Mapping geospatial processes affecting the environmental fate of agricultural pesticides in Africa

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Abstract

Background: The application of agricultural pesticides in Africa has potential negative effects on human health and the environment. To analyse these effects, spatial data quantifying the environmental fate of agricultural pesticides is needed. However, poor availability and quality of data that quantify pesticide application and pesticide fate limit direct analysis. This study serves as a first step in the identification of potential pesticide accumulation areas in Africa.

Methods: The study reviewed existing pesticide fate models to select key geospatial processes involved in the environmental fate of agricultural pesticides and mapped spatial variation in each process by combining data from available geospatial databases. A database of insecticide residues measured in soil, sediment, water and air was compiled in order to test whether the data layers constructed could be used to predict the location of residues in the environment.

Results: Maps of geospatial variation associated with leaching, surface runoff, sedimentation, soil storage and filtering capacity, and volatilization across Sub-Saharan Africa were created using existing geospatial datasets. The potential and limitations of the created maps are discussed.

Conclusion: This study provides a set of key processes associated with pesticide fate that can be used to support the identification of pesticide accumulation areas in Africa. Ideally, these maps should be used in combination with data on where pesticides are being applied.

Keywords: pesticide fate, crop protection, environmental data, insecticide residue, satellite data, tropics.

1. Background

The environmental fate of agricultural pesticides can have direct and indirect impacts on human health and the environment. Human exposure to toxic levels of dichlorodiphenyltrichloroethane (DDT) can result in spontaneous abortion by women (1), carbamates and organophosphates in the environment can result in biodiversity loss (2), and there is evidence that pesticide exposure can play a role in neurodegenerative conditions like dementia (3) and Parkinson's disease (4). Agricultural insecticides can also drive the spread of resistance in non-target insects that are involved in the transmission of human diseases such as malaria (5,6). In this case, agricultural pesticides can have an indirect impact on human health by reducing the efficacy of insecticide-based interventions.

It is known that agricultural pesticides are regularly being used in African farming systems (7,8). Although the average national quantity of pesticide use is relatively low in Africa, the potential negative effects on human health and the environment are high (8). This is mainly due to illiteracy among farmers, lack of awareness about the danger of pesticide misuse, difficulties with extrapolating the prescribed pesticide dose ratio to the size of an agricultural field, and lack of knowledge of pests and diseases (9). Minimizing the harmful health and environmental effects caused by pesticide exposure requires, amongst others, spatial data on the fate of pesticides.

To understand the health and environmental effects caused by pesticide exposure, it is essential to know where this exposure is occurring. This requires spatial data on the environmental fate of pesticides. However, these data cannot directly be derived for the whole of Africa, due to the large extent of the continent, the very limited volumes of pesticide application or residue data available and data quality issues. Registered governmental data on pesticide use are outdated, often only available at national scale and underestimate the actual pesticide use (10,11). Other data sources, such as the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) database, confirm that the use of pesticides can be much higher than the registered amount.

Pesticide fate models can be used to predict where pesticides will end up in the environment. However, pesticide fate models are mainly developed, calibrated and validated with data from temperate regions. (12). The accuracy of the results cannot be guaranteed when using these models for tropical Africa. Adapting or developing pesticide fate models for Africa as an alternative is difficult, because pesticide behaviour in the environment is generally less understood in tropical regions compared to temperate regions (13–15).

This study aims to make a first step in the identification of areas where agricultural pesticides potentially accumulate in Africa. The study identifies and selects key processes affecting pesticide fate and models the spatial variability of each key process.

2. Materials and methods

2.1. Review of pesticide fate models

To select key processes affecting the environmental fate of agricultural pesticides in Africa, we first reviewed existing pesticide fate models and identified all variables that were used in these models. Key processes were then selected based on criteria that considered the importance of the process and the feasibility of modelling the process at continental-scale.

2.1.1. Identify pesticide fate models

Different sources were consulted to identify available pesticide fate models. Models that were applied or developed, calibrated and validated in tropical areas were identified using the Web of Knowledge and the search term 'pesticide fate model' AND 'tropic*'. Other pesticide fate models that were suitable for this review were found through the CEAM (Center for Exposure Assessment Modeling), OPPT (Office of Pollution Prevention and Toxics), CEMC (Canadian Environmental Modelling Centre), FOCUS (Forum for the Co-ordination of pesticide fate models and their Use), OECDs (Organization for Economic Co-operation and Development) model database, RIVM (National Institute of Public Health and the Environment) and WENR (Wageningen Environmental Research). Two review papers were also used (12,16).

The following selection criteria were applied: (i) select models that operated at catchment scale or coarser, (ii) select models that operated at daily scale or coarser, (iii) select models that were not developed for one specific process or crop, (iv) discard complex models that required detailed input data (e.g., SWMS_3D, FEHM), and (v) discard models that were derived from a combination of other pesticide fate models. A total of 24 models met the selection criteria (Table 1).

2.1.2. Selecting key processes affecting pesticide fate

The variables pesticide fate models used were listed (Additional file 1). The key processes were then selected based on the following criteria: i) inclusion in at least ten of the selected pesticide fate models, ii) relevant at the resolution and extent of this study, i.e. a 2.5 arc-minute resolution applied across Africa, iii) relevant to the fate of pesticides after application (as opposed to factors related to the application rate), and iv) generally applicable to all pesticides (as opposed to pesticide-specific processes such as transformation and degradation). These criteria resulted in the selection of four key processes: leaching, surface runoff, soil storage and filtering capacity, and volatilization. The criterion of inclusion in at least ten pesticide fate models was relaxed for the process of sedimentation, because sedimentation may play a more important role in Africa. Approximately 25% of African land surface is prone to water erosion (17). The combination of high rainfall intensity, sloping land and soils that are, in general, poor in nutrients and organic matter increase erosion risk in Africa (18). Therefore, sedimentation was a fifth process selected for this study.

The key processes selected for this study are visualised in Fig. 1 and defined as follows:

- Leaching is the process by which rain or irrigation water infiltrates and percolates to deeper groundwater layers.
- Surface runoff is the process by which rain or irrigation water flows overland to other streams or surface water.
- Sedimentation is the process by which soil particles in suspension settle out of fluid, water in this instance, and come to rest.
- The soil storage and filtering capacity indicates the capacity of a soil to store and filter substances (e.g., water or pesticides).
- Volatilization is the process whereby a chemical substance is converted from a liquid or solid state to a gaseous or vapour state.

2.2. Satellite and soil data

Existing geospatial datasets were used to model the five key processes affecting pesticide fate. For the selection of the most suitable data source, priority is given to the dataset that: (i) covered Africa and had a resolution of 2.5 arc-minute or finer (approximately 5x5km pixels at the equator), (ii) was most up-to-date, (iii) was established by an agency (e.g., NASA) or recognized by other studies, and iv) was accompanied by a quality assessment. Further details of the existing geospatial datasets are provided in Additional file 2. Some datasets did not cover islands (e.g., Cape Verde, Comoros, Mayotte) or only covered Sub-Saharan Africa, but met the other criteria or was the only dataset available. Based on these geographic limitations, the extent of some processes was restricted.

2.3. Mapping key processes affecting pesticide fate

Some key processes required input data that could not be obtained from existing geospatial datasets. Table 2 gives an overview of which input data were actually required and which data were finally used as input data to model the key processes. The key processes were mapped at 2.5 arc-minute resolution, because they were initially constructed for a wider project on insecticide resistance in malaria vectors that operated at 2.5 arc-minute resolution (19).

