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Emission Inventories-From Basic Estimates to Advanced Systems using GIS, Remote Sensing and Big Data: A Review

Bhanu Pratap[1], Sandeep Gupta[2]
[1] M. Tech. Student, Department of Civil Engineering, I I T Kharagpur
[2]Associate Professor, Department of Civil Engineering, College of Technology, G B Pant University of Agriculture and technology, Pantnagar, Udham Singh Nagar, Uttarakhand
Corresponding Author: Sandeep Gupta

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ABSTRACT: Accurate air quality assessment and management rely on emission inventories that document pollutant types and sources. This review examines methodologies for creating emission inventories, highlighting advancements in data collection, technology and statistical tools. It compares regional practices, noting common challenges and innovative solutions. The review covers the evolution of inventories from basic estimates to advanced systems incorporating GIS, remote sensing, and big data and emphasizes the importance of validation and uncertainty assessment. The synthesis of existing research identifies gaps and underscores the need for continuous improvement in methodologies to address emerging challenges and support global pollution reduction. Key studies included in the review focus on emissions from various sources and regions, demonstrating the value of detailed and accurate inventories for effective air quality management.

KEYWORDS: Emission Inventories, GIS, Remote Sensing, Big Data, Air Quality.

I. INTRODUCTION

Accurate air quality assessment and management are vital for public health and environmental protection. Central to this effort are emission inventories, which detail pollutant types and quantities from various sources. These inventories are essential for identifying pollution sources, evaluating regulatory compliance and developing mitigation strategies.

This literature review examines methodologies used in emission inventory preparation across regions, focusing on data collection techniques, technological advancements, and statistical tools. It compares regional practices to highlight common challenges and innovative solutions.The review covers the historical evolution of emission inventories from basic estimates to advanced systems, emphasizing the role of GIS, remote sensing, and big data. It also addresses the importance of validation and uncertainty assessment for credibility and their impact on air quality modeling and policy.By synthesizing existing research and identifying knowledge gaps, this review aims to be a valuable resource for scholars and practitioners, underscoring the need for ongoing improvements in inventory methodologies to tackle emerging challenges and support global pollution reduction efforts.

II. LITERATURE REVIEW

[8].Prashant Gargava and A.L. Aggarwal (1997)developed an emission inventory for Cochin, a, southern India city, highlighting the need for accurate inventories in polluted coastal areas. It categorized emissions from point, line, and area sources. Industrial sources were found to be the main contributors to particulate matter, sulfur oxides, and ammonia, while automobiles were major sources of hydrocarbons, nitrogen oxides, and carbon monoxide, accounting for 95%, 77%, and 70% of these emissions, respectively. Domestic sources had minimal impact. The inventory showed that industries emitted about 85% of particulate matter and 95% of sulfur oxides, whereas automobiles were responsible for 95% of hydrocarbons, 77% of nitrogen oxides and 70% of carbon monoxide.

[5].A. F. Bouwman et al. (1997) developed a global inventory of ammonia (NH_3) emissions for 1990, using a 1° x 1° grid for atmospheric models. Global emissions were estimated at 54 teragrams of nitrogen per year, with major sources being animal excreta (21.6 Tg N/yr), synthetic fertilizers (9.0 Tg N/yr), oceans (8.2 Tg N/yr), biomass burning (5.9

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Tg N/yr), crops (3.6 Tg N/yr) and human activities (2.6 Tg N/yr). Asia contributed to about half of the global emissions, primarily from food production which accounted for 70%. Highest emission rates were in Europe, the Indian subcontinent and China. The inventory had an overall uncertainty of 25%, higher at regional levels. Emissions were expected to increase with global population growth, particularly from food production.

[14].It described the development of an emission inventory for the Seasonal Model for Regional Air Quality (SMRAQ) project, based on Ozone Transport Assessment Group (OTAG) inventories from 1990 and 1995. The study detailed the processing strategy for simulations from May to September, including corrections and quality assurance steps for OTAG data. Spatial maps and time series charts showed hourly, gridded emissions of NO_x, ROG and CO, with significant NO_x peaks from electric utilities and urban sources. ROG emissions were affected by biogenic isoprene in the southern U.S. and CO emissions were mainly from area and mobile sources with less variability. Comparisons with Photochemical Assessment Monitoring Stations (PAMS) data revealed discrepancies in nonmethane organic gases to NO_x ratios.

