JAMES | Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE
10.1029/2018MS001367

Soil Chemistry Aspects of Predicting Future Phosphorus Requirements in Sub-Saharan Africa

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Key Points:
- Soil geochemical theory is implemented into a widely used phosphorus (P) model, which predicts P required based on food demand
- To estimate the P requirements in Sub-Saharan Africa, the soil heterogeneity, especially in Vertisol soils, should be included in analysis
- This study presents a simple model that incorporates soil chemistry and P pools in crop-soil modeling

Supporting Information:
- Supporting Information S1

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Citation:
Magnone, D., Niasar, V. J., Bouwman, A. F., Beusen, A. H. W., van der Zee, S. E. A. T. M., & Sattari, S. Z. (2019). Soil chemistry aspects of predicting future phosphorus requirements in Sub-Saharan Africa. *Journal of Advances in Modeling Earth Systems*, *11*, 327–337. https://doi.org/10.1029/2018MS001367

Received 6 MAY 2018
Accepted 26 DEC 2018
Accepted article online 2 JAN 2019
Published online 27 JAN 2019

Abstract Phosphorus (P) is a finite resource and critical to plant growth and therefore food security. Regional- and continental-scale studies propose how much P would be required to feed the world by 2050. These indicate that Sub-Saharan Africa soils have the highest soil P deficit globally. However, the spatial heterogeneity of the P deficit caused by heterogeneous soil chemistry in the continental scale has never been addressed. We provide a combination of a broadly adopted P-sorption model that is integrated into a highly influential, large-scale soil phosphorus cycling model. As a result, we show significant differences between the model outputs in both the soil-P concentrations and total P required to produce future crops for the same predicted scenarios. These results indicate the importance of soil chemistry for soil-nutrient modeling and highlight that previous influential studies may have overestimated P required. This is particularly the case in Somalia where conventional modeling predicts twice as much P required to 2050 as our new proposed model.

Plain Language Summary Improving food security in Sub-Saharan Africa over the coming decades requires a dramatic increase in agricultural yields. Global yield increase has been driven by, among other factors, the widespread use of fertilizers including phosphorus. The use of fertilizers in Sub-Saharan Africa is often prohibitively expensive, and thus, the most efficient use of phosphorus should be targeted. Soil chemistry largely controls phosphorus efficiency in agriculture; for example, iron and aluminum, which exist naturally in soil, reduce the availability of phosphate to plants. Yet soil chemistry has not been included in several influential large-scale modeling studies, which estimate phosphorus requirements in Sub-Saharan Africa to 2050. In this study we show that predictions of phosphorus requirement to feed the population of Sub-Saharan Africa to 2050 can significantly change if soil chemistry is included (e.g., Somalia with up to 50% difference). Our findings are a new step toward making predictive decision-making tool for phosphorus fertilizer management in Sub-Saharan Africa considering the variability of soil chemistry.

1. Introduction

Phosphorus (P) is an element that is crucial to plant growth and has been described as *life's bottleneck* (Cordell & White, 2014). Yet it is also a finite resource for which estimates of remaining stores differ greatly (Cordell et al., 2009; Cordell & Neset, 2014; Van Vuuren et al., 2010). Its supply is critical to food security, and as the global population grows, demand will continue to increase as well. Therefore, global P requirement over the coming century has become a major concern (Bouwman et al., 2017; Elser & Bennett, 2011; Sattari et al., 2012, 2016). Current estimates suggest that 1,200 Gt of P will be required globally to support food production to 2050. Of this 140 Gt will be required in Sub-Saharan Africa (SSA). However, the crisis is most serious in SSA because the P application should increase from 4.0 $kg \cdot ha^{-1} \cdot yr^{-1}$ in 2007 to 22 $kg \cdot ha^{-1} \cdot yr^{-1}$ by 2050, a 5.6-fold increase. To put this into context, the only other continent, which is also expected to require an increase in P application, is North America, which requires a 1.55-fold increase (from 11 to 18 $kg \cdot ha^{-1} \cdot yr^{-1}$ in the same period). All other continents are predicted to either maintain or decrease P application rates (Sattari et al., 2012).

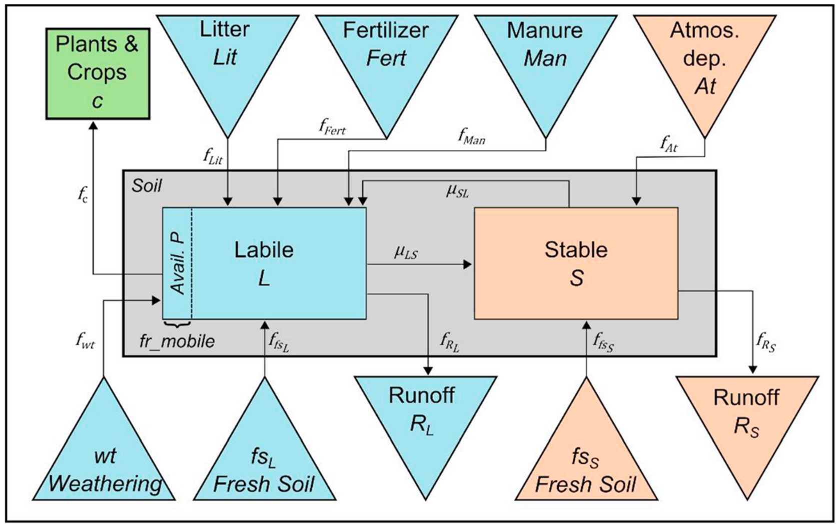

Figure 1. Sketch of the dynamic phosphorus pool simulator (after Zhang et al., 2017).

