found on the GLanCE Grids webpage using the Parameters tab while the grids can be found using the Grids tab as well as on GLanCE TILE shapefiles webpage on Github.

2.2. Description and Format of SDS

Table 1. GlanCE product table.

Layer Name	Short Name	Description	Units	Scale Factor	Valid Range	Data Type	Fill value
Land Cover Class	LC	Integer identifier for class in the current year.	Class #	1	[1,7]	UInt8	255
Quality Flag for Land Cover Class	QA	Integer ranging from 1 (highest quality) to 4 (lowest quality) based on posterior probability from classification; 5 indicates back-up	Dimensionless	1	[1,5]	UInt8	255

		algorithm.					
Previous Class	PrevClass	Integer identifier for class in previous year, if change has occurred; N/A if no change.	Class #	1	[1,7]	UInt8	255
Change Date	ChgDate	Estimated day of year of change; N/A if no change.	Day of Year	1	[1,365]	UInt16	32767
EVI2 median	EVI2med	Median EVI2 in the current year.	EVI2	0.0001	[-10000, 10000]	Int16	32767
EVI2 amplitude	EVI2amp	Amplitude of EVI2 in the current year.	EVI2	0.0001	[0, 20000]	UInt16	32767
EVI2 rate	EVI2rate	Rate of change in EVI2 (yr^{-1}).	EVI2	0.0001	[-20000, 20000]	Int16	32767
Change EVI2 Median	EVI2chg	Change in EVI2 median from previous year to current year; N/A if no change in land cover.	EVI2	0.0001	[-20000, 20000]	Int16	32767
Leaf type	LeafType	Integer indicating broadleaf (0) or needleleaf (1); Tree cover, NA elsewhere.	Class #	1	[0, 1]	UInt8	255
Leaf phenology	LeafPheno	Integer indicating deciduous (0) or evergreen (1); Tree cover, NA elsewhere.	Class #	1	[0, 1]	UInt8	255

EVI2 metrics included in the data set are calculated based on synthetic data (Zhu et al. 2015) derived from the modeled time segments generated by CCDC. EVI2 change rates are computed using the period defined by each CCDC time segment. This results in some years before, after or in between segments with no assigned rate of change. All other EVI2 statistics were computed from multi-temporal synthetic values, and are available for all years in the study period. EVI2 amplitude may appear higher for a single year compared to the directly preceding or subsequent years due to change or disturbance in land cover.

2.3. Classification Legend

The GLanCE Level 1 land cover legend includes 7 cover types, which are defined in Table 2.

Table 2. Land cover classes included in the GLanCE Level 1 classification scheme.

Name	Value	Description
Water	1	Areas covered with water throughout the year: streams, canals, lakes, reservoirs, oceans.
Ice/Snow	2	Land areas where snow and ice cover is greater than 50% throughout the year.
Developed	3	Areas of intensive use; land covered with structures, including any land functionally related to developed/built-up activity.
Barren/Sparsely Vegetated	4	Land consists of natural occurrences of soils, sand, or rocks where less than 10% of the area is vegetated.
Tree Cover	5	Land where the tree cover is greater than 30%. Note that cleared trees (i.e., clear-cuts) are mapped according to current cover (e.g., barren/sparsely vegetated, shrubs, or grasses).
Shrublands	6	Land with less than 30% tree cover, where total vegetation cover exceeds 10% and shrub cover is greater than 10%.
Herbaceous	7	Land covered by herbaceous cover. Total vegetation cover exceeds 10%, tree cover is less than 30%, and shrubs comprise less than 10% of the area.

3. Dataset knowledge

3.1. FAQ's

None at this time.

3.2. Known Issues

1. Version 1.0 of the data set does not include data in the Quality Assurance, Leaf Type and Leaf Phenology SDSs. We plan to include data for these layers in future releases of the data product.
2. EVI2 SDS values may be missing, or of lower quality, during years when land cover change occurs. This issue is a by-product of the fact that CCDC does not fit models or provide synthetic reflectance values during short periods of time between time segments.
3. The accuracy of mapping results varies by land cover class and geography. Specifically, distinguishing between shrubs and herbaceous cover is challenging at high latitudes and in arid and semi-arid regions. Hence, the accuracy of shrub cover, herbaceous cover, and to some degree bare cover, is lower than for other classes.

