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Comparative Evaluation of Top-Down GOSAT XCO₂ vs. Bottom-Up National Reports in the European Countries

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Abstract: Submitting national inventory reports (NIRs) on emissions of greenhouse gases (GHGs) is obligatory for parties of the United Nations Framework Convention on Climate Change (UNFCCC). The NIR forms the basis for monitoring individual countries' progress on mitigating climate change. Countries prepare NIRs using the default bottom-up methodology of the Intergovernmental Panel on Climate Change (IPCC), as approved by the Kyoto protocol. We provide tangible evidence of the discrepancy between official bottom-up NIR reporting (unit: tons) versus top-down XCO₂ reporting (unit: ppm) within the European continent, as measured by the Greenhouse Gases Observing Satellite (GOSAT). Bottom-up NIR (annual growth rate of CO₂ emission from 2010 to 2016: −1.55%) does not show meaningful correlation (geographically weighted regression coefficient = −0.001, R² = 0.024) to top-down GOSAT XCO₂ (annual growth rate: 0.59%) in the European countries. The top five countries within the European continent on carbon emissions in NIR do not match the top five countries on GOSAT XCO₂ concentrations. NIR exhibits anthropogenic carbon-generating activity within country boundaries, whereas satellite signals reveal the trans-boundary movement of natural and anthropogenic carbon. Although bottom-up NIR reporting has already gained worldwide recognition as a method to track national follow-up for treaty obligations, the single approach based on bottom-up did not present background atmospheric CO₂ density derived from the air mass movement between the countries. In conclusion, we suggest an integrated measuring, reporting, and verification (MRV) approach using top-down observation in combination with bottom-up NIR that can provide sufficient countrywide objective evidence for national follow-up activities.

Keywords: top-down; bottom-up; GOSAT XCO₂; national inventory report; carbon footprint; MRV

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1. Introduction

National inventory reports (NIRs) are required for tracking national adherence to treaty obligations and recommendations arising from Nationally Determined Contributions (NDCs) mechanisms under the Paris Agreement and United Nations Framework Convention on Climate Change (UNFCCC) [1]. An NIR consists of CO₂ emissions and removal from five categories (energy, waste, industrial process and production use, agriculture and land use, land-use change and forestry [LULUCF]). The calculation of CO₂ emissions in an NIR is based on the carbon footprint concept, which considers all relevant carbon sources, sinks, and storage within the country boundary [2]. An NIR presents the quantity of greenhouse gases (GHGs) estimated with the emission factors and units of emission-generating activity emitted into the atmosphere by an individual, organization, process, product, or event from within a specified country boundary [3]. Once CO₂ is emitted into the atmosphere, it increases the atmosphere's net resident CO₂ [4]. In this

regard, atmospheric CO₂ density can potentially provide an independent validation reference to bottom-up NIR carbon footprint [5]. Satellite-based XCO₂ (column-averaged CO₂) carries large amounts of information from the bottom atmospheric layer (near-ground) to the top of the atmosphere, including background atmospheric CO₂ [6,7]. Nonetheless, top-down satellite observation needs the high-resolution, bottom-up energy statistics and emission-generating activities data to explore errors caused by the inherent limitation of the remote sensing technology such as inversion model errors, noise from aerosols and clouds [8]. For parties of the global climate treaties, guidance should be provided on the relative advantages of the two carbon measurements under different conditions and interests of parties in accounting for CO₂ emissions.

A comparative evaluation of GOSAT XCO₂ concentrations and NIR carbon footprint could present the pros and cons for the alternative that can be considered as the second option for the bottom-up inventory of IPCC. For example, GOSAT XCO₂ concentrations identify country-specific parameters influenced by certain events (such as economic downturn, El Niño, a milder winter). Previous studies were performed to compare the differences between source data (e.g., land use) of the carbon inventories and the real atmospheric carbon observations [9,10]. Hakkarainen et al. [11] reported that the Orbiting Carbon Observatory-2 (OCO-2) satellite-based XCO₂ shows a positive correlation with the Open-Source Data Inventory for Anthropogenic CO₂ (ODIAC) among the main pollution regions: eastern USA, central Europe, and East Asia. There is also literature that features comparisons between ground-based atmospheric observations (eddy flux tower measurements) and the publicly available inventory for urban atmospheric carbon dioxide (CO₂) in the city scale [12,13]. However, no studies have been performed to explore the tangible difference between top-down versus bottom-up techniques by comparing NIRs with carbon satellite data. The aim of this study was to investigate the differentiated variations of spatial and temporal patterns in the European area between atmospheric CO₂ concentrations measured by GOSAT and the carbon inventory data presented in the NIR. The results of this study can be used as a crucial evidential reference for confirming a discrepancy range in spatial distribution patterns among individual countries to be considered when linking the NIR and carbon satellite signatures to explore national follow-up activities for treaty obligations.

