Organisation for Economic Co-operation and Development

OECD Climate and Environment regional statistics
Metadata

Dataset access	OECD Climate and Environment regional statistics http://dotstat.oecd.org/Index.aspx?DataSetCode=REGION_ENV
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Objective

While most OECD countries aim for climate neutrality by 2050, progress is uneven and most regions and countries will need to do more to achieve their ambitious goals. Challenges in reducing the emissions from electricity production differ by region because energy sources and infrastructure for electricity generation vary substantially across places. The objective of the OECD Climate and Environment regional statistics is to document progress on the environmental transition of regions through a wide range of indicators, including energy use, emissions by sector and exposure to extreme climate events.

The OECD Climate and Environment regional statistics dataset is released the 15th November 2022. It presents subnational statistics for OECD member and partner countries. The data production is undertaken by the Directorate of Centre for Entrepreneurship, SMEs, Regions and Cities using data sources and methodologies described as below.

Indicators

code	description_eng
CLIMATE_HAZARD	Climate hazard: Flooding, heat stress, wildfires and droughts
FLOOD	Flooding
FLOOD_R	River flooding
FLOOD_R_POP	Population exposure to river flooding
FLOOD_R_RP10_POP_SH	Share of population exposed to river flooding, 10-year return period
FLOOD_R_RP20_POP_SH	Share of population exposed to river flooding, 20-year return period
FLOOD_R_RP50_POP_SH	Share of population exposed to river flooding, 50-year return period
FLOOD_R_RP100_POP_SH	Share of population exposed to river flooding, 100-year return period
FLOOD_R_AREA	Regional area exposed to river flooding

FLOOD_R_RP10_AREA_SH	Share of regional area exposed to river flooding, 10-year return period
FLOOD_R_RP20_AREA_SH	Share of regional area exposed to river flooding, 20-year return period
FLOOD_R_RP50_AREA_SH	Share of regional area exposed to river flooding, 50-year return period
FLOOD_R_RP100_AREA_SH	Share of regional area exposed to river flooding, 100-year return period
FLOOD_R_BUILT	Built-up area exposed to river flooding
FLOOD_R_RP10_BUILT_SH	Share of built-up area exposed to river flooding, 10-year return period
FLOOD_R_RP20_BUILT_SH	Share of built-up area exposed to river flooding, 20-year return period
FLOOD_R_RP50_BUILT_SH	Share of built-up area exposed to river flooding, 50-year return period
FLOOD_R_RP100_BUILT_SH	Share of built-up area exposed to river flooding, 100-year return period
FLOOD_C	Coastal flooding
FLOOD_C_POP	Population exposure to coastal flooding
FLOOD_C_RP10_POP_SH	Share of population exposed to coastal flooding, 10-year return period
FLOOD_C_RP25_POP_SH	Share of population exposed to coastal flooding, 25-year return period
FLOOD_C_RP50_POP_SH	Share of population exposed to coastal flooding, 50-year return period
FLOOD_C_RP100_POP_SH	Share of population exposed to coastal flooding, 100-year return period
FLOOD_C_AREA	Regional area exposed to coastal flooding
FLOOD_C_RP10_AREA_SH	Share of regional area exposed to coastal flooding, 10-year return period
FLOOD_C_RP25_AREA_SH	Share of regional area exposed to coastal flooding, 25-year return period
FLOOD_C_RP50_AREA_SH	Share of regional area exposed to coastal flooding, 50-year return period
FLOOD_C_RP100_AREA_SH	Share of regional area exposed to coastal flooding, 100-year return period
FLOOD_C_BUILT	Built-up area exposed to coastal flooding
FLOOD_C_RP10_BUILT_SH	Share of built-up area exposed to coastal flooding, 10-year return period
FLOOD_C_RP25_BUILT_SH	Share of built-up area exposed to coastal flooding, 25-year return period
FLOOD_C_RP50_BUILT_SH	Share of built-up area exposed to coastal flooding, 50-year return period
FLOOD_C_RP100_BUILT_SH	Share of built-up area exposed to coastal flooding, 100-year return period
FLOOD_C_CROP	Cropland exposed to coastal flooding
FLOOD_C_RP10_CROP_SH	Share of cropland area exposed to coastal flooding, 10-year return period
FLOOD_C_RP25_CROP_SH	Share of cropland area exposed to coastal flooding, 25-year return period
FLOOD_C_RP50_CROP_SH	Share of cropland area exposed to coastal flooding, 50-year return period
FLOOD_C_RP100_CROP_SH	Share of cropland area exposed to coastal flooding, 100-year return period
FIRES	Wildfires
FIRES_POP_SH	Share of population exposed to at least one forest fire
FIRES_AREA	Total area burned (in km²)
FIRES_AREA_SH	Area burned as a share of total area
FIRES_CROP_SH	Cropland area burned as a share of total cropland area
FIRES_FOREST_SH	Forest area burned as a share of total forest area
FIRES_BUILT_SH	Built-up area burned as a share of total built-up area
DROUGHTS	Droughts
SOIL_MOIS_CHANGE	Percentage change in soil moisture (0-7 cm depth layer) compared to the reference period 1981-2010
SOIL_MOIS_CHANGE_CROP	Percentage change in cropland soil moisture (0-7 cm depth layer) compared to the reference period 1981-2010
URB_HEAT_ISLAND_EFFECT	Urban heat island
URB_HEAT_ISLAND_DAY	Daytime urban heat island: difference in land surface temperature (in °C) between the built-up area and its surroundings
URB_HEAT_ISLAND_NIGHT	Nightime urban heat island: difference in land surface temperature (in °C) between the built-up area and its surroundings
URB_HEAT_ISLAND_SUMMER_DAY	Summer daytime urban heat island: difference in land surface temperature (in °C) between the built-up area and its surroundings
URB_HEAT_ISLAND_SUMMER_NIGHT	Summer nighttime urban heat island: difference in land surface temperature (in °C) between the built-up area and its surroundings
CDD_HDD	Heating and cooling degree days
CDD	Cooling degree days
HDD	Heating degree days
CDD_CHANGE	Additional cooling degree days, compared to 1981-2010