The quantitative P requirement for 2050 at a continental scale has been estimated using the dynamic two P-pool simulator (DPPS) in combination with the Millennium Ecosystem Assessment (MEA) scenarios (Sattari et al., 2012; Zhang et al., 2017). The MEA was a large project commissioned by the United Nations between 2001 and 2004 assessing of the state of global ecosystems and the effects this would have on human well-being. The findings outline a range of resource scenarios (e.g., for clean water, food, forest products, flood control, and natural resources) to 2050 dependent upon different global behaviors (Millennium Ecosystem Assessment, 2005). The conceptual framework of Shared Socioeconomic Pathways has been specifically developed to account for human behavior the field of environmental and climatic modeling. It outlines five alternative plausible societal trends, which will have varying impacts on ecosystems and the economy (O'Neill et al., 2014; van Vuuren et al., 2014). These predictive scenarios are used to constrain future elements of DPPS (Mogollón et al., 2018; Zhang et al., 2017). DPPS results have been highly influential both within the scientific community and in policy development (e.g., Parliamentary Office of Science and Technology, 2014).

The DPPS model distinguishes two soil P pools, labile, and stable P. The labile pool comprises P that is partially available to plants and can be up-taken from soil, while stable P refers to the fraction that is inaccessible to plants. In DPPS, these pools are utilized to understand current P trends and make future predictions (Figure 1; Sattari et al., 2012; Wolf et al., 1987; Zhang et al., 2017). DPPS calculates how much P is required to keep pace with the population growth and associated food demand and agricultural production and land use as defined by MEA (Alcamo et al., 2005). A recent development of DPPS is the spatially specific gridded version, which predicts P use globally on a 0.5 by 0.5° grid (Zhang et al., 2017). The input and output data for this approach are from the Integrated Assessment of Global Environmental Change (IMAGE), an ecological-environmental model framework which assess and predicts consequences to the environment of anthropogenic activities globally (Stehfest et al., 2014). Included within this are data on P uptake for each grid cell based on Food and Agriculture Organization (2018); these do not represent uptakes of individual crops but rather the sum of the P uptake of all the crops in that grid cell. The crop uptake predicted by the model using P input data is compared to the data on total P uptake for historical years. For the future, DPPS uses projected crop uptake to compute the required inputs.

In soils the P exchange between the pools is largely controlled by the concentration of oxalate extractable iron and aluminum (i.e., the amount of amorphous iron and aluminum; Freese et al., 1992; van der Zee & van Riemsdijk, 1988). The higher these iron and aluminum concentrations are, the greater the sequestration of P from labile to stable will be (Freese et al., 1992, 1995; van der Zee & van Riemsdijk, 1988). Including such sorption processes in catchment scale P-models have increased precision (Della Peruta et al., 2014; Jackson-Blake et al., 2016); however, in previous continental, regional, and country-scale studies, the role of soil chemistry in P requirement assessment has been ignored. Accounting for soil chemical spatial heterogeneity when addressing the P-deficit question has been highlighted as an area in need of urgent research (Magnone et al., 2017).

In this study, we aim to investigate the impact of soil heterogeneity on estimated P requirement in different soil types in SSA. We combine a soil-P chemical model that has been used in diverse soil types and climate zones (Freese et al., 1992; van der Zee & van Riemsdijk, 1988), with a large-scale soil P dynamics model, DPPS (Sattari et al., 2012; Wolf et al., 1987; Zhang et al., 2017). This integrated model (referred to as GDPPS) is used to characterize how spatial variability of soil properties translates in differences in P requirements across SSA. Additionally, we address the long-term behavior of the SSA countries in response to the P application depending on their indigenous soil types.

We study eight countries in SSA (Burkina Faso, Nigeria, Angola, Mozambique, Cameroon, D. R. Congo, Somalia and Sudan) divided among four dominant soil types (Alfisol, Ultisol, Oxisol, and Vertisol). Each country has been selected to be representative of a relatively high or low P input throughout the 20th century. Additionally, we studied four countries with mixed soils (Cote d'Ivoire, Ethiopia, Kenya, and Tanzania) for model verification.

2. Methods

2.1. Model Formulations

DPPS calculates the concentration of P inputs required to maintain food production for a given scenario. It has two P pools, the partially plant-accessible labile pool (Olsen et al., 1954) and the inaccessible stable pool (Sattari et al., 2012; Yang et al., 2013). Of the labile pool it is only the mobile phase (determined by *fr_mobile*), which is available to plants (Olsen et al., 1954; Zhang et al., 2017). Each pool has different inputs and outputs: litter, manure, and fertilizer to the labile pool and atmospheric deposition and fresh soil input to the stable pool. Outputs include runoff for both pools as well as plant uptake for the labile. P can be transferred between the labile and stable pools at different rates, referred to as μ_{SL} and μ_{LS} (Figure 1). Within DPPS, the mass transfer rates between the two pools are constant in time but vary spatially (Sattari et al., 2012, 2016; Vitousek et al., 2009; Wolf et al., 1987). The DPPS governing equations are given by equations (1) and (2) (Sattari et al., 2012; Zhang et al., 2017):

$$\frac{dL}{dt} = \mu_{SL}S - \mu_{LS}L + f_{\mathrm{Lit}} + f_{\mathrm{Fert}} + f_{\mathrm{Man}} + f_{\mathrm{wt}} + f_{\mathrm{fs_L}} - f_{\mathrm{R_L}} - f_{\mathrm{c}} \tag{1}$$