2. Materials and Methods

The NIR and GOSAT XCO₂ are represented by two different measurement units: bottom-up carbon footprint (ton) and top-down atmospheric CO₂ data (unit: ppm). To compare the two datasets under the same unit of measurement, the annual growth rate of the two datasets was calculated as a percentage (%). The integrated variation was calculated by subtracting the annual growth rate of the previous year from the annual growth rate of the following year. For instance, if a country had 1% variation in 2010–2011 and 1.5% variation in 2011–2012, the integrated variation from 2010 to 2012 was estimated as 0.5%. That is why the integrated variation is smaller than the individual variation.

2.1. Study Area

According to the Kyoto protocol, Annex I countries (which developed country parties in 1992) must submit an updated NIR each year. Uncertainties in NIR data are relatively low for Annex 1 countries due to well-developed statistical systems and their capacity to use higher-tier methods [14]. Europe is the second smallest continent in the world after Australia and Oceania, but as 44 countries are concentrated in one area, it is an ideal region for studying carbon emissions among countries. Europe is also ideal for investigating carbon inventories in various climates, due to diverse land cover and forests, such as the Mediterranean forest, temperate forest, tundra, coniferous forest, and steppes [15].

The Total Carbon Column Observing Network (TCCON) is a global network of instruments that measure the amount of carbon dioxide and other trace gases in the Earth's atmosphere [16]. TCCON provides the primary validation dataset for the GOSAT, and it has been used to validate other space-based measurements of CO₂ [7,17,18]. Out of a

total of 23 worldwide TCCON sites, eight are in Europe; therefore, there is a relatively large distribution of verification points of satellite measurements in comparison to other continents. In this regard, GOSAT XCO₂ data acquired in Europe have been produced with more validation procedures than those from other continents. Therefore, Europe is an ideal continent with an adequate land mosaic for comparing bottom-up CO₂ emissions and top-down column abundance XCO₂, because various types of countries with diverse human and natural environments are concentrated in a small area, and there are a large number of GOSAT XCO₂ validation points. We selected the 33 European countries belonging to Annex 1 countries. We did not include Iceland because it is too far from the European continent.

2.2. GOSAT XCO₂ Observations

The GOSAT orbits at an altitude of approximately 666 km, with 10.5 km of spatial resolution and three-day temporal resolution [19]. The observation instrument onboard GOSAT is the Thermal and Near Infrared Sensor for Carbon Observation (TANSO) composed of two subunits: the Fourier-Transform Spectrometer (FTS) and the Cloud and Aerosol Imager (CAI). The TANSO-FTS operates with spectral resolution in three narrow bands in the short-wavelength infrared (SWIR) region (0.76, 1.6, and 2.0 μm) and a wide thermal infrared band (5.5–14.3 μm). TANSO-CAI operates with spectral resolution in four narrow bands in the near-ultraviolet to a near-infrared region (0.38, 0.674, 0.87, and 1.6 μm). TANSO can detect optically thick clouds inside the TANSO-FTS instantaneous field of view (IFOV) and correct aerosols' effect in the TANSO-FTS spectrum data [20,21]. In this study, we used the GOSAT SWIR Level 2 product (column-averaged mixing ratios of CO₂, V02.75) for 2010–2016 (total 20,929 data points) retrieved with the National Institute for Environmental Studies (NIES) CO₂ retrieval algorithm [22], which is corrected with the regression coefficients (0.89) between GOSAT XCO₂ and TCCON data [23].