HDD_CHANGE	Additional heating degree days, compared to 1981-2010
GHG_EMISSIONS	Green house gas emissions
GHG_TOTAL	Total greenhouse gas emissions (in Mt of CO2 equivalent)
GHG_TOTAL_PC	Total greenhouse gas emissions per capita (in tons of CO2 equivalent per capita)
GHG_INDUSTRY	Greenhouse gas emissions from industries
GHG_POWER	Greenhouse gas emissions from the power sector
GHG_BUILDINGS	Greenhouse gas emissions from buildings
GHG_AGRICULTURE	Greenhouse gas emissions from agriculture
GHG_WASTE	Greenhouse gas emissions from waste
GHG_TRANSPORT	Greenhouse gas emissions from transport
GHG_ROAD_TRANSPORT	Greenhouse gas emissions from road transport
ELECTRICITY	Electricity generation by energy sources
ELEC_CARB_INTENS	Carbon intensity of electricity
ELEC_FOSSIL_SH	Share of fossil fuels in electricity generation
ELEC_COAL_SH	Share of coal in electricity generation
ELEC_OIL_SH	Share of oil in electricity generation
ELEC_GAS_SH	Share of gas in electricity generation
ELEC_NUCL_SH	Share of nuclear power in electricity generation
ELEC_RES_SH	Share of renewable energy sources in electricity generation
ELEC_HYDRO_SH	Share of hydro power in electricity generation
ELEC_WIND_SH	Share of wind power in electricity generation
ELEC_SOLAR_SH	Share of solar power in electricity generation
ELEC_OTHERRES_SH	Share of other renewable sources in electricity generation (biomass, geothermal, waste, wave and tidal)
ELEC_OTHER_SH	Share of other sources in electricity generation
ELEC_TOT	Total gross electricity generation (GWh)
ELEC_FOSSIL	Gross electricity generation from fossil fuels (GWh)
ELEC_COAL	Gross electricity generation from coal (GWh)
ELEC_OIL	Gross electricity generation from oil (GWh)
ELEC_GAS	Gross electricity generation from gas (GWh)
ELEC_NUCL	Gross electricity generation from nuclear (GWh)
ELEC_RES	Gross electricity generation from renewable energy sources (GWh)
ELEC_HYDRO	Gross electricity generation from hydro power (GWh)
ELEC_WIND	Gross electricity generation from wind power (GWh)
ELEC_SOLAR	Gross electricity generation from solar power (GWh)
ELEC_OTHERRES	Gross electricity generation from other renewable sources (biomass, geothermal, waste, wave and tidal) (GWh)
ELEC_OTHER	Gross electricity generation from other sources (GWh)
MUN_WAST	Municipal waste
WASTE	Municipal Waste (in kilo-tonnes)
WASTE_RA	Municipal Waste Rate (kilos per capita)
WAST_RECYCL	Volume of recycled waste (Ktonnes)
WAST_RECYCL_SH	Share of municipal waste recycled
WAST_LANDFILL	Municipal waste used in controlled landfilling (Ktonnes)
WAST_LANDFILL_SH	Share of municipal waste used in controlled landfilling
POLLUT	Pollution
PWM_EX	Air pollution in PM2.5 (average level in µg/m³ experienced by the population)
SPEX_MORE_THAN_5	Share of population exposed to a PM2.5 concentration above 5 µg/m³
SPEX_MORE_THAN_10	Share of population exposed to a PM2.5 concentration above 10 µg/m³
SPEX_MORE_THAN_15	Share of population exposed to a PM2.5 concentration above 15 µg/m³
SPEX_MORE_THAN_25	Share of population exposed to a PM2.5 concentration above 25 µg/m³
SPEX_MORE_THAN_35	Share of population exposed to a PM2.5 concentration above 35 µg/m³

