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Quantifying Future Annual Fluxes of Polychlorinated Dibenzo-P-Dioxin and Dibenzofuran Emissions from Sugarcane Burning in Indonesia via Grey Model

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Abstract: The open burning of sugarcane residue is commonly used as a low-cost and fast method during pre-harvest and post-harvest periods. However, this practice releases various pollutants, including dioxins. This study aims to predict polychlorinated dibenzo-p-dioxins and dibenzofurans (PCDD/Fs, or dioxins) emissions using the Grey Model (GM (1,1)) and to map the annual flux spatial distribution at the provincial level from 2023 to 2028. Using the activity rate of dry crop residue from national agencies and literature, and following the guidelines set by the United Nations Environment Programme (UNEP), an annual emission inventory was developed at the provincial level. The distribution of emissions from 2016 to 2022 was then mapped. The average PCDD/Fs emission values exhibit significant variation among the provinces, averaging 309 pg TEQ/year. Spatially, in line sugarcane production, South Sumatra and East Jawa consistently show high emissions, often exceeding 400 pg/m². Emissions based on the UNEP emission factor tend to be higher compared to other factors, due to its generic nature and lack of regional specificity. The emission predictions using the Grey Model GM (1,1) indicate that North Sumatra is expected to experience a steady increase in PCDD/Fs emissions, whereas South Sumatra and Lampung are projected to see a slight decline. This forecast assumes there will be any changes in regional intervention strategies. Most regions in Jawa Island show a gradual increase in emissions, except for East Jawa, which is predicted to have a slight decline from 416 pg/year in 2023 to 397 pg/year in 2028. Additionally, regions like Gorontalo and parts of East Jawa are projected to remain "hotspots" with consistently high emissions, suggesting the need for targeted interventions. Future studies should consider developing monthly emissions profiles to account for local agricultural practices and seasonal conditions. The emission data generated in this study, which includes both spatial and temporal distributions, is valuable for air quality modeling studies. Utilizing this data can help assess the impact of current and future emissions on ambient air quality.

Keywords: dioxin; sugarcane; open burning; grey model

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1. Introduction

Among of all agriculture production in Indonesia, sugarcane account as the 3rd largest that increase from year to year, recorded in 2022 reach up to 32.4 million tonnes [1]. In sugarcane harvesting, inadequate post-harvest handling will contribute to environmental degradation due to the accumulation of cane trash. High-fiber portions of the sugarcane plant are left on the plantation, resulting in post-harvest waste. This waste includes fresh and dry leaves, plant sticks, portions of stalks, and roots left on the plantation [2]. Prolonged presence of this waste can reduce soil moisture [3], inhibits ratoon cane shoot growth and disrupts soil processes during subsequent sugarcane planting [4]. In fact, most of region are inseparable from practically use open burning in sugarcane crop residue, commonly regarded as a swift and low-cost method for field clearance [5], significantly impacts the environmental dynamics of agricultural regions. This practice typically involves the burning off leaves, the thorough desiccation of cane tops, and the meticulous removal of agricultural

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debris from the soil. This meticulous approach aids in the efficient stalk harvest by minimizing unwanted biomass and effectively reducing the risks posed by snakes and insects.

Studies have consistently demonstrated that sugarcane burning releases various pollutants: particulate matter, black carbon, sulfur dioxide, and greenhouse gases such as CO_2, N_2O and CH_4 [6–8]. Notably, highly toxic pollutants from sugarcane like PCDD/Fs [6,9,10] contribute significantly to air pollution. Recent study [11] reveal that approximately 90% of dioxin in Indonesia originate from open burning, including agriculture practices. Sugarcane open burning itself in Thailand contribute approximately 26% to these sectoral emission [12]. Prior studies on dioxin emission inventories reveal intriguing insights. In the total U.S. inventory for the year 2000, dioxin emissions were estimated at approximately 1500 g TEQ [13]. Within the agriculture sector, including sugarcane, emissions accounted for 131 g TEQ per year in 2012, representing 4.52% of all sources [14]. Meanwhile in Portugal, uncontrolled combustion (including open burning in agriculture) ranked as the second-highest contributor to dioxin emissions, constituting around 28.9% of all sources or approximately 0.31 g TEQ per year [15]. Then in China, the annual release of PCDD/PCDF from open burning reached 12 g TEQ in 2015 [16]. Notably, Zhang, *et al.* [17] emphasized that constructing a comprehensive dioxin emission inventory specifically for sugarcane biomass combustion remains challenging due to the diverse factors influencing dioxin emissions. In Southeast Asia there is limited study has been conducted, Thailand using country-specific activity data, emphasizing the environmental impact of biomass combustion and reveal open burning in sugarcane fields is acknowledged as a significant contributor to air pollution [18].

Previous study mentioned either flaming or smouldering, significantly impact the emission of dioxins during sugarcane burning [17]. Besides, there is a significant correlation between exposure to high concentrations of PCDD/Fs and an increased relative risk of mortality from all causes [19]. PCDD/Fs are known to have detrimental effects on health like carcinogenic effects mediated by the aryl hydrocarbon receptor to noncancerous effects like atherosclerosis, hypertension, and diabetes [20,21]. On top of that, PCDD/Fs have a substantial environmental concern due to their persistence in ecosystems and their ability to accumulate in the food chain. Notwithstanding at low levels exposure, dioxins may lead to long-term health effects.