The study highlighted limitations in emissions modeling and validation efforts, noting discrepancies with PAMS ambient data. It stressed the importance of precise air quality modeling and ongoing evaluation. Future improvements could involve finer grid resolutions and better data integration to align emissions data with atmospheric conditions.

[4].A detailed emission inventory for sulfur dioxide (SO_2), particulate matter (PM) and toxic metals from industrial sources in Greater Mumbai was conducted. The study developed a fuel consumption database and used emission factors suited to Indian conditions. For 2001-02, SO_2 emissions from fossil fuels were estimated at 55.591 Gg yr^-1, PM at 9.794 Gg yr^-1 and metals at 0.375 Gg yr^-1. Thermal power plants (TPPs) were the major contributors, accounting for 27% of SO_2, 19% of PM and 62% of metals. Total fossil fuel energy consumption in the industrial sector was 145 PJ, with 29% used in power plants. Projections for 2010 indicated expected reductions in PM and metal emissions, with decreased concentrations of gaseous pollutants. The study highlighted that fuel oil (FO) was responsible for 59% of SO2 and 37% of PM emissions, while low sulfur heavy stock (LSHS) contributed 60% to metal emissions.

[6].It used a 1° × 1° grid with 392 cells to map CO emissions in India for 2001. Bio-fuels contributed about 34,282 Gg, or 50% of total CO emissions, mainly from rural areas. High CO levels were observed around Mumbai, coastal regions and eastern Uttar Pradesh, correlating with population density. Urban emissions near Chennai and central Tamil Nadu were significant but lower than rural emissions. Vehicle emissions totaled around 6,285 Gg, lower than bio-fuels but expected to rise with increasing vehicle numbers, especially in urban areas.

The study developed a GIS-based method for detailed emissions mapping using CO, showcasing the G-SMILE model's effectiveness. It allocated CO emissions by local sources and activities, distinguishing high and low emission areas at a finer scale than state-level inventories. The 1° × 1° grid was suited for global models but adaptable for regional models. This approach provided crucial surface emission data for enhancing model simulations of tropospheric ozone and offered more detailed insights.

The study presented a GIS-based method to refine surface emissions data into detailed grids, using Carbon Monoxide (CO) emissions for India as a case study. The total CO emissions for India in 2001, estimated at 69.0 Tg/year, were disaggregated from state-level to district-level and further gridded to an 11x11 resolution, with minimal data loss of 13%. This method identified emission hotspots and effectively assessed source contributions. The study highlighted the value of GIS-based methods for spatially detailed emission inventories, crucial for atmospheric modeling and pollution management. The approach demonstrated its effectiveness in enhancing the resolution of emission data and improving model simulations for tropospheric ozone distribution.

[22].It developed the Regional Emission Inventory in Asia (REAS) Version 1.1 inventory to track Asian emissions from 1980 to 2020, covering SO_2, NO_x, CO, NMVOC, BC and OC. The inventory, with a 0.5°×0.5° resolution, showed significant emissions increases due to energy use, particularly in China, driven by coal combustion and industry. From 1980 to 2003, emissions rose substantially: BC by 28%, OC by 30%, CO by 64%, NMVOC by 108%, SO2 by 119% and NOx by 176%. In China, NO_x emissions increased by 280%. Trends from 1996 to 2000 showed declines in BC, OC and CO due to reduced biofuel use. Projections for 2020 indicated substantial growth, highlighting the need for effective emission controls and research.

[2].This paper presents a comprehensive methodology for managing air quality, involving emission inventory creation, air-quality modeling,

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validation, mapping, hotspot identification and pollution control strategies. Using the ISCST3 dispersion model, the study identified key PM_{10} sources in Kanpur City, India, including industries, vehicular traffic, road dust and domestic fuel use. Findings highlighted high background PM_{10} levels (>30 µg/m³) and significant unpredicted pollution (35% in winter, 45% in summer). Recommendations include enhancing road conditions, improving residential fuel quality and prohibiting solid fuel in industries. The model's predictions aligned well with observed PM_{10} levels, revealing that the largest point source, a coal-based power plant, had minimal impact on ambient air quality due to its high stack height. The ISCST3 model provides reliable source apportionment results, aiding in precise pollution source assessment.