Data sources

Indicator	Source	Year	Territorial level
Agricultural droughts	Copernicus Climate Data Store ERA5-Land monthly average data product.	1981-2021	2, 3, FUA
Electricity indicators	Byers, L. et al. (2021), *A Global Database of Power Plants*, https://datasets.wri.org/dataset/globalpowerplantdatabase. Dunnett, S. et al. (2020), "Harmonised global datasets of wind and solar farm locations and power", *Scientific Data*, Vol. 7/130, https://doi.org/10.1038/s41597-020-0469-8.	2019	2, 3
Forest fires	Joint Research Centre's (JRC) Global wildfire dataset for the analysis of fire regimes and fire behaviours, based on MODIS burned area product Collection 6. See methodology in Annex C	2001-2020	2
Greenhouse gas (GHG) emissions	Emissions Database for Global Atmospheric Research (EDGAR), version 6.0 of the European Commission (EC) JRC	1998-2018	2, 3
Population: Exposure to floods	River Flood Hazard Maps at European and Global Scale, 100, 50, 20 10-year return periods.		2

Municipal waste

Country	Source	Last year	Territorial level
Australia	National Waste report	2018	2
Austria	Environment Agency Austria (UBA) - Austrian Federal Waste Management Plan and related Status Reports	2019	2
Belgium	Statbel (Bruxelles data collected from Brussels Environment, Flemish Region data collected from OVAM)	2020	2
Chile	INE, Chile. Pollutant Release and Transfer Register (PRTR) - Registro de Emisiones y Transferencias de Contaminantes (RETC)	2017	2
Colombia	DANE	2019	2
Costa Rica	INEC	2020	2
Czech Republic	Czech Statistical Office CZSO, Annual statistical survey	2020	2
Estonia	Eurostat, Municipal waste (env_rwas_gen)	2013	2
France	Odd-numbered years: Ademe survey data; Even-numbered years: SDES estimates	2019	2
Germany	Waste Statistics of the Federal Statistical Office and the Statistical Offices of the Federal States, Spatial Monitoring System of the BBSR	2020	2
Hungary	HCSO, Hungarian Central Statistical Office	2019	2
Israel	Central Bureau of Statistics Israel	2017	2
Italy	ISPRA (Italian Institute for Environmental Protection and Research)	2020	2
Japan	Ministry of Internal Affairs and Communications	2020	2
Korea	Korean Ministry of Environment	2020	2
Latvia	Official statistics "2-Waste" by Latvian Environment, Geology and Meteorology Agency	2020	2
Luxembourg	Eurostat, Municipal waste (env_rwas_gen)	2013	2
Mexico	INEGI. Censo Nacional de Gobiernos Municipales y Delegacionales 2017	2020	2
Netherlands	Statistics Netherlands	2020	2
Norway	Statistics Norway	2020	2
Poland	Central Statistical Office	2020	2
Portugal	Statistics Portugal, Urban waste statistics	2020	2
Slovak Republic	Statistical Office of the SR statistical survey	2020	2
Slovenia	SURS, Generated amounts	2020	2
Sweden	Swedish Environmental Protection Agency	2020	2
Türkiye	Municipal Waste Statistics Survey	2014	2
United Kingdom	Department for Environment, Food and Rural Affairs, Local Authority Collected Waste Statistics	2020	2