$$\frac{dS}{dt} = \mu_{LS}L - \mu_{SL}S + f_{\mathrm{At}} + f_{\mathrm{fs_S}} - f_{\mathrm{R_s}} \tag{2}$$

where the temporal change of the labile pool size (dL/dt) is due to input fluxes ($\mathrm{kg \cdot ha^{-1} \cdot yr^{-1}}$) from fertilizer ($f_{\mathrm{Fert}}$), litter ($f_{\mathrm{Lit}}$), manure ($f_{\mathrm{Man}}$), fresh soil ($f_{\mathrm{SL}}$), and weathering ($f_{\mathrm{wt}}$) and outputs from runoff (f_{RL}) and crop uptake (f_{c}). Additionally, there are transfer fluxes between the two pools, μ_{SL} ($\mathrm{yr^{-1}}$) and μ_{LS} ($\mathrm{yr^{-1}}$), which represent the transfer rates stable to labile pool and labile to stable pool, respectively—in DPPS these parameters are constrained by history matching (Sattari et al., 2012; Zhang et al., 2017). The change in stable pool size (dS/dt) is controlled by the balance of input fluxes ($\mathrm{kg \cdot ha^{-1} \cdot yr^{-1}}$) from atmospheric deposition (f_{At}), fresh soil (f_{fsS}), and outputs of runoff (f_{RS}).

To develop the GDPPS model, we incorporated a soil chemistry model into DPPS based on the van der Zee and Van Riemsdijk model (vdZ-vR; Freese et al., 1992; van der Zee & van Riemsdijk, 1988). This characterizes the kinetic relationship between the labile and stable pools. The vdZ-vR model was successfully applied to the Brazilian tropical soils similar to those of SSA (Alleoni et al., 2012; de Campos et al., 2016), across a range of pH-values (Andersson et al., 2016; do Carmo Horta et al., 2010; do Carmo Horta & Torrent, 2007; Freese et al., 1995; House et al., 2004; Maguire et al., 2001); all of which were within the range of SSA soils (Hengl et al., 2017). vdZ-vR (Freese et al., 1992; van der Zee & van Riemsdijk, 1988) states that the concentration of the stable pool controlled by the chemical kinetics (S_c, $\mathrm{kg \cdot ha^{-1}}$) is proportional to the size of weathered (amorphous, oxalate-extractable) Fe and Al oxide concentrations and the size of the labile pool. It is described as follows:

$$S_c = k \cdot M \cdot \ln(a \cdot L \cdot t) \tag{3}$$

where L is the labile pool ($\text{kg} \cdot \text{ha}^{-1}$), a is the rate constant ($\text{ha} \cdot \text{year}^{-1} \cdot \text{kg}^{-1}$), M is the oxalate iron and aluminum ($\text{kg} \cdot \text{ha}^{-1}$), and k is a dimensionless activity constant. By differentiating vdZ-vR (Freese et al., 1992; van der Zee & van Riemsdijk, 1988) with the chain rule a local approximate kinetic soil P model is derived (equations (4) and (5)). This controls the transfer of P between labile and stable pools with the amorphous fractions of iron and aluminum oxides and hydroxides, which are commonly quantified by the acid-ammonia oxalate (oxalate) extraction in a routine soil analysis procedure (van der Zee & van Riemsdijk, 1988).

$$\frac{dS_c}{dL} = \frac{kM}{L} \tag{4}$$

$$\frac{dS_c}{dt} = \frac{dS_c}{dL}\frac{dL}{dt} = \frac{kM}{L}\frac{dL}{dt} \tag{5}$$

Where the labile pool increases, the μ_{LS} transfer is equal to dS_c/dt. The opposite rate transfer, μ_{SL}, is assumed to be caused by the dissolution of the total stable pool (S, $\text{kg} \cdot \text{ha}^{-1}$) at a constant rate ($r$, yr^{-1}). Thus, multiplying the stable pool by the rate, $S \cdot r_S$ provides the flux from stable pool dissolution ($\text{kg} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$). Substituting these into DPPS (equations (1) and (2)) provides the governing equations for GDPPS equations (6) and (7):

$$\frac{dL}{dt} = \frac{f_{\text{Lit}} + f_{\text{Fert}} + f_{\text{Man}} + f_{\text{wt}} + f_{\text{fs}_\text{L}} - f_{\text{R}_\text{L}} - f_{\text{c}} + S \cdot r_S}{1 + \frac{k \cdot M}{L}} \tag{6}$$

$$\frac{dS}{dt} = f_{\text{At}} + f_{\text{fs}_\text{S}} - f_{\text{R}_\text{s}} - S \cdot r_S + \frac{k \cdot M}{L} \cdot \frac{dL}{dt} \tag{7}$$

2.2. Model Parameterization

For both models, consistent with Zhang et al. (2017), the input and output data were from the IMAGE project (E. Stehfest et al., 2014) and initial pool sizes were provided by Yang et al. (2013). Initialization for both models occurs in 1900 assuming a steady state condition. During the historical part (<2006), the equations are solved with the unknown *fr_mobile*,and the size of the pools is determined for each year. For the scenario mode *fr_mobile* is provided by using a regional specific multiplier for the 2005 value (which is different for the two models). Annual *fr_mobile* values are provided in the supporting information.