The Grey Model (1,1) stands as a well-established and fundamental model in grey prediction theory, as highlighted by [22]. Renowned for its linear properties [23], the GM(1,1) model has found extensive application across various fields due to its computational efficiency [24]. The benefits of using the grey prediction model include its ability to function effectively with limited modelling data [25], particularly in situations where comprehensive datasets are unavailable or difficult to obtain. This characteristic makes it highly suitable for early-stage research and preliminary assessments. Additionally, the computational simplicity of the grey prediction model means that it requires fewer resources and less time to implement compared to more complex predictive models. Despite its ease of calculation, the grey prediction model is renowned for its high simulation accuracy, making it a reliable tool for forecasting. Due to these advantages, the grey prediction model has found extensive application across various domains. Furthermore, its versatility extends to fields such as environmental science, where it helps predict pollution levels and natural resource availability, and in healthcare for predicting disease outbreaks and patient outcomes [26]. The model's ability to produce accurate predictions with minimal data inputs and straightforward calculations [25] makes it a popular choice in both academic research and practical applications. Notably, it has been employed in diverse studies, including CO_2 emission inventory related energy consumption in Turkey [27], CO_2 emission in China [28], CO_2 emission in Vietnam [29], and SO_2 emission in China [30].

Despite the scarcity of research on dioxin emissions from agriculture in Indonesia, specifically related to sugarcane, we intend to estimate PCDD/Fs emissions resulting from the open burning of sugarcane crop residues between 2012 and 2022. Following UNEP guidelines to calculate the dioxin emission inventory, then we also map the distribution of annual flux emissions at the provincial level. The main aim of our study is leverages the Grey Model (1,1) to predict future emissions. In our study, we delve into time series forecasting for dioxin emission in 2023 – 2028, particularly when faced with incomplete information and uncertain factors. The approach involves converting original data of annual emission inventory of PCDD/Fs in 2016 – 2022 into a cumulative form using Accumulated Generating Operation (AGO) to reduce randomness and enhance trend visibility. Subsequently, we

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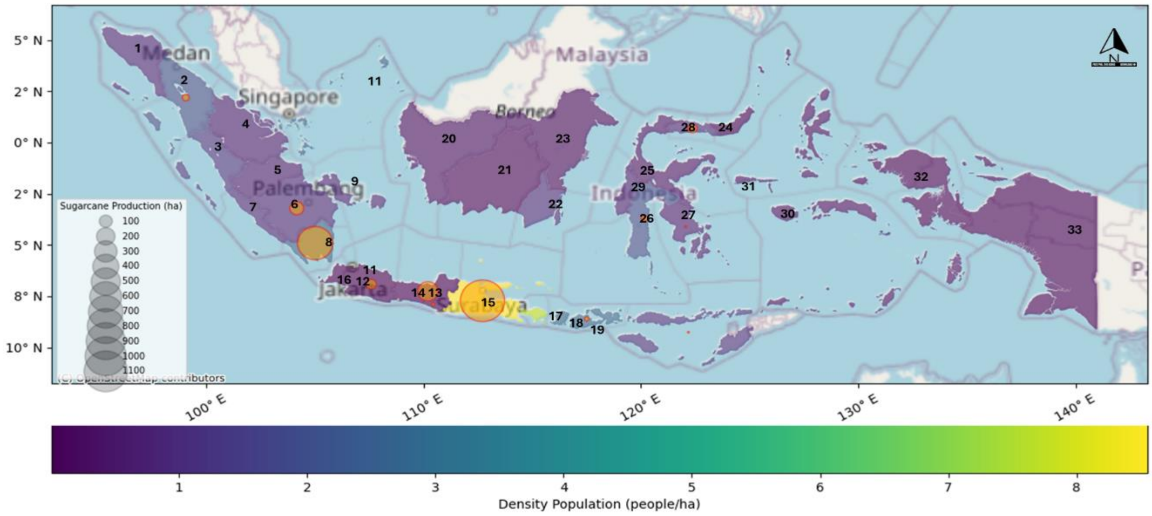
calculate the first-order difference sequence, discrete accumulated generating operation (DAGO) from the cumulative data and extrapolate sequence so we can get the dioxin prediction emission.

2. Material and Methods

2.1 General Introduction of Indonesia

Indonesia, spanning from 0° 47' 21.39'' S to 113° 55' 16.78'' E, is located in Southeast Asia. It has a population of approximately 275.5 million and covers an area of 1.9 million square kilometers. The country comprises 33 provinces, many of which are separated by the sea. Indonesia has an agriculture-dependent economy, with sugarcane being one of the key crops, influenced significantly by local temperature, humidity, and rainfall patterns. The country experiences two distinct seasons: a dry season from March to September and a rainy season from October to February. Figure 1 illustrates the population density and sugarcane production across each province in 2022.



Province List:

1 :	Aceh	13 :	Central Jawa	21 :	Central Kalimantan
2 :	North Sumatra	14 :	D.I. Yogyakarta	22 :	South Kalimantan
3 :	West Sumatra	15 :	East Jawa	25 :	Central Sulawesi
4 :	Riau	16 :	Banten	26 :	South Sulawesi
5 :	Jambi	17 :	Bali	27 :	Southeast Sulawesi
6 :	South Sumatra	18 :	West Nusa Tenggara	28 :	Gorontalo
7 :	Bengkulu	19 :	East Nusa Tenggara	29 :	West Sulawesi
8 :	Lampung	20 :	West Kalimantan	30 :	Maluku
9 :	Bangka Belitung Island	21 :	Central Kalimantan	31 :	North Maluku
10 :	Riau Island	22 :	South Kalimantan	32 :	West Papua
11 :	D.K.I Jakarta	23 :	East Kalimantan	33 :	Papua
12 :	West Jawa	24 :	North Sulawesi		

