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

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Abstract

The application of agricultural pesticides in Africa has high negative effects on human health and the environment. To analyse the effect, spatial data characterizing the environmental fate of agricultural pesticides are needed. However, poor availability and quality of data that quantify pesticide application and pesticide fate limit direct analysis of the effect. This study selected key geospatial processes affecting the environmental fate of agricultural pesticides utilizing pesticide fate models and modelled the spatial variation of each process using existing geospatial databases. Maps associated with leaching, surface runoff, sedimentation, soil storage and filtering capacity, and volatilization were created using existing geospatial datasets and, if applicable, existing methods. The potential and limitations of the created maps were discussed. An insecticide residue database was created to test the maps. The database contains 10,076 observations, but only limited number of observations remain when extracting a standard dataset for one compound. This study provided a complete set of key processes affecting pesticide fate that can be used in the identification of areas vulnerable to pesticide accumulation. The created maps have potential when used in combination with data on pesticide application or, when it is known which pesticides a crop receives, data on agricultural land use.

Keywords: artificial compound, crop protection, environmental data, insecticide residue, satellite data, tropics.

1. Introduction

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), carbamate and organophosphate 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 spread resistance in non-target insects that are involved in the transmission of human diseases such as malaria and dengue (5,6). In that case, agricultural pesticides 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 environmental fate of pesticides.

Pesticide fate models can be used to obtain these data. However, this option is not very likely to success in Africa due to two main issues. Firstly, pesticide fate models require data on pesticide application, which are sparsely and inconsistently collected through space and time in Africa. For example, registered governmental data and the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) database contain data on pesticide application that were outdated, not covering the whole continent, and typically underestimating the actual pesticide use (10,11). Secondly, pesticide fate models were mainly developed, calibrated and validated with data from temperate regions (12). The accuracy of the results could not be guaranteed when using these models for tropical Africa without calibrating and validating the models first. Adapting or developing pesticide fate models for Africa as an alternative is difficult, because it requires many observations and pesticide behaviour in the environment is generally less understood in tropical regions compared to temperate regions (13–15). These issues limit direct analysis on the effect of pesticide application on the environment. Therefore, we first need to explore the areas that are vulnerable to pesticide accumulation. This study aims to select key geospatial processes affecting the environmental fate of agricultural pesticides and models the spatial variation of each process. When data on pesticide application becomes available, these maps can help indicate the areas where pesticides might end up in the environment.

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 in table S1 and S2. 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.
- 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 (approximately 5x5km pixels at the equator) or finer, (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 table S3. 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).

A global groundwater depth map at 30 arc-second resolution is available (24). This map is based on limited observations (431 sites) for Africa, but it is the best spatially exhaustive prediction on groundwater depth available. Data on bedrock depth were obtained from SoilGrids (25). 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 Shuttle Radar Topography Mission 90m Digital Elevation Database v4.1 (26). 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 environmental data were influencing leaching, the relationships between these data and leaching are location and pesticide dependent (20,21). Lack in data on leaching also hampers the use of statistical algorithms to find the best relationship. Therefore, the data were combined using a linear relationship (Eq.1).

$$L = D + (1 - GW) + (1 - DB) + (1 - SL) + SM \quad [1]$$

Where, *L* represents the vulnerability to leaching, *D* is the drainage class, GW is the normalized groundwater depth, *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 modelled 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 (27). Each process required five variables (Table 2). The method is described in more detail (28). 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 (28). The existing model (29) 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 (30). This product collated land use data between 2001 and 2012 and categorized the data into 17 different land use classes. Based on background information (28,31), 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 (28). Data on slope were obtained from the SRTM-DEM. Catchment capacity is estimated using the Horton form factor (32). 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 (33). 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 (28). How the first three indicators were obtained is described above. Flow accumulation was obtained from HydroSHEDS (33).

The correlation coefficient between the three surface runoff processes and a global insecticide runoff vulnerability (34) was derived as an indicator for deviation.

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 highly acknowledged USLE equation (Eq.1) (35).

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

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 (36) 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 (29).

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

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.

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

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 (25). Data on soil structure were obtained from the Harmonized World Soil Database (HWSD; 37).

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 (38) 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) (39).