4. Due to the combined effects of large solar zenith angles, short growing seasons, lower availability of high resolution imagery to support training data, the representation of land cover at land high latitudes in the GLanCE product is lower than in mid latitudes.
5. Shadows and large variation in local zenith angles decrease the accuracy of the GLanCE product in regions with complex topography, especially at high latitudes.
6. Mapping results may include artifacts from variation in data density in overlap zones between Landsat scenes relative to mapping results in non-overlap zones.
7. Regions with low observation density due to cloud cover, especially in the tropics, and/or poor data density (e.g. Alaska, Siberia, West Africa) have lower map quality.
8. Artifacts from the Landsat 7 Scan Line Corrector failure are occasionally evident in the GLanCE map product.
9. High proportions of missing data in regions with snow and ice at high elevations result in missing data in the GLanCE SDSs.
10. The GlanCE data product tends to modestly overpredict developed land cover in arid regions.
11. Pixels with low data density (particularly towards the end of the time series) may result in mismatches among the change date and previous land cover class layers. This issue is present in the North America dataset (v001) but may be addressed for the remaining continents.
12. Some pixels may present incorrect EVI2 rate values of -32768, due to an error in the computation of predicted EVI2 values, resulting in values outside the valid range and in very large, negative, incorrect rate values that exceed the range of the pixel data type. This issue is present in the North America dataset (v001) but will be fixed for the remaining continents.

4. Dataset Access

The following tools offer options to search the LP DAAC data holdings and provide access to the *G*lobal *Lan*d *C*over *E*stimation (GLanCE) yearly 30 m (GLanCE30.001) Product data:

Bulk download: LP DAAC Data Pool and DAAC2Disk
Search and Browse: NASA Earthdata Search

5. Contact Information

LP DAAC User Services
U.S. Geological Survey (USGS)
Center for Earth Resources Observation and Science (EROS)
47914 252nd Street
Sioux Falls, SD 57198-0001

Phone Number: 605-594-6116
Toll Free: 866-573-3222 (866-LPE-DAAC)
Fax: 605-594-6963
Email: LPDAAC@usgs.gov
Web: https://lpdaac.usgs.gov

For the Principal Investigators, please contact Mark Friedl at friedl@bu.edu or Paulo Arevalo at parevalo@bu.edu.

Project web site: GLanCE: Global Land Cover Estimation

6. Data Citation

The recommended citation in APA or Chicago style is available on the Digital Object Identifier (DOI) Landing page (10.5067/MEaSUREs/GLanCE/GLanCE30.001).

An example of a citation using the Chicago style format for the MS-LSP dataset is provided below.

Arévalo, P., Stanimirova, R., Bullock, E.L., Zhang, Y., Tarrio, K., Turlej, K., Hu, K., McAvoy, K., Pasquarella, V.J., Woodcock, C.E., Olofsson, P., Zhu, Z., Gorelick, N., Loveland, T., Barber, C., Friedl, M.A. (2022). *G*lobal *Lan*d *C*over *E*stimation (GLanCE) yearly 30 m (GLanCE30.001) V001, 2022, distributed by NASA EOSDIS Land Processes DAAC, https://doi.org/10.5067/MEaSUREs/GLanCE/GLanCE30.001. Accessed YYYY-MM-DD.

7. Publications

1. Arévalo, P., Bullock, E. L., Woodcock, C. E., & Olofsson, P. (2020). A Suite of Tools for Continuous Land Change Monitoring in Google Earth Engine. *Frontiers in Climate*, *2*, 576740. https://doi.org/10.3389/fclim.2020.576740
2. Elmes, A., Alemohammad, H., Avery, R., Caylor, K., Eastman, R.J., Fishgold, L., Friedl, M.A., Jain, M., Kohli, D., Bayas, J.C.L., Lunga, D., McCarty, J.L., Pontius, R.G., Reinman, A.B., Rogan, J., Song, L., Stoynova, H., Ye, S., Yi, Z.F. and L. Estes (2020), Accounting for training data errors in machine learning applied to Earth observations, *Remote Sensing*, 12(6), 1034: https://doi.org/10.3390/rs12061034
3. Friedl M.A., Woodcock C.E., Olofsson P., Zhu Z., Loveland T., Stanimirova R., Arevalo P., Bullock E., Hu K.T., Zhang Y., Turlej K., Tarrio K., McAvoy K., Gorelick N., Wang J.A., Barber C.P., and C. Souza (2022). Medium Spatial Resolution Mapping of Global Land Cover and Land Cover Change Across Multiple Decades From Landsat, *Frontiers in Remote Sensing*, 3, https://doi.org/10.3389/frsen.2022.894571
4. Graesser, J., R. Stanimirova, K. Tarrio, E.J. Copati, J.N. Volante, S.R. Verón, S. Banchero, H. Elena, D. de Abelleyra and Mark A. Friedl (2022). Temporally-Consistent Annual

Land Cover from Landsat Time Series in the Southern Cone of South America, *Remote Sensing* 14, no. 16: 4005. https://doi.org/10.3390/rs14164005

5. Graesser, J., Stanimirova, R. and M. A. Friedl (2022) "Reconstruction of satellite time series with a dynamic smoother," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 1803-1813, *http://doi.org/10.1109/JSTARS.2022.3146081*.

