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RESEARCH ARTICLE

AN AGRICULTURAL 'SYSTEMS-BASED' FRAMEWORK FOR INDEXING POTENTIAL EXPOSURE TO FARMING PESTICIDES: TEST FINDINGS FROM ASIA-PACIFIC, AND ASEAN

Ellis Wongsearaya

Three Percent Earth Foundation, 101 Moo 6, Liap Klong Prapa Road, Ban Mai, Pakkret, Nonthaburi, Thailand, 11120.
****Corresponding Author Email: info@threepercentearth.org***

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ABSTRACT

The issue of ASEAN food security has led to chemical pesticides-driven policy directives as economic convention for protecting crop yields while concomitantly conferring an implicit ecological and health risk-based 'trade-off' that works to undermine SDG target indicators 2.4, 3.9, and 6.3. In this study the Pesticides Consumer-Environmental Indexing System (PCE-ISys), a conceptual heuristic 'systems-based' framework is proposed to explore needed policy-informing option(s) beyond the largely cost-externalising rubric of chemical crop protection management, by indexing (the potential for and magnitude of potential) pesticides exposure (EIR-IS) using a semi-quantitative tiered percentile-based, continuous-to-discrete variable transform that captures the stochastic distribution arising from the 'generalisable' interconnectivity of political governance, agricultural economy, and natural environment. 1990-2016 indexing results revealed 'high' EIR-IS levels for 52% and 63% of Asia-Pacific and ASEAN nations, respectively, with 28% of Asia-Pacific countries scoring at 'highest' indexing levels demonstrating pervasive and expansive pesticides-use and/or tonnage contrary to IPM sustainable agricultural practices.

KEYWORDS

Agricultural Economy; Food Systems; Pesticides Exposure; Public Health; Southeast Asia

1. INTRODUCTION

Around the middle-to-late twentieth century rapid population growth, and increased food demand helped drive the impetus for what would become the green revolution, a set of broad technological, agricultural, and economic policy directives aimed at ending food hunger across large swaths of the developing world such as Southeast Asia (ASEAN). Producing sufficient crop output to feed millions of people (over a relatively short-term) necessitated a shift from subsistence farming to high production volume agricultural methods dependent upon intensive use of land and natural resources (Hazell 2009; Paddock, 1970; Pingali, 2012). Today, the aim of global food security is set forth in United Nations (UN) Sustainable Development Goal (SDG) 2 (United Nations Development Programme, 2021).

1.1 Agroeconomic Systems, Pesticides, and Human Health Risk

Agricultural intensification in line with green revolution policies was (and still is) characterised by the adoption of pervasive chemical pesticides-use as economic convention for protecting crop yields (EU Parliament, 2021; Fernandez-Cornejo et al., 1998; Glass and Thurston, 1978; Pingali, 2001; Pinstrup-Andersen, 2002; Popp et al., 2013; Popp and Hantos, 2011; Repetto, 1986; Sharma et al, 2019; Zhang, 2018; Zilberman et al., 1991). Worldwide, pesticides are largely managed by way of a cost-benefit derived regulatory approach defined by quantitation of risk that extrapolates 'safe' or 'acceptable' exposure levels from toxicity study data, i.e., MRLs. The outcome has been (and is) a politically tolerated (if not widely accepted) risk-based 'trade-off' with health and environment despite the ever-growing repository of information demonstrating the ecological and public health impacts associated with their use (United States International Trade Commission, 2020; Zilberman et al., 1991; Zilberman and Millock, 1997).

This compromise, however, arguably works to fundamentally undermine the purpose of SDG target indicators such as 2.4, 3.9, and 6.3. The convergence of numerous factors including, pesticides physico-chemical properties, conditions of climate, air, land, and water, as well as collective political and regulatory decision-making aimed at meeting food consumption demand and economic growth objectives all potentially influence population-based risk from high production volume chemical farming pesticides (Organisation for Economic Co-operation and Development, 2018) commonly used within (highly complex) social-environmental systems of food and agriculture (Bonmatin et al., 2015; Boxall et al., 2009; Del Prado-Lu, 2015; Fernandez-Cornejo et al., 1998; Gereslassie et al., 2019; Kennedy et al., 2019; Obilo et al., 2006; Rice et al., 2007; Skevas, 2012; United Nations Environment Programme-HELI, 2004). Figure 1 depicts a diagram of a complex 'generalisable' agroeconomic environmental system.

Development-focused policy that guide systems of agricultural economy have resulted in a strong propensity for pesticides exposure at the population-level (Aktar et al., 2009; Bonmatin et al., 2015; Economy and Environment Institute, 2017; EU Parliament, 2021; Gereslassie et al., 2019; Lam et al., 2017; Pingali, 2001). Conventional agroeconomic policy regimens rarely (if at all) take into account the health and environmental impact(s) of likely residual concentration(s) found in food commodities, as well as almost certain contamination of air, soil, and water; a shortcoming further reinforced by risk-based regulatory policy (Del Prado-Lu, 2015; Leach and Mumford, 2008; Pretty and Waibel, 2005; Aktar et al., 2009; EU Parliament, 2021; Obilo et al., 2006; Zillberman and

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Millock, 1997). An exploration of decision-support option(s) aimed at harmonising public health principles and measures with agricultural food systems policy is logical for evolving beyond a largely 'cost-externalising' governance approach.

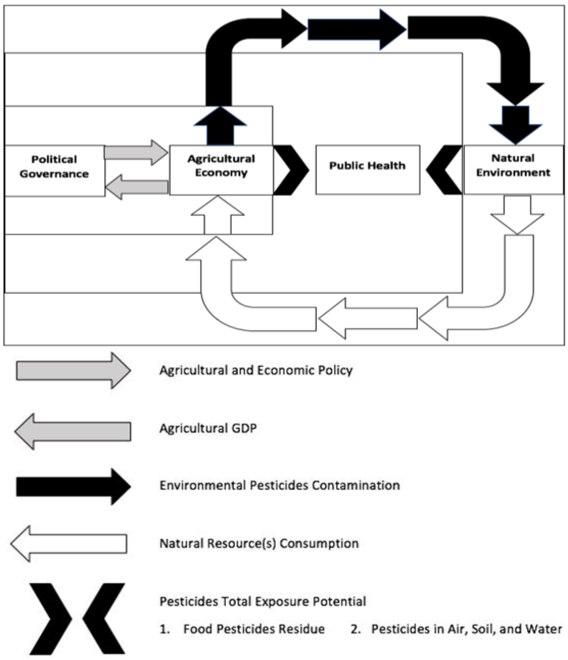


Figure 1: Diagram of a 'generalisable' agroeconomic environmental system (g-AEES)

1.2 Indexing as a Policy Decision-Support Tool

Policy decision-support is an essential informational component for helping guide governance-based decision making such as addressing the role of agriculture in achieving economic goals tied to food production, trade, and consumption (Lencucha et al., 2020; Rose et al., 2016; Udias et al., 2018). Indexing is a widely accepted, and reasonably transparent heuristic approach for evaluating relevant data in support of specific or broad policy goals across a full range of social, economic, and environmental issues, such as air quality, monetary policy, and pesticides impact(s) (Corporate Finance Institute, 2021; Gorai and Goyal, 2015; Kovach et al, 1992; Sherrick, 2017; Surminski and Williamson, 2012; World Bank, 2021). For pesticides this type of evaluation device is principally designed to comparatively score or rank chemicals, or chemical-related outcomes for purposes of risk reduction.

Pesticides scoring frameworks including the environmental impact quotient (EIQ) used in support of IPM, and the pesticides environmental risk indicator model (PERI) used in farm-level decision(s) to limit pesticides groundwater contamination are designed to index based on physico-chemical, environmental, and/or health related parameters, the former using a simple (5=high, 3=medium, 1=low) coding system corresponding to pesticides toxicity and physico-chemical reference values, and the latter relying on ecotoxicity and K_{ow} values, as well as the groundwater ubiquity score (GUS) (Benbrook and Davis, 2020; Chou et al., 2019; Kookana et al., 2005; Kovach et al., 1992; Kromann et al., 2011; Muhammetoglu et al., 2010; Reus et al., 2002; Soudani et al., 2020; Van Bol et al., 2005; Van Bol et al., 2003).

Some indexing models are strictly data-driven in methodology such as the decoupling index used to address the 'connectivity' between agricultural economy and agricultural pollution, while others such as the environmental performance index (EPI) evaluate multivariable complex 'systems,' by statistically modelling data from 32 sustainability indicators across two broad evaluation categories, 'ecological vitality,' and 'environmental health,' measured against macroeconomic indicators for 180 countries (Li et al., 2019; Wendling et al., 2020). The use of indexing methods as policy decision-support in navigating, for example, the inherently complex milieu of pesticides use within agricultural food systems offer regulators, policy makers, farmers, and civil society a transparent and pragmatic evaluation approach from which to draw practical conclusions about risk reduction guidance measures, and strategies for achieving ecological, and health-protective goals as a part of the broader social-economic framework (Choi et al., 2019; Gorai and Goyal, 2015; Kookana et al., 2005; Kovach et al., 1992; Kromann et al., 2011; Wendling et al., 2020).

