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Biomass burning emission inventory of multi-year PM_{10} and $PM_{2.5}$ with high temporal and spatial resolution for Northern Thailand

Anuttara Hongthong*, **Kampol Nanthapong**, **Thongchai Kanabkaew**

Faculty of Public Health, Thammasat University, Pathumthani 12121 Thailand

*Corresponding author, e-mail: anuttara1978@gmail.com

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ABSTRACT: The biomass burning emission inventory reported by the Global Fire Emissions Database is at a coarse temporal (monthly) and spatial resolution (0.25°–0.25°) and may not be appropriate for a model simulation or disease burden investigation. This study estimated an emission inventory of PM_{10} and $PM_{2.5}$ caused by biomass burning in the nine provinces of Northern Thailand during 2012–2016 based on daily, monthly, and annual. The Visible Infrared Imaging Radiometer Suite (VIIRS) fire counts (375 m-resolutions), land uses, emission factors, and activity data were applied for the bottom-up estimation. According to the findings, Mae Hong Son (29%), Chiang Mai (20%), and Chiang Rai (38%), respectively, had the highest proportion of forest fires, savanna and grassland fires, and agricultural fires. There was a consistent trend between estimated emission and measured PM. The difference in emission ratio of $PM_{2.5}$ between the current study and GFED4 was 1.2–2.6, 1.4–2.2, and 1.4–2.5 for forest, savannas and grasslands, and agricultural lands, respectively. The uncertainty range of $PM_{2.5}$ and PM_{10} emissions from the three types of biomasses were the same with relative errors of −15% to 27%, −8% to 7%, and −17% to 10%, respectively. The VIIRS fire count can be used for estimation of biomass burning with finer resolution in both temporal and spatial terms.

KEYWORDS: biomass burning, VIIRS, PM_{10}, $PM_{2.5}$, Northern Thailand

INTRODUCTION

PM_{10} and $PM_{2.5}$ emissions in Southeast Asia are a significant problem recognized by all Asian countries, and the major source of these two pollutants is anthropogenic biomass burning. Its emission rates and distribution trends have been examined during the past decade [1]. Northern Thailand is a critical region experiencing the most severe haze problems in the dry season, and the atmospheric PM_{10} and $PM_{2.5}$ during this period exceeded the National Ambient Air Quality Standards [2]. In addition, a high concentration of PM_{10} and $PM_{2.5}$ contributed to a potential health risk to the local population [3]. An emission inventory is an important record which shows actual emissions of air pollutants, and these data can be used as input to an air pollution forecasting model for appropriate decisions [4, 5]. Investigations of PM_{10} and $PM_{2.5}$ emissions have been adopted in many Asian countries. In Thailand, estimations of PM_{10} and $PM_{2.5}$ emissions from biomass burning between the base years of 2005–2014 were developed [6–8]. However, it was found that only a few studies included a high resolution of both temporal and spatial distributions for the Northern part of Thailand.

Fire hot spots provided crucial information for the estimation of emissions from areas subject to biomass burning [7]. The VIIRS active fires with 375-m resolution of the MODIS fire detection instrument has been improved for the detection of small fires and nighttime occurrences [9]. The VIIRS-375 m fire result showed a higher rate of small fire detections and a greater number of hot spots using MODIS at 1 km resolution such as MOD14A1/MYD14A1, which has made it possible to estimate the high resolution of emissions than the Global Fire Emission Database (GFED) [6] which did not cover small fires [10]. Crop fires that were sporadic were not detected by the repeat cycle of satellites like active fires, resulting uncertainty in estimation. The burned area product (MCD64A1) can be used to validate the estimated burned area of a hot spot from the VIIRS. The Geographic Information Systems (GIS) was employed as a tool to generate a temporal-spatial distribution and the concentration of particulate matters [11, 12]. Evaluation was an essential process in the quantification of an emission inventory to determine the uncertainties of emission factors, activity data and estimated emissions. The Monte Carlo method has been adopted which is frequently used to quantify the uncertainty of air pollutant emissions from biomass burning.

The purpose of this study was to estimate an emission inventory of PM_{10} and $PM_{2.5}$ from each type of biomass burning with high temporal and spatial resolutions based on daily, monthly, and annual, by using the fire count data from the VIIRS instrument which was gridded to the 1 km × 1 km resolution by the GIS tool. The uncertainty of the calculated emissions, emission factors and activity data were evaluated by the Monte Carlo method. In addition, the trend between the estimated emissions and the monitored PM concentrations were plotted. This study would be the first nationally to develop a high temporal (daily) and spatial resolution (1 km × 1 km) of biomass emission inventory from the active fire.

MATERIALS AND METHODS

Study domain

The nine provinces in the Northern Thailand including Chiang Mai, Chiang Rai, Lampang, Lamphun, Mae Hong Son, Nan, Phayao, Phrae, and Tak are located between latitudes 14.90° N–20.46° N, longitudes 97.32° E–101.40° E and they are adjacent to the border of Myanmar and Laos (Fig. S1). The entire area covers 102 259 km^{-2} with a total population of 6.5 million. The main geographical features are mountainous areas with a variety of forests and agriculture. This region exposed to air pollution haze episodes over the last decades. Many fire hots spot is frequently found in the inner forest areas with a high slope topography which is difficult to access and control [8]. The level of PM_{10} concentrations from most of the PCD air monitoring stations in the study domain were approximately 1 to 3 times higher than Thailand's daily ambient air quality standard (120 $\mu g/m^3$) in the dry season [2, 13, 14] and similarly for $PM_{2.5}$ concentrations, for which the daily ambient air quality standard was 50 $\mu g/m^3$ during this period.

