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Application of Geographic Information Systems and Remote Sensing for Pesticide Exposure and Health Risk Assessment in Thailand

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Abstract

In Thailand, pesticide use has increased exponentially over the past 15 years causing critical public health concern. We used a geographic information system and applied a remote sensing method in an integrated manner on land use data to model the spatial patterns of pesticide exposure. We also used toxicological data to quantify the health effects in terms of disability-adjusted life years (DALYs) attributed to pesticide use in Thailand. We found that 56%of the total population (35,144,284 persons) had potential pesticide drift at their residences. Pesticide exposure was mostly due to glyphosate and paraquat applied to rice farms and atrazine applied to sugarcane farms, which were more widespread in the central and northeastern regions of the country. The total burden caused by pesticide use equated to 10,045 DALYs, of which more than half (52%) was due to use of paraquat. Regarding policy implications, all relevant sectors should work on reducing paraquat use in crop fields. Reduction of pesticide exposure should be placed as the top priority for making health-related pesticide management policies.

Keywords: pesticide, glyphosate, paraquat, remote sensing, GIS, Thailand

Introduction

Pesticides are commonly used to protect crops from pests and to increase agricultural productivity.[1] Pesticide use in Thailand has increased significantly over the past 10-20 years and the importation of pesticides has also shown a rising trend.[2] These rising trends are of public health concern as pesticide exposure can cause both short- and long-term adverse health consequences.[3,4] Apart from the farmers or gardeners who apply pesticides, others living near agricultural fields which have been treated with pesticides are also at risk of exposure due to the 'pesticide drift' effect – the unintentional diffusion of pesticides and its negative effect on surrounding areas.

Remote sensing (RS) from satellite data is a useful tool for assessing pesticide exposure on a wide scale. A geographic information system (GIS) is also a commonly used tool that helps detect spatial dimensions of the determinants of interest through geo-referenced spatial databases. Evidence-based and transparent decision-making often requires spatial information to help stakeholders assess the issues of interest more comprehensively.[5] The examination of these variables in a GIS leads to a better understanding of how agricultural systems function and interact over space and time.

This study aims to quantify the magnitude and geographical distribution of disease burden in terms of disability-adjusted life years (DALYs) attributable to pesticide exposure through application of GIS and RS.[6]

Methods

We used a GIS and RS of land use data in an integrated manner to model the spatial patterns of pesticide exposure and applied an exposure-based approach based on toxicological data to quantify the human health effects in terms of DALYs attributed to pesticide use in Thailand during 2017. The 'Global Burden of Disease Risk Assessment Framework' was employed as a conceptual framework for this study (Figure 1). The framework highlighted two components: (i) exposure and effect size estimation, and (ii) health impact indicators assessment.[7]

Exposure and Effect Size Estimation

Exposure and effect size estimation was conducted through a GIS-based exposure model. The model describes interactions between pesticide drift distance and populations living near the crop fields. The estimation was divided into subcomponents as follows.

Pesticide-Use Data

Concerning pesticide selection, we selected the most frequently used pesticides in Thailand, namely, atrazine, glyphosate, paraquat and chlorpyrifos, based on the import quantity ranking.[8] Pesticide use data was published in the report from the Food and Agriculture Organization of the United Nations (FAO) and the World Health Organization (WHO) between 2009 and 2014.[9,10] Noting that the FAO/WHO report did not include local pesticide use, we therefore assumed that the total pesticide use was twice the amount reported by the FAO/WHO. This assumption was supported by a prior study by Lamers et al.[11]