Figure 1. Population Density and Sugarcane Production by Province in 2022

2.2 Emission Inventory

The emission inventory relies on the UNEP Toolkit (UNEP, 2012). Nonetheless, the limitation of this study is that we do not use local emission factors; instead, we rely on a general emission factor from UNEP for open burning of crop residue in sugarcane. The emission factor for air emissions is 4 μg TEQ/t (toxic equivalent per ton) of material burned (UNEP, 2012). Sugarcane production is calculated on a dry weight basis in tonnes per year (Ps), combined with the sugarcane residue-to-cane production ratio (RPPs) to estimate the quantity of dry sugarcane residue (Qs), as shown in equation (1). The assumption of RPPs is 33%. Using the activity rate, which accounts for the quantity of dry sugarcane residue in tonnes per year within the harvested area in hectares (A), we determine the biomass fuel load (BL) on a dry mass basis (kg/m^2). This is calculated by dividing Qs by A and

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adjusting the scale by a factor of 10^{-1}, as specified in equation (2). The next step involves calculating the actual biomass consumed (Bb, in kg/m²) during combustion, which is obtained by multiplying the biomass fuel load (BL) by the combustion factor (Cf, set at 0.64) as outlined in equation (3). Equation (4) computes the annual flux of PCDD/Fs (in kg/m²) for spatial emissions by multiplying the biomass consumed (Bb) by the Emission Factor (EF), which is determined by the UNEP guideline for open burning of crop residue in sugarcane: PCDD/Fs Annual Flux Emission. Finally, PCDD/Fs emissions are calculated using equation (5), where emissions are the product of the Emission Factor (EF) and the activity rate. To estimate uncertainty, we employ Monte Carlo method, leveraging activity rate data. This approach involves generating many random samples to simulate the variability in the activity rate, thereby providing a probabilistic distribution of possible outcomes.

$$Q_s = P_s \; x \; RPP_s \quad (1)$$

$$BL = \left(\frac{Qs}{A}\right) \mathrm{x} 10^{-1} \quad (2)$$

$$Bb = BL \times Cf \quad (3)$$

$$PCDD/F \; Anual \; Flux \; Emission = Bb \times EF \; (4)$$

$$PCDD/F \; emissions = Emission \; factor \; (EF) \; x \; Activity \; rate \quad (5)$$

2.3. Emission Factors

The UNEP Toolkit recommends an emission factor of 4 µg TEQ/t of material burned for estimating the release PCDD/Fs and dioxin-like polychlorinated biphenyls (dl-PCBs) from sugarcane burning, as informed by the assessment conducted by Black, *et al.* [31]. The reason of chosen to use this emission factor is because it is supported by relatively consistent results published in peer-reviewed literature, indicating reliability. Although there is a wide range of results within this sub-category, the UNEP Toolkit's emission factor is derived from a comprehensive assessment, which considers a variety of influencing factors such as combustion facilities, operating conditions, fuel composition, and accidental addition of contaminants [17]. This makes it a robust choice, especially given the limited geographic range of other studies that might not fully capture the diverse conditions present in sugarcane burning practices.

However, in Table 1, we observe variations among the published emission factors associated with sugarcane burning, comparing different countries and experimental methods. These factors exhibit a wide range, highlighting the impact of both geographical location and experimental approach on the results. For instance, a burn facility in Hawaii, USA, reports the highest mean EF at 126 µg TEQ/t fuel, with a range of 98-148 µg TEQ/t fuel, suggesting high emission levels under controlled conditions. Conversely, a sugarcane pile burn facility in Florida, USA, exhibits the lowest mean EF at 0.34 µg TEQ/t fuel. Field experiments in Queensland, Australia, and Florida, USA, show mean EFs of 0.95 µg TEQ/t fuel and 1.39 µg TEQ/t fuel, respectively, with varying ranges and standard deviations, indicating differences in burning practices and environmental conditions. Laboratory burn tunnel experiments in Queensland, Australia, demonstrate a mean EF of 4.4 µg TEQ/t fuel, with a notable standard deviation of 3.7, reflecting high variability in emissions. These findings emphasize the importance of considering both location and method when assessing emission factors for sugarcane burning.

Table 1. Comparison of Different Emission Factor of Dioxin.

Country	Exp approach	Mean EF ug TEQ/ (t fuel)	Range	stdv	Ref.
UNEP	Field	4	-	-	[32]
Sugarcane QLD, Australia	Field	0.95	0.52-1.4	-	[9]
Sugarcane QLD, Australia	Lab burn tunnel	4.4	1.6-9.6	3.7	[10]

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Sugarcane HI, USA	Burn Facility	126	98-148	-	[9]
Sugarcane FL, USA	Burn Facility	6.9	4-9.8	-	
Sugarcane standing FL, USA	Burn Facility	2.3	1.6-4.4	-	
Sugarcane pile FL, USA	Burn Facility	0.34	-	-	
Sugarcane FL, USA	Field	1.39	0.85–2.3	0.57	[9,10]
Sugarcane FL, USA	Field	1.9	0.96–2.8	-	[9]

2.4. Activity Data

The national statistical agency [1,33–36] collects annual sugar cane production data for each province. This dataset includes information on production area (in hectares) and total production (in tons) from 2016 to 2022. Using this data, we calculate the ratio of harvested sugarcane to residue. Table S1 resents annual sugarcane production data for each Indonesian province. As seen in the table, only 9 province engage in sugarcane production from total 33 provinces. In 2016, the annual production ranged from approximately 3,000 tons, harvested from an area of around 7,000 hectares. West Nusa Tenggara began sugarcane production in 2017, followed by East Nusa Tenggara in 2021. The decrease in harvested area is not always the same as production, seen in several areas like West Jawa) experienced a decrease in harvested area (9889 hectares less in 2020 compared to 2019), production showed an opposite trend, increasing from 32,488 tons in 2019 to 39,492 tons in 2020. However, the production increase is attributed to the adoption of local sugarcane varieties that are more resistant to pests and diseases, require less water, and have higher sugar recovery rates at the mills [37,38]. This will certainly impact the ratio of residue to production across different provinces.