2.3. Bottom-Up NIR

NIR contains detailed descriptive and numerical information and common reporting format (CRF) tables for all Kyoto protocol GHG [24,25]. On the contrary, GOSAT only provides the column abundance of CO₂ (the number of the gas molecule in a vertical unit column). To perform a comparative evaluation of the NIR data and GOSAT XCO₂ data, we used direct CO₂ emissions (CRF Table 10s2 submitted to UNFCCC in 2018; Table 1) [26]. NIR 4 sectors and NIR 4 sectors + LULUCF (i.e., NIR 5 sectors) from 2010 to 2016 in EU-33 countries showed a range of 0.1 Mt CO₂-equivalent to 833.7 Mt CO₂-equivalent and −3.1 Mt CO₂-equivalent to 816.6 Mt CO₂-equivalent, respectively (Table 1). GOSAT XCO₂ from 2010 to 2016 in EU-33 countries had a range of 384.2 ppm to 403.2 ppm. The mean values of XCO₂ in EU-33 countries showed the constant increasing trends from 387.1 ppm to 401.3 ppm during 2010–2016 (Table 1).

2.4. Visualization Utilizing GOSAT Level 3 Products

GOSAT Level 3 data were generated to visualize the spatial distribution of XCO₂ on a regional scale by using the empirical Bayesian kriging (EBK) surface interpolation approach (Figure 1). EBK is a geostatistical interpolation method that automatically calculates a K-Bessel semi-variogram model through a process of sub-setting simulations [27,28]. GOSAT XCO₂ detects the column-averaged abundance of CO₂ in the atmosphere at the time of data acquisition (in real-time). Therefore, GOSAT XCO₂ strongly reflects regional CO₂ concentration, such as the presence of CO₂ sources and the difference in CO₂ flux due to the photosynthesis and respiration from the terrestrial biosphere [29]. CO₂ emitted from a source moves continuously with the flow of the atmosphere. Emissions strongly affect atmospheric CO₂ concentration; however, the farther away from the source, the lower the impact on the CO₂ concentration [30]. By dividing the input GOSAT point data into small subsets, EBK derived the different semi-variograms reflecting distance away from

the emission source [27]. Figure 1b shows the results of the EBK, reflecting regional CO₂ distribution characteristics in accordance with the non-stationary flow of the atmosphere.

Table 1. Descriptive statistics of 33 individual European countries' GOSAT XCO₂ and net CO₂ emissions in NIR from 2010 to 2016. NIR 4 sectors: The total of net CO₂ emission from energy, industrial processes, and production use, agriculture, and waste. NIR 5 sectors: NIR 4 sectors + LULUCF.

Category	Year	Min	Max	Mean	Std. Dev
NIR 4 sectors (Mt CO ₂ -equivalent)	2010	0.1	833.7	142.6	183.6
	2011	0.1	810.8	139.2	178.5
	2012	0.1	815.2	137.6	179.5
	2013	0.1	832.6	134.6	178.9
	2014	0.1	793.6	128.5	169.8
	2015	0.1	797.1	129.1	170.7
	2016	0.1	801.8	129.5	171.2
NIR 5 sectors (Mt CO ₂ -equivalent)	2010	0.1	815.6	127.5	177.2
	2011	0.1	793.4	124.7	172.0
	2012	0.1	799.0	123.1	173.3
	2013	0.1	816.6	120.0	172.1
	2014	0.1	777.0	114.1	162.7
	2015	−3.1	781.0	114.6	163.2
	2016	−2.1	785.5	115.6	163.7
GOSAT XCO ₂ (ppm)	2010	384.2	388.7	387.1	1.0
	2011	387.5	390.6	389.1	0.9
	2012	390.1	393.9	392.1	1.0
	2013	390.7	395.0	394.0	0.9
	2014	393.1	398.5	396.3	1.3
	2015	394.5	400.5	398.3	1.4
	2016	398.3	403.2	401.3	1.1

