

Article

Harmonized Global-to-Regional Gridded Methane Inventories in a Discrete Global Grid Framework

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Abstract

Heterogeneous gridded environmental datasets are increasingly used in Earth system modeling, atmospheric studies, and spatial analytics, but differences in coordinate reference systems, spatial resolutions, sector classifications, reporting units, and data formats hinder interoperability and cross-dataset comparison. Conventional latitude–longitude grids further introduce unequal cell areas that bias aggregation and regional comparison. This study presents a framework for harmonizing heterogeneous gridded datasets within a Discrete Global Grid System (DGGS), using explicit grid-selection criteria, area-weighted mass-preserving conversion, cross-scheme sector mapping, and five measurable evaluation criteria. Using methane as a demanding case, we transformed 13 open-access inventories from global to subnational scales into the rearranged Hierarchical Equal-Area isoLatitude Pixelization (rHEALPix) DGGS, harmonizing 324 source variables from five classification schemes and standardizing values to megagrams per year per cell. Conversion preserved emission totals, with negligible differences for continental, national, and regional inventories and differences within 2% to 3% for global inventories. Cell area is constant by construction, aggregation along the hierarchy is exact, and inventories at different resolutions can be compared after aggregation. The framework is reproducible and extensible to other gridded spatial data.

Keywords: discrete global grid systems; rHEALPix; methane emission inventory; spatial harmonization

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1. Introduction

The rapid growth of environmental and Earth observation datasets has created increasing demand for interoperable geospatial frameworks capable of supporting cross-scale analysis, reproducible workflows, and machine-readable integration across heterogeneous data sources [1,2]. Environmental datasets are now routinely used in Earth system modeling, atmospheric studies, climate risk assessment, geospatial analytics, and data-driven applications [3]. However, large-scale integration of these datasets remains challenging because products are often distributed using different coordinate reference systems (CRSs), spatial resolutions, data structures, semantic classifications, and reporting units. Even when datasets describe similar environmental phenomena, substantial preprocessing is typically required before they can be compared, aggregated, or jointly

analyzed. These inconsistencies create barriers to interoperability, reproducibility, and scalable geospatial analysis [4].

A further challenge arises from the widespread use of latitude–longitude graticules as the default spatial framework for environmental data products. Because grid-cell areas decrease toward the poles, latitude–longitude grids introduce spatial distortions that complicate cross-region comparison, aggregation, and interpretation of areal intensity patterns [5,6]. Although normalization approaches and auxiliary area grids are commonly used, they do not fully resolve the structural limitations associated with unequal-area tessellations. As environmental datasets continue to grow in spatial extent, temporal frequency, and thematic diversity, there is an increasing need for spatial data infrastructures that provide equal-area representation, hierarchical scalability, and consistent indexing across resolutions and domains.

Discrete Global Grid Systems (DGGS) have emerged as a promising geospatial framework for addressing these challenges. DGGS partition the Earth’s surface into a globally exhaustive and hierarchically refinable set of indexed cells that support consistent spatial representation across scales [5]. Equal-area DGGS frameworks ensure that cells at the same resolution have equal area regardless of latitude, so equal per-cell emission totals correspond to equal areal intensities. Their hierarchical indexing also supports straightforward aggregation across nested resolutions without repeated reprojection or custom spatial transformations. The persistent indexing structure of DGGS also facilitates integration between heterogeneous geospatial datasets through table-style joins and machine-readable spatial keys [7–9]. Recent studies have demonstrated the utility of DGGS in diverse geospatial applications, including multi-source maritime risk modeling [10], climate-informed flood mapping [11], interoperable land-use mapping [12], spatial prediction of social phenomena [13,14], and machine-learning-ready spatial databases, where the grid provides the spatial organization and indexing of thousands of variables across multiple granularities [15]. These studies highlight the potential of DGGS to function not only as a spatial indexing system but also as a scalable spatial data fabric for interoperable Digital Earth applications.

Gridded methane emission inventories provide a particularly demanding demonstration case for DGGS-based harmonization because they are widely used across atmospheric science, emissions monitoring, and climate mitigation applications while exhibiting substantial heterogeneity in spatial representation and reporting structure. These inventories serve as spatially explicit priors for atmospheric inversions, support comparisons between modeled and observed methane concentrations, and provide baseline information for regional assessments and mitigation planning. Regional atmospheric inversions in western Canada revealed discrepancies relative to widely used methane priors [16], satellite-based analyses in the Permian Basin used gridded inventories to contextualize detected variability [17,18], and national assessments have compared inventories across scales to evaluate consistency and spatial patterns [17,19,20]. Beyond inverse modeling, spatially explicit inventories also support alignment with field measurements and simulation of short-duration high-emission events [21,22]. At the same time, existing methane inventories differ substantially in CRS, spatial resolutions, file formats, sector classification schemes, reporting units, and temporal coverage. Some products are distributed as global latitude–longitude rasters [23–26], while others use projected coordinate systems, such as the Swiss inventory in CH1903/LV03 [27], or high-resolution regional grids, such as the New York State inventory at 100 m resolution [28]. Sector definitions may follow the Intergovernmental Panel on Climate Change (IPCC) classifications, Common Reporting Tables (CRT), Gridded Nomenclature for Reporting (GNFR), or custom schemes, while reporting units range from flux-based representations to mass-per-area and total-emission formats. Even when inventories are internally consistent, these

differences complicate like-for-like comparison, aggregation, and integration with observations or analytical workflows. Furthermore, most gridded inventories are provided on latitude–longitude graticules, where cell areas vary with latitude. This non-uniformity can distort visual interpretation and complicate intensity calculations, particularly at higher latitudes. While some datasets provide per-cell area to aid normalization, comparisons across regions and scales remain non-trivial. In practice, these differences require custom data processing for each analysis, making it difficult to scale, reproduce, or combine results across multiple inventories.

In this study, we adopt the rearranged Hierarchical Equal-Area isoLatitude Pixelization (rHEALPix) DGGS as a standardized spatial framework for harmonizing heterogeneous methane emission inventories from global to regional scales. We harmonize 13 open-access gridded methane inventories spanning global, continental, national, and sub-national domains, including datasets for the United States, Canada, Mexico, Europe, China, India, Australia, Switzerland, and New York State. This DGGS-based approach provides an equal-area, congruent, hierarchically nested tessellation with consistent cell indexing, enabling alignment across spatial resolutions while preserving emission mass during spatial transformation. By converting heterogeneous native grids into standardized rHEALPix cells, we harmonize the spatial reference (“where” emissions occur), semantic classification (“what” emission sources represent), and quantitative reporting (“how much” emissions are reported), resulting in a spatially and semantically coherent dataset optimized for comparison and reuse. The objectives of this study are to define the grid properties required for harmonizing gridded inventories, standardize spatial structure, sector classification, and reporting units within a unified workflow, establish measurable evaluation criteria, and demonstrate the framework using 13 methane inventories. Equal-area DGGS have been assessed as a framework for methane emissions management using facility-level activity data [29]. This study harmonizes independently produced gridded inventories and provides a mass-preserving conversion workflow, a crosswalk of five sector classification schemes to IPCC 2006, standardized reporting units, and a validated dataset released for reuse. This work does not re-estimate emissions or resolve uncertainties in the original inventories, but focuses on improving comparability, interoperability, and reusability across heterogeneous environmental datasets.

2. Materials and Methods

2.1. Source Gridded Inventories

This study includes 13 open-source, bottom-up gridded methane inventories developed since 2010 and made publicly accessible through peer-reviewed publications or official repositories. The selected datasets span global, continental (Europe), national (United States, Canada, Mexico, China, Switzerland, India, and Australia), and high-resolution subnational (New York State) inventories. Particular emphasis is placed on energy-related methane emissions, including coal mining and oil and gas systems, given their dominant role in anthropogenic methane budgets and their high relevance for climate mitigation [30]. For datasets available in multiple versions, the most recent release was used in this study, except for the Global Fuel Exploitation Inventory (GFEI), for which three distinct versions corresponding to different reporting years (2016, 2019, and 2020) were included. Table 1 lists spatial coverage, CRS, spatial resolution, temporal coverage, file formats, sector classification schemes, and reporting units. Further details on individual datasets are provided in the Supplementary Information.

These inventories differ substantially in their original formats, CRS, sectoral classification schemes, spatial resolutions, and reporting units. For example, Emissions Database for Global Atmospheric Research (EDGAR) v8.0 Greenhouse Gas Emissions and GFEI provide global grids at $0.1^\circ \times 0.1^\circ$ resolution in NetCDF format under the Geographic

Coordinate System WGS84 [23–26]. Several national gridded inventory products adopt the same convention, including the U.S. Anthropogenic Methane Emissions (2012–2018), Canada Anthropogenic Methane Emissions in 2018, and Mexico Anthropogenic Methane Emissions in 2015 [20,31,32]. However, some of the other national datasets follow different approaches, such as China’s CHN-CH₄ product at about 10 km × 10 km resolution in the Krasovsky 1940 Albers projection in GeoTIFF format [33], and Switzerland Greenhouse Gas Inventory at 500 m × 500 m resolution in CH1903/LV03 with NetCDF format [27]. The Copernicus Atmosphere Monitoring Service Regional (CAMS-REG) emissions inventory provides European coverage at 0.05° × 0.1° resolution on a WGS 84 latitude–longitude grid, distributed as NetCDF or CSV files [34]. The Gridded New York State Methane Emissions Inventory dataset is at 100 m × 100 m resolution in UTM Zone 18N with NetCDF format [28]. As shown in Table 1, category codes also vary across inventories. Some datasets report emissions directly using IPCC 2006 or 1996 codes, others follow the CRT, and some lack explicit coding schemes. The CAMS-REG v8.1 Emissions Inventory for Europe adopts the 14-group GNFR sector classification, which is consistent with the reporting conventions used in European air-pollutant inventories [34]. Units span molecules cm^{−2} s^{−1}, kg h^{−1}, Mg km^{−2} a^{−1}, etc., reflecting the heterogeneity in original reporting systems. The CAMS-REG inventory reports emissions in kg m^{−2} s^{−1} or Tg, and in this study, the data were provided in Tg units.