2.5. Grey Model

In this study, the predict of PCDD/Fs emissions from 2023 to 2028 based on data from 2016 to 2022 that employ the 'Grey Model First Order One Variable' (GM (1,1)). This model is particularly useful when dealing with limited and uncertain data. The GM (1,1) model is advantageous due to its simplicity and has short time series data, where traditional statistical methods may not be as effective to be used [39]. This approach involves converting original data into cumulatiove using AGO. Despite its simplicity, this model still achieving excellent prediction results [40]. The concept shown in the figure 1 below, the input data being processed through predictive modeling to output. This model uses feedback mechanisms to adjust predictions based on input data, ensuring accurate and reliable emission forecasts. After gather and order the input data sequencially according to the years then we initiate the model.

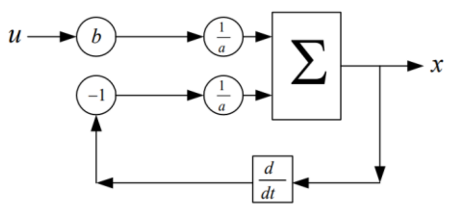

Figure 1. GM (1,1) Concept of Feedback Control System.

Firstly, the process begins by organizing the input data chronologically. The initial step involves converting the raw data into an accumulative sum to improve the data regularity, which is crucial for handling the exponential growth characteristics typical in grey models. This accumulation helps in smoothing out random fluctuations in the time series data. The first-order differential equation of the model is described in Equation 6. The calculation known as the DAGO from the cumulative data and extrapolate this sequence to predict dioxin emissions.

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \qquad (6)$$

where a and b are parameters estimated using the least squares method applied to the cumulative data series. Continuing with inverse accumulated, time response to predict the future PCDD/Fs emission. $x^{(0)}$ (1) is the first value of original historical emissions data and k is the time step. This constructed model will forecast future values. By inputting the values of k for the years 2023 to 2028, the model will predict the corresponding PCDD/Fs emissions (equation 7). The Inverse Accumulated Generating Operation (IAGO) is used to convert the predicted accumulated values back to the original scale, providing the forecasted emissions for each year.

$$\hat{x}^{(1)}\,(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a} \qquad (7)$$

GM (1,1) performance evaluation is assessed through cross-validation of mean absolute percentage error (MAPE) and Mean Absolute Error (MAE). In equation 8, e_i and Y_i are the error and observation values (here using 3rd year prediction data) of the ith period. While MAE the is a measure used to quantify the accuracy of a forecasting model by averaging the absolute errors in the predictions show in equation (9).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{Y_i}\right| x100 \qquad (8)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \qquad (9)$$

3. Results and Discussion

3.1. Annual Emission and Geographical Distribution

The activity rate of sugarcane crop residue burning is influenced by biomass fuel load (BL), biomass sugarcane consumption (Bb), and the quantity of dry sugarcane residue (Qs). Table S2 provides a comprehensive overview of BL, Bb, and Qs in Indonesian provinces from 2016 to 2022. The data indicates substantial differences of sugarcane residue among the provinces. For instance, D.I. Yogyakarta shows consistently high values in both BL and Bb, with sugarcane residue quantities peaking at 367,918 tonnes/year in 2016 and 340,266 tonnes/year in 2022. Similarly, West Jawa displays significant biomass fuel load and consumption, reaching a Bb of 0.14 kg/m^2 and Qs of 72,365 tonnes/year in 2022. Compared to Thailand, where the biomass fuel load was 10.15 million tons in 2012 [18], Indonesia's biomass fuel load is significantly smaller, highlighting differences in agricultural practices between the two countries. However, there are other also other factors that influence the activity rate like moisture content mentioned in a simulation study conducted by Spaunhorst, *et al.* [41] demonstrated that different biomass densities, ranging from 6.1 to 24.2 Mg/ha with 44% moisture content during lower wind speeds, resulted in a smoldering effect. This effect reduced weed emergence by 23% compared to burning postharvest residue with 30% moisture during breezy conditions.

Table 2 summarizes the descriptive statistics of PCDD/Fs emissions across Indonesian provinces from 2016 to 2022. The revised statement based on the data provided in the table would be as follows:

The average PCDD/Fs emission values exhibit significant variation among the provinces. North Sumatra records a mean emission of 232 pg/yr, whereas East Nusa Tenggara displays the lowest mean emission at 187 pg/yr. Notably, East Jawa shows the highest mean emission value at 435 pg/yr, indicating significant variability in emissions between provinces. The standard deviation values also exhibit considerable variation, with D.I. Yogyakarta presenting the highest variability (std = 70), suggesting fluctuating emission levels over the years. In contrast, East Nusa Tenggara has a relatively high standard deviation of 153, but this is based on a limited sample size (n=2), which may affect the reliability of the PCDD/Fs emission inventory. The range of minimum emission values spans from as low as 50 pg/yr in East Nusa Tenggara to 290 pg/yr in D.I. Yogyakarta. Conversely, the maximum values range from 294 pg/yr in East Nusa Tenggara to 487 pg/yr in Gorontalo, illustrating a wide dispersion in emission levels across the provinces. The 50th percentile (median) values align closely with the mean values in most provinces, indicating a symmetrical distribution of emission data. However, provinces like West Nusa Tenggara show a substantial difference between the median (276.5 pg/yr) and the mean (435 pg/yr), hinting at potential outliers or skewed data. The 50th percentile (median) values align closely with the mean values in most provinces, indicating a symmetrical distribution of emission data. However, provinces like West Nusa Tenggara show a substantial difference between the median (276.5 pg/yr) and the mean (435 pg/yr), hinting at potential outliers or skewed data.

Table 2. Annual Dioxin Emissions by Province (2016–2022, pg/yr).