United States	n.a.	-	-

Methodologies

Methodology to estimate soil moisture anomaly

Water content in the superficial layers of the soil is important for water supply and vegetation health. Soil moisture anomaly is a suitable indicator for monitoring the intensity of agricultural droughts. This publication measures agricultural droughts in terms of cropland soil moisture anomaly using the Copernicus Climate Data Store ERA5-Land monthly average data product (European Centre for Medium-range Weather Forecasts, 2022[7]). It is a global gridded product with a 0.1° spatial resolution (~ 11.1 km) from 1950 to the present and provides land variables related to the energy and water cycles over several decades. It contains per-pixel information of the monthly average volume of water in the surface soil layer of 0 to 7 cm deep, expressed as m^3 of water per m^3 of soil. The Copernicus annual 300 m land cover (CCI-LC) (European Space Agency Climate Change Initiative, 2019[8]) enables to get cropland boundaries. Cropland here includes: cropland, rainfed, irrigated or post-flooding; mosaic cropland (>50%)/ natural vegetation (tree, shrub, herbaceous cover) (<50%); and mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%)/cropland (<50%). Once soil moisture grid cells for each year are selected based on cropland land cover, cropland soil moisture anomaly is obtained by computing the percentage change based on the reference period (1981-2010).

Methodology to estimate public transport accessibility

Public transport accessibility is measured using Open Street Map (OSM) (Haklay and Weber, 2008[9]) to get public transport stops. Because of the lack of reliability of OSM in small cities, this publication only focuses on the largest FUA of each OECD country. The Mapbox isochrone API (Mapbox, 2022[10]) then enables to compute isochrones from these public transport stops to get to all the areas located within 10-min walking distance. The Global Human Settlement Population layer 2015 then enables to get the share of the population in each FUA who has access to public transport in less than a 10-min walk.

Methodology to estimate exposure to wildfires

Burnt area by land cover was obtained using JRC's Global wildfire dataset for the analysis of fire regimes and fire behaviours (Artes Vivancos et al., 2019[11]), based on MODIS burned area product Collection 6. This dataset provides monthly individual fire perimeters for 2001-20. Burnt areas are aggregated at the yearly level and then crossed with Copernicus annual 300 m land cover (CCI-LC) data (European Space Agency Climate Change Initiative, 2019[8]).

Population exposure to wildfires over 2010-20 was computed by merging monthly wildfire perimeters and by then taking a 5 km buffer. The Global Human Settlement Population layer for 2015 (Schiavina, Freire and MacManus, 2019[12]) enabled then to compute the population exposed to at least one fire over 2010-20.

Methodology to estimate exposure to river floods

Population exposure to river floods was estimated using the River Flood Hazard Maps at European and Global Scale (Dottori et al., 2021[13]). For OECD countries located in Europe and the Mediterranean Basin, the regional map was used, as the spatial granularity is 250 m. For the remaining OECD countries, the global map with a spatial granularity of 1 km was used. These datasets identify flooded areas for river flood events of different return periods (10 to 500 years). A return period refers to the estimated time interval between floods of similar intensity. Here a return period of 100 years is considered. The 100-year return period is calculated based on past events but the frequency of such climate-related disasters is likely to increase. Changes in flood risk are unevenly distributed, with the largest increases in America, Asia and Europe but without higher flood protection standards, flood events are projected to rise in all continents. Therefore, 100-year floods are likely to happen more often going forward.