In this project study a novel conceptual framework is proposed with the aim of helping inform policy-relevant decision-making and aiding to further the sustainable agricultural development dialogue relating to reliance of pesticides within global/regional food systems, and its public health implications. The Pesticides Consumer-Environmental Indexing System (PCE-ISys) is developed from a 'generalisable' agroeconomic 'systems-based' concept (g-AEES), and supported by semi-quantitative methodology that draws on a 'three-tiered' (upper 25^{th} percentile, median, and lower 25^{th} percentile) data distribution coding designation to transform continuous data variable(s) to discrete value(s) for a practical and transparent measure by which to index agricultural pesticides potential exposure defined as pesticides 'total exposure potential' (EIR-IS). Analysis of the indexing functionality of PCE-ISys is showcased from the perspective of select Asia-Pacific and ASEAN countries.

2. Methods

2.1 Rationale Supporting PCE-ISys

1.	The potential for population-level pesticides exposure, and the magnitude of potential exposure (exposure potential) to chemical farming pesticides arise from an agricultural economic system of crop cultivation, food production, trade, and consumption integrated with the broader natural environment and political domain (g-AEES); and that the potential for exposure, and exposure potential do not occur in an environmentally or economically 'isolated,' or 'compartmentalised' manner. In other words, the nature, and magnitude of pesticides total exposure potential is multi-factorial, and an integrated part of the system.
2.	There are many social and economic factors that contribute to the potential for human agricultural pesticides exposure, and exposure potential. Four key variables, however, are essential in order to conceptualise, quantify, and rate the potential for such presumed exposure. I) Use of chemicals for the express purpose of crop protection, II) A requisite goal of producing measurable crop outputs for commercial food markets, and livestock productivity, III) Quantifiably discernible land-use allocated for agricultural production, and IV) A quantifiably discernible population cohort associated with the given system of economic crop cultivation, food production, consumption, trade and natural environment.
3.	Economic, agricultural, and land-use policy decisions (characteristic of agroeconomic environmental systems) are governance variables that affect the potential for population-level pesticides exposure, and exposure potential.
4.	Population-based potential for pesticides exposure, and exposure potential occurs from collective (multi-aggregated) pathways, i.e., the summation of potential exposures from dietary intake of food products, drinking water, occupational, and non-occupational inhalation, and dermal routes.
5.	Physico-chemical properties of pesticides, and environmental variability and uncertainty are inherently associated with the nature and degree of population-based potential for exposure, and exposure potential.
6.	The main source(s) for the potential for population-based pesticides exposure, and exposure potential arise from aggregate agricultural and economic policy decisions from within a population cohort's own country where pesticides are used as inputs for agricultural production.
7.	Population-based potential for pesticides exposure, and the magnitude of potential exposure (and risk) are continuously 'shifted' vis-à-vis food commodities consumed, and traded at local, regional, national, and international levels. Thus, the 'distribution' of exposure and risk potential across populations are constantly shifted from one geographical space to another, and that the net 'influx-efflux' of total exposure potential is in a state of variable commercial and ecological 'equilibrium.' This assumption is supported by the measurable ubiquity of pesticides in food commodities, and the natural environment (on a global scale).
8.	The existence or absence of, and/or the degree of robustness in health-based regulatory policy (including, compliance and enforcement) impact(s) the extent to which the potential for pesticides exposure, and exposure potential can occur.
9.	Agricultural pesticides usage, including intensity of use, and tonnage are not the only variables that contribute to population-based exposure potential, and total exposure potential, but [usage] *is* the primary agroeconomic systems-based input necessary for human exposure to occur, and for total exposure potential to be observed and evaluated.
10.	The Precautionary Principle – Chemical farming pesticides are inherently hazardous to all biological organisms, albeit to varying degrees. Thus, the basis for the PCE-ISys model output(s), i.e., the potential for exposure, and daily magnitude of potential exposure (per person) assumes that pesticides lower total exposure potential (by population) is always more favourable compared with higher total exposure potential. Thus, the concept of 'total exposure potential' should be woven into policy strategy for reducing and/or preventing pesticides-related health and environmental impact(s) in lieu of (or in conjunction with) a risk-based approach.

Figure 2: Working Suppositions that Support the Rationale for the PCE-ISys Construct

The Pesticides Consumer-Environmental Indexing System (PCE-ISys) is a policy evaluation framework built on principles, and indicators of agricultural economy supported by semi-quantitative methods. The model is purposed to provide a data-driven screening of population-based pesticides potential exposure associated with (presumed) economic macro-policy decisions that impact key agricultural systems inputs and outcomes, i.e., pesticides-use, agricultural land-use, and crop productivity. The PCE-ISys decision-support model is based on the principal assumption that the potential for population-level exposure together with the magnitude of potential exposure, i.e., 'total exposure potential' arises from the summation use of pesticides across the broader system of crop cultivation, food production, trade, consumption, and environment.

The PCE-ISys concept works by indexing the potential for pesticides exposure, and quantifying and indexing the magnitude of potential exposure on a 'per capita' basis. The rationale for the indexing scheme is based on the idea that substantially limiting, or preventing potential exposure at the macro-level is central to reducing pesticides related impact(s), which *can* happen when consideration is given to integrating measures of public health into policy decision frameworks that promote agricultural economy in the context of sustainable development. Figure 2 shows that the PCE-ISys concept is developed from, and buttressed by a series of working suppositions that help form the basis for the index construct.

The ten working suppositions help illuminate how a 'generalisable' system of agricultural economy manifests the reality of pesticides usage, total exposure potential, and its likely public health implications.

2.2 Index Scoring Methodology

PCE-ISys is defined by the capacity to index the total exposure potential of chemical pesticides arising from industrialised systems of agricultural economy (g-AEES), the key inputs of which include, total estimated land-use for agricultural production, total estimated output from crop seeding and cultivation, and average total annual pesticides-use all in relation to the total population cohort for a given country. This makes PCE-ISys an evaluation scheme built on 'macro-level' agricultural indicators, the purpose and scope of which serves as a decision-support tool focusing on total exposure potential in the context of **collective** governance and farm-level decisions that may include policy directives such as implementation of GAP or IPM strategies, targeted crop, or pesticides subsidisation, or agricultural tax policy that incentivises, or limits specific farming methods and/or practices.

2.2.1 Methods-Driven Requirements for PCE-ISys Indexing

Indicators that help explain complex systems (such as g-AEES) are inherently fraught with variability, uncertainty, and randomness arising from a host of factors ranging from environmental condition(s) to policy decision-making processes; in turn, leading to challenges in how health and environmental outcomes stemming from those system(s) may be interpreted. The PCE-ISys model construct is both data-driven and stochastic, so interpretative applicability of its indexing results rely on three key elements,

- First, evaluation dataset(s) of adequate sample size. Cochran's Formula for estimating sample size (modified for 'smaller' populations) at 95% confidence is used to determine the minimum required sample size of nations for the project study (Bartlett II, et al., 2001; Pourhoseingholi et al., 2013).

$$n_0 = Z^2pq/e^2 \rightarrow n = \frac{n_0}{1+(n_0-1)/N}$$

  with 'p' (the proportion of the population with the defining attribute) characterised by crop production (by country), where p = 0.91892, Z = 1.96, e = .05, and N = 224, q = 1 - p
- Second is data transformation of g-AEES indicator(s) from continuous to discrete variable for indexing purposes to allow for direct 'country-to-country' observational comparability on a relative basis.
- Third, a linear correlation assumption to allow for valid statistical inference in supporting the model indicator variable(s) within the PCE-ISys design construct, i.e., g-AEES, with the model's response output variable, i.e., EIR-IS. Figure 3. shows an (approximately 'normal-distribution shaped') histogram of pesticides total exposure potential scores for all country observations from 1990 - 2016.