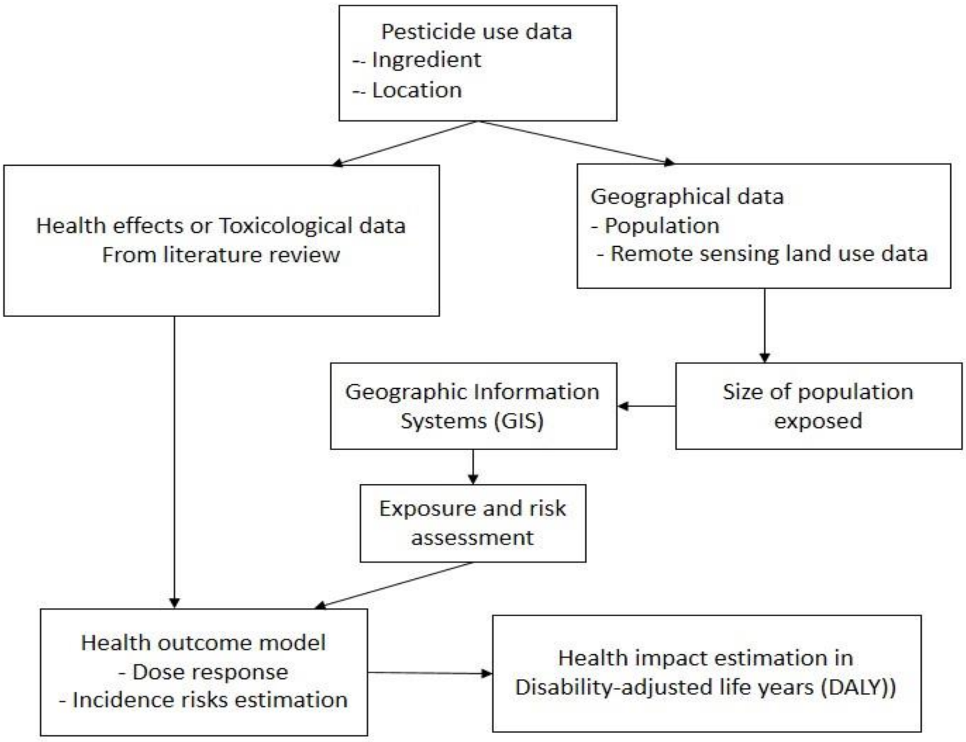


Figure 1. Conceptual framework of this study

Crops Data

We obtained the Moderate Resolution Imaging Spectroradiometer satellite crops data processed from the Geo-Informatics and Space Technology Development Agency in 2014. The analysis was limited to four types of crops: rice, cane, cassava and corn.[12] The ground data between January 2014 and December 2014, the most recent annual data available, were provided in the form of Geographical Positioning System reference data points.

Population-Weighted Pesticide Exposure Model

We modelled the population-weighted pesticide exposure in residential areas and crop fields using RS land use data and pesticide drift distance. We created a pesticide exposure map by applying the pesticide fate and the fraction loss in the environment and in crops.[13] Population data and the pesticide exposure model were combined together to estimate the population at risk of pesticide drift. The population data was obtained from the US grid population dataset, generated in 2000 by the Socioeconomic Data and Applications Center, Columbia University.[14] The population data were arranged in grids of size 30 arc-second (approximately 1 km at the equator).

We assumed no dynamic population movement around the residential areas because we had no information on farmers' activities at their place of residences or in the fields. Based on the literature review, any person living within a buffer distance of 110 meters from the centroid of a grid in which a pesticide was applied were assumed to be exposed to that pesticide (so-called, pesticide drift).[15,16] 110 meters was used to differentiate exposure from non-exposure based on previous studies by Fritz et al and Longley et al.[17,18]

Health Impact Estimation

We used risk and regulatory hazard-based toxicological effect indicators to estimate the pesticide health damage factors (HDFs) in terms of DALYs.[19] HDFs are the estimates of toxicological impacts that are attributable to the emission of pesticides into the environment over time and space.[19,20] The HDFs consisted of two factors: (i) the intake fraction: the fraction of a release taken by the population taking into account the fate of chemical exposure , and (ii) the effect factor: the incidence of chronic toxicological effect per unit intake by the population (in this study, focusing on cancers).[19] The equation for HDF is described as: HDFs = IF × β × D where IF is the intake fraction of the mass of pesticide (in kg) released into the environment of a population grid, β is the dose-response slope factor (also known as ED50 – the median effective dose) and D is the burden of disease (DALYs/incidence). More than 99.9% of pesticides applied for pest control application remained contaminated in the residence and environment outside field application, and another study reported that application of indoor-released chemical in residences produced approximately 10^{-3} to 10^{-1} of intake.[13,21] We therefore assumed that fraction of 1% of pesticide residue in population-weight pesticide exposure entered the human.