Despite these differences, the inventories share a common methodological foundation. Each is a bottom-up product, typically constructed from national inventory reports submitted to the United Nations Framework Convention on Climate Change (UNFCCC), complemented with sector-specific activity data and emission factors derived from IPCC guidelines or country-specific studies [35,36]. Spatial allocation to grids is generally achieved using proxy data, including facility locations (e.g., oil and gas wells, coal mines, landfills), infrastructure databases (e.g., pipelines, refineries, wastewater plants), and other geospatial layers such as population, land use, livestock distributions, and satellite products [17,31].

Table 1. Summary of the gridded methane emission inventories included in this study.

Dataset	Spatial Coverage	CRS	Resolution	Temporal Coverage	File Format	Sector Classification Scheme	Reporting Unit	Reference
EDGAR v8.0 ¹	Global	Geographic Coordinate System WGS 84	0.1° × 0.1°	1970–2022	NetCDF	IPCC 2006 and IPCC 1996	metric ton a ^{−1}	Crippa et al. [26]
GFEI ²	Global	Geographic Coordinate System WGS 84	0.1° × 0.1°	2016(v1) 2019(v2) 2020(v3)	NetCDF	IPCC 2006	Mg a ^{−1} km ^{−2}	Scarpelli et al. [23], Scarpelli et al. [24], Scarpelli et al. [25]
CAMS-REG v8.1 ³	Europe	Geographic Coordinate System WGS 84	0.05° × 0.1°	2005–2022	NetCDF or CSV	GNFR	kg m ^{−2} s ^{−1} or Tg	Kuenen et al. [34]
U.S. Anthropogenic Methane Emissions ⁴	Contiguous United States	Geographic Coordinate System WGS 84	0.1° × 0.1°	2012–2018	NetCDF	CRT	molecules CH ₄ cm ^{−2} s ^{−1}	Maasakkers et al. [31]
Canada Anthropogenic Methane Emissions	Canada	Geographic Coordinate System WGS 84	0.1° × 0.1°	2018	NetCDF	CRT	Mg a ^{−1} km ^{−2}	Scarpelli et al. [20]
Mexico Anthropogenic Methane Emissions	Mexico	Geographic Coordinate System WGS 84	0.1° × 0.1°	2015	NetCDF	IPCC 2006	Mg a ^{−1} km ^{−2}	Scarpelli et al. [32]

China Anthropogenic Methane Emissions	China	Krasovsky 1940 Albers projection	~10 km × 10 km	1990–2020	GeoTIFF	-	Mg a ⁻¹ km ⁻²	Guo et al. [33]
Switzerland Greenhouse Gas Inventory	Switzerland	Swiss CH1903/LV03	500 m × 500 m	2011	NetCDF	-	g m ⁻² a ⁻¹	Hiller et al. [27]
U.S. Oil and Gas Methane Emissions	United States	Contiguous Geographic Coordinate System WGS 84	0.1° × 0.1°	2021	NetCDF	-	kg h ⁻¹	Omara et al. [37]
CMS Datasets on Methane Flux for Oil and Gas Systems ⁵	Canada	Geographic Coordinate System WGS 84	0.1° × 0.1°	2013	NetCDF	-	molecules CH ₄ cm ⁻² s ⁻¹	Sheng et al. [38]
	Mexico			2010				
China Coal Mine Methane Emissions	China	Geographic Coordinate System WGS 84	0.25° × 0.25°	2011	NetCDF	-	Mg a ⁻¹ km ⁻²	Sheng et al. [39]
India and Australia Coal Mine Methane Emissions	India and Australia	Geographic Coordinate System WGS 84	0.1° × 0.1°	2018	CSV	-	metric ton a ⁻¹	Sadavarte et al. [40]
Gridded New York State Methane Emissions ⁶	New York State	UTM Zone 18N projection	100 m × 100 m	2020	NetCDF	IPCC 1996	kg m ⁻² s ⁻¹	Loman et al. [28]

¹ Emissions Database for Global Atmospheric Research (EDGAR). EDGAR v8.0 provides estimates of emissions from the three leading greenhouse gases (CO₂, CH₄, and N₂O) and fluorinated gases, per sector and country, and we only include CH₄ emissions. ² Global Fuel Exploitation Inventory (GFEL). Three publicly available versions correspond to 2016, 2019, and 2020. According to the data description, additional emission grids for 2010–2019 are available upon request, but only the three accessible years are included here. ³ Copernicus Atmosphere Monitoring Service Regional (CAMS-REG) v8.1 Emissions Inventory for Europe. It includes CH₄ alongside the major air pollutants, NO_x, SO₂, CO, NH₃, NMVOC, PM₁₀, and PM_{2.5}, with full sectoral detail. ⁴ Monthly emission scaling factors are available for the Gridded Annual U.S. Anthropogenic Methane Emissions (2012–2018) covering 26 source categories (Gridded GHGI). An additional ‘Express Extension’ provides gridded annual emissions for 2012–2020 with 27 source categories. In this dataset, we include only the Gridded GHGI and exclude the Express Extension. ⁵ Carbon Monitoring System (CMS) datasets on Methane Flux for Canadian and Mexican Oil and Gas Systems. The dataset is available for Canada in 2013 and Mexico in 2010. ⁶ Monthly scaling factors and weekday scaling factors are also available in the source datasets.

2.2. rHEALPix DGGS Framework

The rHEALPix DGGS is a geospatial extension of the HEALPix tessellation, originally developed for astronomy and later adapted for Earth-system applications [41–43]. Its properties are well suited to emission-inventory harmonization [29]. rHEALPix provides equal-area cells at each resolution, so equal per-cell emission totals correspond to equal areal intensities regardless of latitude. Comparative evaluation of open-source DGGS implementations has shown that rHEALPix- and Icosahedral Snyder Equal Area (ISEA)-based grids preserve cell area most closely [44]. Congruence depends on the grid geometry and refinement ratio of the particular variant [5]. Each parent cell is subdivided into a 3 × 3 array of nine children without gaps or overlaps, giving a refinement ratio of nine [5]. This structure enables aggregation to coarser resolutions by summation (Figure 1) and supports hierarchical indexing through shared prefixes. Child cells also preserve parent orientation and, except for polar dart cells, form skew quadrilaterals compatible with raster row-and-column structures.

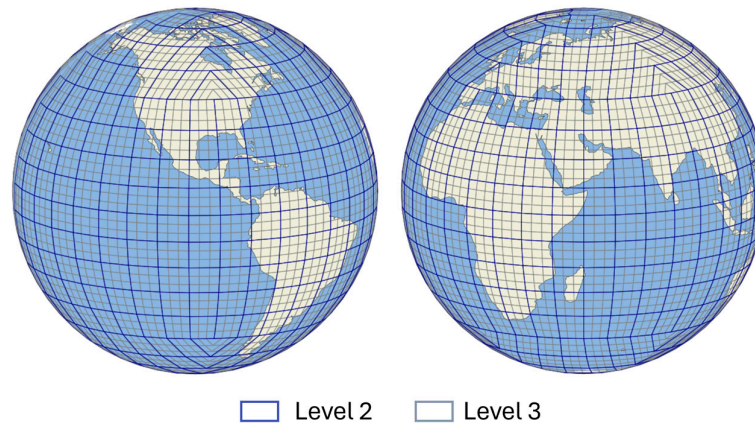


Figure 1. The rHEALPix Discrete Global Grid System with resolution levels 2 and 3 superimposed, shown on two views of the globe, where dark blue lines delineate level 2 and light blue lines delineate level 3.

The area-weighted redistribution applies to any equal-area tessellation, while mass closure is enforced through an explicit scaling step. The grid therefore mainly determines how the harmonized product is indexed, aggregated, and joined. We evaluated candidate grids against three criteria required by these operations. First, cell area must be equal by construction at every level so that per-cell totals are comparable without area normalization. Second, refinement must be congruent, with each parent cell exactly equal to the union of its children, so that aggregation to a coarser level is obtained by summing cells that share an index prefix. Third, each cell must have a hierarchical indexing structure in which parent-cell identifiers retain the prefix of their child cells. This supports efficient database queries and enables aggregation over larger regions through prefix-based grouping [45].

