COMPARISON OF MEASURED AND SIMULATED RESPONSES OF MAIZE TO PHOSPHORUS LEVELS IN GHANA

By

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Efficient nutrient management in agricultural systems requires the availability of tools that can help in meeting research objectives of understanding the transformations that nutrients undergo to become available to plants and predicting how these transformations are related to economic outputs from the systems. The crop models in the Decision Support System for Agrotechnology Transfer (DSSAT) have been recognized worldwide for meeting these objectives for nitrogen. However, without a phosphorus model, the applicability of the DSSAT crop models in phosphorus deficient environments will remain questionable. In this study, a soil-plant phosphorus model linked to DSSAT was described, analyzed and tested.

The sensitivity of the model to six key input factors was studied based on a global sensitivity analysis approach. The model was tested on two P-deficient soils from Ghana (Kpeve and Wa) with maize as the test plant. Processes accounted for by the model include phosphorus movements between inorganic (labile, active and stable), organic (active and stable) pools and plants. Results of the sensitivity analysis showed the greatest effects of initial inorganic labile P (initial PiLabile) and fertilizer P on biomass, grain yield and total P uptake (sensitivity index of 0.11 for initial PiLabile and 0.30-0.43 for P fertilizer). Smaller effects were found for the fraction

of root labile P that is soluble (sensitivity index of 0.03-0.04), the shoot P (sensitivity index of 0.03-0.09) and seed P (sensitivity index of 0.15) on total P uptake.

Statistical analysis of grain yield and biomass did not reveal any significant differences at the 0.05 probability level at Kpeve because the phosphorus content of this soil was at the limit between deficiency and sufficiency and the organic matter content of the soil was relatively high (close to 2.0%). Grain yield and final biomass responded at Wa with 100% increases in the 60 kg $[P_2O_5]$ ha^{-1} treatments over the nil-P treatments. Biomass and yield were stable between the two treatments of 60 and 90 kg $[P_2O_5]$ ha^{-1} at Wa.

Evaluation of the model indicated that the model was able to achieve good predictability skill at Kpeve with a grain yield RRMSE of 8% and a final biomass RRMSE of 5%. The congruence between simulation and measurement was fair at Wa. The RRMSE was 14% for grain yield and 30% for final biomass. At Wa however, the model gave a reasonable prediction of the pattern of variability among measurements with an LCS averaged over the five sampling dates of 17%. Because the complex soil P chemistry makes the availability of phosphorus to plants extremely variable in general, further testing of this model in other agro-ecological conditions should precede its application.

CHAPTER 1
INTRODUCTION TO MODELING PHOSPHORUS LIMITATIONS TO CROP PRODUCTION

Introduction

Phosphorus (P) is recognized as a major nutrient that must be present in living organisms to enable them to maintain a continuous life cycle. It is an essential component of adenosine triphosphate (ATP), the energy currency of the living cell. The energy-consuming biochemical processes that continuously take place in the cell are driven by the energy-rich phosphate group contained in ATP. For example, in crop nutrition, the uptake and assimilation of nutrients use energy in the form of ATP. The synthesis of new molecules responsible for mass accumulation in living organisms and perpetuation of species on earth all involve P either as ATP or deoxyribonucleic acid (DNA) or ribonucleic acid (RNA). Phosphorus is transferred from one organism to another through the various food chains. For terrestrial organisms, soils satisfy most of their P need mainly through plants (Johnston, 2000). The P content of healthy plant leaf tissue is low however, ranging from 0.2 to 0.4% of the dry matter (Brady and Weil, 2002).

Although plant uptake of P is constrained by the low quantity of this element present in soil and the very low solubility of P compounds found in soils, most natural ecosystems have developed relatively well without any P management programs (Brady and Weil, 2002). These systems are naturally organized to recycle the nutrient and maintain an overall non thermodynamic equilibrium.

Phosphorus Problem in Agricultural Systems

In agricultural systems where most nutrients' balances have been displaced by human intervention, the relatively low mobility of P in many soils has led to the appearance of areas of soil accumulation and depletion of this nutrient.