For GDPPS values for M were provided by ISRIC through the SoilGrids project and maintained constant and throughout the duration of the modeled period (Hengl et al., 2017). We determined the activity constant, k, for each individual grid cell from the virgin soils conditions assuming that a is unity (i.e., $a = 1$; van der Zee & van Riemsdijk, 1988) and that soils had been in equilibrium for 400 years (Goldewijk et al., 2010; Nicholson et al., 2013). The dissolution rate constant, r, was determined individually for all grid cells and kept constant throughout the modeled period. This determination was achieved using virgin soils and only *natural* forcings (i.e., deposition, weathering, and runoff) and no anthropogenic (i.e., fertilizer) for the year 1900 (i.e., year 0). We assumed that under virgin conditions, there would be no net annual change in pool size and calculated r was calculated to ensure this occurred. For this study, k ranges from 0.01 to 1.06 with a mean (± standard deviation) of 0.13 ± 0.10 (skew = 2.29) and r for DPPS ranges from 0.011 to 0.02/year with a mean (± standard deviation) of 0.019 ± 0.005/year (skew = 0.31), while GDPPS ranges from 9.47×10^{-7}/year to 7.79×10^{-4}/year with a mean of $6.20 \pm 7.04 \times 10^{-5}$/year (skew = 2.41). We note that GDPPS provides a more realistic dissolution rate when compared to experimental data from Nigerian soils, which indicated a dissolution rate of approximately 2×10^{-5}/year (Agbenin, 2004).

2.3. Sub-Saharan African Countries

Ten SSA countries were selected based on soil type and P input history (Bouwman et al., 2006). For each soil type, two countries with contrasting, or at least different, P histories were chosen (Table 1). Four additional countries Côte d'Ivoire, Ethiopia, Kenya, and Tanzania were also selected for model validation as there are excellent data sets in those countries during the 20th century (Leenaars, 2013).

Table 1
Study Countries Defined by Soil Type and Mean P Budget (Inputs-Outputs) for the 1970 to 2006 Period

Soil type	Alfisol	Oxisol	Ultisol	Vertisol
Country (High P)	Burkina Faso	Angola	Cameroon	Somalia
P budget	2 kg/ha	1 kg/ha	1 kg/ha	10 kg/ha
Country (low P)	Nigeria	Mozambique	D.R. Congo	Sudan
P budget	−1 kg/ha	−1 kg/ha	0 kg/ha	1 kg/ha

Note. P budget is the mean difference between P inputs and P uptake for the 1970–2006 period (data from IMAGE; Bouwman et al., 2006).

Chemically, Alfisols have mostly moderate extractable Fe and Al concentrations (100–200 $mg \cdot kg^{-1}$ and 400–800 $mg \cdot kg^{-1}$, respectively). Oxisols also have moderate extractable Fe concentrations (100–200 $mg \cdot kg^{-1}$). However, Al concentrations are much greater in these soils with most of Angolan soils having a concentration of approximately 1,000 $mg \cdot kg^{-1}$ but Mozambique's soils ranging from 700 to 1,000 $mg \cdot kg^{-1}$. Ultisols have extractable Fe concentrations in the range of 100–300 $mg \cdot kg^{-1}$ and extractable Al concentrations in the range of 750–1200 $mg \cdot kg^{-1}$. The highest Al concentrations in Ultisols are in Cameroon and the lowest in D.R. Congo. Finally, Vertisol soils are characterized by high extractable Al concentrations (>1,000 $mg \cdot kg^{-1}$) but relatively low extractable Fe concentrations (100–200 $mg \cdot kg^{-1}$; Hengl et al., 2017).

2.4. Model Validation

To validate the model, modeled available pool sizes were compared to measured available pool sizes. Available P data were from the ISRIC Africa Soil Profiles Database. This consists of 17,160 georeferenced soil profiles from across the continent mostly collected between 1950 and 2000. Inevitably for a repository of such geographically and temporally spread, data are collected using a range of methods so where possible these results have been standardized by the original authors. Additionally, for each country data were not collected from a single site, rather multiple different locations, which changed through time (Leenaars, 2013). As such we calculated a mean available P concentration for each country for each year and use this to compare to the modeled data.

The model was validated using four statistical techniques for the 2051 to 2010 period. Student's *t* test was used to compare the similarity of measured data to the modeled data in terms of mean values over the period. In addition, a lack of fit test (Whitemore, 1991), root-mean-square error (RMSE), and Wilmot's index of agreement (Willmott et al., 2012) were all analyzed. All analysis was conducted in R using the basic functions and the additional packages of alr3 and HydroGOF for lack of fit and index of agreement, respectively.

2.5. Sensitivity Analysis

Sensitivity analyses were performed over a time period of 150 years (1900–2050) with results aggregated for the whole SSA region. Sensitivity analyses were performed using the same approach as Mogollón et al. (2018) according to the SSP2 scenario, which represents the current trajectory (i.e., using current baseline technical agricultural trends for agricultural yields). The sensitivity of DPPS and GDPPS for variation within a range using a uniform distribution for all parameters shown in the table below is analyzed using Latin Hypercube sampling based on 150 runs (Table 2). The sensitivity is expressed by the Standardized Regression Coefficient (SRC), which assume values between −1 and +1. The sign of SRC indicates the

Table 2
Model Parameters Included in the Sensitivity Analysis, Their Symbol and Description, and the Minimum and Maximum Value Considered for the Sampling Procedure