2.3.1. Leaching

Data on soil drainage rate, groundwater depth, bedrock depth and type, slope, and soil moisture were required to create a map on the geospatial variation in leaching (20,21).

Data on soil drainage class were obtained from AfSoilGrids (22). The dataset classifies drainage based on soil organic matter content, soil structure, and soil texture. AfSoilGrids combines the Africa Soil Profiles (AfSP) database and the AfSIS Sentinel Site database with explanatory variables to spatially predict soil drainage classes using the random forest method. Low infiltration rates correspond to <15 mm/hour, moderate infiltration rates correspond to 15-50 mm/hour and high infiltration rates correspond to >50mm/hour (23).

The only map of groundwater depth available for Africa did not meet the criteria, because the data were only available at 15 arc-minute resolution (24). Besides, the map did not have data for Madagascar, and was only based on 283 aquifer summaries. Several studies have found a relationship between groundwater depth and elevation (25–27). Although the map on groundwater depth for Africa (24) and elevation showed a weak relationship (r = -0.14), elevation is currently assumed to be the best available predictor for groundwater depth. Data on elevation were obtained from the Shuttle Radar Topography Mission 90m Digital Elevation Database v4.1 (28), hereafter called SRTM-DEM.

Data on bedrock depth were obtained from SoilGrids (29). Bedrock type is an indicator for porosity. Leaching takes more easily place in bedrock with high porosity. The porosity of the bedrock is strongly related to the soil drainage rate and therefore, data on the soil drainage class serves as an indicator for bedrock type. Slope was derived from the SRTM-DEM. The mean soil moisture content was obtained from NASA-USDA Global Soil Moisture Data. These data were only available at 12.5 arc-minute, but because this is the only data on soil moisture available, the selection criterion was relaxed for this geospatial dataset.

Although we know which data were needed to model leaching, the relationships between these data and leaching are location and pesticide dependent (20,21). Therefore, the data were combined using a linear relationship after each parameter was normalized between 0 and 1 (Eq.1).

$$L = D + (1 - H) + (1 - DB) + (1 - SL) + SM \qquad [1]$$

Where *L* represents leaching, *D* is the normalized drainage class, *H* is the normalized elevation, *DB* is the normalized depth to bedrock, *SL* is the normalized slope and *SM* is the normalized mean soil moisture content between 2010 and 2018. Not taking non-linearity into account might result in an over- or underestimation of estimates of geospatial variation in leaching. The individual datasets can be combined in more sophisticated ways when knowledge on the relationships between the input data and leaching is available.

2.3.2. Surface runoff

Surface runoff was divided into three processes; the susceptibility for surface runoff generation, transfer and accumulation. These processes were created based on the Indicator of Intense Pluvial Runoff (IRIP) method. This method creates comprehensive maps of areas susceptible for surface runoff without explicit hydrological modelling (30). Each process required five variables (Table 2). More detail on the method is provided by a study that described and evaluated surface runoff susceptibility using the IRIP method (31). However, in comparison to this study, we used normalized continuous maps as input data instead of binominal data.

Data on soil drainage rate, soil thickness, soil erodibility, topography, and land use were required to model the spatial variability in surface runoff generation (31). The model of (32) was used to obtain a map on the soil erodibility. This method is explained in more detail in section 2.3.3. The topography indicator of the IRIP method is a combination of slope and topographical wetness index (TWI) and were both derived from the SRTM-DEM. Land use classes were obtained from the Global Mosaics of the standard MODIS land cover type data product MCD12Q1 (33). This product collated land use data between 2001 and 2012 and categorized the data into 17 different land use classes. Based on background information (31,34), we categorized the MODIS land cover type data product into five classes and gave a weight to each class to indicate how infiltrative or impervious surfaces under a certain land use class are (Table 3).

Data on surface runoff generation, slope, break of slope, catchment capacity and artificial linear axes were required to model surface runoff transfer (31). Data on slope were obtained from the SRTM-DEM. Catchment capacity is estimated using the Horton form factor (35). This factor is the ratio of area to length of the sub-watershed defined by the drained area at the considered pixel. The area of the watershed and the stream length were both obtained from HydroSHEDS (36). The continental extent of our study did not allow for the inclusion of ‘Break of slope’ and ‘Artificial linear axes’.

Data on surface runoff generation, slope, break of slope, TWI, and flow accumulation were required to model surface runoff accumulation (31). How the first three indicators were obtained is described above. Flow accumulation was obtained from HydroSHEDS (36).

The correlation coefficient between the three surface runoff processes and a global insecticide runoff vulnerability (37) was derived.

2.3.3. Sedimentation

Data on the erosion rate within a catchment area were required to map geospatial variation in sedimentation. The erosion rate was quantified using the USLE equation (Eq.1).

$$E = R * K * C * LS * P \quad [1]$$

Where, E is the annual average soil loss through water erosion (in t/ha/yr), R is the rainfall erosivity (in MJ·mm/ha/h/yr) that represents the power of rainfall to cause soil erosion by water, K is the soil erodibility factor in (t ha h)/(ha MJ mm) that represents the non-resistance of soils to erosion, C is the cover-management factor that represents the influence of land use and management on soil erosion, LS is the topographic factor that represents the effect of slope length and steepness on erosion, and P is the support practices factor which represents the effects of human practices on erosion prevention. The USLE equation was chosen because it requires relative little input data and most input data can be obtained from geospatial datasets.

The global rainfall erosivity map (38) was used to represent the rainfall erosivity factor. In this study, a Global Rainfall Erosivity Database was compiled and Gaussian Process Regression was applied to construct the rainfall erosivity map. The soil erodibility factor was estimated by Eq.2 (32).

$$K = \left[\frac{2.1*10^{-4}M^{1.14}\,(12-OM)+3.25(s-2)+2.5(p-3)}{100}\right] * \ 0.1317 \qquad [2]$$

Where, *M* is the textural factor calculated by Eq.3, *OM* (%) is the organic matter content, *s* is the soil structure class where 1 is very fine granular, 2 is fine granular, 3 is medium or coarse granular and 4 is block, platy or massive, and *p* is the soil drainage class.

$$M = m_{silt} + m_{vfs} * (100 - m_c) \qquad [3]$$

In Eq.3, m_{silt} (%) is the silt fraction (0.002-0.005mm), m_{vfs} (%) is the very fine sand fraction (0.05-0.1mm), which equals 20% of the sand fraction, and m_c is the clay fraction (<0.0002 mm). Data on soil texture, organic matter content and drainage class were obtained from SoilGrids (29). Data on soil structure were obtained from the Harmonized World Soil Database (HWSD; 39).

The slope-length factor (LS) depends on two components; slope and length of the slope. This study only considered the component slope, because the length of the slope affects erosion rate at much finer resolution (40) than the 2.5 arc-minute that was used in our study. Including the length of the slope would increase the error. To estimate the slope-factor (*S*), distinction was made between slopes steeper than 0.09 degrees (Eq.4a) and flatter than 0.09 degrees (Eq.4b) (41).

$$S = 16.8 * \sin(\theta) - 0.5 \qquad \text{if slope} > 0.09 \text{ degree} \qquad [4a]$$

$$S = 10.8 * \sin(\theta) + 0.03 \qquad \text{if slope} \leq 0.09 \text{ degree} \qquad [4b]$$

Where θ is the slope in degree.