	North Sumatra	South Sumatra	Lampung	West Jawa	East Jawa	D.I Yogyakarta	East Jawa	West Nusa Tenggara	East Nusa Tenggara	South Sulawesi	Gorontalo
N (years)	7	7	7	7	7	7	7	6	2	7	7
mean	232	301	428	301	331	247	435	242	187	287	414
stDev	41	39	24	26	25	70	18	107	153	80	85
min	178	255	387	245	290	120	407	50	78	149	237
25%	202	266.5	418	302.5	319.5	225.5	425	210	132	262	405
50%	225	301	431	305	341	239	439	276.5	186	289	441
75%	261	333	438	316	349	294	448	315	240	325	460
max	293	351	464	322	353	334	455	333	294	400	487

As shown in figure 2, the trend of PCDD/Fs emissions at provincial level from 2016 – 2022. The average dioxin from sugarcane residue burning emissions in Indonesia, at approximately 309 pg TEQ/year, are notably lower compared to the emissions reported from the United States in 2001, which included states like Florida, Hawaii, Louisiana, and Texas, each by 37.5 g TEQ/yr [9]. Despite the US utilizing smaller emission factors (ranging from 0.017 to 0.025 ug TEQ/kg), factors such as higher combustion efficiency (90%) and a greater proportion of the harvested area being burned (50%) contribute to these increased emissions. Nonetheless, from all sectors, Indonesia still count as among the top five countries in terms of PCDD/Fs emissions, releasing 1.17 to 2.04 kg TEQ across all sector and all media (atmosphere, soil, and water) [42].

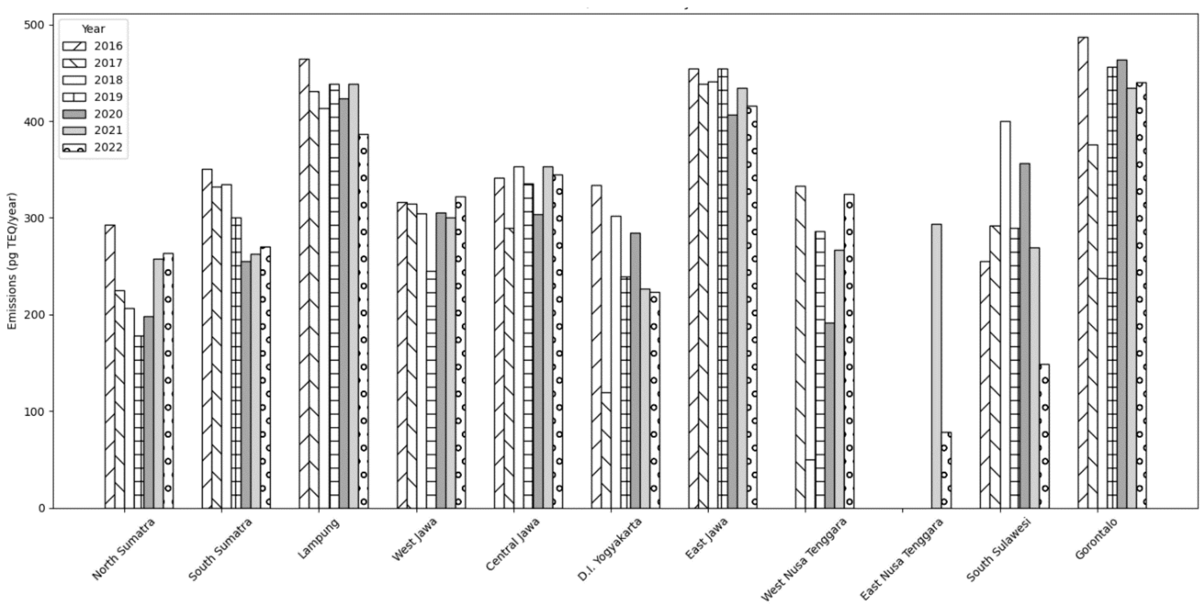

Figure 2. Total Annual Dioxin Emission in Each Province over 2016 – 2022.

In this emissions inventory, there are several factors that might influence uncertainty: emission factor, activity rate and model for prediction. Unfortunately, the study of dioxin emission factors remains limited in Indonesia and Southeast Asia. To address this gap, we compare the emission results using factors from several field simulation studies conducted in the USA [31] and Australia [10]. Table 3 presents a comparison of PCDD/Fs emissions (in picograms per year) from sugarcane open burning in Indonesia, utilizing emission factors derived from these field measurements. This approach allows us to utilize established and peer-reviewed emission factors to estimate emissions more accurately, despite the regional limitations of direct local studies.

Table 3. Comparison Of PCDD/Fs Emission (Pg/Yr) By Different Emission Factors.

Year	UNEP (4μg TEQ/t material burned)	USA (1.39μg TEQ/t fuel)	Australia (0.95μg TEQ/t fuel)
2016	5311	1883	1644
2017	4836	1095	749
2018	5010	1057	723
2019	4955	1686	1152
2020	5018	1108	757
2021	4998	1229	840
2022	4838	1119	765

From the table, it is evident that there are significant differences when using different emission factors. Markly, emissions based on the UNEP factor tend to be higher compared to the other two factors. The UNEP factor, more generic nature, and lack of regional specificity. While The USA and Australia factors might be more accurate for their respective contexts. Sugarcane burning conditions (e.g., temperature, moisture content, combustion efficiency) impact dioxin formation. Variations in field practices, such as pre-harvest burning versus post-harvest burning, contribute to differences. Sugarcane composition varies globally. Factors like sugarcane variety, soil nutrients, and growth conditions affect the chemical makeup. Different compositions lead to varying dioxin emissions. Regarding activity-related uncertainty, it may also stem from the ratio of produced sugarcane to burning residue. In this study, we assume a uniform 33% residue ratio [43] across all provinces, which is higher than the ratio observed in India (20%) according to S. Bhuvaneshwari, *et al.* [44]. However, variations in this ratio are likely due to different sugarcane varieties and harvest conditions.