Parameter	Min	Max	Explanation
fr_fertilizer_to_uptake	0.1	0.3	Fraction of fertilizer that is directly available for uptake (default 0.2).
fr_manure_to_uptake	0.05	0.15	Fraction of manure that is directly available for uptake (default 0.1).
default_max_uptake	400	600	Maximum uptake used in the Michaelis-Menten equation (default 500 kgP/ha).
LP_file_factor	0.75	1.25	Multiplier to change the initial LP size in 1900 and for new soils.
Pcontent_file_factor	0.75	1.25	Multiplier to change the total P in the soils in 1900 and for new soils.
init_recovery_file_factor	0.75	1.25	Multiplier to change the initial recovery for each grid cell.
uptake_factor	0.75	1.25	Multiplier to change the demanded uptake (only used after the year 2005).
manure_factor	0.75	1.25	Multiplier to change the amount of manure.
fr_mobile_min_scen_sensi	0.0125	0.0375	The minimum fraction of available P in the LP pool is increased between 2006 and 2016.
fr_mobile_multiplier_factor	0.75	1.25	Multiplier to change the fraction of available P in the LP pool.
oxFeAl_file_factor	0.90	1.10	Multiplier to change the oxalate-extractable Fe and Al oxide concentrations for each grid cell.
vdz_k_file_factor	0.90	1.10	Multiplier to change the vdZ-vR activity constant for each grid cell.
deposition_file_factor	0.90	1.10	Multiplier to change the amount of deposition.

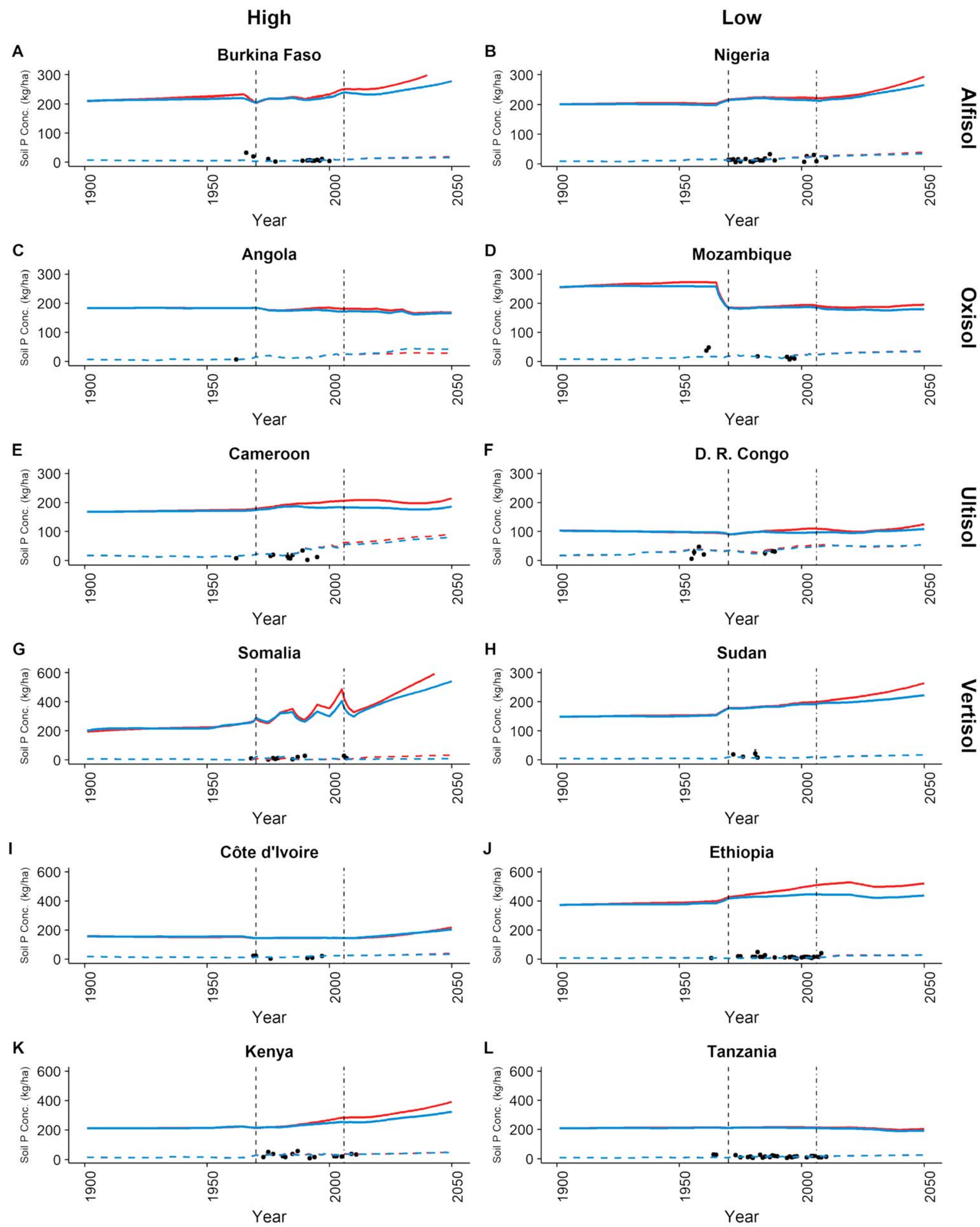

Figure 2. Labile pool and available P pool as modeled by dynamic phosphorus pool simulator (DPPS) and geochemical DPPS (GDPPS) sizes with mean measured available P pool results as points ($kg \cdot ha^{-1}$). High and low refer to the relative P inputs in each country. For complete data of measured vs modeled available P refer to the supporting information.

direction of change due to variation of the parameter considered. A positive value indicates that a larger parameter value results in a larger output. Outputs considered are Fertilizer application, LP and SP.