The cover-management factor required data on land management, which was not available for the African continent. Therefore, the enhanced vegetation index (EVI) was assumed to be a good proxy for the cover-management factor (42). Gap-filled data on the mean EVI were available for Africa (43). This study extracted data for the African continent from the MODIS Enhanced Vegetation Index (EVI) dataset, and daytime and night-time Land Surface Temperature (LST) datasets, and applied two complementary gap-filling algorithms and a variety of run-time options to create data on the EVI. No spatial data on support practices were available for Africa and therefore the factor was excluded in the model.

Applying the USLE equation gave an estimation of the erosion rate across Africa. The sediment load per watershed could now be estimated by combining the erosion map and a map on watershed areas that was derived earlier from the SRTM-DEM. Sedimentation takes place at locations where water can accumulate. Therefore, sedimentation was estimated by multiplying the map on sediment load per watershed and the map on surface runoff accumulation.

2.3.4. Soil storage and filtering capacity

Data on soil organic matter, clay content, soil pH and cation exchange capacity (CEC) were required to map geospatial variation in soil storage and filtering capacity (44). In this study, similar patterns were found between filtering capacity and storage capacity and therefore one map was constructed for both.

All input data were obtained from SoilGrids (29). This data source provided soil characteristics at seven fixed depths ranging from 0 to 200cm depth. Soil profile data were obtained by taking depth weighted averages of these seven layers. The soil storage and filtering capacity was estimated based on Eq. 5.

$$SFC = OC + C + (1 - pH) + CEC \qquad [5]$$

Where *SFC* is the soil storage and filtering capacity, *OC* is the normalised organic carbon content and *C* is the normalized clay content. Soil pH and CEC were also normalized. Areas where the SFC was low are more susceptible to pesticide fate. The individual datasets can be combined in more sophisticated ways when knowledge on the relationships between the input data and the soil storage and filtering capacity becomes available.

2.3.5. Volatilization

Data on potential evapotranspiration (PET), wind speed, air temperature, solar radiation and relative humidity were required to map volatilization (45).

Long-term annual average PET data were obtained from the CSI-CGIAR Global Potential Evapotranspiration Climate Database (46). Long-term (1970-2000) average monthly wind speed and solar radiation data were obtained from WorldClim V.2 (47). Monthly maps on the average land surface temperature were derived from daily data MODIS product MOD11A1 V6. Data on relative humidity between 2015 and 2018 were obtained from the Global Forecast System (GFS) of the National Centers for Environmental Prediction (NCEP). Based on these years, average monthly relative humidity was estimated. The key variable associated with volatilization was estimated using Eq. 6.

$$\mathrm{V}_i = WV_i + S_{rad,i} + \mathrm{T}_i + \mathrm{PET} + (1 - \mathrm{RH}_i) \qquad [6]$$

Where, V_i is the key variable associated with volatilization in month *i*, $\mathrm{WV_i}$ is normalized long-term wind velocity in month *i*, $S_{rad,i}$ is the normalized long-term solar radiation in month *i*, $\mathrm{T_i}$ is the normalized long-term average day-time surface temperature in month *i*, PET is the normalized long-term annual average potential evapotranspiration and $\mathrm{RH_i}$ is the normalized average relative humidity in month *i*. The individual datasets can be combined in more sophisticated ways when knowledge on the relationships between the input data and volatilization becomes available.

2.4. Testing the potential of the maps associated with pesticide fate

Ideally, each map should be validated using observational data for that process, which means that the map for leaching should be validated using data from studies that have measured leaching at multiple locations across Africa, and so on. However, no observational data were available for these key processes. Therefore, the maps constructed here were not validated, but the potential of these maps to predict locations where pesticide residues accumulate was tested instead. To test the potential of the maps for modelling pesticide residues in the environment, observational data on pesticide residues was required.

2.4.1. Insecticide residue database

This study is part of a wider project on insecticide resistance in malaria vectors (19) and therefore an observational database on insecticide residues was compiled for Africa. The database was compiled from a literature review in Web of Knowledge to identify studies that measured insecticide residues in soil, sediment, water and air. The search terms that were used and the resulting database are available in Additional file 3. The following data were systematically extracted from individual papers: year and month(s) of sampling, sample collection methods and depth, insecticide extraction method, insecticide quantification method, quantification and detection limits, insecticide and insecticide class, the measured insecticide concentration and geographical coordinates.

The database contained 10076 observations of which 9867 could be georeferenced. 9688 of these observations were located in our study area. The observations were collected from 68 studies. Within this insecticide residue database, 93 different types of insecticides were measured. Georeferenced observations located in our study area were measured in 2328 soil samples, 3008 sediment samples, 3866 water samples and 486 air samples. A lack of standardisation in the collection, extraction and detection methods makes it hard construct a standard dataset for further analysis. The number of samples that were measured at unique locations and within the study area dropped rapidly to no more than 63 if a single insecticide was selected. Figure 2 provides an example for the insecticide compound that was most frequently measured in the different substrates; soil, sediment, water and air.

2.4.2. Testing the potential of the constructed maps

Overall, pp’Dichlorodiphenyldichloroethane (pp’DDD) was the most frequently and most consistently measured compound in the substrates soil and sediment. pp’DDD observations measured in soil and sediment were extracted from the database to obtain a single standard dataset. This resulted in the extraction of 385 observations measured from 100 locations. This standard dataset for pp’DDD was used to test the potential of the constructed maps to predict residues in the environment. We used Moran’s I statistic to test the presence of a spatial structure in the observations. In this framework, the null hypothesis assumes complete spatial randomness. When this null hypothesis is rejected, we investigated whether the maps that were created in this study can be used as covariates in a model that spatially predicted pp'DDD in soil and sediment using the standard dataset as response data. We ran a second model to test whether the uncertainty of the predictions decreased when adding horticultural land cover, as a proxy for pesticide application, as an additional covariate. The horticultural land cover layer was obtained by combining two MODIS Land Cover classes (33); annual crop cover, and natural vegetation-crop mosaic land cover. More background information on the model is available in Additional file 4.

3. Results and discussion

3.1. Identifying pesticide fate models and select key processes

Only three out of 24 identified models were developed, calibrated and validated in tropical or sub-tropical areas: the Dynamic Multimedia Environmental Fate Model (48) was developed for the tropical floodplains of Brazil, the Chemical Fate Model (49) was developed for a tropical river catchment in Australia and the Pesticides RIsks in the tropics to Man, Environment and Trade Pesticide model (PRIMET; 50) was developed in Southeast Asia and later adapted to Ethiopia (PRIMET-Ethiopia; 51). Some models were developed elsewhere, but applied in tropical and sub-tropical areas. For example, the Soil and Water Assessment Tool (SWAT) model (52,53) was developed in the U.S.A., but, had, for example, frequently been applied in Southeast Asia. The Pesticide Root Zone Model (PRZM; 54) and the TOXic substances in Surface Waters (TOXSWA) model (55) were developed in the U.S.A and The Netherlands respectively, but the models have been applied in Ethiopia (56). The Environmental/Policy Integrated Climate (EPIC) model (57) was developed in the U.S.A, but has, amongst others, been applied in West Africa and Brazil (58), and the Coastal Zone Model for Persistent Organic Pollutants – Version 2 (CoZMo-POP-2; 59) was also developed in the U.S.A., but has been applied in Botswana (60). Nearly all of the 24 identified pesticide fate models were not developed in or for Africa, neither were many pesticide fate models applied in an African country. As a consequence, we had to assume that the selected key processes were also key for Africa.