Fire count analysis

The result for fire counts were obtained from the Visible Infrared Imaging Radiometer Suite (VIIRS I-Band) distributed by NASA's Fire Information for Resource Management System (FIRMS). The high spatial resolution of fire counts at 375 m from VIIRS has been improved to give a better response to small fires and the mapping of large fire perimeters as well as nighttime detection. Normally, the VIIRS provides a full global coverage every 12 h with nominal equator-crossing overpass times at 1.30 pm and 1:30 am. Fortunately, the location of the north and the south of Thailand are in the middle latitudes, therefore, two more rounds of VIIRS overpass Thailand at approximately 12:40 pm (ascending node) and 12:40 am (descending node) [9]. The land cover data at 500 m × 500 m resolution for the years 2012–2016 were obtained from the Combined Terra and Aqua Land Cover Type (MCD12Q1). The 17 classes of MCD12Q1-land cover were reclassified into 5 main classes according to the actual land use type of the study area included forests, shrublands, savannas and grasslands, agricultural, and others (Fig. S2), however, class no. 5 containing barren, water bodies, permanent wetlands, and urban built-up lands was not considered. Fire counts were then overlaid on the reclassified land cover layer to generate the biomass fire types.

Emission factors and activity data

Emission factors, burning efficiency, and dry matter density of forests, savannas and grasslands, and agriculture were comprehensively collected from the published literature. The priority of data selection was given to the data obtained in Thailand, followed by the data from other Asian countries. If these data were insufficient for Thailand and other Asian countries, the global data were accepted as shown in Table S1. Emission factors and activity data influence the accuracy of emission estimations; therefore, it was necessary to establish the level of uncertainty.

Emission estimation

A bottom-up approach has been adopted to estimate particulate matter emissions from anthropogenic sources in various studies [8]. In this study, emissions from the four main biomass types were initially calculated for the smallest administrative unit in Thailand which is called "a sub-district" using the bottom-up approach to develop a high resolution of PM_{10} and $PM_{2.5}$ emissions on a daily, monthly, and annual basis using the following equations.

$$E_{i,j} = \sum_i M_j \times EF_{i,j} \tag{1}$$

where $E_{i,j}$ is the total emission of pollutant i (PM_{10} or $PM_{2.5}$) from each biomass type j, M_j is the amount of burned biomass type j (kg), $EF_{i,j}$ is emission factor of biomass type j (g/kg of dry matter). Amount of biomass burned (M_j) was calculated by Eq. (2) [31].

$$M = A \times \rho \times \eta \tag{2}$$

where A is area of biomass burned (hectare; ha) which is calculated by the Eq. (3).

$$A = N_p \times R_p \times 10^{-4} \tag{3}$$

where N_p is the number of fire counts from the VIIRS instrument, R_p is the resolution of VIIRS fires (375 m-resolution), ρ is dry matter density (tons/ha), and η is the burning efficiency of each biomass type (Table S3). Nevertheless, estimated $PM_{2.5}$ emissions from the bottom-up method were compared to the GFED4 emission.

Burned area estimation

The monthly biomass burned area in hectares was calculated from the number of VIIRS fire counts using Eq. (3) and validated against the burned area product from MODIS collection 6 with a grid cell resolution of 500 m (MCD64A1).

Temporal allocation

According to the temporal resolution of the VIIRS fire counts, the daily, monthly, and annual emissions of

PM_{10} or $PM_{2.5}$ were estimated based on the number of fire counts on each land cover type (forests, savannas and grasslands, and type of agriculture), and then allocated to the sub-district level. The temporal distribution of PM_{10} or $PM_{2.5}$ emissions were validated by the monitored concentration levels of the 13 PCD stations located in the study domain.

Spatial allocation

The average annual and five-year emissions of PM_{10} or $PM_{2.5}$ were allocated to grid cells of 1 km × 1 km resolution by the Inverse Distance Weight (IDW) method in ArcGIS, as the distribution of fire counts in the study area was not dense enough to capture the extent of local surface variations, and then the emission values of PM_{10} or $PM_{2.5}$ for nearby fire hot spots were approximated accordingly.

Evaluation of estimated emissions and uncertainty analysis

Estimated emissions were then evaluated by comparing them with the monitored particulate matter data. Because of the limitations of $PM_{2.5}$ data from the PCD monitoring station during our study period, the trend between estimated PM_{10} emissions and the monitored PM_{10} of each PCD monitoring location were only examined. Moreover, emissions from this study were compared to the GFED4 emissions. Because emission factors and activity data were gathered from various sources, there was a major factor influencing the inventory's uncertainty. The Monte Carlo simulation was used to quantify the variation of air pollutant emissions and its input parameters (emission factors and activity data) [7]. Normally, the specified probability distributions are a fundamental part of Monte Carlo simulations which generate the random values of input parameters, and emissions are estimated accordingly. The mean and standard deviations of the emission factors and activity data were determined using the data in Table S1, and then incorporated into the Monte Carlo simulation with the Crystal Ball software at 100 000 iterations. The number of iterations was decided by a sample size, as many iterations increase accuracy. Finally, the range of estimated uncertainties in terms of relative error (%) at a 95% Confidence Interval (CI) was determined according to the Monte Carlo simulation.