Methodology to estimate population exposure to heat stress

Population exposure to heat stress was estimated using the Universal Thermal Comfort Index (UTCI). The UTCI considers air temperature, wind, radiation and humidity and enables to assess the impact of atmospheric conditions on the human body: 32°C < UTCI < 38°C is considered as strong heat stress, 38°C < UTCI < 46°C as very strong heat stress, and UTCI > 46°C as extreme heat stress.

The Copernicus Climate Data Store provides hourly thermal comfort indices grids derived from ERA5 reanalysis (CDS, 2022[14]). The spatial resolution is 0.25°x0.25°. To obtain the population exposure to strong heat stress, we applied the following steps:

- Compute daily maximum UTCI grids.
- Apply a threshold of 32°C on these daily masks and sum by year to get yearly grids of the number of days of strong heat stress or worse.
- Compute by large region zonal statistics weighted by population by using the GHSL-POP layers.
- Consider 1981-2010 as the reference period to get the reference average number of days of strong heat stress and compare this value with recent years.

Methodology to estimate electricity indicators at the regional level

To estimate the electricity indicators at the regional level, the Global Power Plant Database (GPPD) (Byers et al., 2021[15]), the International Energy Agency (IEA) electricity and heat database (OECD, 2022[16]) and the harmonised global dataset of wind and solar farm (GWS) locations and power (Dunnett et al., 2020[17]) are used.

The GPPD provides information on power plants located in 167 countries all over the world, including the 38 OECD countries. For each power plant, the GPPD provides the geographic co-ordinates and the following attributes:

- The energy source: oil, gas, coal, petroleum coke, cogeneration, hydro, wind, waste, biomass, wave and tidal, geothermal, solar, nuclear and others.
- The generation capacity, which is the maximum power (in megawatts, MW) that the plant can deliver. The capacity is a facility-specific characteristic and does not change over time, unless extension or upgrade of the power station, or a shutdown of a part of it.
- The annual electricity generation, which provides the amount of electricity generated over a year (in GWh). This indicator is reported over the period 2013-19. When no electricity generation was reported, the annual electricity generation was estimated. The annual generation corresponds to the gross generation, i.e. the electricity consumption of the power plant for its operation is not deducted.

- The country where the power plant is registered.

As the coverage of wind and solar power plants in the GPPD was not satisfying, the GWS farm locations and power was used instead to get the locations of wind and solar power sources.

The International Energy Agency (IEA (IEA, 2022[18])) database includes national-level electricity generation data by energy source for most OECD countries. The IEA dataset used to estimate electricity generation indicators at the local level corresponds to the gross electricity production by energy source in 2019. A breakdown of 53 different sources is available.

Electricity generation estimates

In order to remain consistent across countries and energy sources, electricity generation was estimated at the power plant level based on the relative capacity of each power plant (from the GPPD and GWS) and on the total national electricity generation form each energy source (from the IEA). The methodology follows the four steps below:

1. Map energy sources from the IEA to the GPPD classification.

   The IEA electricity production data provides a higher level of detail in terms of breakdown by energy source compared to the GPPD data. For this reason, each energy source type recorded in the IEA database was matched to a source category in the GPPD.

2. Determine the share of national capacity for each power plant.

   For each power plant *p*, located in the country *c* and generating electricity from the energy source *f*, the share of the capacity of the power plant in the national capacity for the source *f* is calculated as:

   $$share_{p,c,f} = \frac{capacity_{p,c,f}}{\sum_i capacity_{i,c,f}}$$

   where *i* ∈ power plants located in the country *c*, and generating electricity from the source f.

3. Allocate a part of the national generation to each power plant.

   For each power plant *p*, generating electricity from source *f*, in the country *c*, the estimated generation is calculated as:

   $$generation_{p,c,f} = share_{p,c,f} * national\ generation_{c,f}$$

Aggregation at local scales

To compute indicators at different geographical scales, a point shapefile was created from the GPPD and GWS databases using the latitude and longitude provided for each facility – each point representing a power plant. The point shapefile was overlapped with two other shapefiles corresponding to the boundaries of the subnational geographies available in OECD countries (TL2 and TL3 regions). Thus, each power plant can be associated to a TL2 region and a TL3 region. Offshore power plants were assigned to the closest region (of the registered host country) based on the distance to the coast.