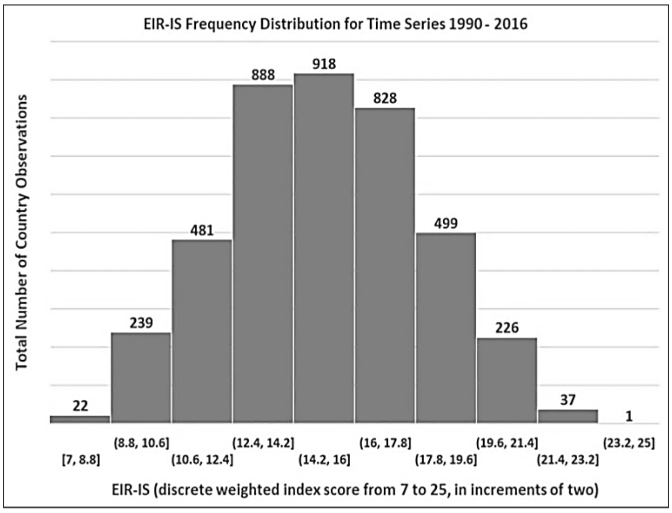


Figure 3: Frequency Distribution of Pesticides Total Exposure Potential (EIR-IS), by Country Observation for Time Series 1990-2016

Key Parameters	Percentile Category (%)	Coded Points	Comments
Total Annual Pesticides Use Rate (PUR) (by country); Agricultural pesticides-use is directly related to the potential for human exposure	Upper 25th	5	A higher pesticide use rate is associated with a higher point score within the context of g-AEES
	Middle 50th	3	
	Lower 25th	1	
Annual Crop Production Index (CPIDX) (by country); Total annual pesticides-use rate is a fixed average measure; therefore, crop productivity is inversely related to potential pesticides exposure	Upper 25th	1	The higher the crop output the lower the pesticide use distribution per unit crop, and thus the lower the score.
	Middle 50th	3	
	Lower 25th	5	
Annual Estimated Agricultural Land Area (AGL) (by country); The product of pesticides use intensity and total estimated area of land used for agricultural function serves as a direct indicator for pesticides tonnage	Upper 25th	5	Land-use is a key factor in estimating pesticides tonnage. The more land area used for agriculture the higher the score.
	Middle 50th	3	
	Lower 25th	1	
Total Annual Estimated Population (AEP) (by country); Population size affects the overall potential exposure implications associated with pesticides-use within a given a country	Upper 25th	1	Exposure potential is 'diluted' with increasing population relative to total average pesticides tonnage.
	Middle 50th	3	
	Lower 25th	5	

Figure 4: PCE-ISys Three-tiered Percentile-based Coded Point Scheme

PCE-ISys (population-based) pesticides total exposure potential is expressed as an aggregated relative measure (by country) called the Exposure Indicator Ratio-weighted Index Score, or 'EIR-IS' representing the potential for exposure, 'weighted' by the average daily magnitude of potential exposure (called 'exposure potential') on a per capita basis,

$$\text{EIR-IS (by country)} = \text{PCE-IS (by country)} + \text{EIR}_{score} \text{ (by country)} \quad (1)$$

EIR-IS is derived from the sum of two relative indexing measures,

- The Pesticides Consumer-Environmental Index Score (PCE-IS), and

- The Exposure Indicator Ratio Score (EIR_{score})

Both metrics are discrete numeric values that correspond to continuous indicator variables. Where the variable(s) fall within one of three percentile categories (Upper 25th, Middle 50th, and Lower 25th) across the distribution of continuous variables for a given evaluation dataset determines the index/indicator score (Han et al., 2012; Toppr, 2020).

- Upper percentile = $(3(n+1)/4)^{th}$ term
- Median percentile = $((n+1)/2)^{th}$ term
- Lower percentile = $((n+1)/4)^{th}$ term

As shown in Figure 4 each percentile category is assigned a designated value, 1-,3-, or 5. '3' is the value 'coded' to continuous indicator variables that fall within the middle 50th percentile of the distribution range. An assigned point score of '1' or '5' corresponds to either the upper or lower 25th percentile, depending on how the respective indicator variable is assumed to behave within g-AEES.

PCE-IS represents the potential for pesticides exposure (by country) for one calendar year. The index score is expressed as,

$$\text{PCE-IS} = \text{PUR (\%ile)} + \text{CPIDX (\%ile)} + \text{AGL (\%ile)} + \text{AEP (\%ile)} \quad (2)$$

and has a score range from 4 to 20 in incremental units of two. The higher the PCE index score the greater the potential for pesticides exposure.

The EIR_{score} represents a discrete relative value for pesticides 'exposure potential.' The score is a numeric 'weighting' factor (when combined) with PCE-IS produces a total exposure potential score (EIR-IS), with an index scale of 5 to 25 (by country). Similar to the PCE-IS scoring methodology, EIR_{score} is scored based on where the Pesticides Exposure Indicator Ratio ($Pi_{exp}R$) variable falls within the data distribution range of all $Pi_{exp}R$ values for the given evaluation dataset (by year), seen in Figure 5.

Key Parameters	Percentile Category (%)	EIR Coded Points	Comments
$Pi_{exp}R$ (by country); a relative measure of daily pesticides exposure potential per capita	Upper 25th	5	EIR_{score} is the numeric relative measure of $Pi_{exp}R$ that is used to 'weight' PCE-IS
	Middle 50th	3	
	Lower 25th	1	

Figure 5: PCE-ISys Percentile-based Coded Point Scheme for PiexpR

The higher the $Pi_{exp}R$ value across the distribution range, the higher the (percentile category based) EIR_{score}. $Pi_{exp}R$ is a unitless continuous variable that represents the relative average measure of daily pesticides exposure potential that is equal to, exceeds, or is below the Pesticides Reference Indicator Ratio ($Pi_{ref}R = Pi_{ref}UC / Pi_{ref}UC$); and is expressed as follows:

$$Pi_{exp}R = Pi_{exp}UC / Pi_{ref}UC \quad (3)$$

where $Pi_{exp}UC$ (the unit-converted Pesticides Exposure Indicator) is a function of the product of the unit-converted pesticides-to-crop productivity ratio (PCPr) and farmland area per capita (FLAC)

$$Pi_{exp} = PCPr \times FLAC\ (kg_{pesticides}\ person^{-1}\ year^{-1})$$

$$\downarrow$$

$$\frac{PCPr_{country}\ (kg_{pesticides} / ha) \times FLAC_{country}\ (ha/person)}{\text{Annual (1-year) [unit conversion]}} = Pi_{exp}$$

$$\downarrow$$

$$(kg_{pesticides}/\text{person-year})\ (1\text{-year}/365\text{ days})\ (1{*}10^{6}\text{ mg} / 1\ kg_{pesticides})$$

$$\downarrow$$

$$\text{Pesticides Exposure Indicator } (mg_{pesticides}\ person^{-1}\ day^{-1}) = Pi_{exp}UC \quad (4)$$

where,

$$\underset{\text{Pesticides-to-Crop Productivity Ratio (PCPr)}}{\frac{\text{Total (Annual) Pesticides Use Rate (kg/ha)}}{\text{Annual Crop Production Index}}} \times \underset{\text{Farmland Area per capita (FLAC)}}{\frac{\text{Total (Annual) Agricultural Land Area (ha)}}{\text{Annual Estimated Country Population (per.)}}}$$

Next, the Pesticides Reference Indicator ($Pi_{ref}UC$) denotes a benchmark level representing the 95% upper bound limit of the mean (unit-converted) Pesticides Exposure Indicator value(s) for all countries (within a given evaluation dataset) that have annual total average pesticides use rate(s) less than or equal to 0.5 kg/ha.

$$Pi_{ref}UC = 95\%\ UCL\ of\ \mu_{Piexp}UC\ (\text{pesticides use rate} \leq 0.5\text{ kg/ha, 'low'}) \quad (5)$$

where,

$$\mu_{Piexp}UC = \frac{\sum Pi_{exp}UC\ (\text{pesticides use rate} \leq 0.5\text{ kg/ha})}{\sum \text{countries (pesticides use rate} \leq 0.5\text{ kg/ha})}$$

Pesticides use rate level(s) such as 0.5 kg/ha were adopted as a modification of the Wachter & Staring guideline protocol for active ingredient use rate(s) (World Health Organization, 1990), and correspond to the economic status, and regulatory sophistication of the given country. Annual use rates of 0.5 kg/ha to 0.1 kg/ha are graded as 'low' while <0.1 kg/ha, and ≥ 1 kg/ha annual pesticides active ingredient use rate are graded as 'very low,' and 'high,' respectively. $Pi_{ref}UC$ reflects the minimum threshold of average daily pesticides exposure potential that is rated as a 'Lower Appreciable' public health concern.

2.2.2 PCE-ISys Public Health Rating Scheme

The PCE-ISys evaluation model is not a tool designed to reflect estimation(s) of risk or impact(s) associated with the use of crop protection chemicals. Instead, [it] is a data-driven construct that produces a relative measure of pesticides-related potential exposure that corresponds to a generic qualitative rating (supported by Working Supposition 10) termed 'public health concern.' The basis for the indexing system's public health-related rating scheme is centred on three basic precepts,

- That chemical pesticides are engineered to produce target organism mortality, but also manifest varying degrees of 'collateral' toxicity to other biological species, including humans.
- That pesticides-related health impact(s) and risk are function(s) of pesticides exposure.
- That pesticides risk reduction through 'integrated' policy and planning measure(s), over the long-term, are best accomplished, and more cost-effective through prevention efforts than through (largely cost externalising) 'command and control' impact mitigation.