RESULTS AND DISCUSSION

Fire count analysis

The four classes of land cover including forests, shrublands, savannas and grasslands, and different type of agriculture were classified as biomass burning sources. However, only a few fire counts were detected in shrublands at around 0.002% of the total fire counts. Thus, only forests, savannas and grasslands, and different types of agriculture were employed for emission estimation. The total number of fire counts from the three biomass burning sources in the five-year interval were 400 630 points which occurred in the years 2012, 2013, 2014, 2015, and 2016 at 81 261; 74 522; 76 886; 75 863; and 92 098 points, respectively. The highest number of fire counts was from savannas and grasslands, followed by forests and agricultural areas. A similar trend of forest for forest fires was observed during 2012–2015, however, it was clearly increased in 2016, which showed the same pattern as presented in the summary report of forest fires and smog with satellite images [32]. While the trend of fire counts from savannas and grasslands and agricultural areas did not change much during the study period as shown in Fig. S3.

The pattern of VIIRS fire counts from forests clearly increased in January and escalated until April, and the highest was in March which shows a similar pattern to that of previous studies [8], and the forest fires in Northern Thailand was normally surface fires from dipterocarp and mixed deciduous forests, which shed their leaves in the dry season. This is the season for forest fires since it is the time of harvesting and preparation of the land for the next planting season in the up-coming rainy season. While the temporal distribution of savanna and grassland fires showed similar pattern to forest fires, it seems that the incidence of fires from savannas and grasslands possibly results from litter build-up in areas where forests have been unusually [33]. There has been a remarkable trend in agricultural fires which differ from that of forests and savannas and grasslands. These agricultural fires usually start in December and continually increase until May. This rising trend results from crop harvesting activity.

The provincial allocation of fire counts on each type of land cover in the nine provinces during 2012–2016 is shown in Fig. S4. High proportions of forest fires were found in Mae Hong Son (29%), Chiang Mai (22%), and Tak (14%), which are like the findings in Junpen [8] who found that the highest density of fire in these three provinces was in the year 2007. The greatest proportion of savanna and grassland fire was observed in Chiang Mai (20%), Tak (19%), and Nan (15%). The highest number of agricultural fires was detected in Chiang Rai (38%) and Phayao (18%), which were related to the burning of crop residues e.g. rice, maize, etc [34].

Burned area estimation

The annual estimated burned area derived from the active fire count (VIIRS) was compared to the burned area product from the MCD64A1. Generally, the estimated burned area from this study was higher. The range ratio of burned area between this study and MCD64A1 for forest, savannas and grasslands, and agricultural from 2012 to 2016 was 1.0–2.1, 1.5–2.3,

Table 1 Comparison of estimated burned area and MCD64A1.

Year	Forest burned area (ha)		Savanna burned area (ha)		Agricultural burned area (ha)		Ratio (VIIRS vs. MCD64A1)		
	VIIRS	MCD64A1	VIIRS	MCD64A1	VIIRS	MCD64A1	Forest	Savanna	Agricultural
2012	437 161	603 769	661 725	423 193	42 384	22 934	0.7	1.6	1.8
2013	412 284	199 135	599 484	265 522	32 175	19 014	2.1	2.3	1.7
2014	497 489	507 023	629 522	389 048	43 748	25 459	1.0	1.6	1.7
2015	463 303	445 659	563 048	372 328	37 167	35 115	1.0	1.5	1.1
2016	636 258	366 311	612 323	419 661	42 609	29 826	1.7	1.5	1.4
Total	2 446 495	2 121 897	3 066 102	1 869 752	198 083	132 348	–	–	–

Ratio is the fraction between estimated burned area of this study and the MCD64A1 burned area. Ratio less than 1.0 mean the estimated burned area of this study was lower than the MCD64A1.

and 1.1–1.8, respectively. The closed ratio between VIIRS and MCD64 burn areas was shown in forest fires during 2014 and 2015 (Table 1). While savannas and agricultural fires were small and short live burning, therefore, the ratio of estimated burning area using fire count from the VIIRS is normally higher than MCD64A1.

Emissions of PM_{10} and $PM_{2.5}$

The total annual PM_{10} and $PM_{2.5}$ emissions (tons) and their standard deviations for each biomass type are summarized in Table S2. The emissions of PM_{10} from all biomass types during 2012–2016 were 298 002, 279 476, 332 750, 308 540, and 415 173 tons, respectively. The total emissions of $PM_{2.5}$ were 217 746, 204 018, 242 502, 224 720, and 301 494 tons, respectively. The emissions for forest, savannas and grasslands, and agriculture areas in this study during 2012–2016 varied between 86.3%–91.9%, 7.3%–12.4%, and 0.8%–1.3%, respectively. Forest fires were the main contributor of PM_{10} and $PM_{2.5}$ emissions that were similar to the results of previous studies [35]. The largest emissions of PM_{10} and $PM_{2.5}$ from forest fires occurred in Mae Hong Son (140 560 and 100 777 tons) and Chiang Mai (107 947 and 77 394 tons), which were consistent with the proportions of their forest area (86.5% and 69.9%, respectively) [5]. PM_{10} and $PM_{2.5}$ from savannas and grasslands were mainly emitted from Chiang Mai (10 067 and 8 358 tons) and Tak (9 982 and 8 275 tons). A high amount of PM_{10} from agricultural areas was released from Chiang Rai (1 913 and 1 688 ton) and Phayao (927 and 818 tons) as both provinces have the two largest agricultural areas of upper-northern Thailand with 48.6% and 40.1% of their total area, respectively (base year 2013–2015) [4].