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

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

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 (40). Gap-filled data on the mean EVI were available for Africa (41). 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

The soil storage and filtering capacity is influenced by the soil organic matter content, clay content, soil pH and cation exchange capacity (CEC) (42). 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 (25). This data source provided soil characteristics at seven fixed depth intervals ranging between 0 to 200cm depth. Soil profile data were obtained by taking depth weighted averages of these seven layers. Although we know which environmental data were influencing the storage and filtering capacity, the relationships between these data and storage and filtering capacity are location and pesticide dependent (42). Lack in data on storage and filtering capacity in African soils also hampers the use of statistical algorithms to find the best relationship. Therefore, the data were combined using a linear relationship (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 (43). Long-term annual average PET data were obtained from the CSI-CGIAR Global Potential Evapotranspiration Climate Database (44). Long-term (1970-2000) average monthly wind speed and solar radiation data were obtained from WorldClim V.2 (45). 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. Again, due to lack in knowledge about the relationship between these data and the volatilization rate, 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*, WV_i is normalized long-term wind velocity in month *i*, $S_{rad,i}$ is the normalized long-term solar radiation in month *i*, 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 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 was validated using observational data. However, for none of the key processes these data were available across Africa. Therefore, the maps constructed here could not be validated, but their potential was tested instead. To test the potential of the maps for modelling pesticide residues in the environment, observational data on pesticide residues were required.

2.4.1. Insecticide residue database

This study was part of a wider project on insecticide resistance (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 table S4. 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. The observations were collected from 68 studies. Within this database, 93 different types of insecticides were measured in 2344 soil samples, 3163 sediment samples, 3874 water samples and 486 air samples. A lack of standardisation in the collection, extraction and detection methods makes it hard construct a standard dataset. The number of samples that were measured at unique locations dropped rapidly 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. Using the created maps to spatially predict pesticide residues

Overall, pp'Dichlorodiphenyldichloroethane (pp'DDD) was most frequently and most consistently measured in the substrates soil and sediment. Therefore, pp'DDD observations measured in soil and sediment were extracted from the database to obtain a standard dataset for one compound. This resulted in the extraction of 385 observations measured from 100 locations between 1992 and 2016. The limited number of observations and the clustered location of the observations makes it not possible to do any spatial prediction on pesticide residues. Before we can analyse the potential of the constructed maps, we need to: (i) test the sampling error, (ii) collect consistently data on pesticide residues to better inform the models, and (iii) create datasets for each pesticide fate process to validate the co-variates.

3. Results and discussion

<u>3.1. Identifying pesticide fate models and select key processes</u>

Only three out of 24 identified models were developed, calibrated and validated in tropical or sub-tropical areas: the Dynamic Multimedia Environmental Fate Model (46) was developed for the tropical floodplains of Brazil, the Chemical Fate Model (47) was developed for a tropical river catchment in Australia and the Pesticides RIsks in the tropics to Man, Environment and Trade Pesticide model (PRIMET; 48) was developed in Southeast Asia and later adapted to Ethiopia (PRIMET-Ethiopia; 49). Some models were developed elsewhere, but applied in tropical and sub-tropical areas. For example, the Soil and Water Assessment Tool (SWAT) model (50,51) was developed in the U.S.A., but had, for example, frequently been applied in Southeast Asia. The Pesticide Root Zone Model (PRZM; 52) and the TOXic substances in Surface Waters (TOXSWA) model (53) were developed in the U.S.A and The Netherlands respectively, but the models have been applied in Ethiopia (54). The Environmental/Policy Integrated Climate (EPIC) model (55) was developed in the U.S.A, but has, amongst others, been applied in West Africa and Brazil (56), and the Coastal Zone Model for Persistent Organic Pollutants – Version 2 (CoZMo-POP-2; 57) was also developed in the U.S.A., but has been applied in Botswana (58). 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.

The model 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 (59). 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 (60,61).

Our resulting maps of surface runoff were compared to the global insecticide runoff vulnerability map (34). 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 (62), 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 (63), the Upper Blue Nile Basin (Ethiopia) receives large quantities of sediments from agricultural areas in the catchments (64,65) and natural processes dominate the soil allocation in Congo (66), although agricultural development and deforestation has increased the sediment load over recent decades (67).

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 (68).

The role soil characteristics play in pesticide binding is less documented and, in general, less understood for tropical soils (69–71). 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 on 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 (72) and only for a few hours after spraying (73), while other studies measured pesticides up to a few kilometres from the source (73) and up to two months after spraying (74). 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.

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 can potentially accumulate in Africa. The created maps have potential when used in combination with data on pesticide application. These data need to include when, how much, and which type of pesticides were applied (75). Instead of pesticide application data, the maps can also have potential when used in combination with land use data. The potential of modelling pesticide application from data on agricultural land use has been explored (76). 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 (76). When data on the latter become available for Africa, this option can be considered. National pesticide legislations and regulations or Global Open Data Portals (e.g., SOILSERIES) might increase the availability of systematically registered pesticide application data.