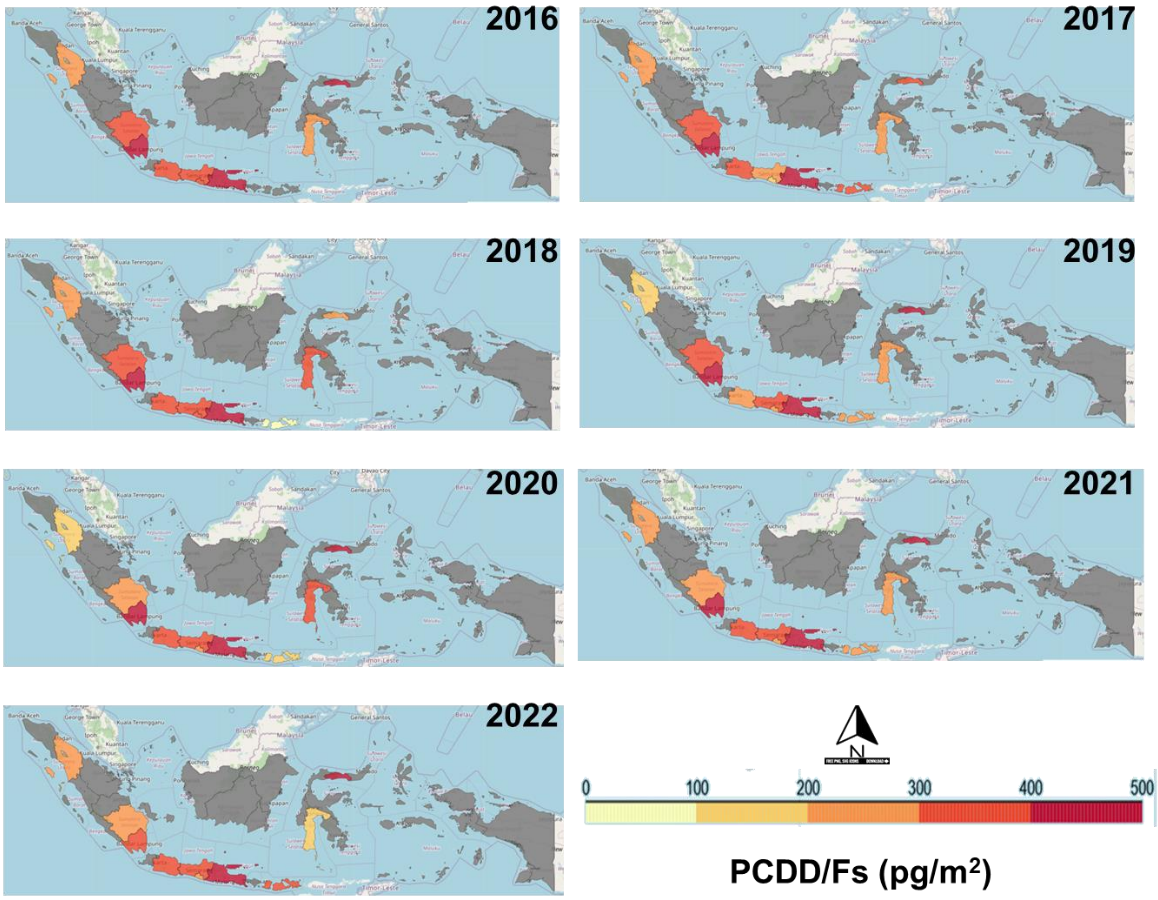

Figure 4. Spatial Distribution Dioxin Emission in Each Province over 2016 – 2022.

Spatially, certain regions in Indonesia consistently exhibit higher PCDD/Fs emissions. Provinces such as Lampung and South Sumatra, known for their extensive sugarcane agriculture, show persistently elevated levels of PCDD/Fs emissions. This trend is likely driven by intensive agricultural activities and the widespread practice of crop residue burning, which releases significant quantities of dioxins. This trend is likely driven by the intensive agricultural activities and the prevalent practice of crop residue burning as a cost-effective method to prepare land for new plantings. Such practices, while economically beneficial in the short term [45,46], release significant quantities of dioxins, which are known for their persistence in the environment and potential to bioaccumulate. High PCDD/Fs emissions are predominantly observed in agricultural regions. For example, South Sumatra and East Jawa have shown consistently high emissions, often exceeding 400 pg/m^2.

This pattern is influenced by the extensive cultivation and agricultural practices in these regions. In contrast, while East Jawa and Central Jawa also engage in substantial sugarcane cultivation, their emission profiles vary, with some regions showing spikes in certain periods followed by reductions. Regions like North Sumatra and West Jawa consistently exhibit high emission levels, reflecting the spatial distribution of intensive agricultural activities. However, new regions such as Gorontalo have begun to show increased emissions, reaching higher levels in recent years. This indicates a spatial expansion of high emission areas beyond the traditional agricultural hubs. The spatial distribution maps for 2020 and 2021 reveal continued high emissions in key areas, with some fluctuations. Notably, East Nusa Tenggara exhibited significant emission levels despite fewer data points, suggesting sporadic yet high-intensity emission events. By 2022, there was a noticeable decrease in emission levels across most provinces, except for Gorontalo and parts of East Jawa, which remained hotspots for PCDD/Fs emissions. However, higher emission intensity over the areas cultivated with sugarcane showed in spatial distributions of annual emissions (0.1° x 0.1°) specifically monthly emissions in the dry season [12]. Yearly trends on the maps also reveal sporadic peaks in emissions in certain years could be linked to less stringent enforcement of environmental policies or temporary increases in agricultural production demands.