3.2. Mapping key variables associated with pesticide fate

3.2.1. Leaching

The map of spatial variation estimates of leaching is highest in Central Africa and in the southern coast of West Africa (Fig.3). The tropical climate of these regions causes high soil moisture contents throughout the year, which has a positive effect on leaching. The regions are also characterized by relatively shallow slopes and low elevation. Steeper and higher areas with arid or semi-arid climate are less prone to leaching, e.g., the Great Rift Valley.

Using elevation as indicator for groundwater depth brings uncertainty in the model, because of a lack in actual groundwater depth measurements and a weak correlation coefficient between the elevation and the 2.5 arc-minute map on groundwater depth (24). The model also does not correct for the more rapid infiltration caused by cracked clay soils. It is known that the hydraulic processes of these soils differ from any other soil (61). These soils, i.e. Vertisols, are especially common in East Africa. The effect of leaching may therefore differ in this part of Africa.

3.2.2. Surface runoff

According to our results, surface runoff generation was highest in areas where soil permeability was low and bedrock was near the surface (Fig. 4A). Steep slopes and high susceptibility for surface runoff generation made Ethiopia especially vulnerable for surface runoff transportation (Fig. 4B) and accumulation (Fig. 4C). Many studies have confirmed high rates of surface runoff in Ethiopia (62,63).

Our resulting maps of surface runoff were compared to the global insecticide runoff vulnerability map (37). Correlation coefficients of 0.32 and 0.33 were found between the global insecticide runoff vulnerability map and the surface runoff transfer and accumulation map respectively. No correlation was found between the global insecticide runoff vulnerability map and the surface runoff generation map we created. The global insecticide runoff vulnerability map was created from country-based data on the rate of insecticide application and the fraction of insecticide high-consuming crops form the FAOSTAT database (64), while we did not use these data on purpose because of data gaps and uncertainty in the data.

3.2.3. Sedimentation

The areas that are estimated as most prone to erosion and sedimentation processes are in Ethiopia, the southern and eastern parts of the Democratic Republic of the Congo and Madagascar (Fig. 5). In some of these areas we estimate up to 45 t/ha/yr soil erosion. Previous studies confirm that these processes take place in large amounts. For example, soils of Madagascar tend to be erosion-prone (65), the Upper Blue Nile Basin (Ethiopia) receives large quantities of sediments from agricultural areas in the catchments (66,67) and natural processes dominate the soil allocation in Congo (68), although agricultural development and deforestation has increased the sediment load over recent decades (69).

3.2.4. Soil storage and filtering capacity

Soil storage and filtering capacity is estimated to be moderate to high in Central Africa, the southern part of West Africa and the Ethiopian Highlands (Fig. 6). These regions have relatively high organic carbon (OC) content, clay content and CEC and a low soil pH. The Ethiopian Rift Valley and the Sahara, Namib and Kalahari Desert have lowest storage and filtering capacity. In general, the soils of these areas have extremely low OC contents, are coarser in texture and have a higher soil pH. Pesticide leaching is a minor problem in deserted regions, because of the limited agricultural activity.

However, the resilience of soils with a low binding capacity is low, which can affect its bio-functioning (70).

The role soil characteristics play in pesticide binding is less documented and, in general, less understood for tropical soils (71–73). Soil storage and binding capacity depends strongly on the chemical composition and the half-life of the pesticide. Pesticides can have a positive or negative charge or they can be non-polar. Differences in the chemical structure of individual pesticides were beyond the scope of the current study.

3.2.5. Volatilization

The map of mean spatial variation estimates of volatilization showed highest values in the Rift Valley, the Horn of Africa and the Namib and Kalahari Desert, and lowest values in the tropical regions and in the Central Highlands (Fig. 7A). The standard deviation was highest in areas with inter-annual variation in temperature and relative humidity, and lowest in the Rift Valley and Central Africa (Fig. 7B).

One of the factors that influence volatilization is wind velocity. We used the mean annual wind velocity in the model, although farmers will attempt to reduce spray drift and volatilization by spraying on days when the wind velocity is low. There is also no consistency in the duration and extent of volatilization, because it depends, amongst others, on the application method and environmental conditions. Some studies measured pesticide concentrations only up to a few meters from the source (74) and only for a few hours after spraying (75), while other studies measured pesticides up to a few kilometres from the source (75) and up to two months after spraying (76). These examples indicate that in some cases monthly maps at 2.5 arc-minute resolution might be too coarse for studying the effect of volatilization on pesticide fate.

3.3. Testing the potential of the constructed map

The results of the Moran's I statistics on our data (n=385.) in our study area suggest that the hypothesis of spatial randomness should be rejected (Moran's I = 0.37 and z-score = 27.37), which suggests the presence of a spatial structure in the data. The results of the model we built to further investigate the potential of the constructed maps are available in Additional file 4. Although over 10,000 observations quantifying insecticides in the environment were collated for Africa, the database incorporated multiple compounds with varied physical and chemical properties that affect their movement in the environment and degradation. When a single compound was selected, this data subset was still confounded by the use of different extraction methods, different quantification methods and threshold values, and measurements taken from different substrates. Further, once the most commonly studied compound, pp'DDD was selected in just two substrates, soil and sediment, the spatial distribution of the data was highly localised to three small regions across the entire continent (Figures 1 and 2, Additional File 4). It is, therefore, unsurprising that model performance was poor and we cannot yet draw any conclusions about the potential of the constructed layers to predict pesticide fate in the environment.

4. Potential and limitations of the created maps

This study mapped a set of key processes affecting pesticide fate, as a first step in the identification of areas where pesticides potentially accumulate in Africa. Ideally, these maps should be used in combination with data on pesticide application or, in place of application data, data on agricultural land use. National pesticide legislations and regulations or Global Open Data Portals (e.g., SOILSERIES) might increase the availability of systematically registered pesticide application data. However, data on where, when, how much, and which type of pesticides were applied are needed for pesticide fate analysis (77). The potential of modelling pesticide application from data on agricultural land use has been explored (78). For example, pesticide application maps were created based on crop type and crop growth data, both of which can be derived from satellite data, and data on which pesticide was applied to which crop (78). When data on the latter become available for Africa, this option can be considered.

Pesticide fate in Africa has dominantly been studied at local or national scale. For example, pesticide use in South Africa was mapped (79), surface water contamination in Ethiopia was assessed (56) and the effect of pesticide leaching on the contamination of Lake Naivasha was mapped (80). Global initiatives have focussed, so far, on aquatic pesticide fate processes only (e.g., Global Pesticide Map; 37). The maps that were created in our study can potentially be used in a wide range of studies because they cover the African continent and consider aquatic, terrestrial and atmospheric pesticide fate processes. However, we need to be careful using the created maps in studies at a fine scale, because pesticide fate processes can be influenced locally by site-specific land management decisions (81). The maps can be used beyond pesticide fate studies. For example, the map estimating spatial variation in sedimentation may be useful for studies on flood risk (82) and surface water eutrophication (67). However, before applying the maps to other studies, we recommend compiling datasets for Africa on each key process that can be used to validate the constructed maps.

Long-term monthly averages were not always available from the existing geospatial datasets used in this study. Therefore, the created maps did not account seasonality in pesticide fate processes, while it is known that seasonality plays a role (83,84). Creating each pesticide fate process individually does not account for interactions between different processes, however, it is possible to use these maps in combination and allow for interactions between these variables. An advantage of creating each process individually is that each map can be used separately. For example, volatilization might be of interest to studies on human health and sedimentation might be of interest to studies on land degradation.