PCE-ISys public health rating categories correspond to pesticides total exposure potential as a function of EIR-IS or PCE-IS percentile-based scoring distribution(s). Figure 6. illustrates that the public health classification measure for the indexing system is a qualitative expression termed 'Appreciable' public health concern.

The scoring classifications across each data distribution range are ordered according to percentile range: Upper 25th%ile = Highest Appreciable, Median = Appreciable, and Lower 25th%ile = Lower Appreciable. Based on the index score distribution(s) for each of the 27 evaluation datasets, the year-to-year threshold levels for each respective percentile range for this project study was as follows (index score distributions were tabulated from data available at www.threepercentearth.org/reports-analysis/),

- EIR-IS ≥ 17 (Upper 25th), EIR-IS = 15 (Middle 50th), EIR-IS ≤ 13 (Lower 25th)
- PCE-IS ≥ 14 (Upper 25th), PCE-IS = 12 (Middle 50th), PCE-IS ≤ 10 (Lower 25th)

Response Output	Percentile Category (%)	Total Exposure Potential Rating or Exposure Potential Rating	Public Health Rating	Comments
EIR-IS or PCE-IS (by country)	Upper 25th	Highest	Highest Appreciable Public Health Concern	EIR-IS or PCE-IS (by country) are categorised into three-tiered percentiles based on the stochastic distribution for each respective evaluation dataset
	Middle 50th	Medium to High	Appreciable Public Health Concern	
	Lower 25th	Lower	Lower Appreciable Public Health Concern	

Figure 6: Public Health Rating Classification Scheme

2.3 Data Methodology

2.3.1 Data Sources

Data that reflect the model input variables for the PCE-ISys model construct are available as open access from FAO and World Bank websites. Pesticides use data was accessed from the FAO website, http://www.fao.org/faostat/en/?#data/RP, and separately downloaded in bulk as Excel files categorised by world regions Africa, Americas, Asia, Europe, and Oceania. Data for the rest of the model input variables were accessed at the following World Bank websites by doing total bulk data downloads as '.csv' files then saved as Excel '.xlsx' files, 1) for Crop Production Index, https://data.worldbank.org/indicator/AG.PRD.CROP.XD, 2) for annual total population estimates by country, https://data.worldbank.org/indicator/SP.POP.TOTL, 3) for annual total land area by country, https://data.worldbank.org/indicator/AG.LND.TOTL.K2, and 4) for annual percent land area for agriculture, https://data.worldbank.org/indicator/AG.LND.AGRI.ZS. Data from the World Bank site representing the model input variables were extracted from the original downloaded spreadsheets and collated into columns in new worksheets that included data from 268 countries, world regions, and other world development classification categories.

2.3.2 Organising the Data, and Data Testing the Model

Data collected from World Bank and FAO websites were organised and managed using Microsoft Office Excel version 16.43 with data analysis functionality. The PCE-ISys working model was developed using Excel because of the transparency, and ease of use of the application's mathematical functions to generate the indicator, and index outputs by country, and by year. A 'source' dataset worksheet was used to consolidate, and organise all raw, and processed data for the project. The basic steps for the worksheet data consolidation and organising process were as follows, 1) all g-AEES (indicator variable) data were entered into the source worksheet. This included all 268 countries, world regions, and other world development classification categories, 2) all categories (except for individual countries) were culled from the source worksheet; use of Cochran's Formula at 95% confidence (section 2.2.1) estimated the minimum required sample size (n) per evaluation dataset for the project study to be (at least) 76 countries, 3) the remaining individual countries were further screened to include only those with average annual pesticides-use rate data ($157 \geq n \geq 133$).

Consumption rate data (by country) were available from years 1990 – 2016 (the evaluation time-series for the project study). 2016 was the terminal year of the time series because (at the time of data collection) there was no crop production index data beyond that time frame. 4) g-AEES indicator variable, total land area was unit-converted from square kilometres to hectares in order to comport with the unit expression used in the PCE-ISys model, then total agricultural land area (by year) was determined by calculating total land area (by country) as a percent of land area allocated for agriculture (by country), 5) eight additional columns were added to the source worksheet dataset.

The four initial data columns included the land area unit conversion, then calculation of total agricultural land, and PCPr and FLAC output calculations, respectively. 6) The final four additional columns included calculation and unit conversion of Pi_{exp} (kg/person-year) to $Pi_{exp}UC$ (mg/person-day), inclusion of $Pi_{ref}UC$ values, calculation of $Pi_{exp}R$ ($Pi_{exp}UC/Pi_{ref}UC$), and then scale-adjusted by a factor of 10 (Adjusted-$Pi_{exp}R = Pi_{exp}UC/Pi_{ref}UC \times 10$). Eighteen auxiliary columns were added to the source worksheet, three columns for each g-AEES indicator variable and EIR_{score} percentile range i.e., Excel '= percentile' function for upper 25th ('75th'), 50th, and lower 25th; and the last three auxiliary columns for index scoring PCE-IS, totalling EIR_{score}, and index scoring EIR-IS. All indicator variable data (by country) for twenty-seven evaluation datasets in the project study were indexed to generate PCE-IS and EIR-IS for all country observations for the time series.

2.4 PCE-ISys Model – Correlation and Variance

2.4.1 Multivariate Test for EIR-IS and g-AEES

A regression analysis was conducted to determine the strength of association between the PCE-ISys weighted index score (output/response variable), and its respective g-AEES (input) variables. First, test(s) of collinearity demonstrated no discernible correlation among indicator (input) variables. Second, it should be noted that neither indexing output trend nor model predictiveness was the focus of the regression exercise. In addition, examining the effect(s) of PCE-ISys database outliers among the 27 non-independent evaluation datasets (and its effect on model output distribution(s)), or use of nested model(s) were considered, but decided against for this particular study.

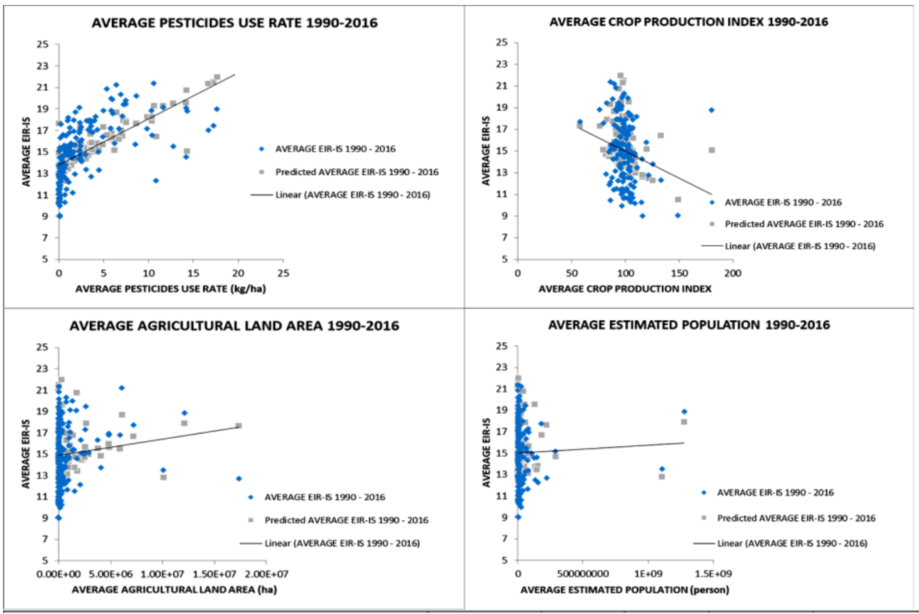


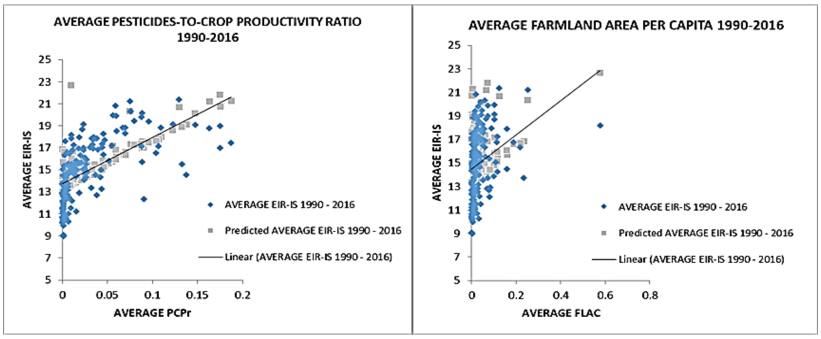
Figure 7: Average EIR-IS as a Function of g-AEES Linear Correlation and Variance

Purposed as a 'screening-level' information dissemination tool the aim, instead, was to offer a basic underpinning of whether a linear relationship exists between pesticides total exposure potential and its model input variables in the context of g-AEES (not by country), but on a global and generalisable scale. A standard multivariate analysis was employed using g-AEES input variable(s), and their respective index output(s), i.e., EIR-IS averaged for all data points within each annual evaluation dataset of the time series (by country). Figure 7. shows the EIR-IS linear response output in relation to the four key indicator variables that define the g-AEES-based model.