Dose-Response Slope Factor (β or ED50)

Since pesticide dose-response slope factor for human toxicity is not available in most substances (including the four pesticides selected in this study), we therefore estimated this factor based on animal-based dose-response data. We then calculated the dose-response slope factor from a chronic lifetime dose of pesticide affecting 50% of the animal population (ED50). ED50 is the chronic dose-rate which would induce cancers in 50% of the tested animals at the end of the standard lifespan.[22] The formula for estimating ED50 is as follows.

$$\beta_i(\mathrm{ED50}) = \mathrm{cfED50} \times \frac{\mathrm{NOEL}_{i,s} \times \mathrm{cfNOEL} \times \mathrm{BW} \times \mathrm{LT} \times 365\ \mathrm{days}}{\mathrm{cf}_s \times \mathrm{cf}_{\mathrm{time}}}$$

where cfED50 = 0.5 equating the human response level corresponding to ED50; NOEL = non-observed level effects (varying by species and substances), cfNOEL = 9 equating NOEL-to-ED50 extrapolation factor, BW = 70 kg/person denoting an average body weight; LT = 70 years denoting an average human lifetime; cf_s = correction factor for the interspecies difference; and $\mathrm{cf}_{\mathrm{time}}$ represents difference in exposure time.

Burden of Disease Data (D)

The burden of disease was described as DALYs/ incidence and categorized into two groups (cancerous versus non-cancerous effects). We relied on burden of disease data obtained from the International Health Policy Program, Thailand, in 2009 and reviewed the literature on selected health outcomes of both cancerous and non-cancerous effects.[23] The relevant diseases were mentioned in a study by Huijbregts et al in 2005.[24]

Model Analysis: Correlation between Estimated Pesticide Exposure and Patient Volume

We determined the association between pesticide exposure and the number of pesticide poisoning cases

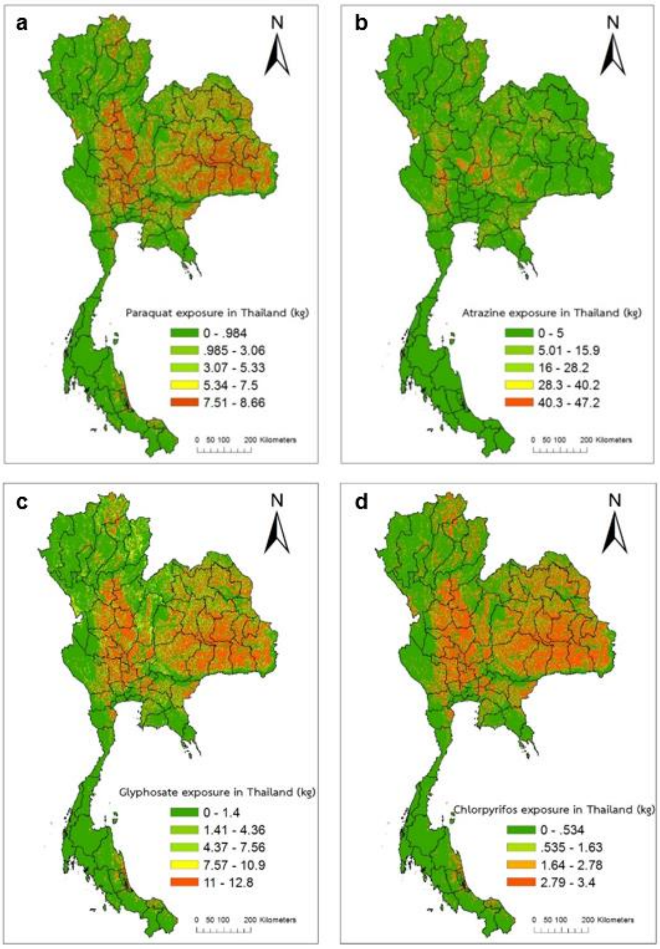


Figure 2. Exposure distribution of four selected pesticides in Thailand: paraquat (a); atrazine (b); glyphosate (c); chlorpyrifos (d)

reported in 2017, defined as any patient with an ICD-10 code of T60 (toxic effect of pesticides) using Pearson's correlation coefficient (r-value). This data was obtained from the National Health Security Office and analysis was done at the provincial level. Statistical significance was set at 0.01 and all *p*-values were two-tailed.