Year of reference

All indicators presented in this document refer to the year 2019, which corresponds to the latest year for which capacity data is available in the GPPD.

Breakdown by energy source categories

The GPPD includes 13 different energy sources. These energy sources were aggregated into 6 categories (coal, gas, oil, nuclear, renewables and others). The energy sources within each category are comparable in terms of technology, risks and impacts on the environment.

Electricity generation indicators

For each region *r*, generation data was aggregated into each category *i* as:

$$generation_{r,i} = \sum_{k \in i} power\ plant\ generation_{r,k}$$

where *k* ∈ {coal, gas, oil, petroleum coke, cogeneration, nuclear, hydro, wind, waste, biomass, wave, geothermal, solar}, *i* ∈ { coal, gas, oil, nuclear, renewables and others}, and $power\ plant\ generation_{r,k}$ is the electricity generation of a power plant located in the region *r*, generating electricity from the source type *k*.

Energy mix indicators

For each region *r*, the share of each energy source category *i* is calculated as:

$$share_{r,i} = \frac{generation_{r,i}}{\sum_j generation_{r,j}} * 100$$

where *j* ∈ {coal, gas, oil, nuclear, renewables, others}.

Greenhouse gas (GHG) emissions from electricity generation indicators

GHG emissions indicators are derived from both the electricity generation by energy source and the emission factors for each energy source. Electricity generation was estimated at the power plant level for each energy source included in the GPPD as described above. Emission intensity by energy source comes from the IPPC estimates on GHG emissions of supply technologies.

For each region *r*, the GHG emissions (in tons of CO_2 equivalent) are calculated as:

$$emissions_r = \sum_{k \in f} generation_{r,k} * emission\ intensity_k$$

where the emission intensity corresponds to the median value of the lifecycle emissions (in gCO2eq/kWh), *f* ∈ {coal, gas, oil, petroleum coke, cogeneration, nuclear, hydro, wind, waste, biomass, wave, geothermal, solar}.

Emission intensity

For each region *r*, the emission intensity (in tons of CO_2 equivalent per GWh) is calculated as:

$$emission\ intensity_r = \frac{emissions_r}{\sum_i generation_{r,i}}$$

where *i* ∈ {coal, gas, oil, nuclear, renewables and others}.

Methodology to estimate GHG emissions by sector

GHG emissions at the subnational level were estimated using the Emissions Database for Global Atmospheric Research (EDGAR) (Crippa et al., 2021[19]), version 6.0 of the EC JRC. EDGAR provides annual sector-specific grid maps for the three main GHGs (CO_2, CH_4, and N_2O) at a 0.1° spatial resolution (~11 km). Other GHGs, such as fluorinated gases, are not available at the moment. The different sectors and subsectors covered are:

- **Energy industry**:
  - **Energy production**: Power industry (IPCC 2006: 1A1a).
  - **Energy transformation**: Oil refineries and transformation industry (1A1b, 1A1ci, 1A1cii, 1A5biii; 1B1b, 1B2aiii6, 1B2biii3, 1B1c).
  - **Energy extraction**: Fuel exploitation (oil, coal, natural gas) (1B1a, 1B2aiii2, 1B2aiii3, 1B2bi, 1B2bii).
- **Manufacturing industry**: Combustion for manufacturing (1A2), chemical processes (2B), iron and steel production (2C1, 2C2), non-ferrous metals production (2C3 to 2C7), non-energy use of fuels (2D1, 2D2, 2D4), solvents and products use (2D3, 2E, 2F, 2G), non-metallic minerals production (2A), oil refineries and transformation industry (1A1b, 1A1ci, 1A1cii, 1A5biii; 1B1b, 1B2aiii6, 1B2biii3, 1B1c).
- **Buildings**: Energy for buildings (1A4+1A5).
- **Waste**: waste water handling (4D), solid waste landfills (4A+4B), solid waste incineration (4C).
- **Transport**: Road transportation (1A3b), aviation (1A3a), shipping (1A3d), railways, pipelines, off-road transport (1A3c+1A3e).
- **Agriculture**: Enteric fermentation (3A1), manure management (3A2), agricultural waste burning (3C1b), agricultural soils (3C2+3C3+3C4+3C7), indirect N_2O emissions from agriculture (3C5+3C6).
- **Other**: Fossil fuel fires (5B), indirect emissions from NOx and NH_3 (5A).