Given that Indonesia contributes 72.81% of the total PCDDs/PCDFs emissions in the air across all inventories in Southeast Asia, trends analyse from 2003 to 2019 [47]. By examining changes over time (from 2016 to 2022), we can identify patterns, such as increasing or decreasing emissions. Furthermore, regions with consistently high emissions emerge as 'hotspots,' which may require targeted interventions. Moreover, the broader environmental impact of these emissions cannot be overstated.

3.2. Uncertainty

The mean values reported for each year represent the expected average quantity of PCDD/Fs emissions in kilograms of toxic equivalents (TEQ). These values are quite low, all around 0.003 to 0.004 ug TEQ per year. This suggests that the typical emission load of PCDD/Fs from sugarcane residue burning is minimal on an annual basis. The standard deviation values range from approximately 0.0107 to 0.0128 ug TEQ, which are significantly larger than the mean values. This high standard deviation relative to the mean indicates a large variability in the estimated emissions. Such variability could be due to several factors. Differences in annual sugarcane yield can cause significant fluctuations in the quantity of available biomass for burning, directly affecting emissions. Changes in the harvested area impact the amount of residue burned and thus influence emissions. Meanwhile variability in how completely the biomass burns (combustion efficiency) and the specific amount of PCDD/Fs produced per ton of burned material (emission factor) can also introduce considerable uncertainty into the emissions estimate.

3.3. Emission Prediction

Table 4 offers a compelling predicted emission from 2023 – 2028, presenting an upward trend in some areas, while others show fluctuating or stable patterns. The Grey Model GM(1,1) is particularly suited due to often the case with environmental data collected from diverse geographical locations like Indonesia. North Sumatra, regions traditionally intensive in sugarcane cultivation, is predicted to experience a steady increase in PCDD/Fs emissions unlike South Sumatra and Lampung with a slight decline. This trend may be attributed to expanding agricultural activities and possibly stagnant technological advancements in crop residue management. The sustained increase underscores the urgent need for implementing more robust sustainable agricultural practices in these regions. Most region in Jawa Island show gradually increase in their emission projections except for East Jawa that has slight decline from 416 pg/yr in 2023 to 397 pg/yr in 2028. These variations could reflect intermittent enforcement of agricultural burning regulations or periodic shifts in agricultural practices. Such data suggests that policy interventions need to be adaptable and responsive to the changing dynamics of agricultural practices in these provinces. West Nusa Tengggara indicate a substantial increase from 296 pg/yr in 2023 to 381 pg/ year in 2028. East Nusa Tengggara that start to plant sugarcane in 2021 has a gradual decrease. This might be indicating the lack of data as input in grey model also that can be seen from the higher MAPE and MAE. South Sulawesi, experience a significant decline emission in all projected years. While Gorontalo with the highest emissions still projected to have highest increase emission. The grey model resulted varying performance across regions (as shown in Table 6), with certain areas, particularly Jawa Island, demonstrating more accurate predictions than others. Factors such as data availability (including the lack of data in East Nusa Tenggara), model complexity, and local characteristics might influence these results.

Table 4. Annual PCDD/Fs Emission Prediction in Each Province over 2023 – 2028 (pg/yr).

	2023	2024	2025	2026	2027	2028
North Sumatra	260	271	282	293	305	317
South Sumatra	242	232	222	213	204	195
Lampung	413	411	409	407	405	402
West Jawa	306	308	310	312	314	316
Central Jawa	351	356	362	367	372	378
D.I. Yogyakarta	270	279	288	298	307	318

	2023	2024	2025	2026	2027	2028
East Jawa	416	412	408	405	401	397
West Nusa Tenggara	296	311	327	344	362	381
East Nusa Tenggara	180	178	176	174	172	170
South Sulawesi	216	201	187	173	161	150
Gorontalo	505	534	564	595	629	664

Such data suggests that policy interventions need to be adaptable and responsive to the changing dynamics of agricultural practices in these provinces. West Nusa Tengggara indicate a substantial increase from 296 pg/yr in 2023 to 381 pg/ year in 2028. East Nusa Tengggara that start to plant sugarcane in 2021 has a gradual decrease. This might be indicating the lack of data as input in grey model also that can be seen from the higher MAPE and MAE. South Sulawesi, experience a significant decline emission in all projected years. While Gorontalo with the highest emissions still projected to have highest increase emission. The grey model resulted varying performance across regions (as shown in Table 6), with certain areas, particularly Jawa Island, demonstrating more accurate predictions than others. Factors such as data availability (including the lack of data in East Nusa Tenggara), model complexity, and local characteristics might influence these results.

Figure 5 complements these insights by visualizing the spatial distribution of emissions across the provinces, emphasizing the diverse emission trajectories. For instance, Gorontalo is predicted to maintain high emissions, highlighting it as a persistent hotspot. Conversely, regions like South Sulawesi and East Nusa Tenggara exhibit high-emission events despite an overall downward trend, suggesting that localized interventions are necessary to effectively mitigate emissions. This variation across provinces highlights the necessity for targeted and adaptable policy interventions to support sustainable sugarcane agriculture and effectively manage PCDD/Fs emissions in Indonesia.