Cross-validation is commonly used to validate how good the kriging model interpolates by comparing the estimated values with the observed values [31]. There are various criteria for the cross-validation of prediction errors for EBK models, such as root mean square error (RMSE), average standard error (ASE), mean standardized error (MSE), and root mean square standardized error (RMSSE) [32]. RMSE provides a measure of interpolation precision, where a lower RMSE indicates a more precise estimation. For this research, ASE was distributed in the range of 1.833 to 2.204 (ppm), whereas RMSE was in the range of 1.765 to 2.121 (ppm; Table 2). As EBK was applied for yearly GOSAT XCO₂ data, the difference of CO₂ concentration by season is the cause of ASE and RMSE deviations in this range [33]. ASE values close to RMSEs imply that the variability in prediction is correctly assessed. The results of this study revealed that ASE was close to RMSE, suggesting a reasonably acceptable level of error, considering that the interpolation was conducted for the fluctuation of carbon concentration occurring on the entire European continent. RMSSEs were calculated by dividing the root average of RMSE by ASE. An RMSSE close to 1 indicates fewer prediction standard errors [27]. MSE was calculated by dividing the sum of the difference between the measured and the predicted values by the kriging variance. An MSE close to 0 indicates that the bias of the EBK model is low [27]. In this study, RMSSE was close to 1, ranging from 0.969 to 0.993, and MSE was also close to 0, from −0.011 to 0.013, indicating that the model's accuracy is reasonably acceptable (Table 2).

Figure 1. Map of 33 European countries and their GOSAT XCO₂ spatial distributions from 2010 to 2016 (a) GOSAT-FTS SWIR Level 2 XCO₂ data products (V02.75) in 2010–2016 (b) Level 3 GOSAT XCO₂ data interpolated with GOSAT-FTS SWIR Level 2 XCO₂ data products (V02.75) using empirical Bayesian kriging (EBK) in 2010–2016.

Table 2. Cross-validation summary statistics from empirical Bayesian kriging (EBK).

Category	RMSE (ppm)	ASE (ppm)	RMSSE	MSE
2010	1.873	1.860	0.993	−0.010
2011	1.787	1.864	0.969	0.009
2012	1.795	1.887	0.969	−0.008
2013	1.920	2.013	0.974	0.003
2014	2.121	2.204	0.976	0.013
2015	2.000	2.091	0.976	−0.011
2016	1.765	1.833	0.981	−0.005

Note. RMSE = root mean square; ASE = average standard error; RMSSE = root mean square standardized error; MSE = mean standardized error.

2.5. Geographically Weighted Regression (GWR)

Atmospheric carbon is a natural phenomenon that flows across national boundaries, interacting with the Earth and the atmosphere [34]. It is normal for top-down satellite data reflecting natural phenomena to retain information on spatial dependence or spatial heterogeneity among neighboring countries sharing a similar space. Therefore, CO₂ fluxes and concentrations are influenced by local parameters, such as climatic conditions and

stationary CO₂ sources (e.g., power plants, oil refineries, etc.) within national boundaries. GWR searches for spatial heterogeneity by applying different regression models to data in different locations in space. Therefore, local regression coefficients were derived for individual countries when using a GWR regression model between NIR and satellite signals, whereas traditional linear regression analysis estimates a single global regression coefficient on the whole area of analysis. With GWR, it was possible to determine different local coefficients for each country and to identify spatially heterogeneous patterns that are difficult to grasp with traditional ordinary least squares (OLS) models.

3. Results

3.1. A Comparative Evaluation of Top–Down vs. Bottom–Up

Annual changing trends of top–down GOSAT XCO₂ (ppm) show strong contradictory trends between bottom–up NIR 4 and 5 sectors (Figure 2a). Regardless of the largely declining pattern in bottom–up net CO₂ emissions, the top–down trend (GOSAT XCO₂, unit: ppm) is steadily increasing. The average net CO₂ emissions in NIR 4 and 5 sectors from 2014 to 2016 are 5.49% and 5.83% lower than emissions from 2010 to 2014 (Figure 2b). NIR 4 and 5 sectors keep decreasing due to the economic downturn from 2011 to 2012 (declining the CO₂ emissions from the industrial production and manufacturing industries), milder winter conditions, and increases in non-combustible renewables for electricity generation in 2013 and 2014 (lower heat demand from households and electricity generations from the fossil fuel combustions) [35–37]. The NIR 4 and 5 sectors rebound in increasing trends was triggered by the higher heat demand by households and services due to colder winter conditions and higher road transport demands from 2014 to 2016 [37–39].