[26].This paper developed a high-resolution emission inventory for PM_{10} and $PM_{2.5}$ in Delhi for 2010 as part of the System of Air Quality and Weather Forecasting and Research (SAFAR) project. Covering a 70 km x 65 km area with 1.67 km resolution, the inventory used GIS techniques and included sectors like transport, power plants, industries, and cooking. Windblown road dust was a major contributor, accounting for 131 Gg yr^{-1} of PM_{10} emissions. Total emissions were 236 Gg yr^{-1} for PM_{10} and 94 Gg yr^{-1} for $PM_{2.5}$. The study highlighted the need to address road dust and transportation-related factors to improve air quality in Delhi.

[35].The Influence of Pollution on Aerosols and Cloud Microphysics in North China (IPAC-NC) project produced a new 2003 air pollutant emission inventory for Huabei, eastern China, including Beijing, Tianjin, Hebei, Shanxi and Inner Mongolia. Estimated emissions for this region were 4.73 Tg SO_2, 2.72 Tg NO_x, 1.77 Tg VOCs, 24.14 Tg CO, 2.03 Tg NH_3, 4.57 Tg PM_{10}, 2.42 Tg $PM_{2.5}$, 0.21 Tg EC and 0.46 Tg OC. For the larger Huabei region, which includes Shandong, Henan and Liaoning, totals were 9.55 Tg SO_2, 5.27 Tg NO_x, 3.82 Tg VOCs, 46.59 Tg CO, 5.36 Tg NH_3, 10.74 Tg PM_{10}, 5.62 Tg $PM_{2.5}$, 0.41 Tg EC and 0.99 Tg OC. Emissions were spatially mapped at a 0.1° resolution. Comparisons with global inventories like Emissions Database for Global Atmospheric Research - CIM-based Integrated Regional Climate and Energy Modelling (EDGAR-CIRCE) showed moderate discrepancies, indicating the need for annually updated inventories to reflect changes in air quality.

[15].This study developed a detailed ammonia (NH_3) emission inventory for China, using a 1 km x 1 km grid for atmospheric modeling. In 2006, China emitted approximately 9.8 Tg of NH_3, primarily from livestock excreta, fertilizer applications, and agricultural soils. Central and Southwest China had the highest emission rates, especially in spring and summer. The inventory integrated local data and statistical datasets, improving accuracy and highlighting significant seasonal variations. Nitrogen

fertilizer and livestock management were the largest sources, contributing 3.2 Tg and 5.3 Tgrespectively. The study identified Henan province as the largest emitter due to its intensive agricultural activities.

[11].It analyzed emissions in Delhi from 2008 to 2011, recording daily average $PM_{2.5}$ at 123 ± 87 µg/m³ and PM_{10} at 208 ± 137 µg/m³ due to motorization, power generation, and construction. Their multi-pollutant inventory for Delhi and surrounding areas estimated 63,000 tons of $PM_{2.5}$, 114,000 tons of PM_{10}, 37,000 tons of SO_2 , 376,000 tons of NO_x, 1.42 million tons of CO and 261,000 tons of VOCs for 2010. Emissions were mapped into 0.01° grids and modeled with ATMoS, showing annual average $PM_{2.5}$ concentrations from 42 ± 10 µg/m³ in Greater Noida to 122 ± 10 µg/m³ in South Delhi.

Key PM_{10} sources included power plants (15%), industries (11%), and brick kilns (11%). Major $PM_{2.5}$ and CO sources were vehicle exhaust (17% for $PM_{2.5}$, 18% for CO), power plants (16% for $PM_{2.5}$, 31% for CO), and brick kilns (15% for $PM_{2.5}$, 12% for CO). Freight transport, especially diesel trucks, was a major NO_x source (53%). SO_2 came mainly from power plants (55%) and industries (23%). Diesel generators contributed 6% to $PM_{2.5}$ emissions. Nearby brick kilns significantly impacted Delhi's air quality. The inventory, using 80 × 80 grids at 0.01° resolution, supported an air quality forecasting system for the NCT, aiding in health alerts and pollution control strategies.

[10].Rapid urbanization in Delhi has led to increased vehicular traffic, significantly impacting air quality with high levels of CO, NO_x and PM. Using the IVE model, emissions for 2008-09 were estimated at 509 tons/day of CO, 194 tons/day of NO_x and 15 tons/day of PM. Personal cars contribute about 34% of CO and 50% of NO_x emissions, while 2-wheelers account for 61% of CO emissions. Diesel-powered heavy commercial vehicles are significant PM emitters. Fuel-wise, petrol is the main contributor to CO and diesel to NOx and PM. Traffic hotspots like ITO exhibit peak emissions, showing the impact of vehicular pollution on Delhi's air quality, which has deteriorated despite mitigation efforts.