Results

Exposure Model

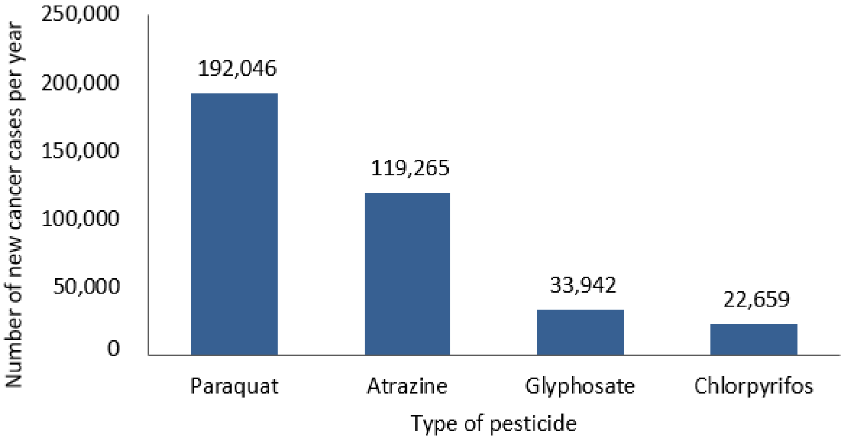
Using the population grid centers, 56.0% of the total population (n=339,448 grids) or 35,144,284 persons had crops planted within 100 meters of their place of residence. The spatial distribution of exposure to the four selected pesticides is presented in Figure 2. The spatial pattern of exposure for all four pesticides were relatively similar. Residents in the central and northeastern region had a higher level of pesticide exposure than those in other regions. The maximal exposure per population grid level for atrazine, glyphosate, paraquat and chlorpyrifos was approximately 47.2, 12.8, 8.7 and 3.4 kg, respectively.

Table 1. Crop-specific level of exposure to different pesticides in Thailand, 2014

Crop	Area (rai[†])	Exposed area (rai[†]) (%)	Population exposed (persons)	Pesticide exposure (1,000 kg)			
				Paraquat	Atrazine	Glyphosate	Chlorpyrifos
Sugarcane	10,530,927	715,382.1 (6.8)	5,159,457	260.9	1,424.4	384.9	102.6
Cassava	8,975,865	469,121.7 (5.2)	3,290,604	171.1	934.1	252.4	67.3
Corn	7,292,697	461,681.3 (6.3)	1,943,210	168.4	919.2	178.0	66.2
Rice	76,927,017	3,438,122.1 (4.5)	24,751,014	1,254.2	-	1,849.8	493.3
Total	103,726,506	5,084,307.1 (4.9)	35,144,284	1,854.8	3,277.6	2,665.1	729.4

Note: Dose response relationship for paraquat, atrazine, glyphosate and chlorpyrifos equated 0.104, 0.037, 0.013 and 0.031, respectively (unit = life-time incidence/kg intake). †1 rai = 1,600 m^2

Figure 3. Estimated yearly incidence of cancer by type of pesticide



The level of exposure for various crops based on our model is summarized in Table 1. The majority of pesticide exposure was attributable to glyphosate and paraquat applied to rice farms and atrazine applied to sugarcane farms. Among the four pesticides, atrazine contributed the greatest level of exposure (3.3 million kg) followed by glyphosate (2.7 million kg).

Health Impact Estimation

Figure 3 shows the estimated yearly number of new cancer cases, including carcinoma, sarcoma, leukemia, lymphoma and myeloma, attributed to each of the four pesticides. Paraquat was responsible for the greatest number of cases (192,046) followed by atrazine (119,265) and glyphosate (33,942).

The incidence/100,000 population exposed by province is shown in Figure 4. A similar pattern for each pesticide was apparent; the Northern and Central regions had higher cancer incidences. Paraquat and atrazine accounted for the highest incidence rates in these regions compared to the other pesticides.