5. Conclusions

This study provides a set of Sub-Saharan African maps for geospatial variation in aquatic, terrestrial and atmospheric processes affecting pesticide fate and serves as a first step in the identification of areas where agricultural pesticides may accumulate. We were able to create the maps using existing geospatial datasets, however, there is a need for data on which and how much pesticide is sprayed. This application of pesticides determines the quantities entering the pesticide fate process and, additionally, many pesticide fate processes are compound dependent. We therefore recommend using the constructed maps in combination with pesticide application data. In the future, the input data that were used for modelling each process can be combined in a more sophisticated way as a greater understanding of the relationships between existing geospatial datasets and pesticide fate processes becomes available for the tropics.

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Figure 1. The selected key processes affecting pesticide fate and how they act in the environment.

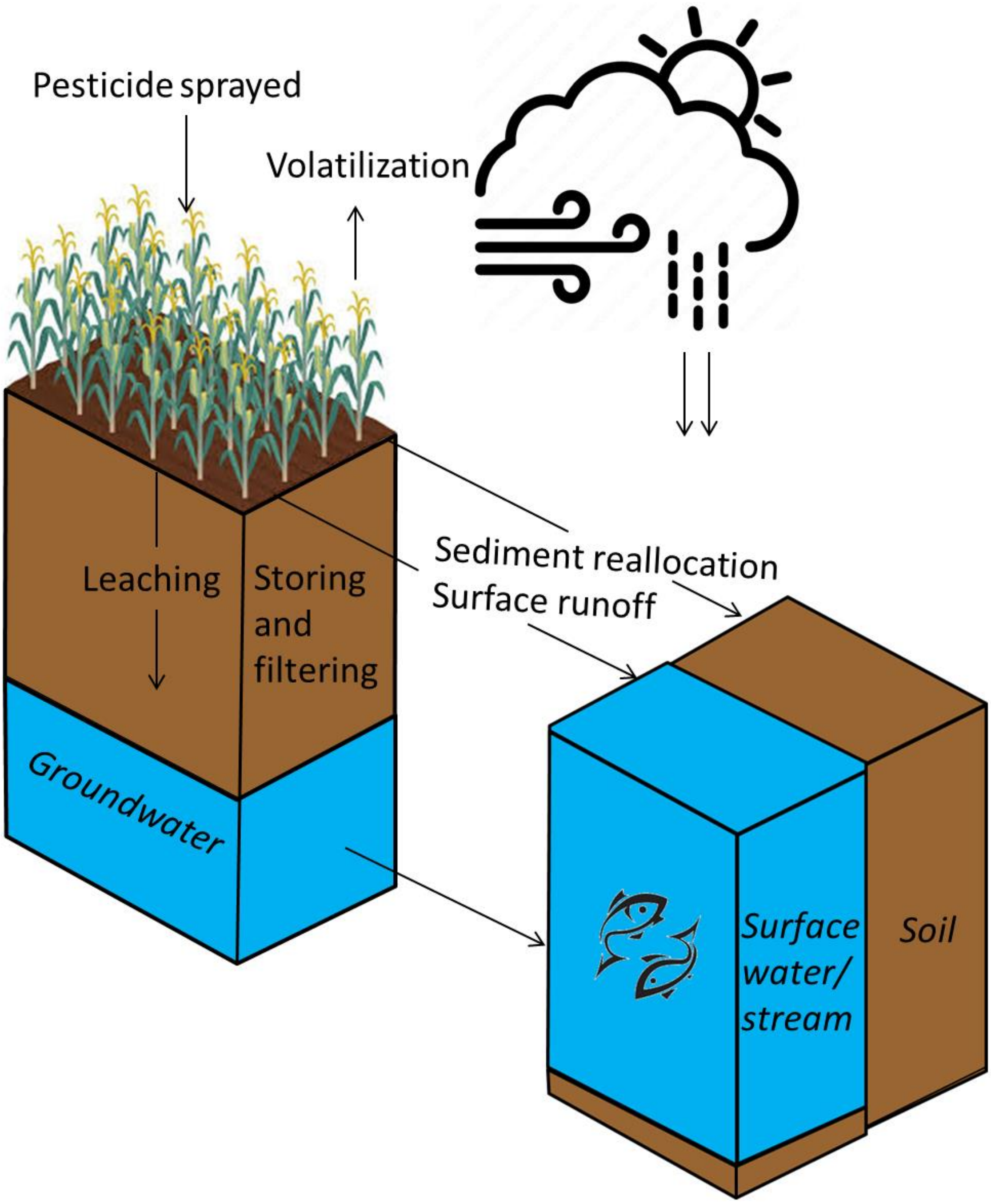

Figure 2. Extracting the number of locations and observations of the insecticide compound that was most frequently measured in soil, sediment, water and air from the insecticide residue database.