Most of the estimated $PM_{2.5}$ emissions from this study were higher than the GFED4 emissions. And the emission ratios in this study ranged from 1.2 to 2.6, 1.4 to 2.2, and 1.4 to 2.5 for forest, savannas and grasslands, and agriculture, respectively (Table 2). However, these range ratios were lower than the study of Boonman [36] that compared the estimated $PM_{2.5}$ emission to the GFED3.1 and found the range ratio of 51 and 31 for forest and agricultural, respectively.

Temporal emission distribution

The monthly PM_{10} and $PM_{2.5}$ emissions from biomass burning of the study during 2012–2016 were shown in Fig. 1(a). The values were conspicuously high in February–April, similar to the variation in the trend of fire counts [35, 37] and burned areas. Fig. 1(b) shows the daily emissions of PM_{10} of the period February–April 2014, which fluctuated over this period of three months with the highest emission volume of 17 950 tons. In addition, the daily PM_{10} variations during this period were consistent with the temporal trends of the maximum PM_{10} concentrations from the PCD station as shown in Fig. 1(b).

Distribution of Spatial emissions

The annual spatial distributions of PM_{10} in Northern Thailand at 1 km × 1 km resolution were shown in Fig. 2. Emission rates varied between 0.5–50 tons/ha depending on the number of fire counts and land cover types. Moderate volumes of PM_{10} emissions (>30 tons/ha) were repeatedly found in Mae Hong Son, Chiang Mai, and Tak during the 5-year period. These areas have a high density of forest. Emissions of PM_{10} in 2005–2009 were reported to range from >0.1 tons/ha with high intensity in Mae Hong Son and the Chiang Mai area [8]. The average five-year PM_{10} emission was significantly high in Mea Hong Son with emissions of over 10 tons/ha which covered all sub-districts and differed from other provinces that showed lower emissions (<10 tons/ha) in some areas. The area with lower PM_{10} emissions (<10 tons/ha) was mainly crop land.

The spatial emission distribution of $PM_{2.5}$ was similar to PM_{10}, but with lower concentration of emissions. Emissions of $PM_{2.5}$ varied between 0.5–40 tons/ha in the study. Moderate emissions of $PM_{2.5}$ (>30 tons/ha) were also found in some sub-districts of Chiang Mai, Mae Hong Son, and Tak during the 5 year period. The

Table 2 Comparison of estimated $PM_{2.5}$ and GFED4 emissions.

Year	Forest emission (tons)		Savanna emission (tons)		Agricultural emission (tons)		Ratio (VIIRS vs. GFED4)		
	VIIRS	GFED4	VIIRS	GFED4	VIIRS	GFED4	Forest	Savanna	Agricultural
2012	187 926	214 640	27 021	17 623	2799	1139	0.9	1.5	2.5
2013	177 299	72 871	24 566	11 057	2154	945	2.6	2.2	2.3
2014	298 343	182 049	25 716	16 201	2884	1265	1.6	1.6	2.3
2015	199 176	160 604	23 047	15 505	2497	1744	1.2	1.5	1.4
2016	273 641	116 833	25 058	17 476	2795	1482	2.3	1.4	1.9
Total	1 136 385	746 997	125 408	77 862	13 129	6575	–	–	–

Ratio is the fraction between estimated emission of this study and the GFED4. Ratio less than 1.0 mean the emission of this study is lower estimated than GFED4.