DALYs lost attributable to the four pesticides are demonstrated in Table 2. The total burden of disease

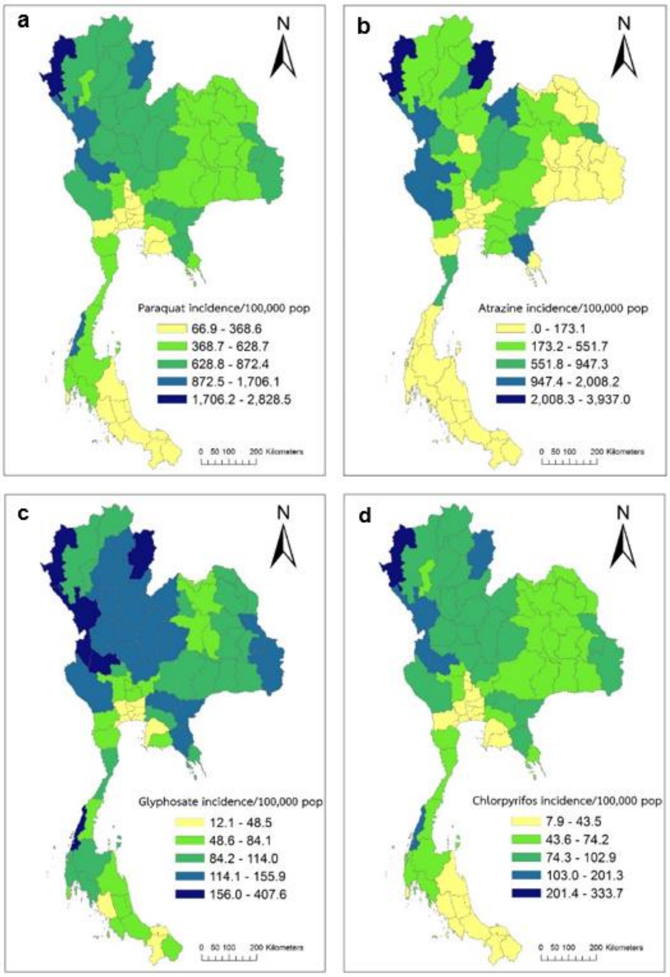


Figure 4. Incidence of relevant cancers per 100,000 population exposed by type of pesticide and province, Thailand, 2014: paraquat (a); atrazine (b); glyphosate (c); chlorpyrifos (d)

caused by all four pesticides accounted for 10,044.7 DALYs. Over half (51.6%) of the burden was due to paraquat exposure (5,185.2 DALYs).

Table 2 Estimated DALYs by type of pesticide.

Pesticide	DALYs (%)
Paraquat	5,185.2 (51.6)
Atrazine	3,220.2 (32.1)
Glyphosate	983.3 (9.8)
Chlorpyrifos	656.0 (6.5)
Total	10,044.7 (100.0)

Table 3 summarizes the correlations between pesticide exposure and pesticide toxicity. All correlations were highly significant, ranging from 0.421 to 0.691.

Discussion

This study presented the geographic health impact from exposure to four commonly used pesticides in Thailand. Results showed that about 56% of the Thai population (about 35 million people) were exposed to pesticides in 2017. About 70% of the exposed population live within 100 meters of rice farms treated with pesticides, of which glyphosate and paraquat were the main ones. Paraquat caused the greatest health impact (about 5,185 DALYs lost) among the four pesticides of interest.

The highest residual pesticide was atrazin with almost three million kilograms used, representing 38.4% of total atrazine imports in Thailand. The amount of residue depended, to a certain extent, on the amount of agricultural land used. Atrazine exposure per population grid in the US was about 2-7 times higher than in our study.[25] This difference might be due to application of pesticide aerial spraying in the US, a method which leads to a more effective distance of pesticide drift. Another study in the US, which applied RS land use data with a buffer distance of 500 meters, reported a pesticide exposure level of about 0.05 kg/rai in agricultural areas.[26] This is approximately one sixth of the estimate reported in our study (0.3 kg/rai). This difference might be explained by differences in the definition of exposed group and in data source. To improve the accuracy of estimated pesticide exposure among the exposed group, the residential mobility should be taken into account. For example, Rull & Ritz simulated a random selection of population controls and applied a zonal exposure model on pesticide use reports in California which contained more in-depth details compared to our study.[26]