Pesticide fate in Africa has dominantly been studied at local or national scale. For example, pesticide use in South Africa was mapped (77), surface water contamination in Ethiopia was assessed (54) and the effect of pesticide leaching on the contamination of Lake Naivasha was mapped (78). Global initiatives have focussed, so far, only 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 covered the African continent and considered aquatic, terrestrial and atmospheric processes. However, we need to be careful using the created maps in studies at finer scale, because pesticide fate processes can be influenced locally by site-specific land management decisions (79). The maps can be used beyond pesticide fate studies. For example, the map on spatial variation estimates of sedimentation can also be used in studies on flood risk (80) and surface water eutrophication (65). 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 created maps.

Long-term monthly averages were not always available from existing geospatial datasets. Therefore, the created maps did not account for the seasonal effect of pesticide fate processes, while it is known that seasonality plays a role in some of the processes (81,82). Creating each pesticide fate process individually does not account for interactions between different processes, which is taken into account by pesticide fate models. However, our approach did not require pesticide application data, and we were able to construct the maps using existing geospatial datasets. Another 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 provided a complete set of aquatic, terrestrial and atmospheric processes affecting pesticide fate in Africa and served as a first step in the identification of areas where agricultural pesticides can accumulation. 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. The created maps can help decision makers to identify areas where the need for pesticide application and residue data is highest to reduce the impact pesticides have on human health and the environment.

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Supplementary material

S1. A list of variables that were used by 23 different pesticide fate models.
S2. The number of times a variable was used in the selected 23 pesticide fate models and the processes that were mapped in this study.
S3. 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.
S4. The search terms that were used to find studies that measured insecticide residues. The literature review is used to compile an insecticide residue database.

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Author 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 tested the potential of the insecticide residue database. All authors contributed to the interpretation of the results and approved the final draft of the manuscript.

Conflicts of Interest

The authors declare that they have no competing interests.

Data availability

The datasets generated during and/or analysed during the current study are available in the FigShare repositories, https://doi.org/10.6084/m9.figshare.7923455.v2 and https://doi.org/10.6084/m9.figshare.7932485.v3.

Supplementary Materials

Table S1. In total, 23 pesticide fate models were selected. The variables that were used in each pesticide fate model are indicated by ‘x’ (Table 1).

	Model	Advection	Baseflow	By-pass flow	Convection	Deposition	Diffusion	Dispersion/ dissolution	Dissipation	Evapo-transpiration	Infiltration
1	BASINS										x
2	CASCADE-TOXSWA										x
3	Chemical fate model	x				x					x
4	CliMoChem	x					x				
5	CoZMo-POP-2 model	x						x		x	
6	CRACK-NP			x							x
7	Dynamic multimedia environmental fate model					x	x	x			x
8	EPIC									x	
9	GIBSI										x
10	GLEAMS								x	x	x
11	HSCTM-2D	x				x	x	x			
12	LEACHM									x	x
13	MACRO		x		x		x			x	x
14	OPUS									x	x
15	PEARL		x		x		x	x	x	x	x
16	PELMO		x					x			x
17	PESTLA		x		x			x			x

18	PLM			x			x			x	x
19	PRIMET									x	x
20	PRZM	x					x	x			x
21	RZWQM		x	x					x	x	x
22	SESOIL	x				x	x			x	x
23	SIMULAT			x					x	x	x
24	SWAT										x

	Model	Lateral throughflow	Percolation	Plant uptake	Sorption	Surface runoff	Transformation and degradation	Volatilization	Wash-off	Water erosion	Wind drift
1	BASINS		x		x	x			x		
2	CASCADE-TOXSWA		x			x				x	x
3	Chemical fate model		x			x	x		x		
4	CliMoChem						x	x			
5	CoZMo-POP-2 model	x		x	x	x	x	x	x		
6	CRACK-NP		x		x						
7	Dynamic multimedia environmental fate model		x				x	x			x
8	EPIC					x				x	x
9	GIBSI					x				x	
10	GLEAMS		x			x			x		
11	HSCTM-2D				x		x			x	
12	LEACHM		x	x	x	x					
13	MACRO	x	x		x	x	x				
14	OPUS		x			x	x			x	
15	PEARL		x	x			x	x	x		

16	PELMO	x	x	x	x	x	x	x	x	
17	PESTLA	x		x		x				
18	PLM	x		x		x				
19	PRIMET	x			x		x			x
20	PRZM	x	x	x	x	x			x	
21	RZWQM	x	x	x	x		x			
22	SESOIL	x		x	x	x	x	x	x	
23	SIMULAT				x					
24	SWAT	x		x	x			x	x	

Table S2. How often a variable was used in the selected pesticide fate models and the processes that were mapped in this study.