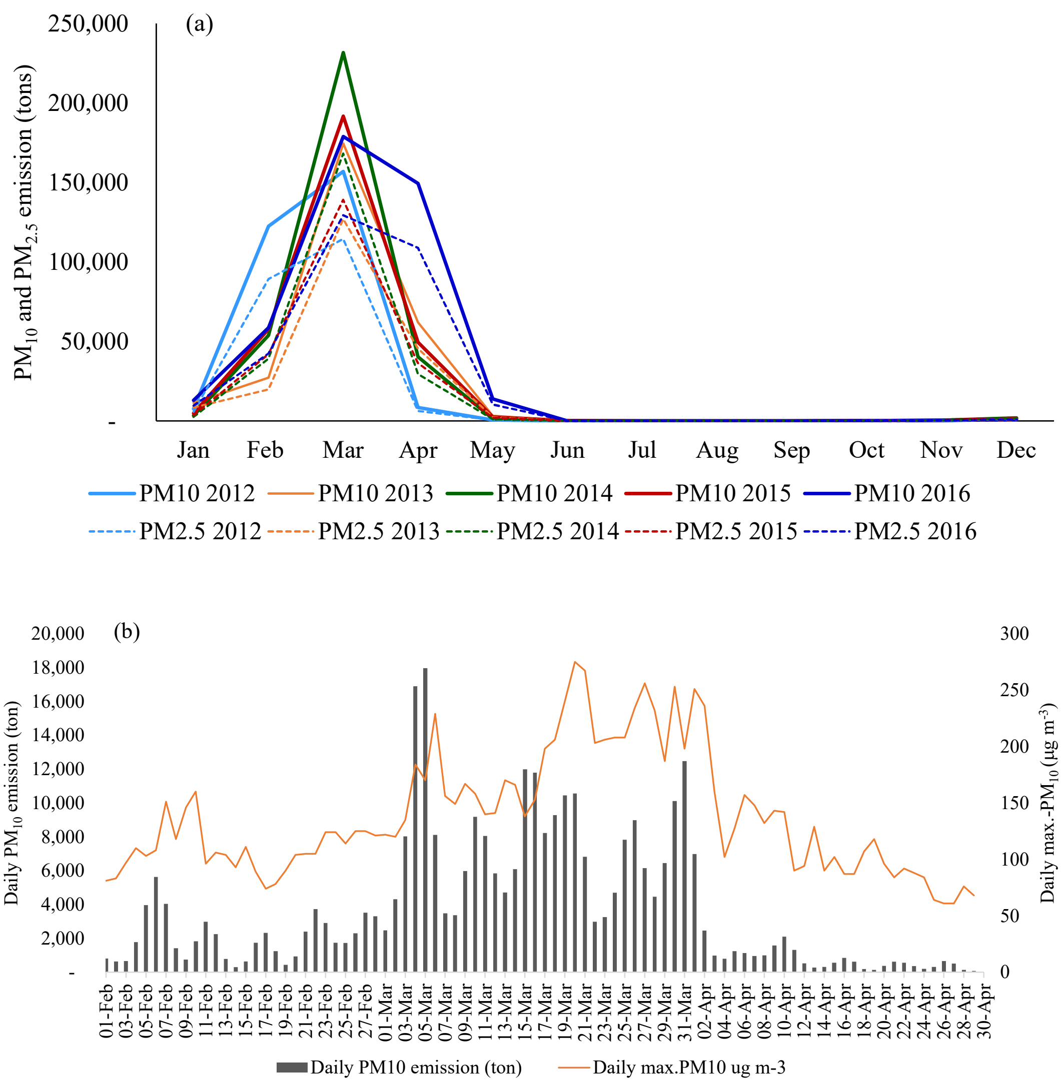

Fig. 1 (a) Monthly temporal distribution of PM_{10} and $PM_{2.5}$ emission during 2012–2016. (b) Daily temporal PM_{10} emission during February to April 2014.

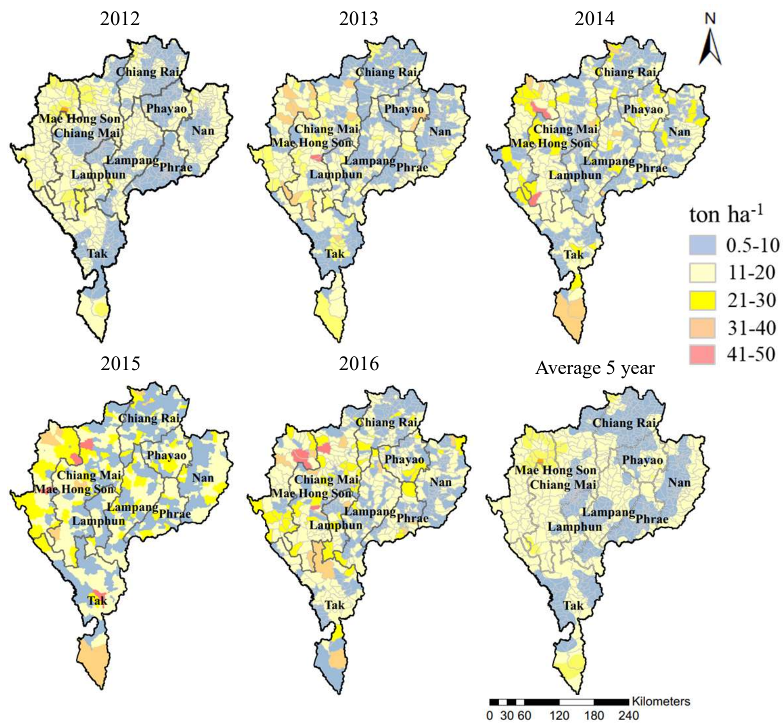

Fig. 2 Annual and average five-year emission of PM_{10} from all types of biomass burning (forests, savannas and grasslands, and agricultures).

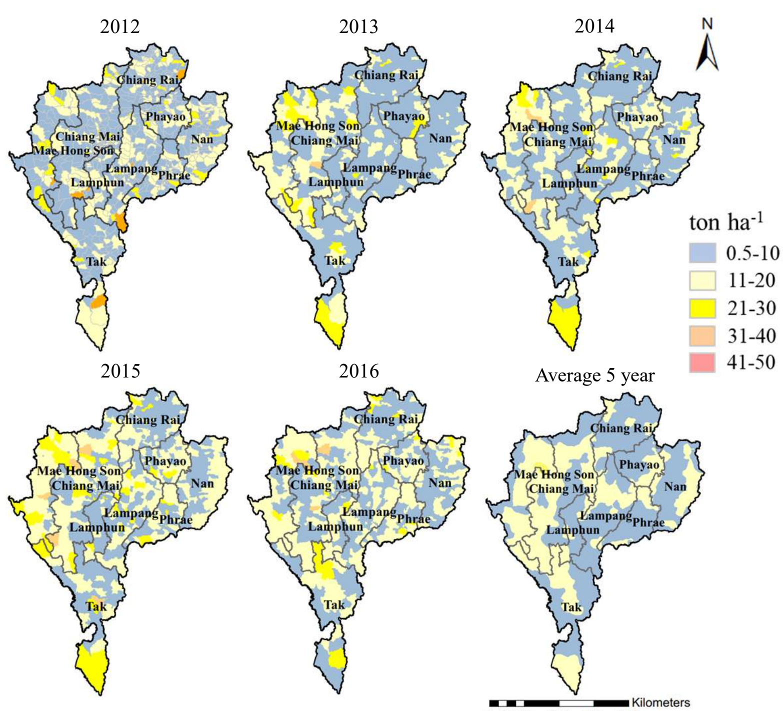

Fig. 3 Annual and average five-year emission of $PM_{2.5}$ from all types of biomass burning (forests, savannas and grasslands, and agricultures).