3. Results and Discussion

3.1. Model Validation

Previous continental scale studies using DPPS have not validated the modeled soil results against measured soil data due to the hitherto lack of available data (Sattari et al., 2012; Zhang et al., 2017). As such this validation marks an important step forward in assessing the quality of DPPS for soil modeling and not merely soil resource modeling. The size of the modeled available pool varied between locations ranging from 0.6 to 63 $kg \cdot ha^{-1}$ with a mean of 14 $\pm$ 11 $kg \cdot ha^{-1}$ for all countries throughout the 1950 to 2010 period. These

Table 3

Summary of Validation Statistics Comparing Measured and Modeled Available P for the Year 1950 to 2010

Country	Soil type	Measured available P ($\mu \pm \sigma$; kg/ha)	p value		Root-mean-square error		Index of agreement (d)		Lack of fit (p)	
			DPPS	GDPPS	DPPS	GDPPS	DPPS	GDPPS	DPPS	GDPPS
Burkina Faso	Alfisol	9.1 ± 8.3	0.18	0.20	1.41	1.51	0.28	0.27	0.33	0.37
Nigeria		14 ± 7.5	0.22	0.07	4.07	4.51	0.59	0.61	0.03	0.04
Angola	Oxisol	N/A	NA	NA	N/A	N/A	N/A	N/A	N/A	N/A
Mozambique		21 ± 16	0.60	0.63	1.96	2.15	0.25	0.23	TFR	TFR
Cameroon	Ultisol	15 ± 9.5	<0.01	<0.01	9.88	10.5	0.41	0.41	0.19	0.18
D.R. Congo		27 ± 13	0.11	0.04	2.54	1.49	N.C.	N.C.	TFR	TFR
Somalia	Vertisol	14 ± 8.7	0.05	0.01	4.27	1.33	0.3	0.45	0.75	0.2
Sudan		15 ± 6.0	0.08	0.08	0.94	0.91	0.5	0.49	TFR	TFR
Côte d'Ivoire	Other (Alfisol & Utisol)	15 ± 9.2	0.1	0.04	7.05	2.89	0.61	0.51	0.79	0.86
Ethiopia	Mixed (inc. Vertisol).	17 ± 9.9	<0.01	<0.01	1.64	1.8	0.41	0.4	0.11	0.11
Kenya	Mixed (inc. Vertisol).	27 ± 15	0.91	0.60	2.7	2.79	0.32	0.38	0.54	0.65
Tanzania	Mixed (inc. Oxisol).	15 ± 6.8	0.05	0.07	2.13	2.2	N.C.	N.C.	0.44	0.34

Note. N/A, not applicable (no measured data); NC, not calculable; TFR, too few replicates (to calculate lack of fit). For complete data refer to the supporting information.

values are comparable to the measured data, which have a max of 57 kg/ha and a mean of 17 ± 11 kg · ha^{-1} (Figure 2). The results of Student's t test indicate that for 9 out 11 (82%) countries for DPPS and 6 out of 11(55%) for GDPPS, the modeled available P had no significant differences between measured and modeled data with p values ranging <0.01 to no significant difference 0.91 for both DPPS and GDPPS (Table 3).

The results of the lack of fit test indicate that for all but one of the countries (Nigeria) $p > 0.05$, this means that the null hypothesis can be rejected and we suggest that there is no lack of fit (i.e., the relationship is assumed to be reasonable). There was no great difference between the models in the lack of fit test. Arguably, the greatest differences between the models occurred in the RMSE. RMSE ranged from 0.91 in Sudan for GDPPS to 10.5 in Cameroon for GDPPS; however, in Cote d' Ivoire, Somalia, and D.R. Congo large differences occurred between the models (Table 3). In these three countries the RMSE is substantially lower for GDPPS than DPPS, indicating that GDPPS follows the measured data more closely. Finally, there was no major difference between the models for the Index of Agreement. The values ranged from quite low with a minimum of 0.23 in GDPPS in Mozambique to moderate 0.61 at both Cote d'Ivoire (DPPS) and Nigeria (GDPPS). The differences between the models were mostly restricted to <0.05 (Table 3).

Table 4

Comparison of Dynamic Phosphorus Pool Simulator (DPPS) and Geochemical DPPS (GDPPS) Results 2006–2050 for Soil P and P Inputs Assuming That Food Production is Sufficient for Population Growth

Country	Soil type	Cumulative P inputs 2006 to 2050 (kg · ha^{-1})[a]			2006 labile pool size (kg · ha^{-1})			2050 labile pool size (kg · ha^{-1})		
		DPPS	GDPPS	Ratio[b]	DPPS	GDPPS	Ratio[b]	DPPS	GDPPS	Ratio[b]
Burkina Faso	Alfisol	447	398	0.89	238	250	1.05	278	334	1.20
Nigeria		407	395	0.97	213	222	1.04	265	293	1.11
Angola	Oxisol	52.8	61.9	1.17	171	181	1.06	165	168	1.02
Mozambique		68.3	70.6	1.03	185	193	1.04	179	195	1.09
Cameroon	Ultisol	345	329	0.95	183	206	1.12	187	214	1.15
D.R. Congo		259	296	1.14	97.2	110	1.13	109	125	1.15
Somalia	Vertisol	1620	909	0.56	359	422	1.18	542	654	1.21
Sudan		289	268	0.93	193	199	1.03	223	264	1.18
Côte d'Ivoire	Other (Alfisol & Utisol)	421	386	0.91	145	145	1.00	205	219	1.07
Ethiopia	Mixed (inc. Vertisol).	303	287	0.95	445	510	1.15	437	522	1.19
Kenya	Mixed (inc. Vertisol).	624	545	0.87	252	283	1.12	324	392	1.21
Tanzania	Mixed (inc. Oxisol).	101	102	1.01	209	213	1.02	190	201	1.06

Note. N/A, not applicable (no measured data).
[a]Cumulative P is the total amount of P required to 2050 (kg) divided by the 2007 area of croplands (ha). [b]Ratio indicates the value for GDPPS/DPPS.