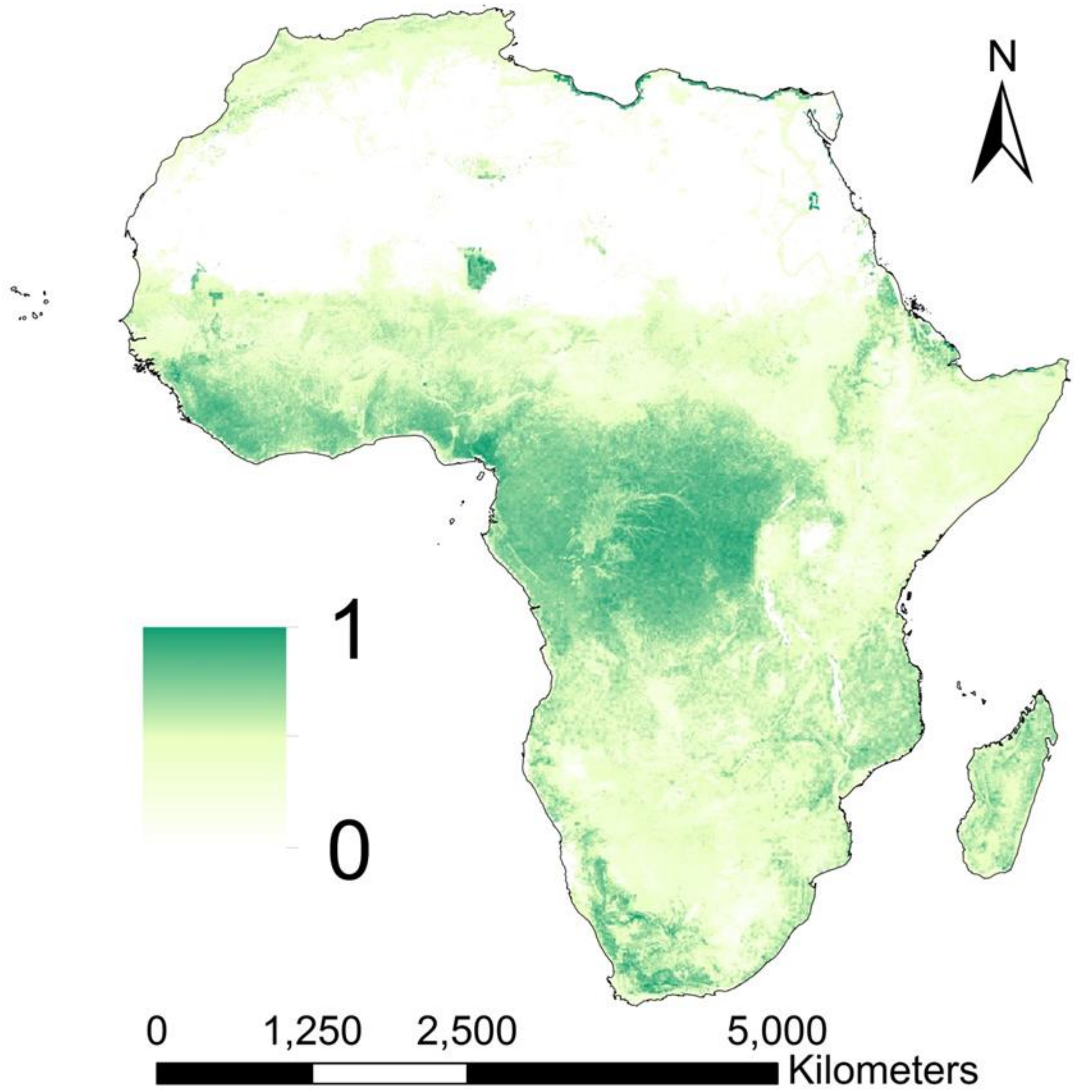

Figure 3. Map of geospatial variation in leaching.

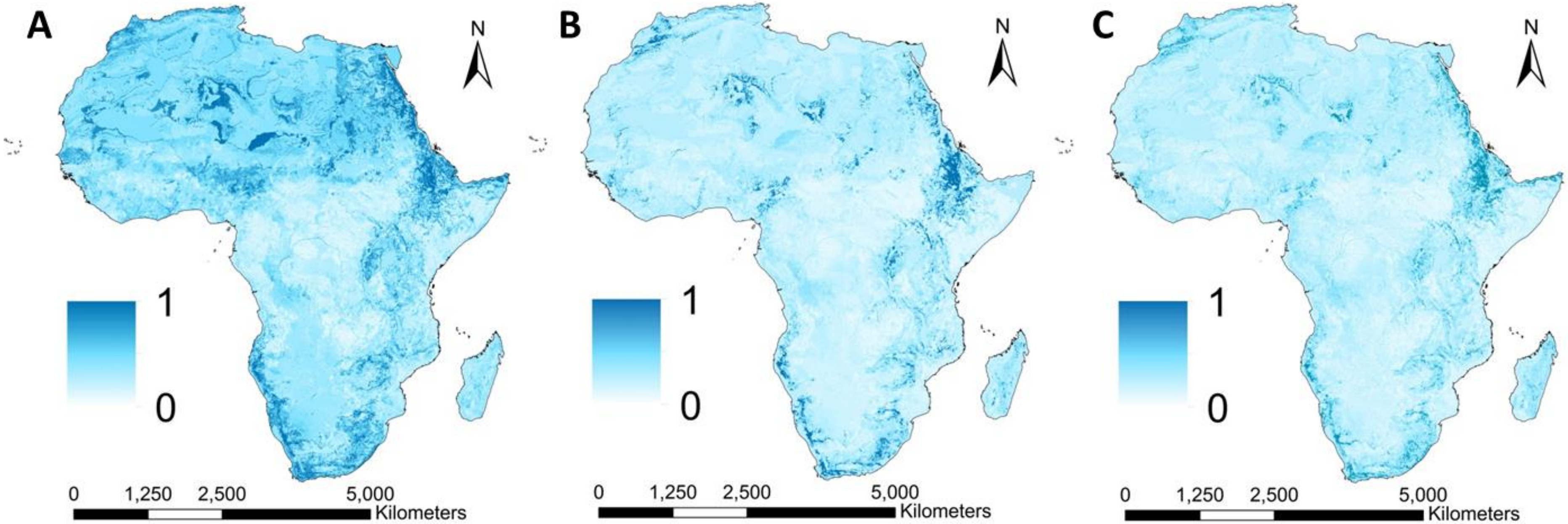

Figure 4. Map of geospatial variation in surface runoff generation (A), transportation (B) and accumulation (C).

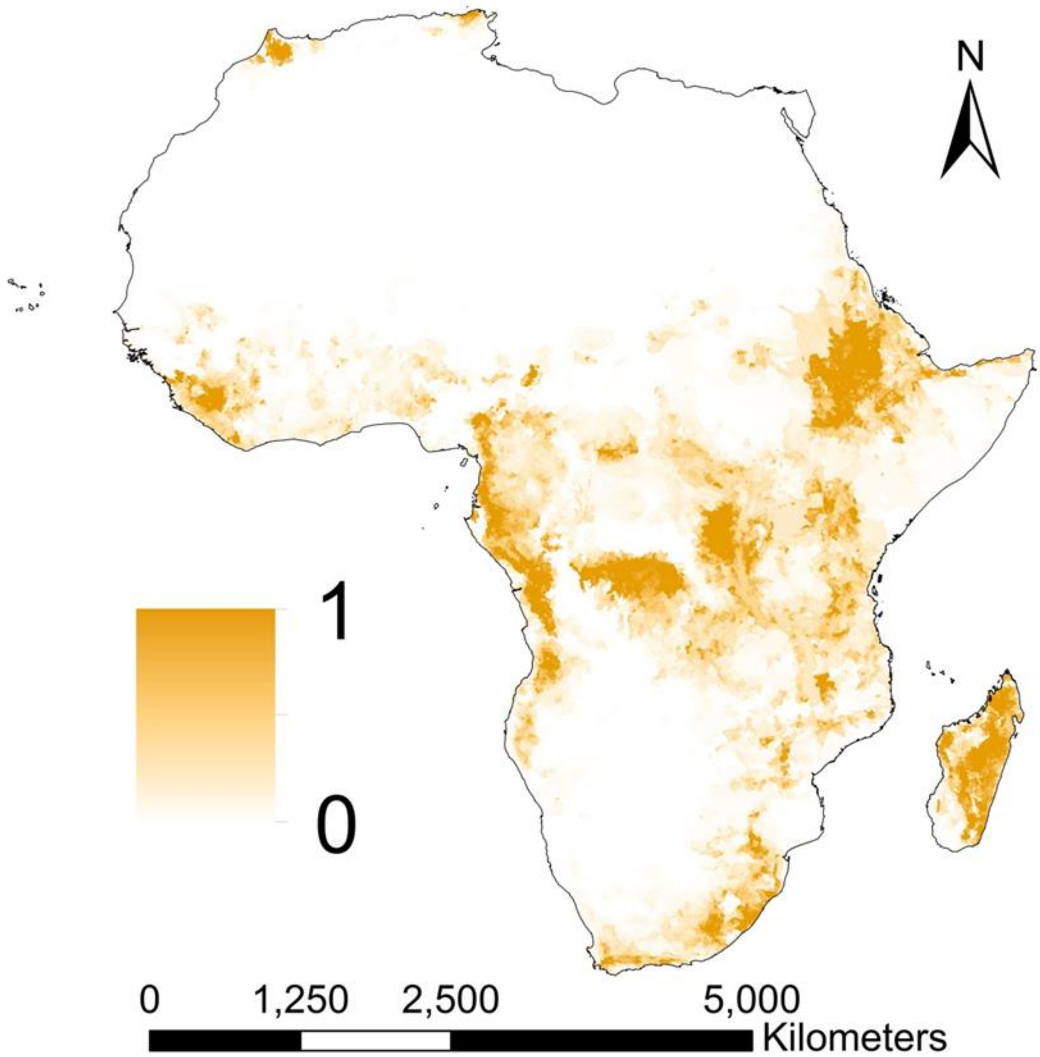

Figure 5. Map of geospatial variation in sedimentation.