Most soils in sub-Saharan Africa have very little capacity to supply P for plant growth, which allows plants grown on those soils to be responsive to P fertilizer applications (Table 1-1). Phosphorus deficiency is thought to be one of the reasons why sub-Saharan Africa is the only major region in the world where per capita food production has actually declined in the past three decades (Brady and Weil, 2002). The phosphorus problem in most sub-Saharan African soils has five facets:

- The soils have developed under conditions conducive to advanced weathering. During these relatively long periods of intensive weathering, extensive losses of P occurred resulting in low P soils. Most soils' solution P ranges from 0.03 to 0.50 ppm with 0.25 ppm considered adequate. For a crop requirement of 40 kg [P] ha-1 for example, the soil solution containing 0.25 ppm must be replenished 80 times in a hectare furrow slice (15 cm deep x 1 ha area), which does not happen naturally;

- The P compounds commonly present in soils are highly insoluble and have a very low diffusion rate in many soils posing a problem for plant uptake. They do not readily release P to the soil solution in a useable form by plants. For example, P fixed by reaction with aluminum in acid soils is insoluble for plant uptake. The readily available pool of P that is in equilibrium with the soil solution P (Figure 1-1) can be as small as 10% in some soils (Table 1-2). The rate of diffusion of P in some soils can be as low as 10^{-12} to 10^{-15} m^2 s^{-1} and high plant uptake rates create a zone around the root that is depleted of P (Schachtman et al., 1998);

- When soils are supplied with external P in the form of fertilizers, the nutrient is fixed, adsorbed or absorbed and with time tends to return to stable forms, strengite, variscite (in acid soils) and apatite (in alkaline soils) (Figure 1-1). As a consequence P fertilizer recovery is low in most agricultural systems relative to the other major nutrients (nitrogen and potassium);

- Crop harvest exports significant amounts of P from the soil with limited amounts of residues returned to the cropping system;

- Use of external P inputs in the form of mineral fertilizers or manure, especially for food crops, is not common practice. Farmers do not have access to the appropriate P fertilizers, or the cost of their being transported and applied is prohibitive. In addition, the fertilizer requirement for improved yield can be high on soils with high P sorption capacity (Table 1-1).

In industrialized areas, P fertilizer use has increased drastically during the past few decades (FAO, 2003). The relatively low plant uptake of P coupled with the low mobility of

the nutrient in some soils mean that much of the P fertilizer applied is not removed with the harvested crop or lost from the soil (Schmidt et al., 1996). In fact, soils in these areas have developed rather high P levels resulting from many years of over-fertilization with P.

Understanding Excess and Deficiency of Phosphorus in Agricultural Systems

The challenge of dealing with both the excess and deficiency of P in agricultural ecosystems is crucial to attempt to restore the P balance in these systems and make P management programs sustainable and environmentally sound. A primary step towards tackling the challenge of P management in agricultural systems is understanding the P behavior in soils in relation to plants' needs and their environment.

Excess P can be detrimental to the aquatic ecology. Although plant proliferation stimulated by supply of limiting nutrients is considered beneficial in terrestrial ecosystems, aquatic systems like lakes, streams and ponds can become unsatisfactory environments when enriched with excessive P through runoff, erosion and, in some cases, leaching. The unwanted growth of algae and of aquatic weeds (termed eutrophication) resulting from this P enrichment can seriously perturb the aquatic ecosystem. When this community of opportunistic algae and weeds die, they sink to the bottom of the water where their decomposition by microorganisms uses much of the oxygen in the water creating anoxic conditions. This process leads to fish kills, displaced nutrients balance, and can make the water unsuitable for drinking (Brady and Weil, 2002; Sturgul and Bundy, 2004).

Phosphorus deficiency can constitute a serious problem for crop production because it has a negative effect on leaf area index (Pellerin et al., 2000) limiting the interception of photosynthetically active radiation by the plant and resulting in low biomass accumulation (Colomb et al., 2000). The rate of leaf appearance is slowed down and the final leaf number is reduced in P stressed plants (Singh and al., 1999). Colomb et al. (2000) showed that in P-

deficient maize plants in their study the rate of leaf appearance and the final area of leaves located below the main ear were reduced by 18 to 27%. The ultimate economic effect of P deficiency is yield reduction (Table 1-1).