For health impact estimation, we selected health outcomes that can be associated with pesticide exposure based on burden of disease data in the Thai population in 2009. Long term pesticide exposure is linked with the development of many diseases, such as Parkinson's disease, respiratory diseases and depression.[27-29] Pesticide exposure is also found to be related to cancer risks, including non-Hodgkin's lymphoma and leukaemia.[30] With respect to previous studies, the use of an average disease-specific health is a good alternative given the lack of critical-effect information.[30,31] However, Huijbregts et al reported that as pesticide can cause multiple diseases, the estimation on health impact should use the disease with the highest DALY to account for the damage factor.[30]

From a methodological point of view, our study had both strengths and limitations. The application of GIS and RS on land use data at a national level meant that our results could partly represent the situation of pesticide use nationwide. Another advantage of using RS data was that it allowed the analysis to delve into the local scale without requiring

Table 3 Pearson's correlation analysis between pesticide exposure and pesticide toxicity

Pesticide	Admission diagnosis*	Pesticide exposure (10^6 kg)	Pesticide toxicity (total number)	Pearson correlation	*P*-value
Paraquat	T60.3	1.85	1,904	0.575	<0.001
	T60all		4,159	0.516	<0.001
Atrazine	T60.3	3.28	1,904	0.691	<0.001
	T60all		4,159	0.421	<0.001
Glyphosate	T60.3	2.65	1,904	0.550	<0.001
	T60all		4,159	0.506	<0.001
Chlorpyrifos	T60.0	0.73	1,904	0.575	<0.001
	T60all		4,159	0.516	<0.001

*Note: * based on the International Statistical Classification of Diseases and Related Health Problems version 10; T60.0 = organophosphate and carbamate insecticides, T60.3 = herbicides and fungicides, T60all = all types of pesticides.*

expensive or time-consuming activities. However, there remained some limitations in this study. First, this study relied on available pesticide application fate and the FAO/WHO report on food residues.[9,10] The actual pesticide used might be much more than that reported by the FAO/WHO.[32] Second, measurement errors may have occurred in terms of the resolution of RS land use data and intake assumption. The pesticide drift distance in this study was based on a local study and a recommendation from the US Environmental Protection Agency.[9,10,15,16] The pesticide drift might spread up from 500 meters to 1 kilometer, depending on the spraying tools. Pesticide spraying data along with its residue detection at field scale are essential to improve the estimation of pesticide application in Thailand. For intake fraction, Bennett et al reported that an intake fraction to exposed population of 10^{-5} to 10^{-7} could be applied as for every kilogram of pollutant released into the environment; but for pesticides with a longer environmental lifetime, the intake fraction might be higher.[33] In addition, we used population grid data from 2000.[34] Updated data is now available that includes demographic characteristics such as age and sex. Application of this new information may improve estimation, especially in vulnerable populations such as children and the elderly. Third, we did not apply a full-scale simulation of the pesticide fate and transport from farmers' pesticide spraying along the food-chain. A related pesticide assessment in aquatic ecosystems would improve the exposure model. Finally, we did not include various neighborhood crops or horticultural areas, such as fruit orchards, rubber tree plantations, and oil palms in this analysis. Some of these crops were reported to have pesticide residue.[35-37] Accounting for these neighborhood crops will help improve the accuracy of health burden estimation in the future.

Conclusions and Recommendations

Our results can be beneficial to researchers and local stakeholders to understand the situation of pesticide exposure and its ecological risks in Thailand. We clearly demonstrated that all four pesticides used in economic crops were associated with risk of cancers in the Thai population. The greatest health gain can thus be realized by reducing pesticide exposure, especially for paraquat and atrazine. This should be the top priority in all health-related agricultural and environmental management plans. In addition, our results can help policy makers design and prioritize pesticide reduction strategies pinpointing the pattern of pesticide use in certain areas based on the GIS and RS data. The database can also help researchers conduct further epidemiological studies related to other chronic diseases such as neurological disorders and birth defects at provincial or national levels. Spatial maps of pesticide exposure and health impact could be used to alert local populations and policy planners to potential contamination of the ecological systems in their residential areas due to pesticide use.

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