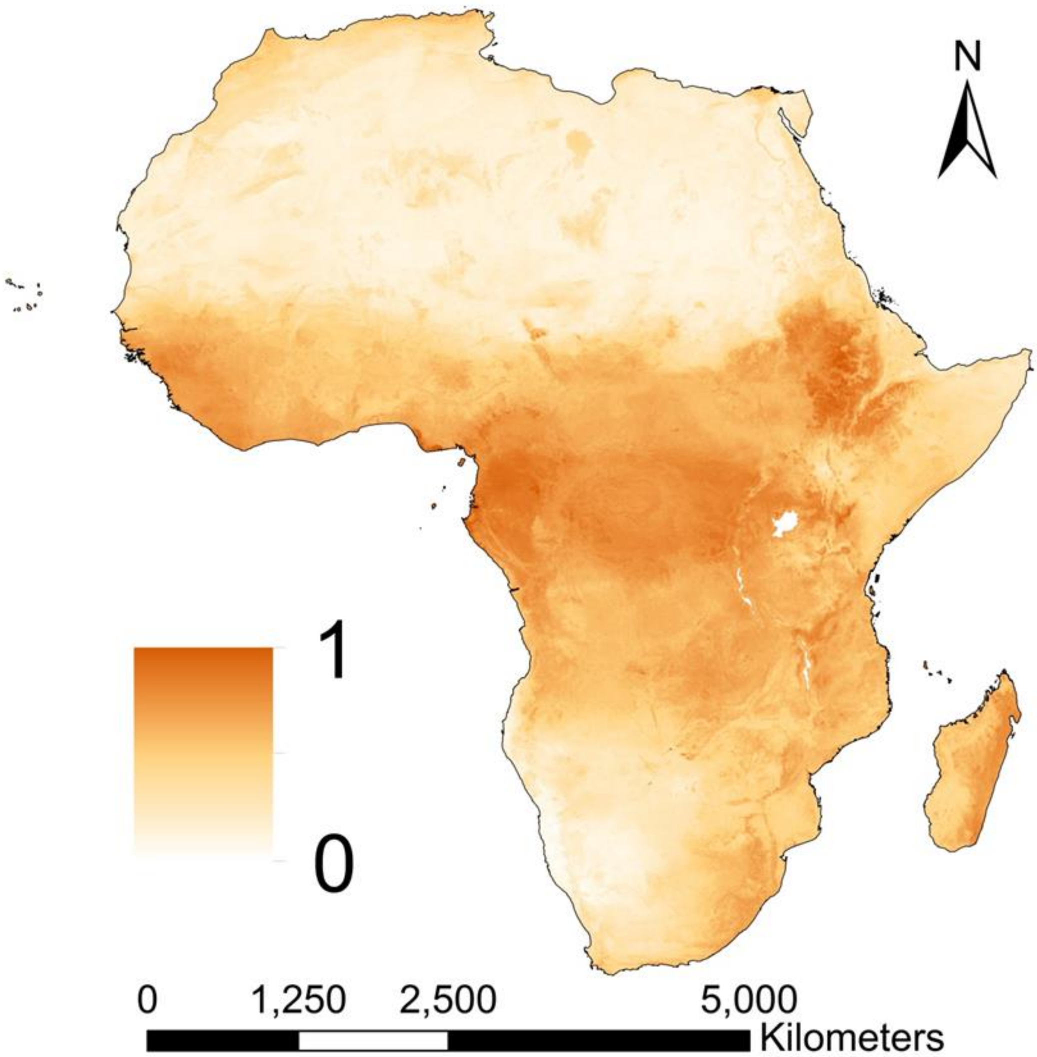

Figure 6. Map of geospatial variation in soil storage and filtering capacity.

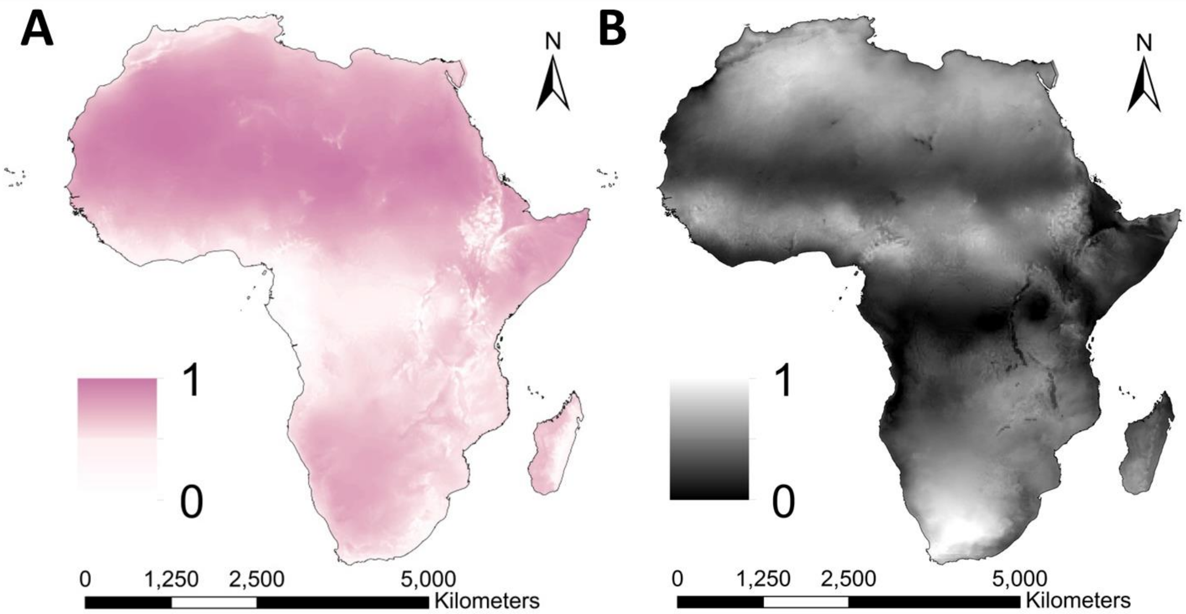

Figure 7. Map of geospatial variation in the annual mean (A) and standard deviation (B) of volatilization.