Coping with Excess and Deficiency of Phosphorus in Agricultural Systems

Extensive and long term agronomic experiments have been conducted to attain a greater understanding of the behavior of soil P and propose options for P management in agricultural systems. The mechanism motivating and the time factor associated with P draw-down or build-up in soils have been examined as steps towards assessing opportunities for reducing P loadings in waters (Kelling et al., 1998; Sartain, 1980). Management strategies proposed for decreasing the P content of high P soils include mining soil P (i.e., harvesting P taken up from the soil by a crop grown without external P addition) (Koopmans et al., 2004), growing appropriate corn varieties as P removal agents (Eghball et al., 2003). With the twofold concern of replenishing soil phosphorus in P deficient agricultural systems while avoiding losses to aquatic ecosystems, continuous applications of small rates of P have been proposed as adapted management strategy for smallscale farming systems (Nziguheba et al., 2002; Schmidt et al., 1996).

Modeling as a Phosphorus Management Tool in Soils and Plants

The necessity of developing P management strategies requires the availability of appropriate tools that empower managers and decision-makers with the ability to control the human-modified P cycle in agricultural systems. Statistical summaries have been routinely used to produce in an integrated way a logic interpretation of agronomic experimental results. However, these parameters and other classical mathematical methods used to study and explain the behavior of nonliving physical or chemical processes may be insufficient (Jones and Luyten, 1998). Agricultural ecosystems involving biological processes are highly complex and

have many components that interact in non linear ways. The non linear interaction means that many disciplines working, for example, on the same P management problem may be looking at the facets that are only meaningful for their study while interacting components that may provide clues to the solution are not given enough attention. An interdisciplinary approach that places the P management problem at the center of the soil-plant-atmosphere system and recognizes the effects on the problem of interactions between disciplines concerned is useful for developing efficient management tools. An ideal P management program is at the minimum concerned with i) understanding the behavior of P in agricultural systems; ii) synthesizing the knowledge and information obtained in an integrated way so that interactions occurring in the system are not lost but harnessed to enhance understanding; iii) producing user-friendly management tools that depict the best understanding of the system. Well-tested simulation models that represent the cropping system with mathematical relationships provide a sound scientific approximation of physical, chemical and biological processes governing complex ecological systems and represent such tools. When appropriately validated, those simulation models provide the opportunity to understand simplifications of the universe (Odum and Odum, 2000); study ecosystems without having to experiment on actual systems (Uehara, 1998) especially when experimentation is impossible or ethically unacceptable; make predictions; support decision making and communicate more efficiently research findings by integrating information into a more useable form (Newman, 2000).

Phosphorus modeling has given attention to soil and plant processes that affect the P cycle. Residual effects of soil P have been of interest because in many soils, the P that is applied to the soil but not taken up by the plant is not lost, and the build-up in the soil toplayer can be reused for crop production (Pheav et al., 2003) and thought of as a capital investment.

Models now exist that address the issues of long term recovery of applied P in the form of fertilizers (Wolf et al., 1987; Janssen et al., 1987; Schmidt et al., 1997), long term changes in soil P extracted using conventional methods (Karpinets et al., 2004), long term P leaching from the soil profile (Del Campillo et al., 1999), and long term effects of erosion-induced soil nutrient loss, including P, on crop productivity (Jones et al., 1984). Lewis and McGechan (2002) compared four soil P models, AMINO from the Netherlands, GLEAMS and DAYCENT from the USA and MACRO from Sweden, in order to ascertain their limitations and evaluate their capability to simulate the transport of soluble and particulate P, surface application, mineralization / immobilization, absorption / desorption, leaching, runoff and uptake by plants. The P module of GLEAMS is actually an essentially unaltered version of the model developed by Jones et al. (1984). Lewis and McGechan concluded from their analyses that all the models only have a partial representation of the soil processes examined. They suggested that more accurate dynamic simulations of soil processes will necessitate a hybrid model that incorporates the different aspects of soil P dynamics that the models studied have failed to critically account for.