10.1029/2018MS001367

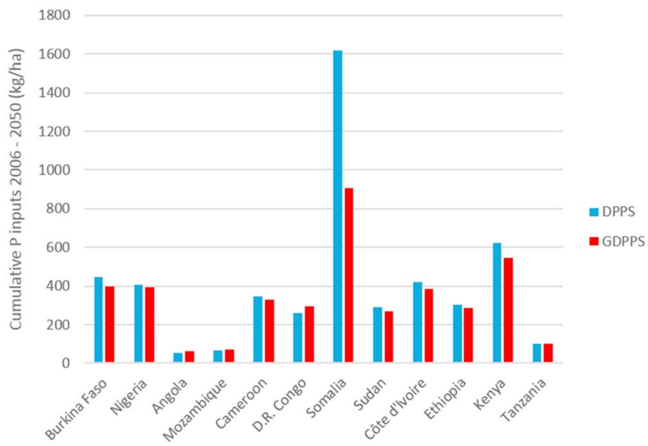

Figure 3. Comparison between dynamic phosphorus pool simulator (DPPS) and geochemical DPPS (GDPPS) of the predicted cumulative P inputs from 2006 to 2050 (Table 4).

Overall these tests indicate that both models provide moderately good representation of the measured soil data; however, neither model is substantially better than the other. The *t* test suggests that DPPS produces the nearest concentrations to measured values, but the RMSE indicates that GDPPS may follow the trends of data better. These conclusions are hampered by the limitations of the measured data over such a long period—as discussed in section 2.4.

3.2. Variations Between Models in Labile Pool Size

For the 1970 to 2006 period a small (mean $\pm$ *SD* of $7.0 \pm 7.1\ \mathrm{kg \cdot ha^{-1}}$) but significant difference ($p < 0.05$ for each country) between DPPS-labile pool size and GDPPS-labile pool size was calculated. The difference ranged from the lowest mean difference of $3.02\ \mathrm{kg \cdot ha^{-1}}$ in Tanzania to the highest of $25.4\ \mathrm{kg \cdot ha^{-1}}$ in Somalia. In all cases, GDPPS predicted a higher labile pool size than the DPPS (Figure 2). For the 2006 to 2050 period the difference between GDPPS and DPPS was even greater with the mean difference across all countries being $19.1 \pm 16.1\ \mathrm{kg \cdot ha^{-1}}$ ($\mu \pm \sigma$). This ranged from the lowest difference of $6.4\ \mathrm{kg \cdot ha^{-1}}$ in Angola to the highest in Somalia $50.1\ \mathrm{kg \cdot ha^{-1}}$ in Somalia (Figure 2). This means that the difference between the labile pool size calculated by GDPPS and DPPS was significantly higher for the 2007–2050 period than the 1970–2006 period ($p < 0.01$), indicating that as time progresses the models diverged more (Figure 2).

This divergence was highlighted in analysis of the labile pool for both models for the years 2006 and 2050 (Table 4 and supporting information). In 2006, the ratio of GDPPS to DPPS labile pool size ranged 1.00 in Côte d'Ivoire 1.18 in Somalia and had a mean of 1.08 for all studied countries. By 2050 this ratio ranged from 1.02 in Angola to 1.21 in Somalia and a mean of 1.14 (Table 4 and supporting information).

Thus, this shows that the labile pool size predicted by GDPPS is significantly larger than that calculated by DPPS for all countries and at most times with the difference increasing through time. For example, the mean labile pool GDPPS to DPPS ratio in 2006 was 1.07 ± 0.06 compared to 1.13 ± 0.07 in 2050 ($p = 0.03$). Vertisols (with prevailing coverages in Somalia, Sudan, Ethiopia, and Kenya) have the greatest discrepancy between GDPPS and DPPS with a mean ratio 1.19 ± 0.01 by 2050 compared to 1.11 ± 0.07 for non-Vertisols ($p < 0.01$).

Table 5
Standardized Regression Coefficients (SRC) Representing the Relative Sensitivity of Fertilizer Use, LP, and SP Representing Aggregated Model Results for the Whole Region to Variation in 13 Parameters

	DPPS			GDPPS		
Parameter	Fertilizer	LP	SP	Fertilizer	LP	SP
fr_fertilizer_to_uptake	−0.61	−0.29	−0.08	−0.31	−0.28	−0.01
fr_manure_to_uptake						
default_max_uptake						
LP_file_factor		0.94	−0.09	0.06	0.76	−0.10
Pcontent_file_factor		−0.04	0.97			1.00
init_recovery_file_factor	−0.14	−0.07	−0.02	−0.18	−0.14	−0.01
uptake_factor	0.54	0.06		0.75	−0.10	0.00
manure_factor	−0.08	0.07	0.04	−0.20	0.23	0.01
fr_mobile_min_scen_sensi	−0.16	−0.09	−0.02	−0.28	−0.20	−0.01
fr_mobile_multiplier_factor	−0.45	−0.26	−0.10	−0.37	−0.45	−0.02
oxFeAl_file_factor				0.04	−0.04	0.01
vdz_k_file_factor				0.05		0.01
deposition_file_factor						

Note. Boxes with numbers are significant, empty boxes indicate not significant SRC. Colored boxes indicate the most important parameters (green is negative; salmon is positive).