We generated and indexed the rHEALPix grids with the DGGAL library [46]. The grid creation process was designed to ensure coverage of both terrestrial and offshore emission sources. First, country geometries from the Database of Global Administrative Areas (GADM) were used to generate land-based rHEALPix cells [47]. Second, offshore oil and gas facilities were extracted from the Oil and Gas Infrastructure Mapping (OGIM) database, including petroleum terminals, compressor stations, injection and disposal sites, tank batteries, and other offshore infrastructure [48]. Each facility point was buffered by a 10 km geodesic radius to provide the areal footprint required for grid generation, extending beyond the GADM land polygons. The buffer encloses about 314 km², which exceeds the footprint of an individual oil and gas facility by several orders of magnitude [49] and therefore acts as an inclusive mask. The buffered footprints were used solely to select the DGGs cells covering offshore facility locations, and emissions were allocated by the area of overlap between source pixels and DGGs cells. The land-based and offshore grids were subsequently merged, and duplicate cells occurring in both layers were removed using their unique DGGs cell identifiers. International Organization for Standardization (ISO) country codes were then assigned to each cell for standardized referencing.

rHEALPix resolution levels were selected so that the DGGs cell area falls within approximately a factor of 2.5 of the native pixel area of each inventory. Because each level has nine times the area of the next finer level, at most one level satisfies this criterion for a given inventory. Table 2 lists the specific characteristics of rHEALPix DGGs at different resolutions, including the average ellipsoidal cell size and the planar cell width. For the Gridded New York State Methane Emissions Inventory dataset (100 m × 100 m, about 0.01 km²), we selected rHEALPix level 10 (about 0.02 km²). For the Switzerland Greenhouse

Gas Inventory (500 m × 500 m, 0.25 km²), level 9 was used (about 0.22 km²). For CAMS-REG at 0.05° × 0.1° resolution, we adopted rHEALPix level 7 (about 17.8 km²). For other global and national inventories with native resolution of 0.1° × 0.1° (about 10 km × 10 km), we adopted level 6 (about 160 km²). The China Coal Mine Methane Emissions dataset, at 0.25° × 0.25° resolution and approximately 640 km² per pixel, is the only exception to this rule. The criterion selected level 5, with an average cell area of about 1441 km², so each DGGS cell covered more than two native pixels. We instead used level 6, at about 160 km² per cell, to better preserve the source resolution, giving a resolution-fidelity ratio of 0.25. For the remaining 13 datasets this ratio ranges from 0.45 to 2.45. All grids were generated programmatically using the DGGAL API, ensuring consistency across datasets and facilitating reproducible integration of diverse inventories into the DGGS framework [46].

Table 2. Summary of the rHEALPix DGGS cell dimensions across resolutions.

Resolution Level	Average Cell Width (m, Planar)	Average Cell Area (m ² , Ellipsoidal)
0	1.00×10^7	8.51×10^{13}
1	3.34×10^6	9.46×10^{12}
2	1.11×10^6	1.05×10^{12}
3	3.71×10^5	1.17×10^{11}
4	1.24×10^5	1.30×10^{10}
5	4.12×10^4	1.44×10^9
6	1.37×10^4	1.60×10^8
7	4.58×10^3	1.78×10^7
8	1.53×10^3	1.98×10^6
9	509	2.20×10^5
10	170	24,408
11	56.5	2712
12	18.8	301
13	6.28	33.5
14	2.09	3.72
15	0.698	0.413

2.3. Spatial Processing

The source inventories used in this study were published in different formats, including NetCDF, CSV, and GeoTIFF, each requiring preprocessing before DGGS conversion. NetCDF files (e.g., EDGAR, GFEL, CAMS-REG, and most of the national gridded inventories) typically contain gridded arrays with latitude–longitude or projected coordinates, time dimensions, and sector-specific variables [20,24–26,31,32,34]. CSV files (e.g., India and Australia Coal Mine Methane Emissions Inventories in 2018) provide point-based grids with explicit latitude, longitude, and emission values [40]. The China Anthropogenic Methane Emissions Inventories are distributed as annual GeoTIFF rasters [33]. For consistency, all inputs were first converted to intermediate raster representations, ensuring one raster per reporting category. Pixel centers were used to define raster alignment, with coordinate transforms shifted by half a pixel to match native grid definitions. When necessary, latitude arrays were reversed to match top-to-bottom raster conventions.

Differences in CRS were harmonized by reprojecting all datasets to the Geographic Coordinate System WGS84 before raster conversion, when necessary (e.g., the Switzerland Greenhouse Gas Inventory in CH1903/LV03 and the Gridded New York State Methane Emissions Inventory in UTM 18N). For projected datasets, pixel areas were calculated directly from affine transforms to account for variable cell sizes. For geographic datasets

(EPSG:4326), pixel areas were derived from spherical geometry or, when available, read from the area attributes in the source datasets.

Following rasterization, emissions were redistributed to the rHEALPix DGGS framework using an area-weighted approach. Each raster pixel was intersected with overlapping DGGS cells, and emissions were proportionally allocated based on the area of overlap. The raster-first approach was adopted for computational efficiency, meaning that non-zero raster pixels were first filtered and their overlapping DGGS cells were identified. Afterward, the contribution of each pixel to the intersecting DGGS cells was calculated based on the area of overlap. This procedure reduced unnecessary geometric operations by limiting calculations to relevant grid cells. The Python package 'uraster' was developed to accomplish this task [50]. To ensure mass conservation, a scaling factor was applied to preserve the total emissions before and after DGGS conversion. For continental, national, and regional datasets, the applied scaling factors were very close to 1, confirming that redistribution introduced minimal numerical deviation. For global inventories, scaling factors were calculated separately for each country, category, and year, ensuring that country-level totals were accurately retained.

The implementation was optimized for efficiency through parallel processing, which distributed category- and year-specific calculations across multiple cores. A raster-first approach minimized geometric overhead, while spatial indexing and bounding box pre-filtering limited intersection checks to relevant pixels and DGGS cells. DGGS cells receive emissions from any overlapping pixel regardless of land or water classification, and per-cell totals are reported in megagrams per year (Mg a^{-1}) on the equal-area DGGS rather than as per-area fluxes. Where source products provide both per-sector fields and a pre-aggregated total field, the total field is removed before redistribution to avoid double-counting. These strategies reduced computation time and memory demands, enabling consistent processing of both extensive global inventories and higher-resolution regional datasets. Figure 2 illustrates the workflow from the original inventories to the DGGS outputs. All computations in this study were performed on the Advanced Research Computing (ARC) high-performance cluster at the University of Calgary.

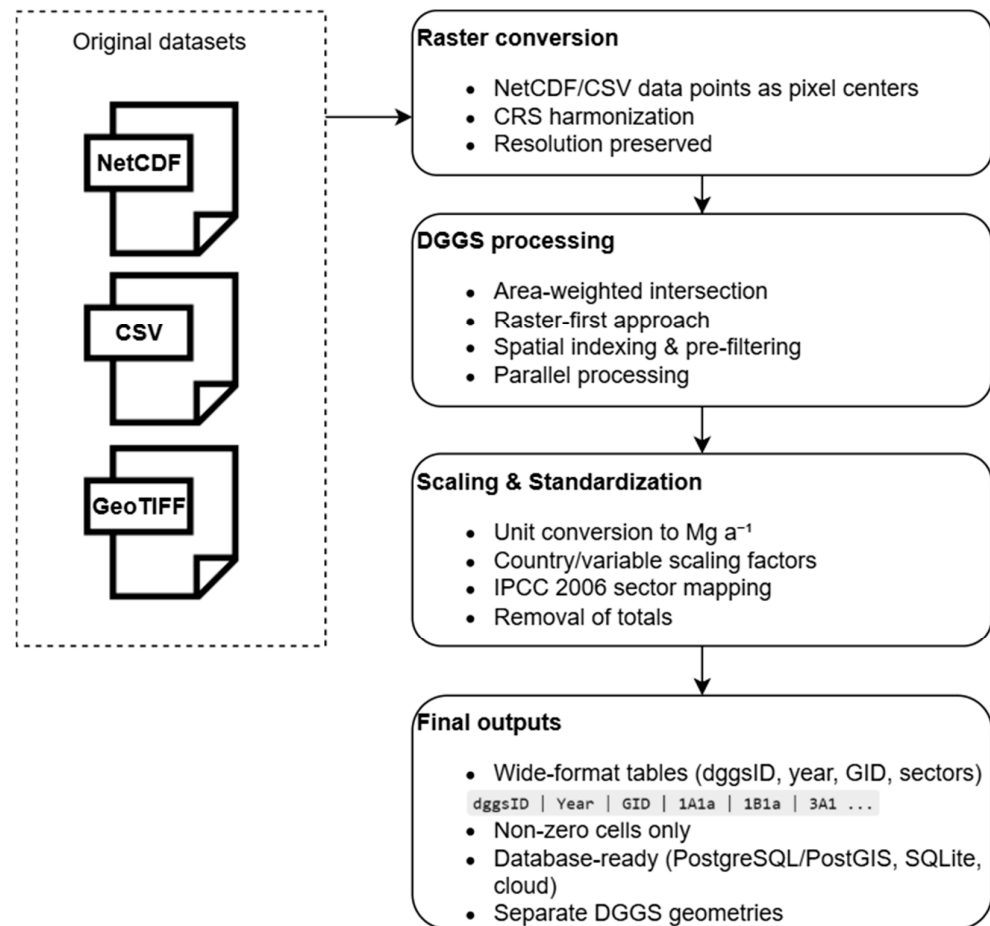


Figure 2. Workflow of converting original gridded methane inventories to DGGs.

2.4. Unit Standardization

Source inventories report methane in heterogeneous units, such as fluxes and areal intensities. Each conversion is mass-conservative, with all per-area inputs first integrated over the source pixel area before redistribution to the DGGs. For comparability in an equal-area DGGs, all variables were converted to megagrams per year (Mg a^{-1}) at the cell level. When inputs were reported as rates per area, we first computed per-pixel totals by multiplying by the pixel area in the native CRS, then mapped to DGGs and conserved mass via the scaling step (Section 2.3). Below are the unit transformations used throughout. In Equations (1)–(5), E denotes the per-cell methane emission total in Mg a^{-1} , V denotes the native reported value in the unit shown for each equation, and A_{pixel} denotes the source pixel area in the units shown for each equation. Where applicable, $31,536,000 \text{ s a}^{-1}$ represents the number of seconds per year and 8760 h a^{-1} represents the number of hours per year, and the factors 10^{-3} and 10^{-6} convert kilograms and grams to megagrams, respectively.