The study's grid-based vehicle emission inventory for Delhi estimates daily emissions and

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reveals that a significant portion occurs during vehicle start-up. Petrol vehicles are the main CO source, diesel vehicles dominate PM emissions and CNG vehicles contribute significantly to NO_x emissions. Despite improvements in methodology, limitations remain, particularly in real-time vehicle count data and emission factors.

[16].The study developed a detailed emissions inventory for Istanbul, focusing on SO_2, PM_{10}, CO, NO_x and NMVOCs. It categorized emissions from industrial, vehicular and residential heating sources. The results showed that industrial and residential coal and fuel oil use were the primary sources of SO_2, contributing 83% of total emissions. Residential heating was the main source of PM_{10} emissions (51%), while traffic was the major contributor for NO_x, NMVOC and CO emissions, accounting for 89%, 68% and 68%, respectively. The study estimated annual emissions as PM_{10} (26,461 t/y), SO_2 (70,467 t/y), NO_x (154,408 t/y), NMVOC (56,968 t/y) and CO (395,224 t/y). Maps highlighted emission hotspots near industrial zones and major roads, aiding targeted pollution control. Future updates aim to include additional pollutant sources and improve accuracy for air quality management and policy in Istanbul.

[30].NO_x emissions in China grew from 11.81 million tons (Mt) in 2000 to 24.33 Mt in 2010, driven by fossil fuel consumption, particularly coal. By 2009, NOx emissions had surpassed SO_2 emissions. Differences in regional economic output and industrial structures cause varying NO_x levels between Eastern and Western China. Major contributors to NO_x emissions include manufacturing, electricity production and transportation, accounting for about 90% of the total. Projections for 2020 suggest energy consumption will reach 3908.5 Mt standard coal equivalent (SCE) and NO_x emissions will be 19.7 Mt. Reducing NO_x emissions requires stringent measures, new emission standards and coordinated efforts across provinces.

[21].This study examines vehicular emission factors and rates in Delhi post the introduction of compressed natural gas (CNG) in 2001. Using the International Vehicle Emissions (IVE) model and field data, the study estimated emissions from 2003 to 2012. Results showed increases in CO, NO_x and PM_{10} emissions, with annual growth rates of 5.4% for NO_x and 1.7% for PM_{10}. Ambient air concentration data from CPCB monitoring stations were analyzed using weighted regression analysis in MATLAB. The study established dynamic emission factors for CO, NO_x and PM_{10}, highlighting two-wheelers and cars as major contributors. Findings align with actual ambient air concentrations, underscoring the need for strict emission standards and advancements in emission control technology.

[9].The study provided a detailed PM10 emission inventory for Delhi, India, focusing on the composition of PM_{10}, including toxic components. For the base year 2007, daily emissions were estimated at 140 TPD for PM_{10} mass, with 22 TPD for organic carbon (OC), 6.4 TPD for elemental carbon (EC), 2.8 TPD for sulphates (SO_4^{--}) and 2.1 TPD for nitrates (NO_3^{---}). Toxic metal emissions included 203 kg/day for Pb, 43 kg/day for Ni, 37 kg/day for V, 26 kg/day for As and 9.4 kg/day for Hg. Challenges included underestimations of Pb and Hg due to difficulties in source identification. PM_{10} emissions were mainly from road dust, construction, power plants, cooking and vehicles. Road dust was the largest source (55%), contributing significantly to OC and EC emissions. The study highlighted the need for better emission data and effective pollution control measures, including dust suppression, cleaner fuels and improved monitoring.

[29]. The study provided a new inventory of NMVOC emissions in India for 2010, incorporating detailed data on solvent use and the oil sector. Total anthropogenic NMVOC emissions were estimated at 9.81 Tg, with residential biomass combustion accounting for 60%, solvent use and oil sectors for 20%, and transport and agricultural residue burning for 12% and 7%, respectively. Alkenes and alkynes were the largest contributors, comprising 38% of emissions. Residential biomass burning and solvent use were major sources, while the transport sector's contribution reflected ongoing improvements in emission standards. The study emphasized the need for cleaner cooking technologies and better emission controls in the transport sector. It suggested using these findings for health impact assessments and ozone modeling, and highlighted the importance of developing indigenous emission factors for future inventories.