6. Stanimirova, R., Graesser, J., Olofsson, P., & Friedl, M. A. (2022). Widespread changes in 21st century vegetation cover in Argentina, Paraguay, and Uruguay. *Remote Sensing of Environment*, *282*, 113277. https://doi.org/10.1016/j.rse.2022.113277

7. Wang, J.A., Baccini, A., Farina, M. R.,Randerson, J.T. and M.a. Friedl (2021). Disturbance suppresses the aboveground carbon sink in North American boreal forests. *Nat. Clim. Chang.* https://doi.org/10.1038/s41558-021-01027-4.

8. Wang, J.A. and M.A. Friedl (2019). The role of land cover change in Arctic-Boreal greening and browning trends. Environmental Research Letters, 14 125007, https://doi.org/10.1088/1748-9326/ab5429

9. Wang, J.A., Sulla-Menashe, D., Woodcock, C.E., Sonnentag, O., Keeling, R.F. and M.A. Friedl (2019). Extensive land cover change across Arctic–Boreal Northwestern North America from disturbance and climate forcing, Global Change Biology; https://doi.org/10.1111/gcb.14804.

10. Zhang, Y., Woodcock, C. E., Arévalo, P., Olofsson, P., Tang, X., Stanimirova, R., Bullock, E., Tarrio, K. R., Zhu, Z., & Friedl, M. A. (2022). A Global Analysis of the Spatial and Temporal Variability of Usable Landsat Observations at the Pixel Scale. *Frontiers in Remote Sensing*, *3*, https://doi.org/10.3389/frsen.2022.894618

11. Zhang, Y., Woodcock, C.E., Chen.S., Wang, J.A., Sulla-Menashe, D., Zuo, Z., Olofsson, P. Wang, Y and M.A. Friedl (2022). Mapping causal agents of disturbance in boreal and Arctic ecosystems of North America using time series of Landsat data, *Remote Sensing of Environment*, 272, https://doi.org/10.1016/j.rse.2022.112935.

8. Cited Literature

Arino, O., Bicheron, P., Achard, F., Latham, J., Witt, R., & Weber, J. L. (2008). GLOBCOVER The most detailed portrait of Earth. *Esa Bulletin-European Space Agency*.

Bonan, G. B., Levis, S., Kergoat, L., & Oleson, K. W. (2002). Landscapes as patches of plant functional types: An integrating concept for climate and ecosystem models. *Global Biogeochemical Cycles*. Retrieved from <Go to ISI>://000178887900007

Bonan, Gordon B. (2008). Forests and climate change: forcings, feedbacks, and the climate benefits of forests. *Science*, *320*(5882), 1444–1449.

Ellis, E. C., & Ramankutty, N. (2008). Putting people in the map: anthropogenic biomes of the world. *Frontiers in Ecology and the Environment*.

Chen, J., Chen, J., Liao, A., Cao, X., Chen, L., Chen, X., et al. (2015). Global land cover mapping at 30m resolution: A POK-based operational approach. *ISPRS Journal of Photogrammetry and Remote Sensing*, *103*, 7–27. https://doi.org/10.1016/j.isprsjprs.2014.09.002

Feddema, J. J., Oleson, K. W., Bonan, G. B., Mearns, L. O., Buja, L. E., Meehl, G. A., & Washington, W. M. (2005). The importance of land-cover change in simulating future climates. *Science*.

Feng, M., Sexton, J. O., Huang, C., Anand, A., Channan, S., Song, X.-P., et al. (2016). Earth science data records of global forest cover and change: Assessment of accuracy in 1990, 2000, and 2005 epochs. *Remote Sensing of Environment*, *184*, 73–85. https://doi.org/10.1016/j.rse.2016.06.012

Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., et al. (2005). Global consequences of land use. *Science*. https://doi.org/10.1126/science.1111772

Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., et al. (2011). Solutions for a cultivated planet. *Nature*. https://doi.org/10.1038/nature10452

Houghton, R. A. (2020). Terrestrial fluxes of carbon in GCP carbon budgets. *Global Change Biology*, *26*(5), 3006–3014. https://doi.org/10.1111/gcb.15050

Friedl, M. A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A., & Huang, X. (2010). MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. *Remote Sensing of Environment*, *114*(1), 168–182.

Fuchs, R., Prestele, R., & Verburg, P. H. (2018). A global assessment of gross and net land change dynamics for current conditions and future scenarios. *Earth System Dynamics*, *9*(2), 441–458. https://doi.org/10.5194/esd-9-441-2018

Goldewijk, K. K. (2001). Estimating global land use change over the past 300 years: The HYDE Database. *Global Biogeochemical Cycles*. https://doi.org/Doi 10.1029/1999gb001232

Gong, P., Li, X., Wang, J., Bai, Y., Chen, B., Hu, T., et al. (2020). Annual maps of global artificial impervious area (GAIA) between 1985 and 2018. *Remote Sensing of Environment*, *236*, 111510. https://doi.org/10.1016/j.rse.2019.111510

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S., Tyukavina, A., et al. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, *342*(6160), 850–853.