For inventories reported in $\text{Mg a}^{-1} \text{ km}^{-2}$ (e.g., GFEI [25]), values were first converted to per- m^2 fluxes by applying a factor of 10^{-6} , and then multiplied by the pixel area in square meters to obtain per-pixel totals, as shown in Equation (1):

$$E_{\text{Mg a}^{-1}} = V_{\text{Mg a}^{-1} \text{ km}^{-2}} \times 10^{-6} \times A_{\text{pixel, m}^2} \quad (1)$$

For fluxes reported in $\text{kg m}^{-2} \text{ s}^{-1}$ (e.g., Gridded New York State Methane Emissions Inventory [28]), the calculation involved multiplying by pixel area and the number of

seconds per year, followed by conversion from kilograms to megagrams, as shown in Equation (2):

$$E_{\text{Mg a}^{-1}} = V_{\text{kg m}^{-2} \text{ s}^{-1}} \times A_{\text{pixel, m}^2} \times 31,536,000 \times 10^{-3} \quad (2)$$

For emission rates in kg h^{-1} (e.g., U.S. Oil and Gas Methane Emissions [37]), a similar approach was applied by scaling by the total hours per year and converting from kilograms to megagrams, as shown in Equation (3):

$$E_{\text{Mg a}^{-1}} = V_{\text{kg h}^{-1}} \times 8760 \times 10^{-3} \quad (3)$$

The national inventories reporting emissions in $\text{g m}^{-2} \text{ a}^{-1}$ (e.g., Switzerland Greenhouse Gas Inventory [27]) were converted by multiplying by pixel area and scaling from grams to megagrams, as shown in Equation (4):

$$E_{\text{Mg a}^{-1}} = V_{\text{g m}^{-2} \text{ a}^{-1}} \times A_{\text{pixel, m}^2} \times 10^{-6} \quad (4)$$

Finally, for datasets expressed as molecules $\text{CH}_4 \text{ cm}^{-2} \text{ s}^{-1}$ (e.g., U.S. Anthropogenic Methane Emissions [31]), a molecular-to-mass conversion was required. Emissions were first multiplied by pixel area (cm^2) and seconds per year, then divided by Avogadro's number to obtain moles of methane. This was converted to grams using the molecular weight of CH_4 (16.04 g mol^{-1}), and finally to megagrams, as shown in Equation (5):

$$E_{\text{Mg a}^{-1}} = (V_{\text{molec cm}^{-2} \text{ s}^{-1}} \times A_{\text{pixel, cm}^2} \times 31,536,000 \div N_A) \times M_{\text{CH}_4} \times 10^{-6} \quad (5)$$

where $N_A = 6.022 \times 10^{23} \text{ mol}^{-1}$ is Avogadro's number and $M_{\text{CH}_4} = 16.04 \text{ g mol}^{-1}$ is the molecular weight of methane.

For datasets already in metric tons per year, values were carried through unchanged. By expressing every variable as Mg a^{-1} per DGGS cell on an equal-area grid, the resulting fields are globally comparable without latitude-dependent area bias and can be directly summed across cells, sectors, or jurisdictions.

2.5. Sector Harmonization

To ensure comparability across heterogeneous methane inventories, all source datasets were harmonized to the IPCC 2006 sector classification. The IPCC 2006 Guidelines for National Greenhouse Gas Inventories define a hierarchical code structure, where top-level categories (e.g., 1 Energy, 2 Industrial Processes and Product Use, 3 Agriculture, Forestry, and Other Land Use, and 4 Waste) are subdivided into finer classes (e.g., 1. A Fuel Combustion Activities, 1. B Fugitive Emissions, 1. C Carbon dioxide Transport and Storage). This hierarchical structure supports aggregation at different levels of detail while maintaining consistency with official reporting standards [36]. It should be noted that the codes cannot always be safely grouped by simple prefix matching, since some subcategories (e.g., 1B2ai and 1B2aii) share prefixes but represent parallel classes at the same hierarchical level due to the use of Roman numerals in the coding system.

The IPCC 2006 classification was adopted because it provides the common reference structure across the source inventories. The products considered here use IPCC 2006 codes, CRT codes, GNFR codes, IPCC 1996 codes, or descriptive labels, all of which can be crosswalked to IPCC 2006 [35,36]. The 2019 Refinement updates methods, emission factors, and guidance where new scientific information is available, but it supplements rather than replaces the 2006 category structure [51]. Harmonizing with IPCC 2006 therefore preserves consistency with the classification framework under which the source inventories are compiled and reported.

Several inventories already provided IPCC 2006 codes for each variable, which were adopted directly. When an original variable represented multiple IPCC 2006 sector codes, for example, "emis_ch4_1A3a,c,d" in the Mexico Anthropogenic Methane Emissions

dataset [32], the corresponding codes were merged into a single combined label using a plus sign, resulting in “1A3a + 1A3c + 1A3d” in this case. Others reported emissions under GNFR codes, CRT codes, or IPCC 1996 codes, where crosswalks were applied to align the reported sectors with their corresponding IPCC 2006 categories [35]. For variables that included both a coarse code level and a descriptive label, the variable was assigned either the original coarse code or a finer-level IPCC 2006 category code, whichever was more appropriate based on the sector definition. For example, the variable “3A (enteric fermentation)–Buffalo” in the Canada Anthropogenic Methane Emissions inventory [20] uses the coarse CRT code “3A,” but was reassigned to 3A1b following the IPCC 2006 Reporting Guidance [36], where the subcategory explicitly represents emissions from enteric fermentation of buffalo. During processing and in the final output, a single value is retained for each unique IPCC 2006 category code. This is achieved by aggregating variables that share the same code and summing their emission values. For datasets containing only text-based variable names without a code scheme, each variable was assigned the closest IPCC 2006 category code, based on careful examination of the original publications and sector definitions. This process ensured a consistent, hierarchical classification system across all inventories. An exception was the Swiss Greenhouse Gas Inventory, which includes natural and semi-natural methane fluxes such as lakes, wetlands, wild animals, and forest soils. Because these sources are not part of the IPCC’s anthropogenic reporting structure, they were retained under their original text labels. Finally, to avoid double-counting, “total” categories present in some inventories were excluded during processing. This ensured that each variable is uniquely assigned to a single IPCC 2006 category code, with no overlaps across categories in each dataset. The complete mapping from original variable names to IPCC 2006 categories is available in the project repository, including the cardinality of each mapping and the basis for each category assignment.

2.6. Evaluation Criteria and Validation Metrics

Harmonization is assessed using five measurable criteria. Mass conservation is quantified by the relative difference in total emissions before and after conversion, together with the normalized root-mean-square error (RMSE) and normalized mean bias (MB) defined below. Area comparability is measured by the coefficient of variation in cell area, which is zero for an equal-area DGGS and positive for latitude–longitude grids. Aggregation exactness is measured by the relative residual between cell totals before and after aggregation to the next coarser level by index prefix. Semantic coverage is the proportion of original variables mapped one-to-one to an IPCC 2006 category, with all remaining mappings classified by type. Resolution fidelity is measured by the ratio of DGGS cell area to the mean native pixel area of each source inventory.

The DGGS conversion performs a spatial re-aggregation rather than a one-to-one mapping, so direct cell-by-cell comparison between the original and converted datasets is not meaningful. Evaluation therefore assessed numerical consistency at the aggregate level, comparing total emissions before and after conversion to the rHEALPix DGGS for each inventory. Three metrics were adopted for this purpose. First, the relative difference quantified year-specific deviations in total emissions, defined in Equation (6) as the converted annual total minus the original annual total, expressed as a percentage of the original total. Negative values indicate that the converted total is smaller than the original. Second, the normalized RMSE provided a dimensionless measure of the typical discrepancy across a time series, which was particularly relevant for multi-year datasets such as EDGAR v8.0 and CAMS-REG v8.1. Third, the normalized MB diagnosed any systematic increase or decrease introduced by the conversion. These three metrics characterized both the magnitude and the direction of any numerical deviation associated with the area-weighted redistribution. For an inventory spanning n years, E_y^{orig} and E_y^{DGGS} denote the

total emissions in year y before and after conversion, as given in Equations (7) and (8). Both metrics are divided by the largest annual total in the original series, which makes them dimensionless and comparable across inventories of different magnitudes.

$$RD_y = (E_y^{\text{DGGs}} - E_y^{\text{orig}}) / E_y^{\text{orig}} \times 100 \quad (6)$$

$$\text{nRMSE} = \left[\left(\frac{1}{n} \sum_{y=1}^n (E_y^{\text{DGGs}} - E_y^{\text{orig}})^2 \right)^{\frac{1}{2}} / \max_y(E_y^{\text{orig}}) \right] \quad (7)$$

$$\text{nMB} = \left[\left(\frac{1}{n} \sum_{y=1}^n (E_y^{\text{DGGs}} - E_y^{\text{orig}}) \right) / \max_y(E_y^{\text{orig}}) \right] \quad (8)$$

3. Results

3.1. The Harmonized DGGs Dataset

The harmonized dataset includes 13 methane inventories spanning various spatial scales and temporal ranges, collectively representing over 4.1 million non-zero rHEALPix DGGs cells. The data were exported in a tabular format optimized for interoperability and analysis efficiency. Each row of data corresponds to a unique combination of an rHEALPix DGGs cell identifier and a calendar year, ensuring one observation per cell-year pair. Columns represent IPCC 2006 emission categories or subcategories. For global inventories, an additional column records the ISO 3166-1 alpha-3 country code [52] to facilitate country-level aggregation. This structure enables direct access to sector-specific emissions while supporting aggregation to higher-level categories via IPCC code prefixes. Nonetheless, the codes cannot always be reliably grouped by simple prefix matching because the coding system uses Roman numerals. The number of retained IPCC 2006 categories per inventory ranges from 1 (for single-sector datasets such as coal-mine methane) to over 50 (for national inventories with detailed source disaggregation), reflecting the sectoral detail available in the original inventory. The crosswalk covers 324 original variables across the 15 converted datasets. Of these, 173 map one-to-one to an IPCC 2006 category, 122 share a category with other variables in the same inventory and are summed during conversion, 25 span multiple categories that are not separated in the source and are retained as combined columns, and 4 natural fluxes in the Swiss inventory retain their original labels. For 44 variables, the source inventory provides descriptive names without a coding scheme, and categories were assigned based on the source publication and IPCC category definitions. To ensure consistency, all emissions values are reported in units of Mg a^{-1} . Rows with all-zero sector values were removed to reduce file size and improve performance. Geometries were not embedded within the tables but are provided separately as GeoParquet files that define polygon boundaries for rHEALPix cells at specific resolutions. This design allows attribute tables to be integrated directly into relational databases or analytical workflows while remaining compatible with geospatial visualization tools through joins with the geometry files.