[24].The study developed a regional emissions inventory for Campania, Italy, focusing on CO, VOCs, NO_x and PM_{10}. Emissions were measured from major industrial sources and estimated for diffuse sources using activity indicators and emission factors. The road transport sector was assessed with the COPERT methodology. The study found road traffic was a major emission source, contributing about 49% of CO, 41% of NO_x, 12% of VOCs and 24% of PM_{10}. The slow update of the vehicle fleet worsened emissions. Future improvements were anticipated with the transition to gaseous fuels and advanced engine technologies. The study provided spatial

emission maps crucial for air quality management and policy planning in Campania, supporting broader efforts in environmental management and modeling.

[27].It developed an emission inventory for the 2010 Commonwealth Games in Delhi to improve air quality forecasting. Using GIS techniques, the inventory covered a 70 km × 65 km area with a 1.67 km resolution, focusing on ozone precursors like NO_x and CO. It included emissions from transport, power plants, industries, residential areas, and cooking, revealing 255 Gg/yr of NO_x and 703 Gg/yr of CO for 2010. The study identified emission hot spots and major sources, aiming to enhance modeling for Delhi during the CWG.

The inventory, with a 1.67 km resolution, provided detailed pollutant estimates for Delhi and its surroundings. It showed NO_x emissions at 255.4 Gg/yr and CO at 703.2 Gg/yr, highlighting significant sources in Central, Eastern, and South-Eastern Delhi and industrial hotspots on the outskirts. Transport was the main source of NO_x, while residential areas were major contributors to CO. This data was crucial for regional modeling and supporting effective pollution control strategies for megacities.

[7].This paper evaluated three black carbon (BC) emission inventories using particle dispersion simulations and observations from Gadanki, India (2008–2012). They found 93–95% of observed BC came from Indian sources, with northern India contributing 33–43%. Wet deposition had little impact due to the site's proximity to sources and the short rainy season. BC concentrations peaked in winter (3.3 µg m^{-3}) and spring (2.8 µg m^{-3}), with models, especially RETRO, underestimating BC, likely due to inadequate accounting for biomass burning and forest fires in southern India. SAFAR-India and ECLIPSE inventories were about 30% more accurate than RETRO. FLEXPART also underestimated BC, suggesting models may not fully capture emissions from southern India.

[17].The study assessed methane (CH_4) emissions from the Panki open dump site in Kanpur for 2010-2030 using the IPCC Default, FOD, and LandGEM models. Results showed CH4 emissions estimates of 197.33 Gg (IPCC Default), 24.27 Gg (FOD), and 25.14 Gg (LandGEM). The IPCC Default method overestimated emissions, while LandGEM, which adjusts parameters for site conditions, provided a more accurate estimate of 25.14 Gg/year. The FOD method also yielded results similar to LandGEM when accurate waste composition data were used. The study concluded that LandGEM is the most suitable method for estimating CH4 emissions from open dump sites and landfills.

[23].In 2011, India's total black carbon (BC) emissions were 901 ± 152 Gg. The main sources were domestic fuel (47%), industry (22%), transport (17%), open burning (12%), and diesel use in mobile towers and irrigation pumps (2%). Firewood emissions alone (177 Gg) exceeded those from transport (154 Gg) and open burning (103 Gg). The Indo-Gangetic Plain (IGP) was the largest BC emitter due to high population density and BC-emitting industries. Uttar Pradesh had the highest emissions within the IGP (140 Gg), followed by West Bengal (57.67 Gg), Bihar (47.8 Gg), Punjab (34.01 Gg), Haryana (26.82 Gg) and Delhi (6.74 Gg). The study developed a detailed BC emission inventory, including sources like kerosene lamps and forest fires, improving estimates. Future work should refine local emission factors and activity data to enhance the accuracy of emission inventories for air quality modeling and policy development.