The g-AEES regression model shown in Figure 7 demonstrated a moderately strong association between average EIR-IS and average pesticides consumption rate, Crop Production Index, agricultural land area, and estimated country population, with r=0.657789, and directional correlation for three of 4 input variables consistent with their assumed behaviour within g-AEES ('population' variable was equivocal). Multivariate R^2 indicated that the model explains between 42% to over 43% of the variance in average pesticides total exposure potential (F-Test Significance = 6.62×10^{-18}).

2.4.2 Multivariate Test for EIR-IS and Exposure Potential

A second regression test was conducted to examine the strength of association between average EIR-IS, and indicator variables used to derive $Pi_{exp}UC$. There was, again, no demonstrated collinearity. Figure 8. shows the EIR-IS linear response output in relation to the two indicator variables used to determine exposure potential, i.e., PCPr and FLAC.



Regression Statistics						
Multiple R	0.699048231					
R Square	0.488668429					
Adjusted R Square	0.482027759					
Standard Error	2.014405792					
Observations	157					
ANOVA	*df*	*SS*	*MS*	*F*	*Significance F*	
Regression	2	597.2089636	298.604482	73.58722044	3.71621E-23	
Residual	154	624.9059269	4.05783069			
Total	156	1222.11489				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	13.1252266	0.225959198	58.086711	1.2468E-106	12.6788469	13.5716063
AVERAGE PESTICIDES-TO-PRODUCTIVITY RATIO (PCPr) 1990-2016	43.18405472	4.012266068	10.7630087	1.7025E-20	35.25787101	51.11023842
AVERAGE FARMLAND AREA PER CAPITA (FLAC) 1990-2016	15.85812391	2.599081995	6.10143272	8.16007E-09	10.72366847	20.99257936

Figure 8: Average EIR-IS as a function of $Pi_{exp}UC$ Linear Correlation and Variance

The multivariate 'exposure potential' ($Pi_{exp}UC$) model also demonstrated a moderately strong positive directional correlation between average pesticides total exposure potential and average daily magnitude of potential exposure (per person) with r=0.699048. Variance in EIR-IS as a function of 'exposure potential' was R^2=0.49 (F-Test Significance = 3.72×10^{-23}) indicating that nearly half the variation in EIR-IS output(s) are explained by pesticides use per unit of crop productivity and agricultural land area per capita (a surrogate indicator of pesticides tonnage). All indicator variables for both models were statistically significant, except for 'Average Estimated (Country) Population,' which was marginally non-statistically significant (p-value = 0.078810616); though this occurrence was not altogether unexpected given the likely complexity of human population dynamics in relation to agricultural food systems.

The fact, however, that FLAC was both strongly statistically significant and linearly correlated to EIR-IS helps support the argument that country population (in relationship with agricultural land-use) is indeed a relevant variable (in the context of pesticides tonnage) for interpreting pesticides total exposure potential, but poses a challenge in defining its contributing influence on EIR-IS from the perspective of g-AEES, indicating that a more in-depth computational modelling exercise is likely necessary to parse out the effect of 'population' within this system.

The machinations of politics, governance, and economic activity that characterise complex 'social-environmental' systems, create inherent degrees of uncertainty, and variability in models that attempt to interpret such systems. Thus, Pearson correlation levels tangibly above 0.5 for both regression tests arguably help inspire a reasonable degree of confidence for the plausibility of PCE-ISys as a workable policy decision-support concept (Samuel and Okey, 2015). Similarly, R^2 values for both regression models indicating that the index construct explains over 40% to nearly 50% of any change in the EIR-IS response variable output is an encouraging prospect for the usefulness of PCE-ISys. Why? 1) The degree of model variance indicated in both g-AEES and $Pi_{exp}UC$ models allude to PCE-ISys agroeconomic predictor variables as basic factors associated with the modern agricultural food system, and that 2) by relying on a highly parsimonious model that precludes other potentially knotty (social, cultural, political, regulatory, and environmental) variables (that, although may 'capture' the remaining difference in model variance) minimises the risk of diminishing the transparency, and confounding the general interpretative capacity of the index output(s) that would arguably undermine its main functional purpose and advantage as a broad-based information dissemination tool.

3. RESULTS AND DISCUSSION

3.1 Pesticides Total Exposure Potential

3.1.1 Ranking Profiles

The primary analytical feature of PCE-ISys is the capacity to (semi-quantitatively) index the potential for exposure to pesticides, 'weighted' by the magnitude of potential exposure (per capita). One particular application derived from this indexing construct is the ability to generate a multi-output 'profile' that includes, EIR-IS, PCE-IS, and $Pi_{exp}R$ used in producing a numeric ranking structure for either a single evaluation dataset or averaged over a given time series. Due to the high number of total individual indexing outputs and their associated g-AEES parameter values (~50000), all parameter-specific data and data-driven outputs (excluding PCPr, FLAC, Pi_{exp} and $Pi_{exp}UC$ categories) for individual country observations per evaluation dataset have been made available as open access at www.threepercentearth.org/reports-analysis/. A time series-averaged EIR-IS ranking chart for 157 countries displayed in Table 1. (Next page) produced interesting results in terms of pesticides total exposure potential (by country) over the 27-year time frame. Each country in the average ranking chart was colour-coded according to world region.

WORLD REGIONS
AFRICA
THE AMERICAS
ASIA-PACIFIC
EUROPE
MIDDLE EAST & CENTRAL/WESTERN ASIA

Percentile-based index score threshold levels were as follows:

- Average EIR-IS = highest average total exposure potential (Highest Appreciable public health concern) ≥ 17.07407,
- 17.07407 > Average EIR-IS = medium-to-high total exposure potential (Appreciable public health concern) > 12.85185, and
- Average EIR-IS = Lower average total exposure potential (Lower Appreciable public health concern) ≤ 12.85185.

Table 1: Time Series-Averaged Exposure Indicator Ratio-Weighted Index Score and Rank (1990 – 2016)