Table 3 summarizes the spatial and temporal coverage, DGGs resolution level, number of DGGs cells with non-zero values, and number of IPCC 2006 categories of converted methane inventories in the rHEALPix DGGs. Figure 3 shows the spatial coverage of the 13 methane inventories included in this study after conversion to rHEALPix DGGs. Although 13 inventories are included in total, 15 individual datasets are displayed on the map because two inventories cover multiple countries, namely the Carbon Monitoring System (CMS) Datasets on Methane Flux for Canadian and Mexican Oil and Gas Systems and the Coal Mine Methane Emissions inventories for India and Australia [38,40]. Most

datasets were mapped at DGGS level 6 (about 160 km²), while higher-resolution inventories such as CAMS-REG v8.1 Emissions Inventory for Europe (0.05° × 0.1°), the Switzerland Greenhouse Gas Inventory (500 m × 500 m), and the Gridded New York State dataset (100 m × 100 m) required higher resolutions of levels 7, 9 and 10, respectively. Resolution therefore varies across the harmonized inventories. Per-cell values are directly comparable among inventories at the same level. Across levels, finer cells can be summed by shared index prefix to recover the corresponding coarser-cell total exactly because the refinement is congruent. The standardized global-to-regional gridded methane inventories on rHEALPix DGGS are stored in the Zenodo repository: <https://doi.org/10.5281/zenodo.17362125> (accessed on 15 October 2025).

Table 3. Summary of converted methane inventories in DGGS, including spatial and temporal coverage, DGGS resolution level, number of DGGS cells with non-zero values, and number of IPCC 2006 categories.

Data Source ¹	Spatial Coverage	Year Range	DGGS Resolution	Number of Non-Zero DGGS Cells	Number of IPCC 2006 Categories
EDGAR v8.0	Global	1970–2022	6	847,790	21
GFEI	Global	2016(v1) 2019(v2) 2020(v3)	6	764,949	15
CAMS-REG v8.1	Europe	2005–2022	7	358,928	12
U.S. Anthropogenic Methane Emissions	Contiguous United States	2012–2018	6	50,874	25
Canada Anthropogenic Methane Emissions	Canada	2018	6	55,182	52
Mexico Anthropogenic Methane Emissions	Mexico	2015	6	13,030	45
China Anthropogenic Methane Emissions	China	1990–2020	6	59,627	8
Switzerland Greenhouse Gas Inventory	Switzerland	2011	9	189,148	8
U.S. Oil and Gas Methane Emissions	Contiguous United States	2021	6	27,446	1
CMS Datasets on Methane Flux for Oil and Gas Systems	Canada	2013	6	32,277	5
	Mexico	2010	6	10,486	5
China Coal Mine Methane Emissions	China	2011	6	10,680	1
India and Australia Coal Mine Methane Emissions	India	2018	6	150	1
	Australia	2018	6	83	1
Gridded New York State Methane Emissions	New York State	2020	10	2,657,699	34

¹ Refer to Table 1 for dataset abbreviations.

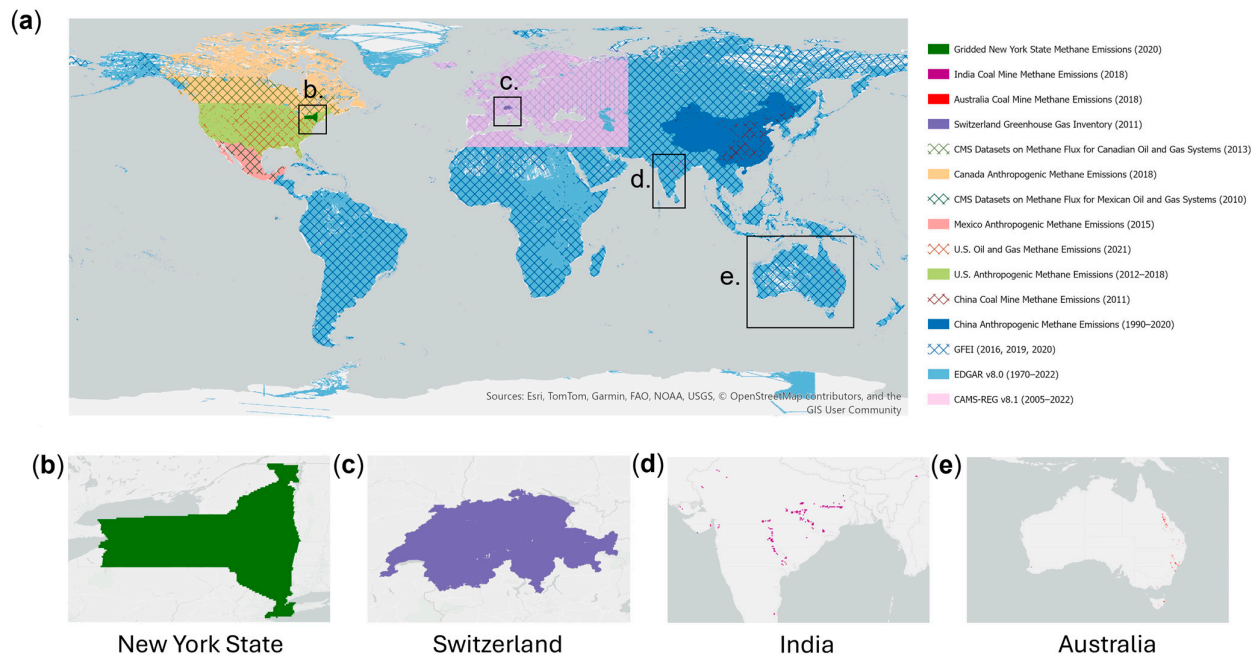


Figure 3. Spatial coverage of the 13 methane inventories after conversion to rHEALPix DGGS. (a) Global extents, with crosshatching where domains overlap. (b–e) Regional examples: (b) New York State (2020), (c) Switzerland (2011), (d) India (2018), and (e) Australia (2018); the coal mine inventories occupy only the polygons containing mines and so read as scattered points.

3.2. Quantitative Validation of the DGGS Conversion

Table 4 (also see the Supplementary Information) summarizes the relative difference in total emissions before and after conversion for all datasets. For continental, national and regional datasets, relative differences are negligible, demonstrating effective conservation of mass during rasterization and cell-to-cell redistribution: Mexico ($-9.48 \times 10^{-4}\%$), Switzerland ($-3.03 \times 10^{-5}\%$), U.S. Oil and Gas ($-1.26 \times 10^{-4}\%$), CMS-Canada (-0.03%) and CMS-Mexico (-0.01%), China Coal Mine ($5.63 \times 10^{-14}\%$), India/Australia Coal Mine ($3.64 \times 10^{-6}\%$ and $-7.25 \times 10^{-6}\%$), and New York State ($-2.07 \times 10^{-5}\%$). Canada anthropogenic methane (2018) shows a small difference of -0.25% . For the U.S. Anthropogenic Methane Emissions time series, annual relative differences over 2012–2018 range from $+0.26\%$ to $+0.57\%$ with a mean of $+0.43\%$ (Table S3). The CAMS-REG v8.1 Emissions Inventory for Europe and China Anthropogenic Methane Emissions series are effectively identical before and after conversion for all years (Tables S2 and S4). Global inventories show slightly higher but still minor relative differences. EDGAR v8.0 ranges from -0.14% to -1.54% across 1970–2022 with a mean of -1.03% (Table S1), and GFEI differences are -2.58% (2016 v1), -3.07% (2019 v2), and -2.77% (2020 v3), as shown in Table 4. These small shortfalls reflect the design choice to apply scaling factors per country, category, and year to preserve country-level totals. When globally re-aggregated after area-weighted mapping to equal-area cells, minor rounding and boundary effects accumulate, resulting in slightly higher discrepancies than for single-country datasets. Table 5 reports the normalized RMSE and MB of annual totals before and after conversion to the DGGS framework for four multi-year datasets. In all cases, both metrics are close to zero, indicating negligible numerical discrepancies associated with the area-weighted spatial re-aggregation. CAMS-REG v8.1 and China Anthropogenic Methane Emissions show normalized RMSE of 1.14×10^{-7} and 6.45×10^{-11} , corresponding to discrepancies of about one part in 10^7 and one part in 10^{11} of the maximum annual total, while EDGAR v8.0 and U.S. Anthropogenic Methane

Emissions exhibit slightly larger but still small normalized errors below 1%. The normalized MB is -0.0086 for EDGAR v8.0 and 0.0042 for the U.S. Anthropogenic Methane Emissions inventory, so each series carries a bias in a consistent direction with a magnitude below 1% of the maximum annual total. For EDGAR, the negative sign follows from applying the scaling factors per country, category, and year, which preserves country totals and leaves boundary and rounding effects in the global sum.

Table 4. Comparison of total methane emissions before and after conversion to rHEALPix DGGS for all inventories included in this study. For EDGAR v8.0, CAMS-REG v8.1, U.S. Anthropogenic Methane Emissions, and China Anthropogenic Methane Emissions, only selected benchmark years are shown here; the full annual comparisons for EDGAR v8.0 (1970–2022), CAMS-REG v8.1 (2005–2022), U.S. (2012–2018), and China (1990–2020) are provided in the Supplementary Information.