[31]. The study developed a GIS-based emission inventory for Lucknow, India, focusing on on-road vehicles and covering pollutants such as SO_2 , NO_2 , CO, PM and various hydrocarbons. Video recordings and parking lot surveys were used to assess traffic flow, vehicle types, and emission factors. Two-wheelers and four-wheelers dominated traffic, accounting for 83% of vehicles and significant NO and CO emissions. Heavy-duty vehicles, despite being only 2% of the fleet, were major contributors to emissions: 23% of SO_2 , 36% of NO_2 and 28% of PM. The city center had the highest emissions due to dense vehicle concentrations. The inventory provides essential data for emission reduction strategies in Lucknow.

[18].It reviewed the development of anthropogenic emission inventories in China, noting the challenges due to varied sources and unreliable measurements. Progress has been made with improved statistics, survey data and local emission factors, enhancing inventory models for sectors like power plants and residential areas. The paper highlights updates in models and data, and suggests future improvements for accuracy.

Uncertainty estimates for emissions used error propagation or Monte Carlo methods. Uncertainties ranged from -15% to 26% for SO_2, -15% to 35% for NOx and -18% to 42% for CO. Primary aerosol emissions, including PM_{10}, $PM_{2.5}$, BC and OC, had higher uncertainties, particularly from the residential sector, due to unreliable emission factors.

[11].This paper assessed air quality and emissions in Bengaluru for 2015, using a high-resolution inventory with a 1 km grid over 4300

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km². Key emissions included 31,300 tons of $PM_{2.5}$, 67,100 tons of PM_{10}, 5300 tons of SO_2, 56,900 tons of NO_x, 335,550 tons of CO and 83,500 tons of NMVOCs. Transport, particularly vehicle exhaust and dust resuspension, was the main source of $PM_{2.5}$ and PM_{10}, contributing 56% and 70% respectively. Projections suggested a 50% increase in emissions by 2030 without intervention, risking breaches of national air quality standards.The WRF and CAMx models showed good alignment with monitored $PM_{2.5}$ levels.

The study highlighted the dominance of transport in emissions and called for stricter controls and urban planning. It recommended enhancing top-down chemical analysis, strengthening air monitoring, and using data for regional photochemistry and public air quality forecasting. Future emissions, driven by transport and construction, are expected to rise despite planned improvements.

[25].The study developed spatially resolved emission inventories for $PM_{2.5}$, black carbon (BC) and organic carbon (OC) from India's on-road transport sector for 2013. National emissions were estimated at 355 Gg/year for PM2.5, 137 Gg/year for BC and 106 Gg/year for OC. Super-emitter vehicles, making up 24% of traffic, were responsible for 67% of PM2.5 and 47% of BC emissions. Using the Community Atmosphere Model (CAM5), the study predicted a positive direct radiative forcing (DRF) of up to 6 W/m² at the top of the atmosphere (TOA) and a negative DRF of up to 10 W/m² at the surface, indicating significant atmospheric energy retention. The results highlighted the need for urgent measures to address BC emissions due to India's rapid economic growth and urbanization.

[13].It assessed traffic-related VOCs in India, where 21 of the 30 most polluted cities suffer from high $PM_{2.5}$ levels. In 2015, they measured emission factors (EFs) for 74 VOCs, identifying toluene, isopentane and acetaldehyde as major contributors. Petrol 2-wheelers and LPG 3-wheelers emitted the highest VOC levels, suggesting that electric vehicles could improve air quality. Existing inventories like EDGARv4.3.2 and REASv.2.1 overestimated VOC emissions due to outdated data.

The study created India's first comprehensive national VOC emission inventory with a 0.1° × 0.1° resolution, incorporating updated EFs and recent data. It identified key VOCs, including toluene, acetaldehyde, 2,2-dimethylbutane, and ethylbenzene, showing significant variations from previous estimates. Notably, acetaldehyde and nitromethane, totaling about 51 ± 6 Gg yr−1, were significant but previously unaccounted for. The study highlighted the need for VOC monitoring and policies to reduce traffic emissions, potentially improving public health in urban areas.

[32].This paper highlights increased emissions from India's transportation sector due to population and economic growth. The study developed an age-wise analysis framework for 2020, estimating fuel consumption at 92 Mt and emissions at 274 Tg CO_2, 4463 Gg CO, 164 Gg PM and 2378 Gg NOx. Diesel accounted for 61% of fuel use. Heavy-duty freight vehicles and two-wheelers were significant emitters. The study compared past inventories, assessed state-wise emissions and identified major emitters. Sensitivity analyses emphasized the importance of vehicle survival rates. Major emitting states included Maharashtra, Tamil Nadu, Gujarat, Uttar Pradesh, Rajasthan and Karnataka. Recommendations included timely data collection, promoting cleaner transport modes, and adopting electric vehicles. Spatial allocation highlighted high per-unit area emissions in Delhi and Chandigarh, suggesting comprehensive state-level measures to curb emissions.