Emissions from Land Use and Land Cover Change (LULCC) are not included. National GHG emissions are disaggregated by using subsector-specific geospatial proxies. For example, the road transport emissions estimates are based on different types of road networks extracted from Open Street Map (Haklay and Weber, 2008[9]) (highways, primary and secondary, residential and commercial roads) and different weighting factors for each road type. Road traffic is not directly considered. For more details about the disaggregation methodology, refer to the *OECD Regional Outlook 2021* (OECD, 2021[20]).

GHG emissions are expressed in CO_2 equivalents using 100-year global warming potential from the IPCC 5th Assessment Report (AR5), i.e. 28 for CH_4, and 265 for N_2O.

Methodology to estimate emissions from key manufacturing sectors

European Union Emission Trading System (EU-ETS, 2020[21]) emissions and ORBIS (Pinto Ribeiro, Menghinello and De Backer, 2010[22]) data were used to estimate emissions in key manufacturing sectors. EU-ETS emissions data cover high emissions installations and provide the exact location of each installation. They cover most emissions in refined petroleum and coke, chemicals, basic metals and other non-metallic minerals. However, publicly available ETS emissions data provide limited information on the sectoral origin of emissions within manufacturing and this information does not follow NACE sectors. Most ETS emissions are attributed to fuel combustion with no breakdown. ETS emissions have been mainly attributed to NACE sectors according to the main activity of businesses owning installations using ORBIS business data.

For more details on the methodology, refer to *Regional Industrial Transitions to Climate Neutrality: Identifying vulnerable regions* (OECD, forthcoming[23])

Methodology to estimate regional energy intensity in European large regions

Regional energy intensity estimates were obtained using the following Eurostat datasets:

- Energy supply and use by NACE Rev. 2 activity (env_ac_pefasu) (Eurostat, 2022[24]).
- SBS data by NUTS 2 regions and NACE Rev. 2 (from 2008 onwards) (sbs_r_nuts06_r2) (Eurostat, 2021[25]).

National energy consumption data by NACE sector for European countries provided in env_ac_pefasu were disaggregated using the NUTS-2 employment data by NACE sector given in sbs_r_nuts06_r2.

References

Artes Vivancos, T. et al. (2019), "A global wildfire dataset for the analysis of fire regimes and fire behaviour", *Scientific Data*, Vol. 6, p. 296. [11]

Byers, L. et al. (2021), *A Global Database of Powerplants*, https://www.wri.org/publication/global-power-plant-database. [15]

CDS (2022), *Thermal Comfort Indices Derived from ERA5 Reanalysis*, Copernicus Climate Change Service Climate Data Store, https://cds.climate.copernicus.eu/cdsapp#!/dataset/derived-utci-historical?tab=overview. [14]

Chakraborty, T. and X. Lee (2019), "A simplified urban-extent algorithm to characterize surface urban heat islands on a global scale and examine vegetation control on their spatiotemporal variability", *International Journal of Applied Earth Observation and Geoinformation*, Vol. 74, pp. 269-280, https://doi.org/10.1016/j.jag.2018.09.015. [2]

Crippa, M. et al. (2021), *EDGAR v6.0 Greenhouse Gas Emissions*, Joint Research Centre (JRC), European Commission, http://data.europa.eu/89h/97a67d67-c62e-4826-b873-9d972c4f670b. [19]

Dingel, J. and B. Neiman (2020), "How many jobs can be done at home?", *Becker Friedman Institute White Paper March*, https://bfi.uchicago.edu/working-paper/how-many-jobs-can-be-done-at-home/. [29]

Dottori, F. et al. (2021), "River flood hazard maps for Europe and the Mediterranean Basin region", Joint Research Centre (JRC), European Commission. [13]