Data Source ¹	Year	Total Emissions Before Conversion (Mg a ⁻¹) ²	Total Emissions After Conversion (Mg a ⁻¹)	Relative Difference (%) ⁴
EDGAR v8.0	1970	244,640,086.78	244,213,826.26	-1.7×10^{-1}
	1980	271,727,781.20	269,895,199.34	-6.7×10^{-1}
	1990	294,670,363.61	292,304,166.09	-8.0×10^{-1}
	2000	302,327,759.24	298,224,666.14	-1.36×10^0
	2010	346,214,967.57	341,225,619.61	-1.44×10^0
	2020	375,833,285.38	370,911,676.80	-1.31×10^0
GFEI	2016	97,224,636.28	94,719,841.73	-2.58×10^0
	2019	80,419,238.44	77,949,246.12	-3.07×10^0
	2020	73,874,620.47	71,831,885.04	-2.77×10^0
CAMS-REG v8.1	2005	58,948,955	58,948,948	-1.18×10^{-5}
	2010	56,851,049	56,851,037	-2.15×10^{-5}
	2015	57,048,963	57,048,966	4.66×10^{-6}
	2020	59,307,306	59,307,311	9.47×10^{-6}
U.S. Anthropogenic Methane Emissions	2012	25,626,259.09	25,692,238.00	2.6×10^{-1}
	2015	25,370,927.66	25,503,835.72	5.2×10^{-1}
	2018	25,225,964.39	25,368,622.74	5.7×10^{-1}
Canada Anthropogenic Methane Emissions	2018	3,655,967.45	3,646,964.48	-2.5×10^{-1}
Mexico Anthropogenic Methane Emissions	2015	5,076,752.83	5,076,704.68	-9.48×10^{-4}
China Anthropogenic Methane Emissions	1990	24,676,397.28	24,676,397.28	-1.27×10^{-10}
	2000	28,417,742.36	28,417,742.36	-7.99×10^{-11}
	2010	45,339,490.63	45,339,490.62	-1.88×10^{-11}
	2020	46,431,934.67	46,431,934.67	-2.32×10^{-10}
Switzerland Greenhouse Gas Inventory ³	2011	162,409.70	162,409.65	-3.03×10^{-5}
U.S. Oil and Gas Methane Emissions	2021	15,610,442.12	15,610,422.41	-1.26×10^{-4}
CMS Datasets on Methane Flux for Oil and Gas Systems	2013 (Canada)	2,329,955.38	2,329,312.28	-3×10^{-2}
	2010 (Mexico)	1,159,660.12	1,159,510.24	-1×10^{-2}
China Coal Mine Methane Emissions	2011	16,555,455.86	16,555,455.86	5.63×10^{-14}
India and Australia Coal Mine Methane Emissions	2018 (India)	823,149.22	823,149.25	3.64×10^{-6}
	2018 (Australia)	969,134.07	969,134.00	-7.25×10^{-6}
Gridded New York State Methane Emissions	2020	690,582.43	690,582.28	-2.07×10^{-5}

¹ Refer to Table 1 for dataset abbreviations. ² Reported values from the original datasets were standardized to units of Mg a⁻¹ for consistency and comparison. ³ The Switzerland Greenhouse Gas

Inventory includes both anthropogenic and natural methane emission sources. ⁴ The relative difference is defined in Equation (6). Negative values indicate that the converted total is smaller than the original.

Table 5. Normalized root-mean-square error (RMSE) and normalized mean bias (MB) of annual emission totals before and after conversion to the DGGS framework, for four multi-year datasets.

Data Source ¹	Normalized Root-Mean-Square Error (RMSE)	Normalized Mean Bias (MB)
EDGAR v8.0	0.0095	−0.0086
CAMS-REG v8.1	1.14×10^{-7}	3.44×10^{-8}
U.S. Anthropogenic Methane Emissions	0.0044	0.0042
China Anthropogenic Methane Emissions	6.45×10^{-11}	-2.01×10^{-11}

¹ Refer to Table 1 for dataset abbreviations.

Table 6 reports the remaining criteria. Cell area across the native graticules has a coefficient of variation ranging from 0.017 to 0.243, with the largest values occurring for global inventories spanning all latitudes, while rHEALPix cell area is constant by construction. The inventories distributed on projected grids vary far less, with coefficients below 0.001, and the Chinese inventory on an equal-area conic projection holds cell area constant. Aggregating a converted dataset to the next coarser level by truncating one character from the cell identifier preserved the total with a relative residual below 3×10^{-15} , consistent with floating-point precision, because the child cells nest exactly within their parents. Resolution fidelity ranges from 0.25 to 2.45, where values above one indicate that the DGGS cell is coarser than the native pixel. Semantic coverage is 173 of 324 original variables mapped one-to-one to an IPCC 2006 category, as reported in Section 3.1.

Table 6. Area comparability and resolution fidelity of the converted inventories.

Data Source ¹	DGGS Resolution Level	Coefficient of Variation (CV) of Native Cell Area ²	Ratio of DGGS Cell Area to Native Pixel Area ³
EDGAR v8.0	6	0.243	1.62
GFEI	6	0.230	1.61
CAMS-REG v8.1	7	0.224	0.45
U.S. Anthropogenic Methane Emissions	6	0.076	1.67
U.S. Oil and Gas Methane Emissions	6	0.072	1.65
Canada Anthropogenic Methane Emissions	6	0.236	2.45
Mexico Anthropogenic Methane Emissions	6	0.035	1.42
CMS Canada	6	0.098	2.15
CMS Mexico	6	0.036	1.43
China Anthropogenic Methane Emissions	6	0.000	1.60
China Coal Mine Methane Emissions	6	0.080	0.25
India and Australia Coal Mine Methane Emissions	6	0.017	1.40
Switzerland Greenhouse Gas Inventory	9	0.00009	0.88
Gridded New York State Methane Emissions	10	0.00075	2.44

¹ Refer to Table 1 for dataset abbreviations. ² Coefficient of variation (CV) is the standard deviation of cell area divided by its mean, computed over each inventory's domain in its native coordinate reference system. rHEALPix cell area has a CV of zero at every resolution level by construction. ³ The ratio in the final column exceeds one where the DGGS cell is coarser than the native pixel.

Overall, the DGGS conversion process successfully preserves mass at intended aggregation levels and provides a consistent, equal-area representation. All scaling factors

were applied deterministically, and the processing code is openly available, ensuring full traceability from original grids to DGGs outputs. These results demonstrate that the harmonization achieves mass balance, internal consistency, and reproducibility, supporting use in analytical and modeling applications.

3.3. Visualization of Harmonized Emission Patterns

To illustrate how the harmonized products enable like-for-like visualization of energy-sector emissions, we render multiple inventories in identical units (Mg a^{-1} per DGGs cell) on the rHEALPix grid. Although a map projection is used for display, the underlying equal-area tessellation gives every cell at a given level the same area on the ellipsoid, so per-cell values are area-comparable across panels [8]. Emissions are classified using $\log_{10}$ decade breaks. The same breaks are applied across all panels within each figure to maintain direct comparability. Figure 4 presents global fuel-exploitation emissions for common years (2016, 2019, 2020) from EDGAR v8.0 and GFEI at DGGs level 6 using the same color scale. For EDGAR, fuel exploitation is the sum of the component variables reported for coal, gas, and oil (original categories PRO_COAL, PRO_GAS, and PRO_OIL). The side-by-side maps demonstrate that heterogeneous source variables from distinct global inventories can be standardized and displayed coherently once mapped to the DGGs.