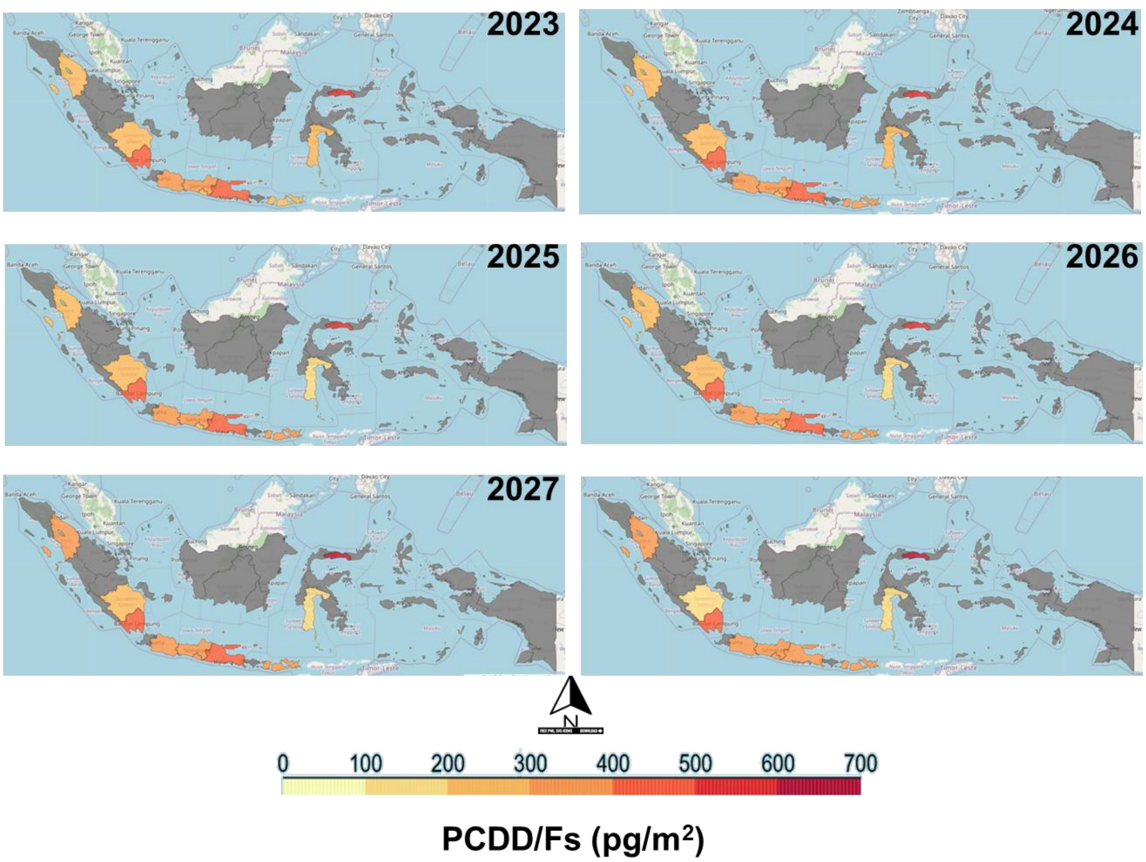

Figure 5. Prediction Spatial Distribution Dioxin Emission in Each Province over 2023 – 2028.

The forecast data provided by the Grey Model GM(1,1) serves as a valuable tool for policymakers and environmental managers in Indonesia. However, model improvements might be necessary. The

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results of the model's performance (Table 6) highlight varying degrees of prediction reliability. Regions like East Jawa and Central Jawa, which demonstrate exceptional prediction accuracy, could serve as benchmarks for refining the model's accuracy in other regions with less precise predictions. For instance, East Jawa shows highly precise model predictions with the lowest MAPE of 1.4% and an MAE of 6. In contrast, East Nusa Tenggara, which has only two years of data, and South Sulawesi exhibit the highest MAPE values at 100% and 83%, respectively, paired with substantial MAEs of 186 and 143.

Table 6. Grey Model Performance Evaluation of Dioxin Emission Prediction.

	MAPE (%)	MAE
North Sumatra	36	95
South Sumatra	9	27
Lampung	6	26
West Jawa	18	58
Central Jawa	3	12
D.I. Yogyakarta	78	177
East Jawa	1.4	6
West Nusa Tenggara	42	140
East Nusa Tenggara	100	186
South Sulawesi	83	143
Gorontalo	29	129

However, It is recommended to have monthly emissions profiles that can show local agricultural practices (such as varying harvesting times for different crop types) and seasonal conditions (dry or wet). The emission data generated in this study deliver spatially and temporally , holds valuable potential for air quality modelling studies like several studies [48,49]. By leveraging this data, researchers can assess the impact of current and future emissions on ambient air quality.

4. Conclusions

From 2016 to 2022 the average PCDD/Fs emission values exhibit significant variability among the provinces, prominently. Gorontalo has the highest mean emission value at 414 pg/yr while East Jawa displayed relatively stable emissions with less variability compared to other provinces. Spatially, certain regions in Indonesia consistently exhibit higher PCDD/Fs emissions. Provinces such as Lampung and South Sumatra. By 2022, there was a noticeable decrease in emission levels across most provinces; however, Gorontalo and parts of East Jawa, which remained hotspots for PCDD/Fs emissions. This regions with consistently high emissions emerge as 'hotspots,' which may require targeted interventions. Related with uncertainty, emissions based on the UNEP factor tend to be higher compared to the previous studies. The Grey Model GM(1,1) predicts future emissions with an upward trend in some areas, while others show fluctuating or stable patterns. However, It is recommended to have monthly emissions profiles that can show local agricultural practices (such as varying harvesting times for different crop types) and seasonal conditions (dry or wet). Further research and refinement are crucial to improving our understanding of dioxin emissions in this region. To enhance accuracy and reduce uncertainty in future research, it may be beneficial to use localized emission factors obtained by conducting field studies and collecting combustion conditions based on fuel types and sugarcane varieties. By identifying regions with increasing emission trends, resources can be strategically allocated to develop and implement effective control measures. These might include promoting non-burning agricultural residue methods, enhancing farmer education and support programs, and investing in research and development for sustainable farming technologies.

Supplementary Information: The following supporting information can be downloaded at the website of this paper posted on Preprints.org. Additional information, as noted in the text, is available in the supplementary materials.

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