Figure 2. Comparison of changing trends between GOSAT XCO₂ versus CO₂ emissions presented in NIR of 33 European countries from 2010 to 2016 (a) annual variations of GOSAT XCO₂ (top–down), NIR 4 sectors (energy, waste, industrial process, and production use, agriculture) and NIR 5 sectors (NIR 4 sectors + LULUCF) in NIR (bottom–up) from 2010 to 2016 within EU-33 (b) descriptive statistics of annual GOSAT XCO₂, NIR 4 sectors, and NIR 5 sectors (NIR 4 sectors + LULUCF) presented in Figure 1b.

Although emissions from the NIR 4 and 5 sectors appeared to increase or decrease relative to the previous year, GOSAT XCO₂ continues to increase. The average GOSAT XCO₂ growth rate from 2014 to 2016 (0.65%) was higher than from 2010 to 2014 (0.56%; Figure 2b). The bottom-up NIR 4 and 5 sectors represent the residual terrestrial CO₂ sinks (terrestrial biosphere) and anthropogenic CO₂ sources. Decreased CO₂ uptakes from terrestrial CO₂ sinks and anthropogenic sources (NIR 4 and 5 sectors) influence atmospheric carbon residuals. Therefore, annual changing trends of top-down GOSAT XCO₂ (ppm) may be positively correlated with NIR CO₂ emissions from terrestrial carbon sinks and anthropogenic sources (NIR 4 and 5 sectors) [40]. GOSAT XCO₂ steeply increased in 2011–2012, as well as 2015–2016. It is assumed to be the natural phenomenon that occurred by the reduction in biospheric CO₂ uptake due to the heavy snowfall (2011–2012) and the El Niño event (2015–2016) [41].

3.2. A Comparative Evaluation among Individual Countries

The top five countries in NIR 4 and 5 sectors are not in good agreement with the top five countries with high GOSAT XCO₂ concentrations (Table 3). There are only five countries (Estonia, Hungary, Slovakia, Slovenia, and the United Kingdom) where GOSAT XCO₂ is decreasing among the 27 countries in which both NIR 4 and 5 sectors are decreasing. Similarly, the bottom five countries in NIR 4 and 5 sectors are not at all consistent with the bottom five countries for GOSAT XCO₂ concentrations (Figure 3; Table 3). In addition, when GWR analysis was performed on top-down and bottom-up changing trends at the national level, there was no significant correlation (R^2 for NIR 4 sectors: 0.070; R^2 for NIR 5 sectors: 0.024) between independent variables and dependent variables (Table 4).

Table 3. Five European countries showing the highest and lowest changing trends in carbon emission from 2011 to 2016.

Category	GOSAT XCO ₂ (Unit: Annual Variations, %)	NIR 4 Sectors (Unit: Ton, %)	NIR 5 Sectors (Unit: Ton, %)
Top countries	1. Bulgaria (0.22) 2. Finland (0.22) 3. Liechtenstein (0.17) 4. Turkey (0.14) 5. Switzerland (0.13)	1. Turkey (3.37) 2. Ireland (0.95) 3. Germany (−0.22) 4. Norway (−0.42) 5. Netherlands (−0.43)	1. Belarus (10.65) 2. Norway (3.24) 3. Turkey (2.57) 4. Portugal (1.94) 5. Ireland (0.95)
Bottom countries	1. Hungary (−0.12) 2. Slovenia (−0.06) 3. Slovakia (−0.05) 4. United Kingdom (−0.02) 5. Estonia (−0.01)	1. Greece (−4.90) 2. Ukraine (−4.68) 3. Luxembourg (−3.71) 4. Liechtenstein (−3.22) 5. Denmark (−3.21)	1. Sweden (−24.17) 2. Finland (−5.26) 3. Greece (−5.11) 4. Romania (−4.77) 5. Ukraine (−4.49)

Table 4. GWR results between top-down GOSAT XCO₂ versus bottom-up NIR from 2011 to 2016.

Category	Period	R^2	GWR Coefficient			Local R^2			p -Value	AIC
			Min	Max	Mean	Min	Max	Mean		
NIR 4 sectors	2011–2016	0.070	−0.069	−0.008	−0.041	0.002	0.102	0.047	0.50	18.57
NIR 5 sectors	2011–2016	0.024	−0.003	0.000	−0.001	0.000	0.004	0.001	0.56	17.78

Note: AIC = Akaike Information Criterion.

Figure 3. Comparative evaluation of CO₂ emission trends across 33 European countries from 2011 to 2016 (a) NIR 4 sectors (b) NIR 5 sectors (c) GOSAT XCO₂ (annual variation).