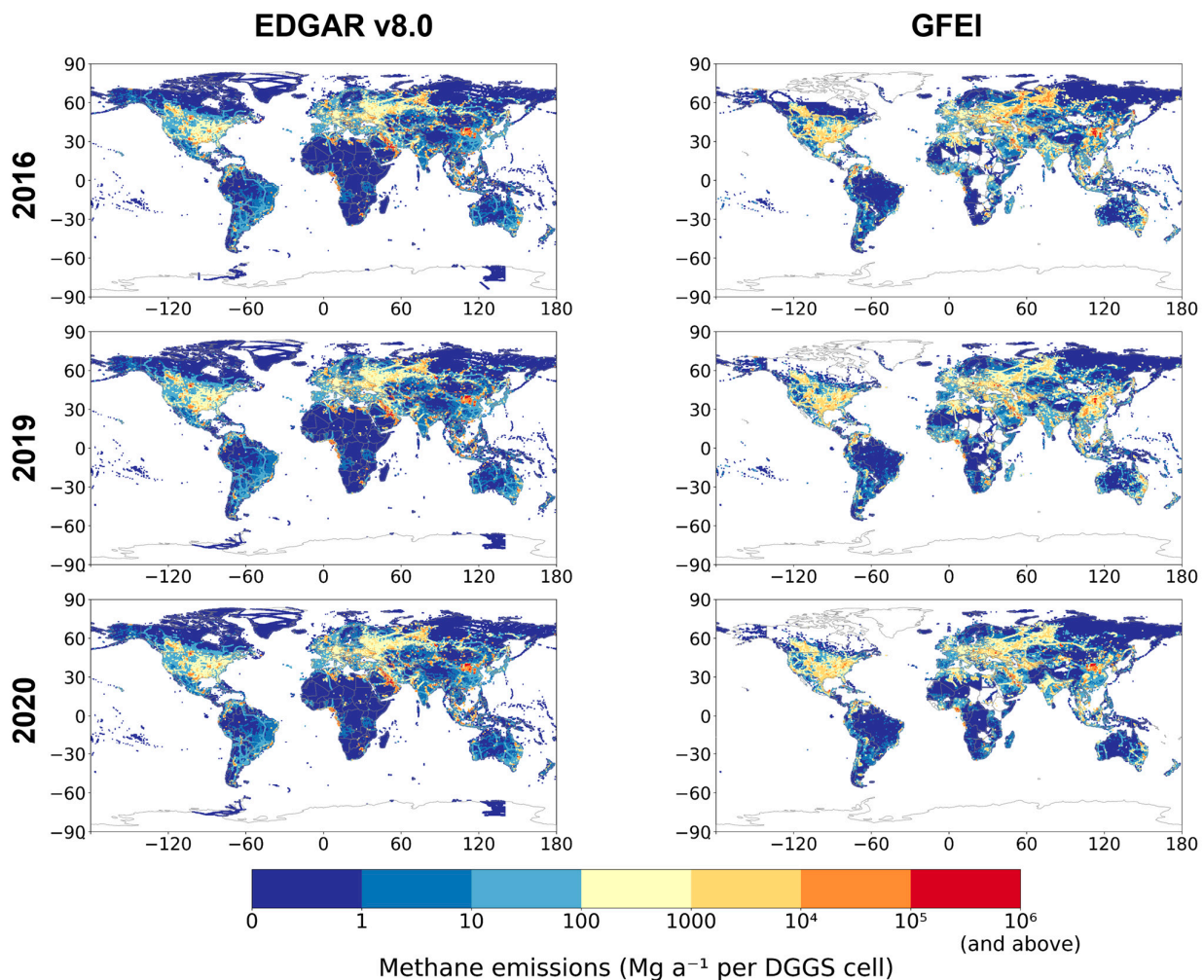


Figure 4. Methane emissions from fuel exploitation (Mg a^{-1} per DGGs cell) derived from EDGAR v8.0 (left) and GFEI (right) for common reporting years 2016, 2019, and 2020, after conversion to the rHEALPix DGGs at resolution level 6 [23–26].

At the national scale (Figure 5), single-year products for U.S. oil and gas (2021), China coal mining (2011), and the CMS oil-and-gas datasets for Canada (2013) and Mexico (2010) are shown with identical symbology at level 6 [37–39]. These panels are intended to be illustrative rather than evaluative. Each dataset originates from different methodologies and reporting conventions, while all can be presented with a common legend and equal-area grid, allowing immediate visual comparison of spatial distributions without implying cross-dataset ranking or accuracy assessment. The uniform treatment of units, sector coding, and grid geometry makes differences in spatial structure legible while avoiding artifacts associated with differing native projections or cell sizes.

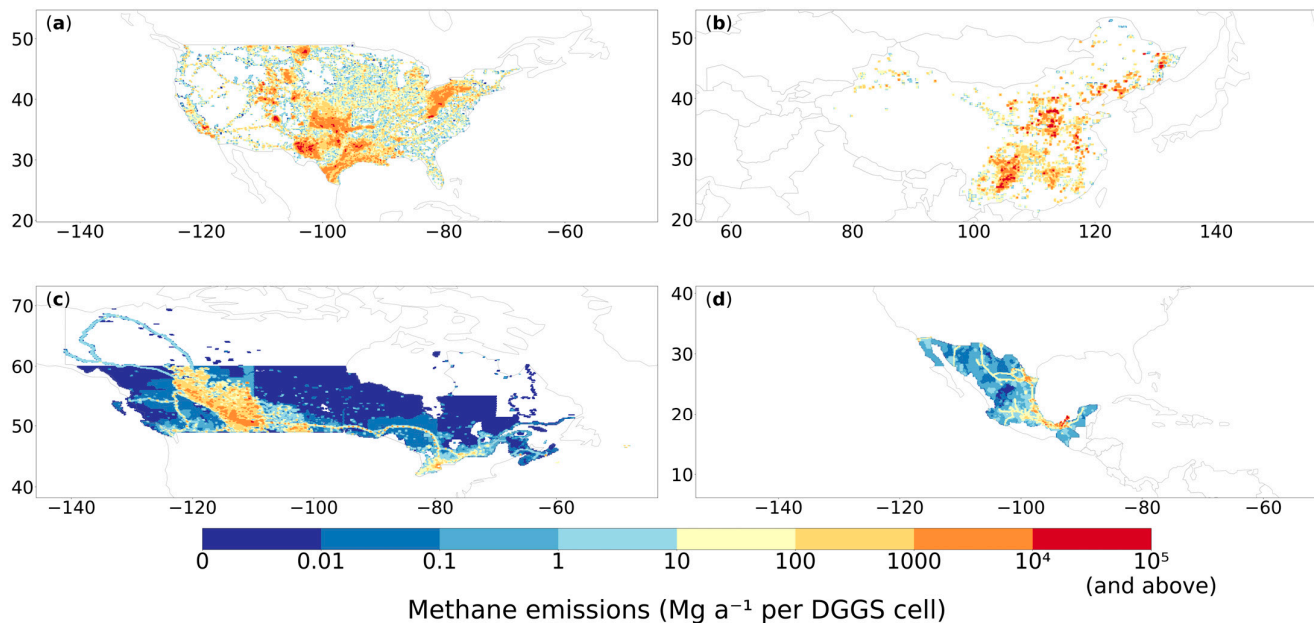


Figure 5. National-scale energy-sector methane emissions (Mg a^{-1} per DGGS cell) converted to the rHEALPix DGGS at resolution level 6 for (a) continental U.S. Oil and Gas Methane Emissions in 2021 [37], (b) mainland China Coal Mine Methane Emissions in 2011 [39], (c) CMS Datasets on Methane Flux for Oil and Gas Systems in Canada in 2013 [38], and (d) CMS Datasets on Methane Flux for Oil and Gas Systems in Mexico in 2010 [38].

Figure 6 presents methane emissions from the CAMS-REG v8.1 Emissions Inventory for Europe in 2005 and 2022 [34], shown at DGGS level 7, with the full annual series in Figure S1. The maps reveal spatially stable emission structures over time, with consistent hotspots associated with major industrial centers. Year-to-year variations across the full series are subtle and largely reflect minor adjustments to reported activity data, illustrating the dataset's internal temporal coherence (Figure S1). Figures 7 and 8 display the first and last year of the energy-sector series for the United States (2012–2018) and China (1990–2020) on the same class breaks, with the full series in Figures S2 and S3 [31,33]. The U.S. sequence shows broadly stable spatial patterns with modest interannual variability (Figure S2). In 2020, cells in northwest China appear visually less intense than those in eastern and central regions despite the increase in national energy-sector totals reported in Table 4. This pattern reflects the absence of fossil-energy consumption emissions reported for these areas in the source inventory and is consistent with the original data. These global, continental, national, and temporal examples demonstrate that diverse inventories can be visualized consistently on an equal-area DGGS, supporting transparent side-by-side comparisons.

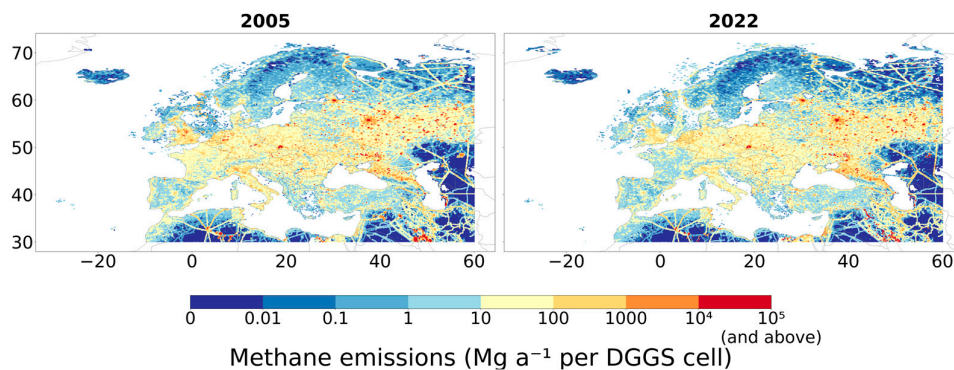


Figure 6. Energy-sector methane emissions (Mg a^{-1} per DGGS cell) from the CAMS-REG v8.1 Emissions Inventory for Europe [34] in 2005 and 2022, converted to the rHEALPix DGGS at resolution level 7. The full annual series is given in Figure S1.

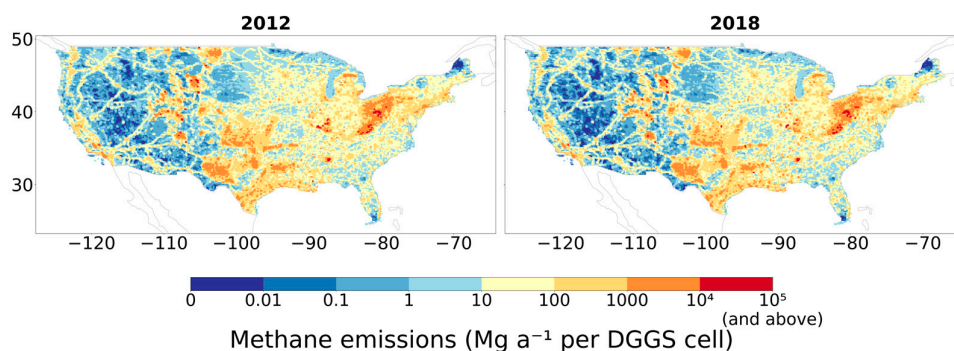


Figure 7. Energy-sector methane emissions (Mg a^{-1} per DGGS cell) from the continental U.S. Anthropogenic Methane Emissions inventory [31] in 2012 and 2018, converted to the rHEALPix DGGS at resolution level 6. The full annual series is given in Figure S2.