Dunnett, S. et al. (2020), "Harmonised global datasets of wind and solar farm locations and power", *Scientific Data*, Vol. 7/1, p. 190, https://doi.org/10.1038/s41597-020-0469-8. [17]

EEA (2020), *Urban Atlas LCLU 2018*, European Environment Agency, https://land.copernicus.eu/local/urban-atlas/urban-atlas-2018. [26]

EU-ETS (2020), *Verified Emissions for 2019*, European Union Emission Trading System, https://ec.europa.eu/clima/eu-action/eu-emissions-trading-system-eu-ets/union-registry_en#ecl-inpage-1121. [21]

European Centre for Medium-range Weather Forecasts (2022), *ERA5-Land Monthly Averaged Data from 1950 to Present*, https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land-monthly-means?tab=overview. [7]

European Space Agency Climate Change Initiative (2019), *Land Cover Classification Gridded Maps from 1992 to Present Derived from Satellite Observations*. [8]

Eurostat (2022), *Energy Supply and Use by NACE Rev. 2 Activity*, https://ec.europa.eu/eurostat/databrowser/view/env_ac_pefasu/default/table?lang=en. [24]

Eurostat (2021), *Structural Business Statistics Data by NUTS 2 Regions and NACE Rev. 2 (from 2008 onwards)*, https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=sbs_r_nuts06_r2&lang=en. [25]

Friedl, M. and D. Sulla-Menashe (2019), *MCD12Q1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 500m SIN Grid V006. NASA EOSDIS Land Processes DAAC*, NASA EOSDIS Land Processes DAAC. [3]

Haklay, M. and P. Weber (2008), "OpenStreetMap: User-generated street maps", *IEEE Pervasive Computing*, Vol. 7, pp. 12-18. [9]

IEA (n.d.), ""OECD - Electricity and heat generation"", *IEA Electricity Information Statistics*, https://doi.org/10.1787/data-00457-en (accessed on 24 October 2022). [18]

JRC (2022), *GHSL Data Package 2022: Public Release GHS P2022*, European Commission Joint Research Centre, https://data.europa.eu/doi/10.2760/19817. [27]

Mapbox (2022), *Isochrone API*, https://docs.mapbox.com/api/navigation/isochrone/. [10]

OECD (2022), "OECD - Electricity/heat supply and consumption", *IEA Electricity Information Statistics*, OECD, Paris, https://doi.org/10.1787/e2da2a08-en (accessed on 13 October 2022). [16]

OECD (2022), *Regional Industrial Transitions to Climate Neutrality: Identifying vulnerable regions*, OECD Publishing, Paris. [23]

OECD (2021), *OECD Regional Outlook 2021: Addressing COVID-19 and Moving to Net Zero Greenhouse Gas Emissions*, OECD Publishing, Paris, https://doi.org/10.1787/17017efe-en. [20]

Pinto Ribeiro, S., S. Menghinello and K. De Backer (2010), "The OECD ORBIS Database: Responding to the Need for Firm-Level Micro-Data in the OECD", *OECD Statistics Working Papers*, No. 2010/1, OECD Publishing, Paris, https://doi.org/10.1787/5kmhds8mzj8w-en. [22]

Schiavina, M., S. Freire and K. MacManus (2019), "GHS population grid multitemporal (1975, 1990, 2000, 2015)". [12]

Tadono, T. et al. (2014), "Precise Global DEM Generation By ALOS PRISM, ISPRS Annals of the Photogrammetry", *Remote Sensing and Spatial Information Sciences*, Vol. II-4, pp. 71-76. [4]

Wan, Z., S. Hook and G. Hulley (2021), *MODIS/Aqua Land Surface Temperature/Emissivity Daily L3 Global 1km SIN Grid V061*. [6]

Wan, Z., S. Hook and G. Hulley (2015), *MOD11A1 MODIS/Terra Land Surface Temperature/Emissivity Daily L3 Global 1km SIN Grid V006*. [5]

Zanaga, D. et al. (2021), *ESA WorldCover 10 m 2020 v100*, https://doi.org/10.5281/zenodo.5571936. [1]