Variables	# models that use this variable	Processes that were mapped in this study
Infiltration	20	Leaching
Percolation	18	Leaching
Surface runoff	17	Surface runoff generation, transfer, accumulation
Transformation and degradation	13	
Sorption	13	Soil storage and filtering capacity
Evapotranspiration	12	Volatilization
Water erosion	9	Erosion
Volatilization	8	Volatilization
Diffusion	8	
Dispersion	7	
Wash-off	8	
Advection	6	
Plant uptake	6	
Base flow	5	
By-pass flow	4	

Deposition	4
Dissipation	4
Wind drift	4
Convection	3
Lateral through flow	2

Table S3. 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.

Property	Unit	Database	Spatial resolution	Spatial coverage	Temporal resolution	Temporal coverage	Source
Cation Exchange Capacity	cmol + /kg	SoilGrids	30-arc second	Sub-Saharan Africa	Static		(1)
Clay content	%	SoilGrids	30-arc second	Sub-Saharan Africa	Static		(1)
Depth to bedrock	cm	SoilGrids	30-arc second	Sub-Saharan Africa	Static		(1)
Elevation	m	SRTM-DEM	3 arc-second	Global	Static		(2)
Enhanced Vegetation Index	--	Weiss et al., 2014	30-arc second	Global	Static		(3)
Flow accumulation	m	HydroSHEDS	30 arc-second	Global	Static		(4)
Groundwater depth	m		30-arc second	Global	Static		(5)
Land use class	--	MCD12Q1	30-arc second	Global	Yearly	2001–2012	(6)
Potential Evapotranspiration	mm/month	CGIAR-CSI GeoPortal	30-arc second	Global	Static	Long-term average 1950-2000	(7)
Rainfall erosivity	MJ·mm/ha/ h/yr	USLE	30 arc-second	Global	Static		(8)
Relative humidity	%	Global Forecast System	15 arc-minute	Global	16-day	2015-present	(9)
Sand content	%	SoilGrids	30-arc second	Sub-Saharan Africa	Static		(1)
Silt content	%	SoilGrids	30-arc second	Sub-Saharan Africa	Static		(1)

Slope	°	SRTM-DEM	3 arc-second	Global	Static		(2)
Soil drainage class	--	AfSoilGrids250m	30-arc second	Sub-Saharan Africa	Static		(10)
Soil moisture	mm	NASA-USDA SMAP Global Soil Moisture Data	15 arc-second	Global	3-days	2015 - present	(11)
Soil organic matter content	‰	SoilGrids	30-arc second	Sub-Saharan Africa			(1)
Property	Unit	Database	Spatial resolution	Spatial coverage	Temporal resolution	Temporal coverage	Source
Soil pH in H_2O	--	SoilGrids	30-arc second	Sub-Saharan Africa	Static		(1)
Soil structure class	--	HWSD	30-arc second	Global	Static		(12)
Soil thickness	cm	S-World	30-arc second	Global	Static		(13)
Solar radiation	kJ/m^2/day	WorldClim V.2.	30-arc second	Global	Long-term monthly average	1950-2000	(14)
Stream length	m	HydroSHEDS	30 arc-second	Global	Static		(4)
Temperature	°C	MOD11A1 V6	30-arc second	Global	1-day	2000-present	(15)
Watershed area	m^2	HydroSHEDS	30 arc-second	Global	Static		(4)
Wind velocity	m/s	WorldClim V.2.	30-arc second	Global	Long-term monthly average	1950-2000	(14)

Table S4. 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. The following data were systematically extracted: year and month(s) of sampling, collection methods and depth, extraction method, quantification method, limit of quantification and detection, insecticide type and class, detected insecticide concentration and geographical coordinates.

‘pyrethroid’ AND spati*’ OR ‘pyrethroid’ AND ‘map*’
‘organophos AND spati*’ OR ‘organophos’ AND ‘map*’
‘carbamate’ AND spati*’ OR ‘carbamate’ AND ‘map*’
‘pyrethroid’ AND ‘watershed’ OR ‘run-off’ OR ‘groundwater’ OR ‘drift’ OR ‘deposition’ OR ‘precipitation’ OR ‘soil’ OR ‘sediment’ OR ‘coverage’ OR ‘atmosphere*’
‘organophos* AND ‘watershed’ OR ‘run-off’ OR ‘groundwater’ OR ‘drift’ OR ‘deposition’ OR ‘precipitation’ OR ‘soil’ OR ‘sediment’ OR ‘coverage’ OR ‘atmosphere*’
‘carbamate AND ‘watershed’ OR ‘run-off’ OR ‘groundwater’ OR ‘drift’ OR ‘deposition’ OR ‘precipitation’ OR ‘soil’ OR ‘sediment’ OR ‘coverage’ OR ‘atmosphere*’
‘residu*’ AND ‘pyrethroid’ OR ‘organophos*’ OR ‘carbamate’ AND ‘COUNTRYNAME’ NOT ‘indoor residual spray*’

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