COUNTRY	AVERAGE EIR-IS	WORLD RANK	COUNTRY	AVERAGE EIR-IS	WORLD RANK	COUNTRY	AVERAGE EIR-IS	WORLD RANK	COUNTRY	AVERAGE EIR-IS	WORLD RANK
Belize	21.37037037	1	Malta	17	42	Gambia, The	14.92592593	81	Bhutan	12.85185185	117
Malaysia	21.22222222	2	Nicaragua	17	42	Bulgaria	14.77777778	82	Timor-Leste	12.85185185	117
Slovenia	20.84	3	El Salvador	16.92592593	44	Qatar	14.77777778	82	Kenya	12.77777778	119
Guatemala	20.33333333	4	Philippines	16.92592593	44	Zimbabwe	14.77777778	82	Estonia	12.76	120
Cyprus	20.18518519	5	Paraguay	16.85185185	46	Peru	14.7037037	85	INDONESIA	12.7037037	121
Ecuador	19.96296296	6	CANADA	16.77777778	47	Venezuela, RB	14.7037037	85	Ireland	12.7037037	121
Portugal	19.88888889	7	Spain	16.77777778	47	Albania	14.62962963	87	Myanmar	12.55555556	123
West Bank and Gaza	19.7826087	8	North Macedonia	16.6	49	Algeria	14.62962963	87	Togo	12.55555556	123
ITALY	19.44444444	9	Netherlands	16.55555556	50	Bahrain	14.62962963	87	Kazakhstan	12.52	125
Maldives	19.41666667	10	Sri Lanka	16.48148148	51	RUSSIAN FEDERATION	14.6	90	Bangladesh	12.48148148	126
Greece	19.14814815	11	Uruguay	16.40740741	52	Ukraine	14.6	90	Hong Kong SAR, China	12.33333333	127
Israel	19.14814815	11	Thailand	16.33333333	53	JAPAN	14.55555556	92	Pakistan	12.25925926	128
Colombia	19.07407407	13	Tunisia	16.33333333	53	St. Kitts and Nevis	14.55555556	92	Madagascar	12.18518519	129
Costa Rica	19	14	Oman	16.11111111	55	Guinea-Bissau	14.48148148	94	Poland	12.18518519	129
Chile	18.85185185	15	Luxembourg	15.94117647	56	Czech Republic	14.47826087	95	Uganda	12.11111111	131
CHINA	18.85185185	15	Morocco	15.81481481	57	Slovak Republic	14.41666667	96	Malawi	11.88888889	132
Turkmenistan	18.84	17	Suriname	15.81481481	57	Egypt, Arab Rep.	14.33333333	97	Namibia	11.88888889	132
St. Lucia	18.77777778	18	Belgium	15.70588235	59	Kuwait	14.33333333	97	Ethiopia	11.66666667	134
Fiji	18.7037037	19	Hungary	15.66666667	60	Armenia	14.28	99	Angola	11.51851852	135
Lebanon	18.55555556	20	AUSTRALIA	15.59259259	61	Tonga	14.25925926	100	Burkina Faso	11.51851852	135
Seychelles	18.33333333	21	Guyana	15.59259259	61	Antigua and Barbuda	14.11111111	101	Norway	11.51851852	135
Georgia	18.28	22	Austria	15.51851852	63	Rwanda	13.96296296	102	Tanzania	11.51851852	135
Vanuatu	18.18518519	23	Brunei Darussalam	15.51851852	63	Papua New Guinea	13.88888889	103	Cabo Verde	11.44444444	139
ARGENTINA	17.96296296	24	Libya	15.51851852	63	Lithuania	13.8	104	Congo, Rep.	11.44444444	139
French Polynesia	17.96296296	24	SOUTH KOREA, REP.	15.51851852	63	Cote d'Ivoire	13.74074074	105	Denmark	11.22222222	141
Dominican Republic	17.88888889	26	Belarus	15.48	67	Guinea	13.74074074	105	Mozambique	11.22222222	141
Honduras	17.88888889	26	Iran, Islamic Rep.	15.44444444	68	Yemen, Rep.	13.74074074	105	Lao PDR	11.07407407	143
Panama	17.88888889	26	Romania	15.44444444	68	Burundi	13.51851852	108	Finland	11	144
Samoa	17.88888889	26	Cameroon	15.37037037	70	INDIA	13.51851852	108	Senegal	10.92592593	145
BRAZIL	17.74074074	30	Kyrgyz Republic	15.16	71	Latvia	13.48	110	Central African Republic	10.7037037	146
Montenegro	17.72727273	31	SAUDI ARABIA	15.14814815	72	GERMANY	13.37037037	111	Lesotho	10.7037037	146
Syrian Arab Republic	17.59259259	32	TURKEY	15.14814815	72	UNITED KINGDOM	13.2962963	112	Botswana	10.62962963	148
Barbados	17.46153846	33	UNITED STATES	15.14814815	72	Azerbaijan	13.16	113	Iraq	10.62962963	148
Jordan	17.37037037	34	Croatia	15.08	75	Zambia	13.14814815	114	Eritrea	10.47368421	150
Vietnam	17.2962963	35	Ghana	15.07407407	76	Comoros	12.92592593	115	Chad	10.33333333	151
Moldova	17.24	36	New Caledonia	15.07407407	76	SOUTH AFRICA	12.92592593	115	Sweden	10.33333333	151
New Zealand	17.22222222	37	Bolivia	15	78				Haiti	10.25925926	153
Trinidad and Tobago	17.16	38	MEXICO	15	78				Niger	10.18518519	154
Mauritius	17.14814815	39	Switzerland	15	78				Nepal	9.962962963	155
FRANCE	17.07407407	40							Mongolia	9.074074074	156
Jamaica	17.07407407	40							Mauritania	9	157

Also, for the project study in this instance, the 'medium-to-high' index distribution range was further subdivided:

- 'high' (17.07407 > Average EIR-IS (Higher Appreciable public health concern) ≥ 15), and
- 'medium-to-lower medium' (15 > Average EIR-IS (Medium Appreciable public health concern > 12.85185).

One noticeable observation gleaned from the time-averaged evaluation appears to reveal a broad, underlying consistency between average annualised pesticides-use per area of cropland, and pesticides total exposure potential, i.e., regions of the world where use rates are deemed consistently high, or low such as in the Americas and Africa (FAOSTAT, 2021), respectively saw overall correspondingly 'highest,' and 'lower' EIR-IS outputs for these same areas. This analysis outcome also draws support from the g-AEES linear correlation and variance results.

Of nations with the highest average pesticides total exposure potential for the time series 38%, and 23% were from the Americas, and Asia-Pacific region, respectively, while 63% of nineteen G7/G20 nations evaluated in the project study demonstrated either 'high' or highest total exposure potential. On first pass, a country-by-country global perspective appears to suggest that the size of a country's economy may be a feasibly reliable indicator for pesticides total exposure potential. However, a closer look at the time series-averaged EIR-IS appears to indicate that developing nations with known 'transitioning' economies may be consistently more vulnerable to higher pesticides total exposure potential. Examples of such places include, Belize, Malaysia, Ecuador, Colombia, Costa Rica, and Fiji, countries that (generally speaking) place a relatively high premium on economic growth and development, while in some cases discounting principles and applications of sustainability (Wendling et al., 2020).

A wide-ranging, prospective policy analysis of the potential factors that may affect EIR-IS, such as human development status, agricultural GDP, degree of regulatory sophistication, or measures of socio-cultural attitudes toward pesticides may be useful in providing greater insight into possible solution(s) for reducing and/or preventing pesticides-related impact(s) arising from politically driven, agroeconomic systems.

3.1.2 Asia-Pacific Region and ASEAN

The PCE-ISys evaluation study included twenty-nine countries located throughout East Asia, South Asia, ASEAN, and Oceania, under the broad heading of 'Asia-Pacific.' Figure 9. illustrates a vertical EIR-IS index chart showing pesticides total exposure potential across the Asia-Pacific region from 1990 – 2016 (by country, region, and worldwide).

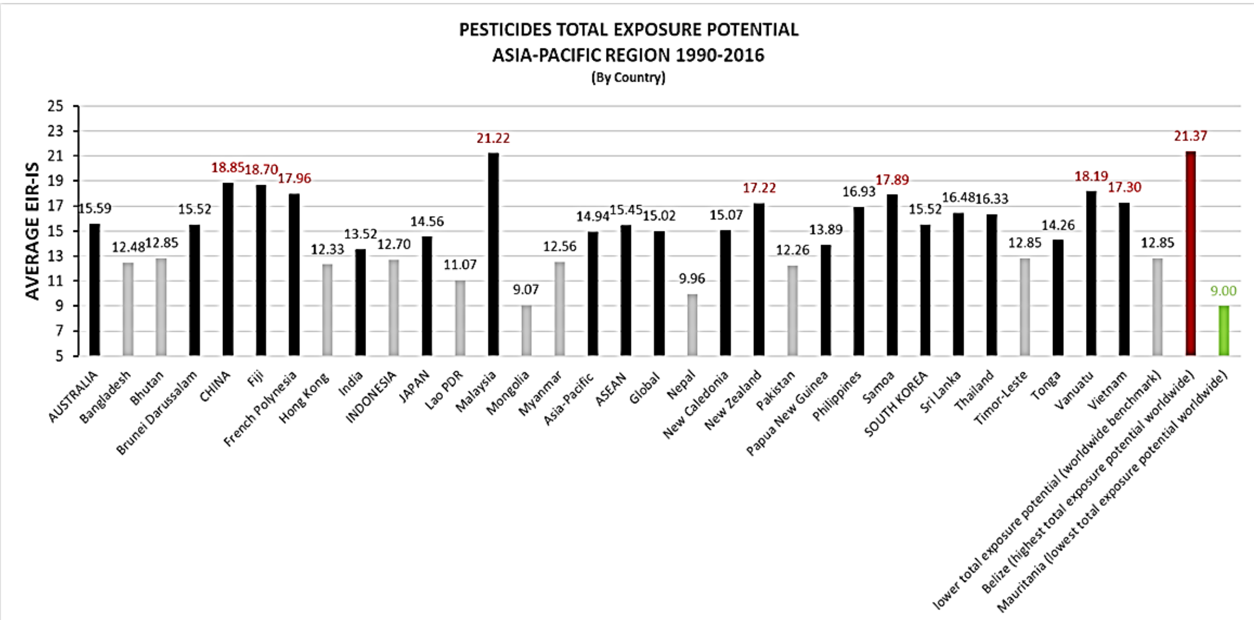


Figure 9: Time Series-Averaged EIR-IS for the Asia-Pacific Region (by country)

Asia-Pacific as a regional designation produced an average EIR-IS of 14.94 (versus 15.02 globally) for the 27-year time series, indicating that agricultural food systems across this region are (on average) characterised by pesticides-related 'Appreciable' public health concern qualified with a sub-group rating of 'medium' total exposure potential. A more detailed look at the Asia-Pacific indexing results reveal that ten of 29 nations (34.5%) across this region produced average EIR-IS ratings at, or below the 12.85 (lower total exposure potential) benchmark, of which Hong Kong (EPI=N/A) is HDI-rated as 'very high' (0.949), and Indonesia EPI=37.8, HDI=0.718 is G20 designated. Over half of the remaining developing nations in this sub-group (excluding Mongolia EPI=32.2, HDI=0.737, Bhutan EPI=39.3, HDI = 0.654, and Bangladesh EPI=29, HDI = 0.632) are largely rated as having medium HDI (on the lower range), and below average environmental performance index score(s) (EPI < 46.44), they include, Lao PDR, Myanmar, Nepal, Pakistan, and Timor-Leste (UNDP Human Development Index, 2021; Wendling et al., 2020).