4. Discussion

The preconditions and tools used in the top–down versus bottom–up methods differ, as shown in Table 5. NIR reveals anthropogenic carbon-generating activity within country boundaries, whereas satellite signal exhibits the trans-boundary movement of atmospheric carbon. It is inevitable that different methods for calculating CO₂ (i.e., calculating concentration units versus volume units) yield different results. Bottom–up IPCC guidelines calculate the total volume of CO₂ emissions by quantifying CO₂ per unit of a particular activity (an emission factor) and multiplying the numbers of emissions-generating activity occurring within the country boundaries [42,43]. Consequently, the emission factors and numbers of emissions activity within boundaries are crucial in determining the range of CO₂ emissions and variations. The units for emission-generating activities and emission factors greatly influence variations in net CO₂ emissions of NIR 4 and 5 sectors. In contrast, top–down GOSAT XCO₂ measures direct column-averaged dry-air mole fractions of CO₂ as ppm using radiance spectra from the sensitive wavelength band [20] (Table 5).

There are inconsistencies in CO₂ emission estimations based on initial assumptions about carbon footprint as CO₂ sources in bottom–up NIR [44], as emission coefficients fluctuate depending on a variety of variables, such as collection and reporting system of energy statistics, data definition, data processing, level of detail and local specific conditions [45]. IPCC guidelines present three bottom–up methods: (1) Tier 1 (global default model), (2) Tier 2 (nation-specific model), and (3) Tier 3 (local-specific model). Bottom–up estimates fluctuate based on how tier stages are set [8]. Unlike the NIR, GOSAT XCO₂ presents atmospheric density accumulated by different types of sources or sinks (background atmospheric CO₂) accumulated during the complete carbon life stages of more than 100 years [46], including other natural and anthropogenic sources or natural sinks that are not present in IPCC guidelines, such as volcano eruptions [47]. In addition, GOSAT XCO₂ detects the direct and indirect CO₂ emissions from terrestrial biotic activity derived from natural disturbances. GOSAT XCO₂ is the integrated CO₂ in a column from the surface to the top of the atmosphere. Therefore, GOSAT XCO₂ has very limited sensitivity to the bottom layer of the atmosphere where human activities are interacting with it. It has been shown that the XCO₂ variability is driven by both surface emissions and atmospheric transport contaminated with clouds and clear sky ratio, according to geolocation [48].

Table 5. Comparison of major components involved in data collection processes between top–down versus bottom–up.

Category	GOSAT XCO ₂ (Top–Down) [20,49]	NIR 5 Sectors (Bottom–Up) [50,51]
Measurement tool	TANSO is composed of two subunits: the Fourier-Transform Spectrometer (FTS) and the Cloud and Aerosol Imager (CAI).	IPCC default methodology (allometric model), field survey and laboratory experiments (determining the quantity of emissions of a particular GHG per unit of activity: emissions factor)
Data type (unit)	Column-averaged dry air mole fractions of CO ₂ data (ppm: density), background atmospheric CO ₂ , trans-boundary real atmospheric CO ₂ density	Statistical data (Kt CO ₂ -equivalents: ton) derived from CO ₂ per unit of a particular emission-generating activity (an emission factor), confined within the national boundary
Influencing variables	Natural disturbances: CO ₂ absorption and concentration from terrestrial biotic activity atmospheric inflow and transport, solar radiation Anthropogenic disturbances: CO ₂ sources such as power plants, chemical and metal factories, oil and natural gas production sites, forest fires, transport, etc.	Energy: fuel combustion activity Industrial processes: uses of fossil fuel carbon in the mineral industry, chemical industry, metal industry, etc. Agriculture: liming to reduce soil acidity LULUCF: carbon stock gain and loss due to biomass growth by afforestation and forest management, decay, degradation, and fire Waste: Solid waste disposal, incineration, etc.