average five-year spatial $PM_{2.5}$ emission distribution was similar to PM_{10} which showed emissions of over 10 tons/ha in provinces with a high density of forest as shown in Fig. 3.

Uncertainty analysis

The uncertainty range of PM_{10} and $PM_{2.5}$ emissions from biomass burning is summarized in Table S4. The highest uncertainty range was found in forests with approximately −15% to 27% at 95% CI, as most of the forest burned continuously day and night, and developed into large fires, so they could be detected by satellite at both day and night which caused a high uncertainty rate. The uncertainty range of forest emissions in this study is like the base year 2005–2009 at approximately 20% [8]. The estimated emissions from the forest with a positive 27% had a large overestimation, while the estimated emissions from agriculture with a minus 17% had the most underestimation. The most accurate prediction of emissions was made in savannas and grasslands.

The uncertainty ranges of biomass burning, including burning straw, and forest and grassland fires in the mainland of China in 2012 were in the same interval with this study at −7% and 6% for PM_{10} and −13% and 1% for $PM_{2.5}$, respectively [38]. However, the type of software and the number of iterations of uncertainty testing may affect the uncertainty estimation result.

CONCLUSION

We investigated the number of fires on each land cover type, forests, savannas and grasslands, and agricultural areas of nine provinces in the Northern Thailand using the fire count data from the VIIRS instrument. Extreme amounts of PM_{10} and $PM_{2.5}$ were emitted from forest fires in Mae Hong Son and Chiang Mai, while emissions of PM_{10} and $PM_{2.5}$ from savanna and grassland fires were high in Chiang Mai and Tak, and there was a significant volume of emissions from agricultural fires in Chiang Rai and Phayao provinces. Annual emissions of PM_{10} and $PM_{2.5}$ emissions during 2012–2016 were 298 002, 279 476, 332 750, 308 540 and 415 173 tons, and 217 746, 204 018, 242 502, 224 720 and 301 494 tons, respectively. The temporal daily estimated PM_{10} emissions were consistent with the maximum PM_{10} concentrations obtained from the PCD monitoring station. The highest uncertainty ranges of PM_{10} and $PM_{2.5}$ emissions from biomass burning were found in forest fires with approximately −15% to 27% at 95% CI. The estimated $PM_{2.5}$ emissions from VIIRS were greater than the GFED4 emissions because they were covered by smaller fires at 375-m resolution. The estimated emission and burned area of this study, on the other hand, were finer in terms of temporal and spatial resolution, with daily and 1 km × 1 km grided. The limitation of our study was the lack of meteorological parameters that affected the emission dispersion, such as wind speed, wind direction, and planetary boundary layer. Therefore, the correlation between these parameters and PM emissions should be given more attention in the future.

Appendix A. Supplementary data

Supplementary data associated with this article can be found at http://dx.doi.org/10.2306/scienceasia1513-1874.2022.040.

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Appendix A. Supplementary data

Table S1 Compiled emission factors and activity data for PM_{10} and $PM_{2.5}$ emission estimation.

Parameters and biomass type	Particle size	Compiled data
Forests	PM_{10} $PM_{2.5}$	18.5 [15], 10.5 [16], 17.8 [17], 12.8 [18] 9.1 [15], 9.1 [16], 13 [17], 9.93 [18], 12.3 [26]
Savannas and grasslands	PM_{10} $PM_{2.5}$	7.2 [8], 10 [20], 8.3 [35] 7.71 [1], 5.4 [4], 6.6 [8], 7.65 [19], 8.3 [20]
Agricultures	PM_{10} $PM_{2.5}$	11.64 [1], 9.4 [4], 8.87 [22], 9.4 [23], 11.95 [23] 6.26 [1], 8.3 [4], 8.25 [21], 8.48 [22], 11.1 [23], 8.3 [37]
Forests	PM_{10}/ $PM_{2.5}$	0.88 [18], 0.78 [21], 0.5 [24], 0.6 [25]
Savannas and grasslands	PM_{10}/ $PM_{2.5}$	0.5 [5], 0.76 [26], 0.73 [35]
Agricultures	PM_{10}/ $PM_{2.5}$	0.92 [25], 0.8 [27], 0.68 [27], 0.9 [28]
Forests	PM_{10}/ $PM_{2.5}$	59.44 [7], 46.7 [28], 68.7 [35]
Savannas and grasslands	PM_{10}/ $PM_{2.5}$	6.2 [8], 10.06 [28], 10 [29]
Agricultures	PM_{10}/ $PM_{2.5}$	9.4 [5], 10.44, 8.9 [14], 5.05 [30]

Table S2 Annual emission of PM_{10} and $PM_{2.5}$ from the three types of biomass burning (tons) during 2012–2016.