This indexing output 'dynamic' appears consistent with evidence that generally lesser developed countries that tend to maintain a relatively more subsistence, or local market index of agriculture may be (on average) less apt to rely on pervasive pesticides-use (which, in some cases, limits pesticides tonnage) compared with their more developed counterparts (World Health Organization, 1990). Of the 'highest total exposure potential' sub-group of Asia-Pacific nations, the majority are recognised as 'developing' (New Zealand EPI=71.3, HDI=0.931 being the exception), and having 'transitioning' economies (with China being a G20). They include, for example, China, Fiji, Malaysia, Samoa, and Vietnam (UNDP Human Development Index, 2021; Wendling et al., 2020).

Asian-Pacific countries undergoing rapid economic development are largely faced with concomitant health and environmental impacts, especially evident in China, and across most of ASEAN. Thus, it is not surprising that governance and policy measures that direct agricultural food systems within these same jurisdictions would also experience (on average) consistently higher systemic pesticides-use rates. Table 2. displays environmental performance index scores, UN human development indexes, the time series-averaged pesticides-use rates, and their associated EIR-IS for the 'highest' and 'lower' total exposure potential Asia-Pacific sub-groups (Wendling et al., 2020).

Table 2: Comparison of Asia-Pacific 'Highest' and 'Lower' Total Exposure Potential Sub-Groups

Countries with ('highest total exposure potential')	EPI	HDI	Average Pesticides-Use Rate (kg/ha)	Average EIR-IS
China	37.3	0.761	10.36	18.85
Fiji	34.3	0.743	1.86	18.70
Malaysia	47.9	0.810	6.43	21.22
Samoa	37.3	0.715	0.99	17.89
Vietnam	33.4	0.704	2.49	17.30
Countries with ('lower total exposure potential')	**EPI**	**HDI**	**Average Pesticides-Use Rate (kg/ha)**	**Average EIR-IS**
Lao PDR	34.8	0.613	0.013	11.07
Myanmar	25.1	0.583	0.176	12.56
Nepal	32.7	0.602	0.092	9.96
Pakistan	33.1	0.557	0.246	12.26
Timor-Leste	35.3	0.606	0.004	12.85

PCE-ISys indexing outputs broadly demonstrate that by-and-large, and irrespective of their EPI 'sustainability' rating higher HDI-rated developing countries within the Asia-Pacific regional designation (generally associated with rapid economic expansion efforts), possess agricultural food systems that appear more reliant on pervasive chemical pesticides use compared to less developed nations within the region. Also, it can be reasonably surmised that the time series-averaged EIR-IS outcomes for each of the countries within their respective sub-groups are evidenced by rates of crop protection chemical use that are consistent with the Wachter & Staring use-guideline criteria template that associate higher or lower active ingredient use-rates with corresponding levels of country economic development, and regulatory capacity (World Health Organization, 1990). Evidence-based information derived from PCE-ISys outputs used in conjunction with other broad-based, empirically derived metrics, such as HDI, GDP, or GNI, for example, may offer policymakers and/or regulatory analysts with a viable (policy analysis) alternative to the dominant risk-benefit based approach to agroeconomic governance.

3.1.3 ASEAN Test Case – Malaysia

Agriculture is an economic mainstay of ASEAN, with farming and fishing industries in 2018 generating 10.6% of total GDP across the region, as well as contributing up to 72% of employment (by country) (Food and Agriculture Organization, 2020). At the same time, across large swaths of the region use of chemical pesticides, perceived as the policy solution of highest convenience for 'ensuring' optimally higher crop yields in line with agricultural intensification goals is marked by surplus evidence of deleterious health and environmental outcomes (Economy and Environment Institute, 2017; EU Parliament, 2021; Lam et al., 2017; Gupta, 2012; FAO-Situation Analysis Report, 2021).

One particularly glaring observation from the year-to-year, and time series-averaged components of the project study was the exceedingly high EIR-IS value(s) for Malaysia. In fact, worldwide, over the 26-year span, only the nation of Belize produced a higher average EIR-IS (see Figure 9), with their being only a 0.7% difference in average index between the two countries. Thus, Malaysia offers a comparative 'point-of-reference' test case for ASEAN, and Asia-Pacific nations (if not, worldwide) in how EIR-IS can be used to screen for the potential public health implications associated with pesticides input(s) within agricultural food systems.

Vietnam was selected for comparative analysis with Malaysia because of the former's similar time series-averaged EIR-IS threshold level and 'Highest Appreciable' public health concern rating. A comparison with lower total exposure potential nations was also deemed necessary. Lao PDR was chosen because of its below benchmark 11.07 time series-averaged EIR-IS (lowest among ASEAN nations), and its measurably lower HDI rating of 0.613; and Indonesia was selected for comparison, also due to its below benchmark rating of 12.70, and its G20 designation. The difference in HDI between the two nations, and Indonesia's comparatively larger economy provide a more enhanced contrast when comparing pesticides total exposure potential with Malaysia. Figure 10. shows the year-to-year trend in annual pesticides use rates for Malaysia, Vietnam, Indonesia, and Lao PDR. Data available at www.threepercentearth.org/reports-analysis/.

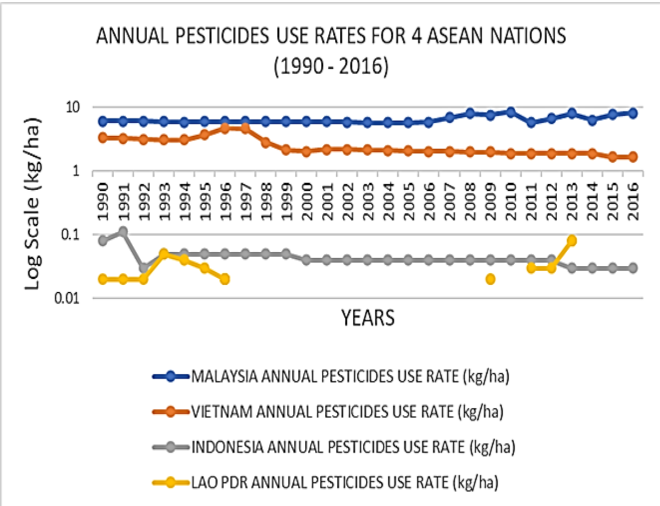


Figure 10: Annual Pesticides Use Rate Trends for Four ASEAN Nations

The average pesticides use rate for Malaysia from 1990-2016 was 6.43 kg/ha compared to Vietnam (2.49 kg/ha), Indonesia (0.045 kg/ha), and Lao PDR (0.01333 kg/ha), exceeding Vietnam's average use rate by 61%, while surpassing Indonesia and Lao PDR use rate trends by an astounding 14.34 and 48.2 orders of magnitude, respectively. According to the Wachter & Staring pesticides use-rating guideline, annual use rates of pesticides active ingredient of, or exceeding 5 kg/ha is deemed 'very high' (World Health Organization, 1990). Also, worth noting is that pesticides use has historically been limited within Lao PDR's agricultural food system (including average use rates approaching zero from 1997-2008, 2010, 2014-2016) possibly reflecting a lesser degree of industrialised farming compared with neighbouring countries such as Indonesia, Malaysia, Thailand, and Vietnam. Next, Figure 11. illustrates the year-to-year relationship(s) reflecting EIR-IS as a function of PCPr for all four countries.

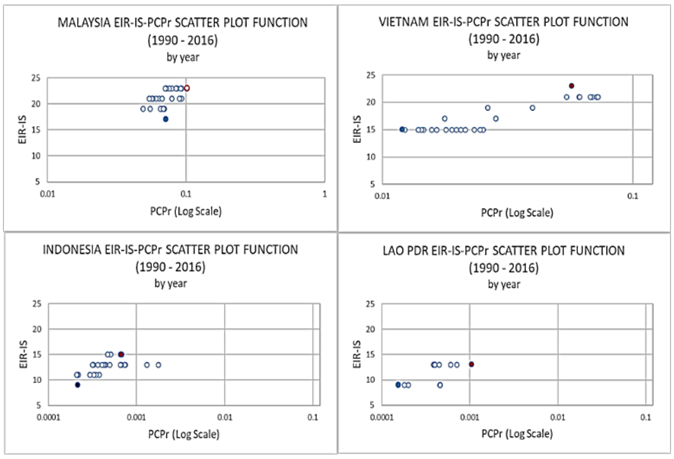


Figure 11: Pesticides Total Exposure Potential as a Function of the Pesticides-to-Crop Productivity Ratio

PCE-ISys 'average' correlation and variance tests point to annual pesticides use rate and Crop Production Index as the strongest indicator variables within the model, with Pesticides-to-Crop Productivity Ratio (PCPr) being the strongest contributing indicator of EIR-IS (regression coefficient = 43.18, p-value = 1.70×10^{-20}) (see Figure 7 and 8). Analysis of the scatter plot results show:

1) (positive) moderately linear cluster(s) for all four nations, but with Lao PDR, and Vietnam's respective profiles exhibiting visibly more data dispersion, the latter of which could be interpreted as a function of the abrupt, then incremental decline in average annual pesticides usage observed after 1997 (see Figure 10).