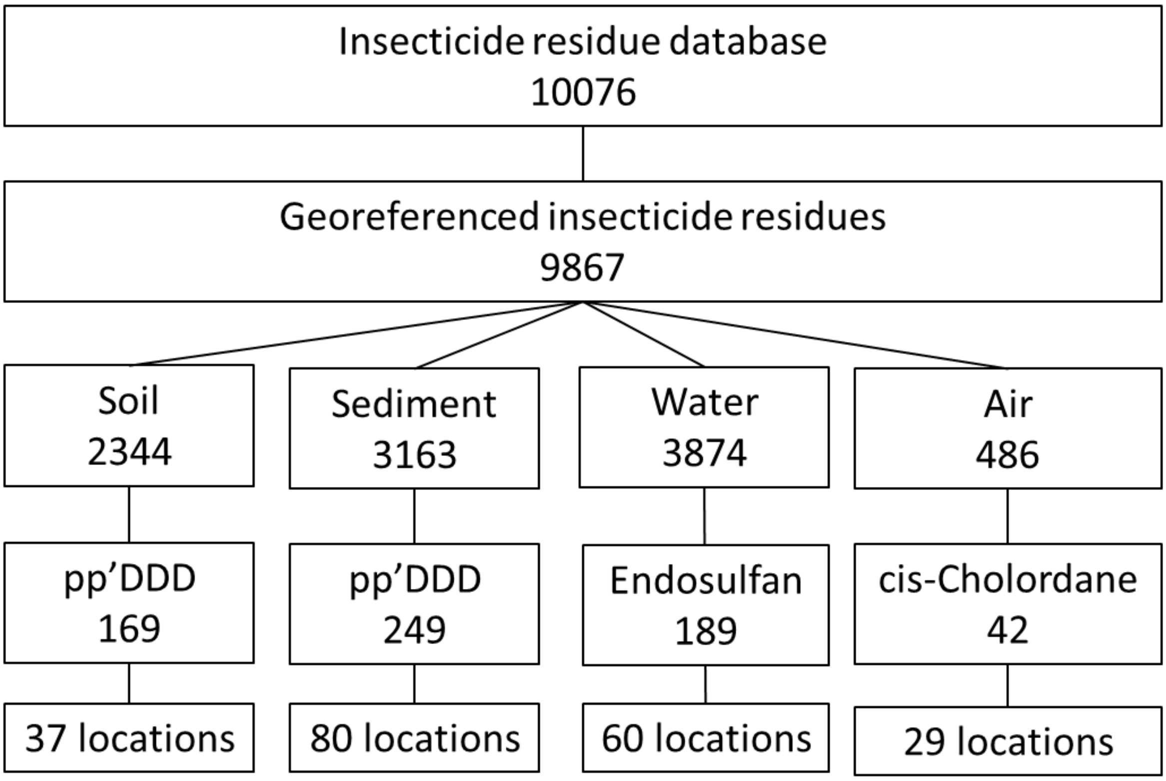

Table 1. The pesticide fate models that are selected for this study.

	Model	Country	Source
1	BASINS	U.S.A.	(85)
2	CASCADE-TOXSWA	The Netherlands	(86)
3	Chemical fate model	Australia	(49)
4	CliMoChem	Global	(87)
5	CoZMo-POP-2	U.S.A.	(59)
6	CRACK-NP	United Kingdom	(88)
7	Dynamic multimedia environmental fate model	Brazil	(48)
8	EPIC	U.S.A.	(57)
9	GIBSI	Canada	(89)
10	GLEAMS	U.S.A.	(90)
11	HSCTM-2D	U.S.A.	(91)
12	LEACHM	U.S.A.	(92)
13	MACRO	Sweden	(93)
14	OPUS	U.S.A.	(94)
15	PEARL	The Netherlands	(95)
16	PELMO	Germany	(96)
17	PESTLA	The Netherlands	(97)
18	PLM	United Kingdom	(98)
19	PRIMET	Southeast Asia	(50)
20	PRZM	U.S.A.	(54,99)
21	RZWQM	U.S.A.	(100)
22	SESOIL	U.S.A.	(101)
23	SIMULAT	Germany	(102)
24	SWAT	U.S.A.	(103)

Table 2. The environmental input data each key process associated with pesticide fate requires and the existing geospatial dataset (and its source) that is selected.

Pesticide fate process	Required input data	Selected geospatial dataset	Source of geospatial dataset
Leaching	Soil drainage rate	Soil drainage class	(22)
	Groundwater depth	Elevation	(28)
	Depth to bedrock	Depth to bedrock	(29)
	Type of bedrock	Soil drainage class	(29)
	Slope	Slope	(28)
	Soil moisture	Soil moisture	(104)
Surface runoff – Generation	Soil drainage rate	Soil drainage class	(29)
	Soil thickness	Soil thickness	(105)
	Soil erodibility	Soil erodibility factor	--
	Topography	Slope	(28)
		Flow accumulation	(28)
	Land use	Land use class	(33)
Surface runoff – Transfer	Surface runoff - Generation	Surface runoff - Generation	--
	Slope	Slope	(28)
	Break of slope	--	--
	Catchment capacity	Watershed area	(28)
		Stream length	(28)
	Artificial linear axes	--	--
Surface runoff - Accumulation	Surface runoff - Generation	Surface runoff - Generation	--
	Slope	Slope	(28)
	Break of slope	--	--
	Topographic index	Elevation	(28)
	Flow accumulation	Flow accumulation	(28)
Erosion	Rainfall erosivity factor	Rainfall erosivity	(38)
	Soil erodibility factor	Silt content	(29)
		Sand content	(29)
		Clay content	(29)
		Soil organic matter content	(29)
		Soil structure class	(39)
	Cover-management factor	Enhanced Vegetation Index	(43)
	Slope length and slope steepness factor	Slope	(28)
	Support practice factor	--	--
Sedimentation	Erosion Surface runoff - Accumulation	Erosion Surface runoff - Accumulation	--

	Watershed area	Watershed area	(28)
Soil storage and filtering capacity	Soil organic matter content	Soil organic matter content	(29)
	Clay content	Clay content	(29)
	Soil pH	Soil pH in H_2O	(29)
	Cation Exchange Capacity	Cation Exchange Capacity	(29)
Volatilization	Evapotranspiration	Potential evapotranspiration	(46)
	Wind velocity	Wind velocity	(47)
	Temperature	Land surface temperature	(106)
	Relative humidity	Relative humidity	(106)
	Solar radiation	Solar radiation	(47)

Table 3. The weights that were allocated to the different land use classes in order to estimate the process affecting surface run-off.

Forest	0
Grass/scrub/woodland	0.2
Barren/very sparsely vegetated land	0.6
Irrigated and rain-fed cultivated land	0.8
Built-up land	1

Declarations

- Ethics approval and consent to participate

Not applicable

- Consent for publication

Not applicable

- Availability of data and material

The insecticide residue database that was compiled for this study is available from 10.6084/m9.figshare.7932485.

The geospatial maps associated with the environmental fate of pesticides are available from: 10.6084/m9.figshare.7923455.

- Competing interests

The authors declare that they have no competing interests.

- Funding

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- Authors' contributions

CH conducted the study with direction from CM. CH and CM wrote the manuscript. HG and DW constructed some of the input data and assisted with the interpretation of these data. AT compiled the insecticide residue database and FW advised on the use of these data. AP developed the model to predict insecticide residues. All authors contributed to the interpretation of the results and approved the final draft of the manuscript.

- Acknowledgements

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Additional files

Additional file 1

- Format: .pdf
- Title of data: Variables used in pesticide fate models
- Description of data: The study selected 23 pesticide fate models. The variables that were used in each pesticide fate model are indicated by x.

Additional file 2

- Format: .pdf
- Title of data: Additional information on geospatial datasets used in this study
- Description of data: Additional information on the existing geospatial datasets that were used in this study for creating maps of the processes associated with pesticide fate after spraying

Additional file 3

- Format: .pdf
- Title of data: Search terms for the literature review on insecticide residues
- Description of data: An insecticide residue database was compiled from a literature review in Web of Knowledge. The table includes the search terms that were used to find studies that measured insecticide residues in soil, sediment, water and air.

Additional file 4

- Format: .pdf
- Title of data: Background information on the geospatial model for predicting insecticide residues
- Description of data: In order to further investigate the processes associated with the observed variation of the occurrence of pp'DDD across our study area, we built a spatial model which aims at explaining and predicting the probability of occurrence of pp'DDD in soil and sediment while taking into account the spatial structure in the data.