The developed countries listed in Annex I of the UNFCCC must submit national GHG inventories of anthropogenic emissions by sources and removals by sinks accounted with IPCC guidelines [52]. The energy sector is the most important CO₂ source affecting the carbon footprint among the five categories in IPCC guidelines as it accounts for approximately 77–80% of total net CO₂ emissions from EU-33 countries' NIR. In particular, solid fuel combustion from public electricity and heat production is a major CO₂ source in the energy sector, accounting for 60.6–67.9% of total CO₂ emission in the energy sector [38]. IPCC guidelines do not count the CO₂ emissions avoided from the use of blast furnaces by reusing by-products of industrial processes or by replacing conventional solid fossil fuels [53] such as anthracite and lignite. Much higher emission factors are being observed in Belgium (238.23 tCO₂/TJ) and Sweden (206.37 tCO₂/TJ) than other EU countries (89.95 tCO₂/TJ to 122.96 tCO₂/TJ) from solid fuels utilized in public electricity and heat production (Figure 4). The blast furnace gas used in Belgium and Sweden emits much more CO₂ than the anthracite and lignite used in the rest of the EU countries. Blast furnace gas is the secondary fuel created as a free by-product derived from blast furnace coke burned in the iron and steel production process [51], while anthracite and lignite are the primary fuels used in conventional coal power plants [54]. The reduced combustible components from free by-products cause much more CO₂ emission than anthracite or lignite because the energy efficiency of blast furnace gas is considerably low (Table 6). In Belgium and Sweden, most electricity (around 80%) is produced using biomass and by-product derived from waste in Sweden [55] and nuclear, natural gas, and renewable energy in Belgium [56], while very few places use coal (around 10%).

The CO₂ emissions accumulated over the complete life stages of a carbon-generating activity (LCA: life cycle assessment) are not estimated by IPCC guidelines because there is a risk of double-counting of emissions transferred from the industrial processes and product use (IPPU) sector [51] to the energy sector. As blast furnace gas is a by-product of industrial processes, there is no energy consumption to exploit, unlike fossil fuels or industrial waste processing. The current IPCC guidelines do not accommodate the positive carbon footprint effect caused by renewable energy and enhanced technologies such as CHP plants (combined heat and power) using blast furnace gas (Table 6).

Table 6. Comparison of emission factors on solid fuels utilized in public electricity and heat production among EU-33 countries.

Category	Belgium and Sweden	Other EU-33 Countries
Fuel types in public electricity and heat production	Blast furnace gas	Anthracite, lignite, etc.
Productions	Secondary fuels (by-product during the production of metals or steels)	Primary fuel (raw materials)
Usage	Combined heat and power (CHP) plants	Conventional power plants
Emission factor	206.37 to 238.23 tCO ₂ /TJ	89.95 to 122.96 tCO ₂ /TJ
Net Calorific Value (NCV)	Lower NCV (0.000003 TJ/Nm ³)	Higher NCV (0.025 to 0.033 TJ/ton) [57]
Density of Combustible component	18–25%	More than 60% (anthracite) to 80% (lignite) [58]
Combustion temperature peak	Limited to get the high temperature over 1199.85 °C [59]	Above 1199.85 °C [60]

Figure 4. Extreme deviations among EU-33 in estimating CO_2 emitted from solid fuels utilized in public electricity and heat production. (a) A distribution curve of EU-33 emissions factors (in this curve, Liechtenstein, Luxembourg, Monaco and Switzerland are excluded because the countries did not provide emissions factors). (b) Descriptive statics of EU-33 versus IPCC default and percentile deviation among individual EU-33 countries.

NIR is always confined within the national boundary of individual countries, unlike GOSAT XCO_2 , where there is no such barrier. The NIR is calculated based on the anthropogenic carbon dioxide according to energy consumption statistics in the different sectors and reflects the socio-economic condition of individual countries in terms of GHG emission. It is possible to use the NIR for monitoring the progress of individual countries to mitigate

emissions from the earth surface, owing to statistical validation using the Monte-Carlo analysis and the time-period of measurement within confined national boundaries [61]. GOSAT XCO₂ is largely driven by the air mass movement between the countries. The air column monitored by GOSAT is not the real representation of emission from the country under investigation. The prevailing lapse rate guided by the direction of the air mass movement and other meteorological factors has a bigger role in making the reflectance column of GOSAT over a country, and thus it cannot be considered the emission from a country [21]. The influence from atmospheric transport in the GOSAT XCO₂ signal is much stronger than anthropogenic sources such as power plants [18,24]. CO₂ flux from the terrestrial biosphere is much higher than that of anthropogenic emissions, which show high uncertainty [62]. In this regard, the NIR has significant limitations in explaining such background atmospheric concentration at the global or regional level required for trans-boundary comparison, which reflects the regional atmospheric stability governed by meteorological parameters such as wind speed, vertical mixing depth, including the effects of long-distance movements.