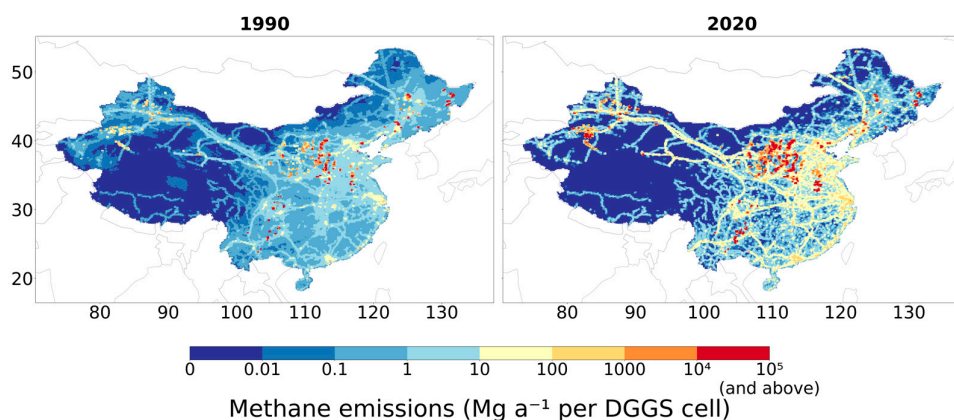


Figure 8. Energy-sector methane emissions (Mg a^{-1} per DGGS cell) from the mainland China Anthropogenic Methane Emissions inventory [33] in 1990 and 2020, converted to the rHEALPix DGGS at resolution level 6. The full annual series is given in Figure S3.

4. Discussion

4.1. Harmonization Axes and Cross-Dataset Comparability

Harmonization is evaluated along three dimensions, each with a distinct criterion and outcome. Spatial harmonization requires equal-area cells, congruent refinement, and hierarchical indexing, which motivate the selection of rHEALPix in Section 2.2. Quantitative harmonization requires mass conservation, enforced by the scaling step and evaluated in Section 3.2. Semantic harmonization requires a common classification and transparent source-to-target mappings. Of 324 source variables, 173 map one-to-one to an IPCC 2006 category, 122 share a category with other variables, and 25 span multiple categories. The published crosswalk records the cardinality and basis of each assignment, making non-unique mappings explicit.

The harmonized dataset addresses a key barrier to the joint use of gridded methane inventories, namely the structural inconsistency among products distributed on different projections, resolutions, and reporting conventions. By representing every source on the rHEALPix DGGS with IPCC 2006 sector codes and values in megagrams per year, the dataset supports comparison across countries, years, and data sources without confounding differences in projection, cell area, or nomenclature. Each inventory retains the resolution level matched to its native grid, with levels 6, 7, 9, and 10 represented in the harmonized collection. Inventories at the same level can be compared cell by cell. Where levels differ, the finer inventory is aggregated to the coarser level by summing cells that share the corresponding index prefix. Congruent refinement makes this aggregation exact without re-intersection or additional area weighting. This aggregation operates directly on the cell identifiers, avoiding repeated reprojection and custom spatial processing. The equal-area property is central to this comparability, because latitude–longitude graticules assign systematically smaller cell areas toward the poles and distort areal intensity patterns. Earlier assessments of open DGGS implementations reported that equal-area tessellations reduce area-related comparison bias and provide stable spatial identifiers for interoperable joins across heterogeneous datasets [29,44]. Because each DGGS cell is fixed in space, temporal trend analysis is also straightforward, as year-to-year changes reflect changes in emissions rather than shifts in grid definition. This combination of equal-area geometry and hierarchical indexing distinguishes the DGGS representation from area-normalization approaches.

4.2. Applications to Downstream Analysis

The standardized fields support a range of downstream analyses. They provide spatially explicit priors for atmospheric inversion [16,53], where the equal-area representation avoids latitudinal area bias and the IPCC-consistent sectors align with common modeling inputs. They also provide baseline conditions for simulating large, short-duration emission events and for evaluating the detectability of such events against local backgrounds [22]. At finer resolutions, the products support localized emission estimation and comparison across measurement campaigns, jurisdictions, and sectors, which enables hotspot screening and targeted mitigation planning [21]. The uniform sector coding, reporting units, and grid geometry also produce a machine-readable structure suited to data-intensive and AI-enabled analysis [45]. Consistent equal-area and hierarchical semantics allow direct ingestion into analytical pipelines for training, inference, and query [45].

4.3. Extensibility of the Harmonization Framework

The dataset and its converters are designed to be extended as new inventories become available. New gridded products can be appended to the unified structure using the

same IPCC 2006 crosswalks and unit conversions, and the open converters support the addition of further inventories with minimal adaptation. The framework also accommodates point-based data, where facility observations are binned to rHEALPix cells in an equal-area manner and incorporated alongside gridded products with full provenance. Because the DGGs index provides a persistent spatial key, future facility information such as wells, compressors, and landfills can be linked directly to cell identifiers. Although the present work focuses on methane, the workflow is gas-agnostic, and the same procedures apply to other greenhouse gases such as carbon dioxide and nitrous oxide and to air pollutants such as nitrogen oxides and sulfur dioxide.

The framework is grid-independent because area-weighted redistribution applies to any equal-area tessellation and mass closure is enforced during conversion. The validation results in Section 3.2 therefore reflect the source inventories and area-of-overlap computation rather than the target grid. Grid choice instead determines the operations supported by the harmonized product. Among equal-area alternatives, ISEA-based grids satisfy the equal-area criterion, while congruent refinement and hierarchical indexing depend on the specific refinement ratio and indexing scheme.

4.4. Limitations

The conversion is restricted to spatial transformation and does not reassess, correct, or reconcile uncertainties in the source inventories. All uncertainties in the original datasets, including those arising from measurement error, sampling representativeness, temporal aggregation, and underlying methodological assumptions, are retained and carried forward. The harmonized products should therefore be understood as a standardized spatial encoding of the original information rather than an uncertainty-resolved or quality-enhanced estimate. Any limitation inherent to a source dataset remains unchanged and should be considered in downstream applications. Harmonization aligns sector labels without altering the underlying estimation methods. Values compiled using the 2019 Refinement are retained under their IPCC 2006 category codes while preserving the methods of the source inventory. In addition, the rHEALPix resolution selected for each inventory balances preservation of native detail against over-smoothing. Analyses requiring a common resolution across all products therefore aggregate to the coarsest level represented, level 6. The hierarchy supports aggregation from finer to coarser levels, but an inventory provided at level 6 cannot recover spatial detail at finer levels. The harmonized dataset reflects the source releases used for conversion. EDGAR v8.0 covers 1970 to 2022, and later EDGAR releases extend the series to 2024 [54]. Version 8.0 was retained because it is the most recent release whose gridded product is described in a peer-reviewed data publication [55]. The converters run unchanged on a newer release, so updating the harmonized product is a matter of re-running the workflow.

5. Conclusions

This study presents a framework for harmonizing heterogeneous gridded emission inventories within an equal-area DGGs and defines criteria for evaluating the harmonization. The framework was demonstrated on 13 open-access methane inventories spanning global to subnational scales. Inventories were transformed through an area-weighted, mass-preserving workflow, with spatial structure, sector classifications, and reporting units standardized under the IPCC 2006 framework and expressed in megagrams per year per cell. Validation showed negligible differences for continental, national, and regional inventories and differences within 2% to 3% for global inventories. Cell area is constant by construction, aggregation by index prefix preserves totals to floating-point precision, and the sector crosswalk records the cardinality and basis of each assignment. By resolving inconsistencies in projection, sector coding, and reporting units, the dataset

supports cell-by-cell comparison among inventories at the same resolution, exact aggregation along the cell hierarchy across resolutions, and integration with broader geospatial and analytical workflows. The harmonization framework itself is independent of the grid. The area-weighted, mass-preserving conversion applies to any equal-area tessellation, and rHEALPix was selected for the indexing and aggregation properties the harmonized product requires. The harmonization workflow is reproducible and extensible to additional inventories, other greenhouse gases, and air pollutants, providing a practical foundation for interoperable, equal-area environmental data infrastructures and for data-intensive analysis of emissions.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/ijgi15100466/s1>, Table S1: Annual comparison of total methane emissions before and after rHEALPix DGGS conversion for the EDGAR v8.0 inventory (1970–2022); Table S2: Annual comparison of total methane emissions before and after rHEALPix DGGS conversion for the CAMS-REG v8.1 inventory (2005–2022); Table S3: Annual comparison of total methane emissions before and after rHEALPix DGGS conversion for the U.S. Anthropogenic Methane Emissions inventory (2012–2018); Table S4: Annual comparison of total methane emissions before and after rHEALPix DGGS conversion for the China Anthropogenic Methane Emissions inventory (1990–2020); Figure S1: Energy-sector methane emissions (Mg a^{-1} per DGGS cell) from the CAMS-REG v8.1 Emissions Inventory for Europe for the years 2005–2022, converted to the rHEALPix DGGS at resolution level 7; Figure S2: Energy-sector methane emissions (Mg a^{-1} per DGGS cell) from the continental U.S. Anthropogenic Methane Emissions inventory for the years 2012–2018, converted to the rHEALPix DGGS at resolution level 6; Figure S3: Energy-sector methane emissions (Mg a^{-1} per DGGS cell) from the mainland China Anthropogenic Methane Emissions inventory for the years 1990–2020, converted to the rHEALPix DGGS at resolution level 6. Reference [56] is cited in the Supplementary Materials.

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Data Availability Statement: The harmonized global-to-regional gridded methane emission datasets generated in this study are publicly available from the Zenodo repository at <https://doi.org/10.5281/zenodo.17362125>. The archive contains all converted inventories in rHEALPix DGGS format, including tabular emission data and corresponding GeoParquet geometry files. The 13 source inventories are open-access products obtained from their original providers, each cited in Table 1 and described in the Supplementary Information, and the harmonized dataset is redistributed with attribution to those providers. The conversion code and the sector lookup tables are available at <https://github.com/UbiSensingAILab/methane-dggs-converter> (accessed on 20 September 2026), release version 1.0.0.

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