[20].This study created the first ultra-high-resolution gridded emission inventory for Kolkata, India, at approximately 0.4 km × 0.4 km. With rising fossil fuel use and urban expansion, understanding emission sources is crucial for regional and global air quality. For 2020, the study estimated annual emissions in Kolkata as: 37.2 Gg/yr of $PM_{2.5}$, 61.4 Gg/yr of PM_{10}, 222.6 Gg/yr of CO, 131.3 Gg/yr of NO_x, 60.3 Gg/yr of SO_2, 120.4 Gg/yr of VOC, 9.5 Gg/yr of BC and 16.8 Gg/yr of OC. Major emission sources identified included transport, industrial zones and municipal solid waste burning. The aging vehicle fleet and industrial activities, along with solid fuel use in slums, significantly contributed to emissions. Wind-blown road dust was a key PM_{10} source. The detailed inventory aids in guiding policy interventions to improve air quality and public health in Kolkata and supports the SaBe National Emission Inventory for India (SNEIIv1.0).

[3].It introduced a GIS-based methodology to create a grid-based emission map of India with a 40 km × 40 km resolution, using data from 593 districts. This inventory supported chemical transport modeling and scenario analyses, such as assessing PM_{10} impacts on Himalayan ecosystems and informed national pollution reduction strategies. It focused on source identification, emission estimation and pollution trends over ten years, highlighting Shimla's ecological sensitivity.

The study constructed a PM10 emission inventory for 2010, identifying total emissions of 11,218 Gg/yr. Contributions were 39% from domestic sources, 28% from industrial, 19% from vehicular and 14% from open burning. Urban areas like Delhi and the Indo-Gangetic Plain had the highest PM_{10} levels. PM_{10} emissions in India grew annually by 3.41% from 8279 Gg/year in 2000 to 16,604 Gg/year in 2020.Over two decades (2000–2020), PM_{10} emissions in Shimla increased by 5.04% and ambient concentrations rose by 2.15%. These trends highlight the need for stringent pollution control policies and future environmental planning in this eco-sensitive city.

[34].This study showcases a GIS-based emission inventory for heavy metals and non-methane volatile organic compounds (NMVOCs) in Delhi for 2018, covering road transportation, road dust and biomass burning. Heavy metal emissions totalled 695.202 Mg/year, with zinc (48%) and copper (21%) being the major contributors. Road transportation was responsible for 78% of these emissions, while road dust contributed 4%. NMVOCs emissions were 1.158 Gg/year, with dung cakes (58%) and fuelwood (41%) as the primary sources. Ethene was the most emitted NMVOC at 29%, and isopropyl benzene was the least at 0.06%. The inventory was mapped in 1 km × 1 km grids, highlighting exhaust emissions as the largest source (78%) of heavy metals. This data aids policymakers in developing strategies to mitigate emissions and enhance air quality.

[33].The study provided a GIS-based inventory of vehicular emissions in Lucknow, including tailpipe emissions of CO, SO_2, PM, NO_x, 1,3 Butadiene, total aldehyde, and total PAH. Tailpipe emissions were estimated at 5.8 tons/day for PM, 0.2 tons/day for SO_2, 58 tons/day for NO_x and 141 tons/day for CO. Non-exhaust sources like brake and tire wear and road dust resuspension contributed significantly, with PM_{10} from road dust reaching 155 tons/day, 27 times higher than tailpipe PM emissions. Non-tailpipe emissions included 575 g/day for 1,3 Butadiene, 853 g/day for Formaldehyde, 113 g/day for Acetaldehyde, 1468 g/day for total aldehyde and 57,542 g/day for total PAH. Addressing road conditions and reducing silt loads were emphasized as crucial for improving PM mitigation strategies in Lucknow.