Type of biomass	Annually PM_{10} emission (tons)						
	2012	2013	2014	2015	2016	Average	Standard deviation
Forests	262,112 (88.0%)	247,290 (88.5%)	298,343 (89.7%)	277,804 (90.0%)	381,664 (91.9%)	293,442	52,828
Savannas and grasslands	32,717 (11.0%)	29,745 (10.6%)	31,137 (9.4%)	27,906 (9.0%)	30,341 (7.3%)	30,369	1,772
Agriculture	3,173 (1.1%)	2,442 (0.9%)	3,269 (1.0%)	2,831 (0.9%)	3,168 (0.8%)	2,977	342
Total (tons)	298,002 (100%)	279,476 (100%)	332,750 (100%)	308,540 (100%)	415,173 (100%)	326,788	53,027
Type of biomass	Annually $PM_{2.5}$ emission (tons)						
	2012	2013	2014	2015	2016	Average	Standard deviation
Forests	187,926 (86.3%)	177,299 (86.9%)	213,902 (88.2%)	199,176 (88.6%)	273,641 (90.8%)	210,389	37,876
Savannas and grasslands	27,558 (12.4%)	25,186 (12.0%)	26,131 (10.6%)	23,421 (10.3%)	25,792 (8.3%)	25,081	1,464
Agriculture	2,799 (1.3%)	2,154 (1.1%)	2,884 (1.2%)	2,497 (1.1%)	2,795 (0.9%)	2,626	302
Total (tons)	218,283 (100%)	204,018 (100%)	242,502 (100%)	224,720 (100%)	301,494 (100%)	238,096	38,056

Table S3 Parameters for emission calculation.

Biomass type	Dry matter density (ρ)	Burning efficiency (η)
Forests	58.28 [11, 28]	0.69 [10, 25, 27]
Savannas and grasslands	8.75 [13, 29]	0.66 [8, 18, 24, 25]
Agriculture	9.92 [1, 26, 30]	0.80 [19, 26, 31]

Table S4 Uncertainties of estimated emission in the nine provinces of the northern Thailand in the five-year interval (2012–2016).

PM type	Biomass type	Average estimated EI (95% CI)	Relative error
PM_{10}	Forests	293,442 (248,772, 373,332)	(−15%, 27%)
	Savannas and grasslands	30,908 (28,491, 33,088)	(−8%, 7%)
	Agriculture	2,977 (2,481, 3,260)	(−17%, 10%)
$PM_{2.5}$	Forests	210,389 (178,362, 267,667)	(−15%, 27%)
	Savannas and grasslands	25,618 (23,598, 27,415)	(−8%, 7%)
	Agricultures	2,626 (2,188, 2,876)	(−17%, 10%)

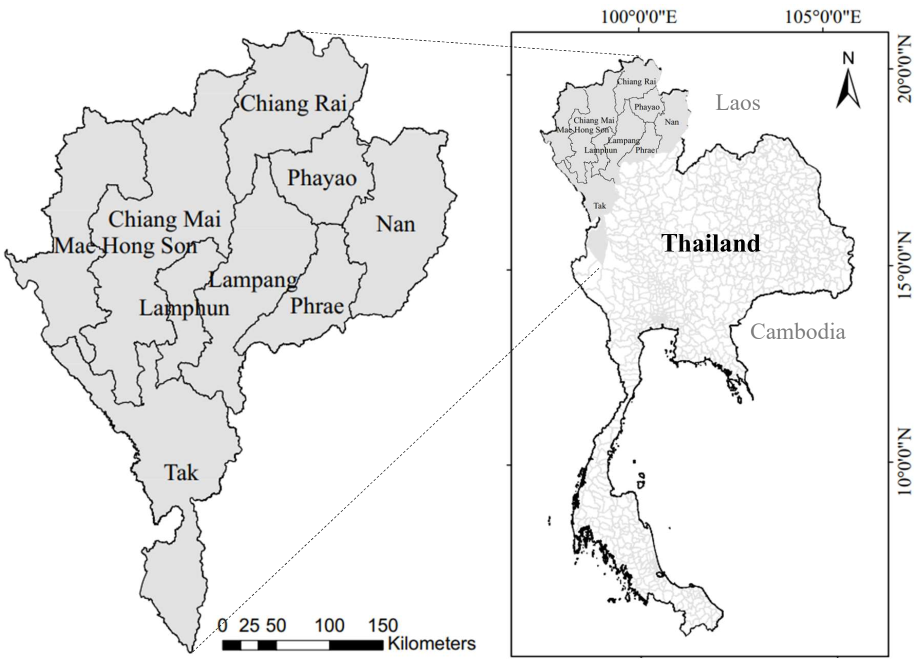

Fig. S1 Study domain.