2) a concentrated cluster pattern of higher EIR-IS levels for Malaysia congruent with persistently concentrated levels of 'high-to-very high' pesticides use per unit of crop productivity (per hectare) over the time series, with observed levels of pesticides use to crop productivity for Indonesia's and Lao PDR's g-AEES consistently 1-2 orders of magnitude below Malaysia's agroeconomic system (data available at www.threepercentearth.org/reports-analysis/).

3) that for Vietnam, pesticides use levels relative to its crop production indices appeared more variable, but consistent with its decreased usage rates and increased productivity trends over the 26-year span (data available at www.threepercentearth.org/reports-analysis/).

Next, a comparison of highest and lowest EIR-IS to PCPr 'pair-function' offer additional perspective on interpreting the EIR-IS-PCPr scatter plots. Table 3. shows the change in the difference in magnitude between highest and lowest PCPr for Vietnam, Indonesia, and Lao PDR compared to Malaysia for the time series.

Table 3: Highest and Lowest Scatter Plot EIR-IS to PCPr 'Pair-Function' PCPr Ratio Difference

COUNTRY	HIGHEST SCATTER PLOT 'PAIR-FUNCTION' (red dots in Figure 11)	LOWEST SCATTER PLOT 'PAIR-FUNCTION' (blue dots in Figure 11)	HIGHEST 'PAIR-FUNCTION' PCPr RATIO (Malaysia relative to comparison nation)	LOWEST 'PAIR-FUNCTION' PCPr RATIO (Malaysia relative to comparison nation)	HIGHEST to LOWEST 'PAIR-FUNCTION' PCPr RATIO DIFFERENCE (Malaysia relative to comparison nation)
MALAYSIA	EIR-IS=23, PCPr=0.101920	EIR-IS=17, PCPr=0.07146			
VIETNAM	EIR-IS=23, PCPr=0.05713	EIR-IS=15, PCPr=0.01202	1.78x	5.95x	(4.17x)
INDONESIA	EIR-IS=13, PCPr=0.00069	EIR-IS=9, PCPr=0.00022	147.71x	324.81x	(177.1x)
LAO PDR	EIR-IS=13, PCPr=0.00105	EIR-IS=9, PCPr=0.00015	97.07x	476.4x	(379.3x)

The magnitude of difference in highest and lowest EIR-IS to PCPr 'pair-function' PCPr ratio for Malaysia relative to Vietnam **(**4.17x**)**, Indonesia **(**177.1x**)**, and Lao PDR **(**379.3x**)**, respectively, is consistent with the latter three nations (especially Vietnam) either reducing, or maintaining considerably lower pesticides consumption per unit of crop productivity in contrast to Malaysia (data available at www.threepercentearth.org/reports-analysis/), whose collective agricultural policy goals likely stayed the economic course over the 27-year time series. 'Brackets in bold' indicate that the magnitude of difference was driven by the lowest 'pair-function' ratio. Table 3. results interpretation draws support from results displayed in Table 4. showing the highest and lowest EIR-IS to PCPr scatter plot 'pair-function' range profiles for Malaysia, Vietnam, Indonesia, and Lao PDR.

Table 4: Comparison of the Range of Difference in Highest and Lowest PCPr (by country)

COUNTRY	Δ HIGHEST to LOWEST PCPr (by country)	% Δ HIGHEST to LOWEST PCPr RELATIVE to HIGHEST PCPr (by country)	Δ EIR-IS
MALAYSIA	0.03046	29.89%	-6
VIETNAM	0.04511	78.95%	-8
INDONESIA	0.00047	68.59%	-4
LAO PDR	0.00089	85.34%	-4

Higher percentage change(s) between the difference in highest and lowest PCPr (by country) relative to highest PCPr (by country) denotes either a greater range of reduction in pesticides use per unit of crop productivity for each hectare of farmed land (per annum), or static use-rates relative to crop output coupled with measurable crop productivity increases. Table 4 results show a comparatively sizable difference in the range of reduction in (or consistently lower) use of pesticides for Vietnam (+49%), Indonesia (+39%), and Lao PDR (+56%) compared to Malaysia. Malaysia's six-point EIR-IS decrease at its minimum range turned out to be a statistical outlier reflecting a largely 'non-diminished' relative effect, i.e., pesticides use-rates data for the country (over the time series) remained consistently 'very high,' as did its overall index pattern with no change in its public health rating category, despite considerable increases in crop productivity (data available at www.threepercentearth.org/reports-analysis/).

Findings from the scatter plot analysis point to pesticides consumption relative to crop productivity as a reasonable indicator corollary to total exposure potential. The broad conclusion drawn from interpretation of the EIR-IS to PCPr scatter plot results (corroborated by FAO and World Bank-sourced data, www.threepercentearth.org/reports-analysis/) is that the ratio of pesticides use to agroeconomic productivity for Malaysia, skewed by 'very high' average pesticides use rates, likely contribute to the country's persistently elevated pesticides total exposure potential. Ministry coordinated policy analysis efforts targeting issue(s) of 'high proportional use-to-productivity' within Malaysia's agricultural food system may serve to reduce future (per capita) health and environmental impact(s) from agricultural pesticides use.

Future research and policy analysis aimed at validating the decision-support functionality of PCE-ISys may include, charting usage trends in conjunction with agricultural land-use changes, and/or evaluating similar scatter plot profiles for other Asia-Pacific nation sub-groups as a way of ascertaining a more comprehensive picture of potential pesticides impact(s) arising from regional food systems, and to what extent those potential impact(s) are shaped by conventional versus sustainable agricultural practices. Other research related consideration(s) for PCE-ISys may involve examining annual $Pi_{exp}UC$ trends relative to registered crop protection chemicals (by country) as a way of extrapolating proportional risk from those select pesticides groupings.

Most indexing systems with policy and/or business application(s) are designed to disseminate 'units' of information on a broadly 'generalisable' scale, captured within a defined scope of time and space context in addressing a given social, economic, or environmental issue (Consumer Finance Institute, 2021; Gorai, AK. and Goyal, P, 2015; Kookana, RS., et al., 2005; Kovach, J., et al., 1992). In this respect, PCE-ISys is no different from other indexing models in that its algorithm processes data drawn from a limited set of parameters, i.e., pesticides use, crop productivity, agricultural land, and population.

One obvious limitation of this type of heuristic evaluation regimen is that the indexing outputs do not necessarily allow for inferential interpretation beyond the scope of its defined parameters. For PCE-ISys that would be g-AEES. Concomitantly, however, what the PCE-ISys model lacks in capability to, for example quantify pesticides impact is replaced by the power of its indexing output(s) to prospectively reframe the debate about the types of measurement outcomes (qualitative vs. quantitative, or precautionary vs. risk-based) that should be prioritised in helping guide agricultural policy-based decision making, especially given that the economic and environmental reality of the world is not 'compartmentalised,' but is in fact based on the interconnectivity [of, and within] social and ecological systems.

4. CONCLUSION

As the Asia-Pacific region, and more specifically ASEAN, begin remission from the COVID-19 pandemic, the resiliency of Southeast Asia's agricultural economy will be showcased. A prime opportunity exists for governments, economic participants of food producing systems, and civil society to begin deliberating in earnest the existing limitations of current risk-based pesticides management for the region. Population across the ASEAN region is projected to exceed 740 million people by 2035, of which a monumental task lies ahead to forge sustainable agricultural food systems that comport with UN SDG target indicators such as 2.4, 3.9 and 6.3. The Pesticides Consumer-Environmental Indexing System (PCE-ISys) is a novel, semi-quantitative framework designed to be a broad-based, decision-support screening tool that works by integrating salient evidence-based information into agroeconomic and environmental policy analysis.

This project study demonstrates the policy-relevant indexing application(s) of PCE-ISys, painting a somewhat nuanced, yet concerning picture of pesticides use throughout ASEAN, and the Asia-Pacific region. By-and-large, agricultural pesticides use remains systemic and expansive, likely posing continued health and environmental risk(s) for this area of the world. Alternatives to largely risk assessment-derived health-based regulatory policy are needed. 'Systems-based' indexing models such as PCE-ISys can be employed to 1.) encourage governing bodies to transition towards harmonised policy concepts that more readily foster sustainable agricultural food systems, and 2.) promote research to further the discourse in sustainable development policy, specifically in order to meaningfully address the inefficient, yet enduring 'policy-compartmentalising' of crop protection chemicals use in food systems, and its associated long-standing resultant impacts to ecological and human health.

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