[28].The study provided a detailed inventory of $PM_{2.5}$ and PM_{10} emissions in India for 2020. Windblown road dust was identified as a major source of PM_{10}, contributing approximately 4371.6 Gg/yr, while transportation and industry were key sources of $PM_{2.5}$. Residential activities, including agricultural residue burning and street vending, contributed around 3682.41 Gg/yr to PM emissions. The road transport sector alone emitted about 1635.41 Gg/yr of PM_{10}. The study recommended strategies such as phasing out older vehicles, promoting cleaner fuels, adopting flexible working hours, maintaining roads, improving public transport, and implementing cleaner industrial practices. These measures aim to reduce emissions and enhance air quality in India. The study estimated annual emissions at 15.8 Tg/yr for $PM_{2.5}$ and 8.3 Tg/yr for PM10, with significant contributions from windblown road dust, transportation, and industry.

[1].In developing countries, solid residential fuels are key for domestic use. This study provides spatially varying emission factors (EFs) for inorganic trace gases (SO_2, NO, NO_2, CO, CO_2, CH_4) from residential fuels in slums and rural areas of the National Capital Territory (NCT), based on tests from 147 locations across 675 slum clusters and 146 rural villages. Emission factors ranged from low SO_2 (0.02±0.01 to 0.04±0.01 g kg−1) to high CO (3.55±1.72 to 6.07±1.53 g kg−1) and CO_2 (up to 129.45±46.94 g kg−1). Hotspots for CH_4, NO, and NO_2 were identified in the north and northwest, and for CO_2 in southern and northern areas. These findings contribute to detailed citywide emission inventories at 0.05° × 0.05° resolution, emphasizing fuelwood and dung cake as major contributors to inorganic trace gases in NCT.

The study examined the impact of biomass burning on pollutants in Delhi's NCT, focusing on fuels like fuelwood and dung cake. It introduced experimentally derived emission factors (EFs) for key gases, revealing regional variations. North and northwest districts had higher CH_4, NO and NO_2 emissions, while southern and northern areas showed elevated CO_2 levels. The findings emphasized the need for local emission data to refine inventories and guide policies for cleaner energy alternatives to enhance environmental quality and public health in the NCT.

[19].It developed the MIXv2 Asian emission inventory under MICS-Asia Phase IV, integrating data from 23 countries in East, Southeast and South Asia. This updated inventory, covering 2010 to 2017, included emissions from open biomass burning and shipping and provided model-ready data for SAPRC99, SAPRC07 and CB05 mechanisms. It detailed emissions of 41.6/1.1 Tg NO_x, 33.2/0.1 Tg SO_2, 258.2/20.6 Tg CO, 61.8/8.2 Tg NMVOC, 28.3/0.3 Tg NH_3, 24.0/2.6 Tg PM_{10}, 16.7/2.0 Tg $PM_{2.5}$, 2.7/0.1 Tg BC, 5.3/0.9 Tg OC and 18.0/0.4 Pg CO_2. The inventory, with 0.1° spatial resolution and monthly variations, highlighted significant emissions from India and Southeast Asia, especially for SO_2, NH_3 and particulate matter.

In 2017, the inventory showed China, India, and Southeast Asia accounted for over 90% of Asian emissions. China led in CO_2, NO_x and CO; India in SO_2, NH_3 and particulate matter; and Southeast Asia was third in most pollutants. Power plants contributed significantly to SO_2 and CO_2, industries to CO_2 and particulate matter and transportation to NO_x. Agriculture was the main NH_3 source and open biomass burning was crucial in Southeast Asia. Asia's emissions were a significant global factor, affecting climate dynamics more than those from the US and OECD-Europe.

III. CONCLUSION

The preparation and analysis of emission inventories are crucial for understanding and mitigating air pollution. This review highlights the diverse methodologies used globally, reflecting the complexity of creating accurate inventories. Advances in technologies such as GIS, remote sensing, and big data analytics have improved the precision of emission estimates and allowed for more dynamic assessments of pollution sources.Case studies reveal common challenges, like data quality, and tailored solutions for specific contexts. The review stresses the importance of robust validation and uncertainty assessments to ensure the credibility of emission inventories for effective air quality modeling and policy development.

Emission inventories are essential for developing air quality management strategies and informing regulatory frameworks and public health initiatives. They provide a clear understanding of pollution sources and trends, crucial for reducing air pollution and associated health risks.

The review concludes with a call for ongoing improvement in inventory methodologies. Future research should focus on better data integration, more detailed emission estimates, and advanced models to predict and address pollution impacts, contributing to a cleaner and healthier environment.

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