Jiang, Z., Huete, A.R., Didan, K., Miura, T., 2008. Development of a two-band enhanced vegetation index without a blue band. Remote Sensing of Environment 112, 3833–3845. https://doi.org/10.1016/j.rse.2008.06.006

Liu, H., Gong, P., Wang, J., Wang, X., Ning, G., & Xu, B. (2021). Production of global daily seamless data cubes and quantification of global land cover change from 1985 to 2020 - iMap World 1.0. *Remote Sensing of Environment*, *258*, 112364. https://doi.org/10.1016/j.rse.2021.112364

Liu, X., Hu, G., Chen, Y., Li, X., Xu, X., Li, S., et al. (2018). High-resolution multi-temporal mapping of global urban land using Landsat images based on the Google Earth Engine Platform. *Remote Sensing of Environment*, *209*, 227–239. https://doi.org/10.1016/j.rse.2018.02.055

Loveland, T. R., Merchant, J. W., Ohlen, D. O., & Brown, J. F. (1991). Development of a Land-Cover Characteristics Database for the Conterminous United-States. *Photogrammetric Engineering and Remote Sensing*.

Kim, D.-H., Sexton, J. O., Noojipady, P., Huang, C., Anand, A., Channan, S., et al. (2014). Global, Landsat-based forest-cover change from 1990 to 2000. *Remote Sensing of Environment*, *155*, 178–193. https://doi.org/10.1016/j.rse.2014.08.017

Pekel, J. F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*. https://doi.org/10.1038/nature20584

Plummer, S., Lecomte, P., & Doherty, M. (2017). The ESA Climate Change Initiative (CCI): A European contribution to the generation of the Global Climate Observing System. *Remote Sensing of Environment*, *203*, 2–8. https://doi.org/10.1016/j.rse.2017.07.014

Sanderson, E. W., Jaiteh, M., Levy, M. A., Redford, K. H., Wannebo, A. V., & Woolmer, G. (2002). The human footprint and the last of the wild. *Bioscience*.

Song, X.-P., Hansen, M. C., Stehman, S. V., Potapov, P. V., Tyukavina, A., Vermote, E. F., & Townshend, J. R. (2018). Global land change from 1982 to 2016. *Nature*, *560*(7720), 639–643. https://doi.org/10.1038/s41586-018-0411-9

Sulla-Menashe, D., Gray, J. M., Abercrombie, S. P., & Friedl, M. A. (2019). Hierarchical mapping of annual global land cover 2001 to present: The MODIS Collection 6 Land Cover product. *REMOTE SENSING OF ENVIRONMENT*, *222*, 183–194. https://doi.org/10.1016/j.rse.2018.12.013

Townshend, J., Justice, C., Li, W., Gurney, C., & McManus, J. (1991). Global land cover classification by remote sensing: Present capabilities and future possibilities. *Remote Sensing of Environment*.

Strahler, A. H. (1980). The Use of Prior Probabilities in Maximum-Likelihood Classification of Remotely Sensed Data. *Remote Sensing of Environment*. https://doi.org/Doi 10.1016/0034-4257(80)90011-5

Zhang, X., Liu, L., Chen, X., Gao, Y., Xie, S., & Mi, J. (2021). GLC_FCS30: global land-cover product with fine classification system at 30 m using time-series Landsat imagery. *Earth System Science Data*, *13*(6), 2753–2776. https://doi.org/10.5194/essd-13-2753-2021.

Zanaga, D., Van De Kerchove, R., De Keersmaecker, W., Souverijns, N., Brockmann, C., Quast, R., Wevers, J., Grosu, A., Paccini, A., Vergnaud, S., Cartus, O., Santoro, M., Fritz, S., Georgieva, I., Lesiv, M., Carter, S., Herold, M., Li, Linlin, Tsendbazar, N.E., Ramoino, F., Arino, O., 2021. ESA WorldCover 10 m 2020 v100. *https://doi.org/10.5281/zenodo.5571936*

Zhu, Z., Woodcock, C.E., 2014. Continuous change detection and classification of land cover using all available Landsat data. Remote Sensing of Environment 144, 152–171. https://doi.org/10.1016/j.rse.2014.01.011

Zhu, Z., Woodcock, C.E., Holden, C., Yang, Z., 2015. Generating synthetic Landsat images based on all available Landsat data: Predicting Landsat surface reflectance at any given time. Remote Sensing of Environment 162, 67–83. https://doi.org/10.1016/j.rse.2015.02.009