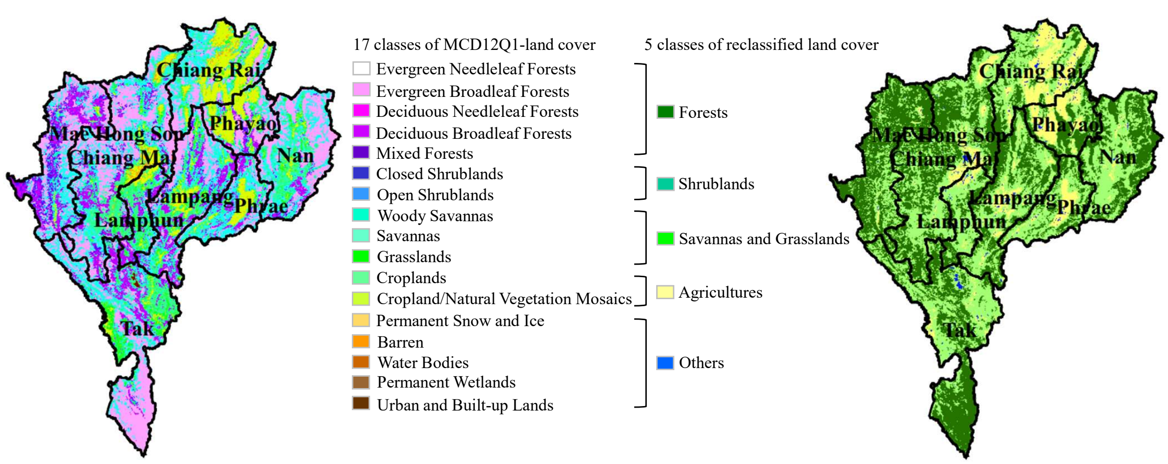

Fig. S2 Reclassification of land cover from 17 classes of MODIS (MCD12Q1) to 5 classes.

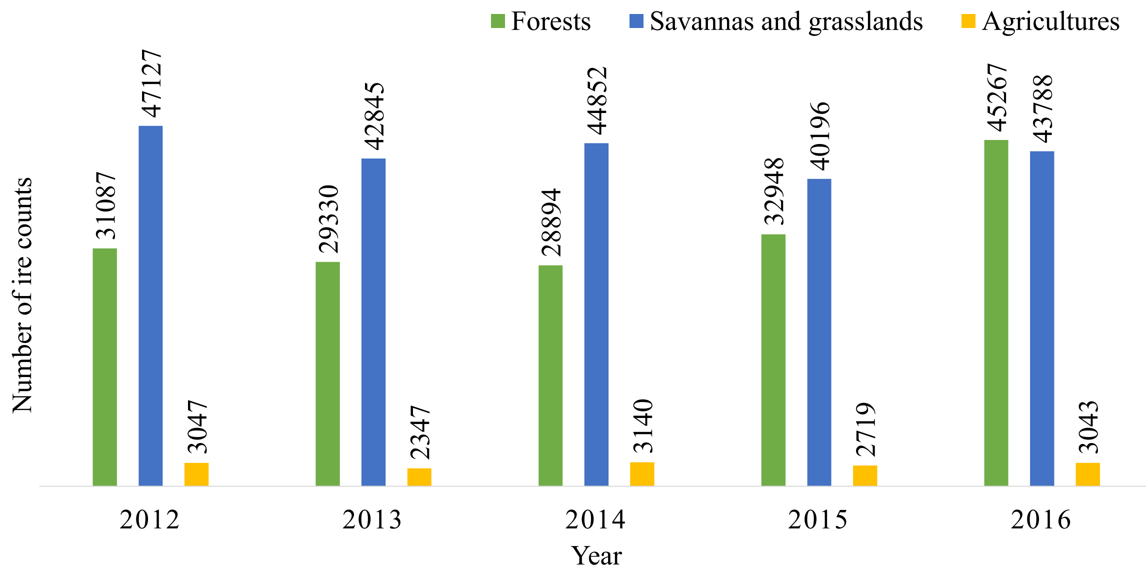

Fig. S3 Annual variations of VIIRS fire counts from the four classes of biomass in the upper-north region 2012–2016.

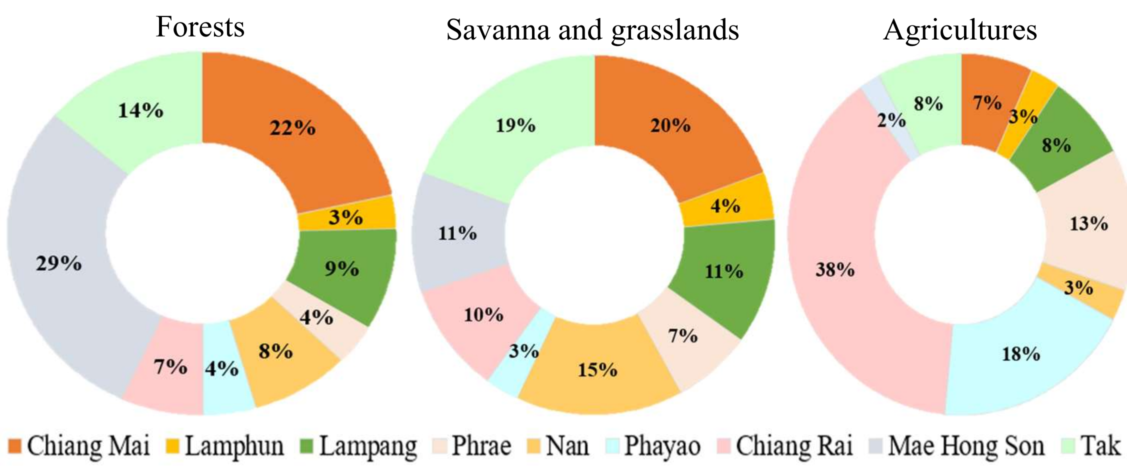

Fig. S4 Provincial allocation of fire counts categorized by land cover type: forest, savannas and grasslands, and agricultures during 2012–2016.