GOSAT XCO₂ is processed by the inverse methods of atmospheric transport [63]. To retrieve XCO₂ (GOSAT level 2) from GOSAT spectra (GOSAT level 1), the observed spectrum is used to minimize the difference between the raw data and surface/atmospheric radiative transfer model that simulating gas concentrations of the earth surface and atmospheric state. Mathematical details of these algorithms can be found in Yoshida et al. [64]. GOSAT level 2 XCO₂ data are processed with a NIES off-line global transport model [65] to simulate and reflect seasonal and spatial distributions of long-lived atmospheric constituents in the lower and mid-troposphere. In this regard, the GOSAT level 2 XCO₂ product has little difference from the inverse transport model-based CO₂ data. The differences between GOSAT level 2 XCO₂ and inverse transport model-based XCO₂ results are mostly within 0.5% globally [64]. The southern wind from the north European area increases the optical depths 0.26–0.43 in eastern Europe. The eastern wind flowing from Spain and Portugal to Belarus increases the optical depths 0.21–0.59 in France, Germany, Czech Republic, Poland, Belarus, 0.31–0.33 in Belgium and the Netherlands and 0.07–0.15 in Switzerland [66,67]. In particular, countries with a narrow land area are intensively concentrated in Europe, as shown below; Belgium (world land area ranking: 141, land area: 30,528 km²), Switzerland (136, 41,284 km²), the Netherlands (135, 41,543 km²), Denmark (134, 43,094 km²). In the case of a country with a small national territory, GOSAT does not measure the amount of carbon emitted from the country where the satellite platform is located but has a signal characteristic that is influenced by neighboring countries due to transboundary effects of atmospheric circulation associated with the asymmetric heating of land and sea. Therefore, it is not possible for the GOSAT data to quantify the amount of carbon emission and absorption caused by natural and anthropogenic carbon-generating activity within country boundaries. Since GOSAT data are processed using the inverse transport model, it has the advantage of measuring the cross-border atmospheric movement of natural and anthropogenic carbon. However, there are significant limitations to assessing the correlation between NIR reporting carbon emissions of individual countries in conjunction with GOSAT signals. Previous research suggests that the progress of actual emission-reducing actions presented in NIR is reliable only if it is verified by direct top-down methods that measure the actual CO₂ density (ppm) in the atmosphere [14]. It is essential to evaluate the CO₂ emissions calculated from various nation-specific emissions factors, activity data, and models by using top-down, standardized references in ppm. However, the IPCC guidelines improved through two revisions (1996, 2006) still strongly lean toward bottom-up methods. We need to develop integrative Measuring, Reporting, and Verifications (MRV) with top-down and bottom-up methods to verify CO₂ emission mitigation actions presented in NIR.

5. Conclusions

The GOSAT data (top-down) provided a trans-boundary real atmospheric CO₂ density (unit: ppm) across 33 European countries from 2011 to 2016. It was particularly useful for

assessing the spatial and temporal intensity of anthropogenic and natural CO₂ sources and sinks. When GOSAT data are evaluated in terms of information required for demonstrating trans-boundary objective evidence for national follow-up activities of UNFCCC, it was a much more powerful tool than bottom-up NIR (unit: ton) by quantifying the extent of trans-boundary carbon concentration (unit: ppm) in the European domain scale. However, GOSAT data have also shown limitations and the measurement error caused by natural phenomena, such as aerosol, diffusion radiations, and clouds. Current estimates of CO₂ emissions presented in NIR are based on the upscaling of emission activity data within defined country boundaries. In this regard, NIR may be a reasonable choice for analyzing anthropogenic activities. The results of this study confirmed that a carbon satellite could be a second-choice option when requiring the validation of NIR by assessing the spatial and temporal distribution of real atmospheric CO₂ density. The MRV problems are not solved entirely by any approach, as no single data-acquisition methodology can satisfy all monitoring needs. However, NIR, aided by carbon satellite, can complement the present national follow-up in a synergistic way.

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