These differences also occurred in the cumulative amount of total P inputs and fertilizer P inputs required to meet the target crop production to 2050 (Table 4, Figure 3, and supporting information). The ratio of total cumulative P inputs of GDPPS to that of DPPS for the period 2006 to 2050 ranged from 0.56 in Somalia to 1.17 in Angola with a mean of 0.95. The ratio of fertilizer P ranged from 0.28 in Somalia to 1.47 in Angola with a mean of 0.28 (Table 4, Figure 3, and supporting information). Again, there is a large discrepancy between mean Vertisol and non-Vertisol ratios, 0.83 ± 0.18 compared to 1.00 ± 0.10, but this difference is not significant ($p = 0.13$).

3.3. Sensitivity Analysis

For 2050 the sensitivity for both models are given with respect to the calculated fertilizer in 2050, the size of the LP and the SP pools. Only significant SRC values are shown (Table 5).

3.3.1. Sensitivity of Modeled Fertilizer Use

For understanding the sensitivity of both models, it is important to note that LP DPPS is smaller than LP GDPPS and that the *ft_mobile* is larger in DPPS and in GDPPS. The combined effect (soil part going to fertilizer) of these differences in LP size and *fr_mobile* and LP leads to a larger supply from LP in GDPPS than in DPPS, and therefore a smaller fertilizer input in GDPPS than in DPPS. Probably, this causes the higher sensitivity of GDPPS to manure inputs (*manure_factor*), because the transfer of P from LP to SP is slower than in DPPS.

Both models show a negative SRC for the fraction of fertilizer directly going to uptake. The GDPPS model is less sensitive for *fr_fertilizer_to_uptake* than the DPPS because the supply from LP to uptake is larger, less fertilizer input is needed GDPPS. This is also the case for the parameter *uptake_factor*, with high SRC values for both models. In GDPPS the SRC is larger than in DPPS, because fertilizer inputs are less in GDPPS and the relative increase in fertilizer inputs is higher than in DPPS.

3.3.2. Sensitivity of Modeled LP and SP

Both models have comparable sensitivity of the LP size to all parameters. An increase in *fr_fertilizer_to_uptake* leads to less input in LP and a lower LP size. Also, a higher *fr_mobile_multiplier_factor* leads to a higher fraction available P for uptake, which results in a lower LP size. The initial LP size is changed with *LP_file_factor*. Even in 2050 this initial setting of the pool sizes (Yang et al., 2013) is still contributing strongly. For GDPPS also the minimum fraction mobile (*fr_mobile_min_scen_sensi*) is important due to the lower fraction mobile in GDPPS. The *manure_factor* (amount of manure) has more influence on the LP size in the GDPPS than in DPPS. GDPPS needs lower inputs to provide the demanded uptake than DPPS, explaining the smaller SRC for GDPPS. The *uptake_factor* is not an important for LP, but the sign of the SRC is different (positive for DPPS and negative for GDPPS). For GDPPS, a higher uptake leads to uptake from the LP pool (mining), while the DPPS builds up LP in that same situation (small effect). The *fr_mobile_min_scen_sensi* is important in GDPPS because *fr_mobile* for GDPPS is smaller than for DDPS for LP and fertilizer. The values of *fr_mobile_multiplier_factor* are comparable for both models for LP and fertilizer. GDPPS is not sensitive to *vdz_k_file_factor* and *oxFeAl_file_factor*. For SP both models are both strongly sensitive to the initial total P in the soil from Yang et al. (2013).

4. Conclusions

We have provided evidence that the effect of spatial heterogeneity of indigenous soil properties can be assessed using a new soil-P model (GDPPS). Both GDPPS and DPPS have been validated against measured available soil P for the first time; however, they provide systematically different results for both predictions of P required to sustain food security and the soil P pool sizes. Across all the SSA countries the differences between the models are most obvious in countries dominated by Vertisol soils. This is highlighted in Somalia where the total P required to 2050 predicted by GDPPS is 56% of the total P input resulting from DPPS. This is caused by large differences in the predicted labile pool. In GDPPS the phosphorus transfer between the labile and stable pool is controlled by the soil chemical *pedo-transfer function* developed in this paper, which general leads to a larger labile pool and more available phosphorus than DPPS. The distinction of regional differences due to the pedo-transfer function within GDPPS is a powerful tool as soil chemistry distributions are nowadays readily available in both national and international soil databases (e.g., Hengl et al., 2017; Romero et al., 2012).

Acknowledgments

This research was funded by an EPSRC Global Challenges Research grant (EP/111676), UMRI grant awarded to V. J. N., and an N8 Agrifood grant awarded to V. J. N. and D. M. Data used for this study were provided by the Integrated Model to Assess the Global Environment (IMAGE), which is publically available (http://themasites.pbl.nl/models/image/index.php/Welcome_to_IMAGE_3.0_Documentation). All authors declare no conflicts of interest, financial or otherwise.

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