The most relevant processes for crop production in P deficient systems include the quantification of development, growth and yield as limited by P. These processes can only be handled by comprehensive simulation models of crop growth and development. For the purpose of enhancing the applicability of a model of this kind, soil P gains by the plant resulting from the mineralization of organic matter, particularly in low input cropping systems must be recognized in addition to P obtained from chemical fertilizers (Probert, 2004). In fact, organic materials are used in many competing ways in smallscale cropping systems including soil fertility replenishment (Fofana et al., 2005). Factors controlling the decomposition of

organic materials in these systems often favor faster mineralization rates of nutrients. The addition of limited amounts of fertilizer tends to offset the negative effect of low-quality organic materials and accelerate their decomposition. Nutrients that would normally cycle over extended periods could therefore be released over a relatively short time, increasing total available nutrients for plant uptake (Kaboneka et al., 2004).

Soil-Plant Phosphorus Simulation Model in DSSAT

To meet these needs, a capability is needed in the Decision Support System for Agrotechnology Transfer (DSSAT) Cropping System Models (CSM) (Jones et al., 2003) to model i) P limited crop growth, development and yield and ii) P released by organic resources. The soil-plant P module that has been linked to the DSSAT CSM and still operates as an experimental version is based on studies by Daroub et al. (2003). A new Soil Organic Matter-Residue module called CENTURY that accounts for nutrient mineralization from organic resources was recently implemented in DSSAT. Gijsman et al. (2002) reported that the CENTURY module simulated with high accuracy the development of SOM content in a long term bare fallow experiment in Rothamsted, UK and gave a fair congruence between simulated and measured data for a 1-year experiment in Brazil.

The Decision Support System for Agrotechnology Transfer is comprised of a suite of models that simulate on a daily basis the development, growth and yield of more than 16 crops. The models are organized under different groups. Among these groups, the CERES family for cereals and the CROPGRO family for legumes are important components that have proven to be successful in their applications worldwide. The system also contains programs that allow the analysis of effects of multiyear variations of factors like weather on crop production. Other programs permit the analysis of rotational and spatial experiments. The DSSAT models use quantitative climate, soil, genetic and management information as inputs to simulate, among

many other outputs, grain yield and its components, crop biomass, anthesis, silking and physiological maturity dates. The Decision Support System for Agrotechnology Transfer has been used in several studies that include residues and inorganic nitrogen management in Nigeria (Jagtap and Abamu, 2003), crop management strategies in extension systems in Kenya (Wafula, 1995), investigating variety and sowing time technologies in Nigeria (Jagtap, 1999) and Togo (Dzotsi et al., 2003), studying the effect of water and nitrogen deficiency on crop duration and yield in Florida, Hawaii, Nigeria and Togo (Singh and al., 1999), analyzing soil fertility research and development options in Malawi (Singh et al., 1993).

Objective and Hypothesis

The overall objective of this study is to present the soil-plant phosphorus model implemented in the DSSAT CSM for maize and results of field testing. The main hypothesis was that P fertilization increases soil inorganic P availability for plant uptake, which promotes higher grain yield and biomass production and shortens the time required for ripening in maize.

Table 1-1. Response of maize to phosphorus application on a phosphorus-deficient soil in a fertilizer experiment carried out in Ghana in 1999

Source of phosphate	P ($kg\ ha^{-1}$)	P_2O_5 ($kg\ ha^{-1}$)	Grain Yield ($kg\ ha^{-1}$)
Control			3949
Triple super phosphate	40	92	5135
Togo rock phosphate	63	144	6252

Source: Adapted from FAO, 2005

Table 1-2. Partitioning of total soil phosphorus in pools specified on Figure 1-1 in a soil from Carimagua, Colombia

Soil phosphorus	Parts per million ($mg\ kg^{-1}$)	Per cent of total soil P (%)	$kg\ ha^{-1}$ in an 1ha-15cm deep soil
Readily available	18	10	36
Stable forms	78	43	156
Organic	86	47	172
Total soil P	182	100	364

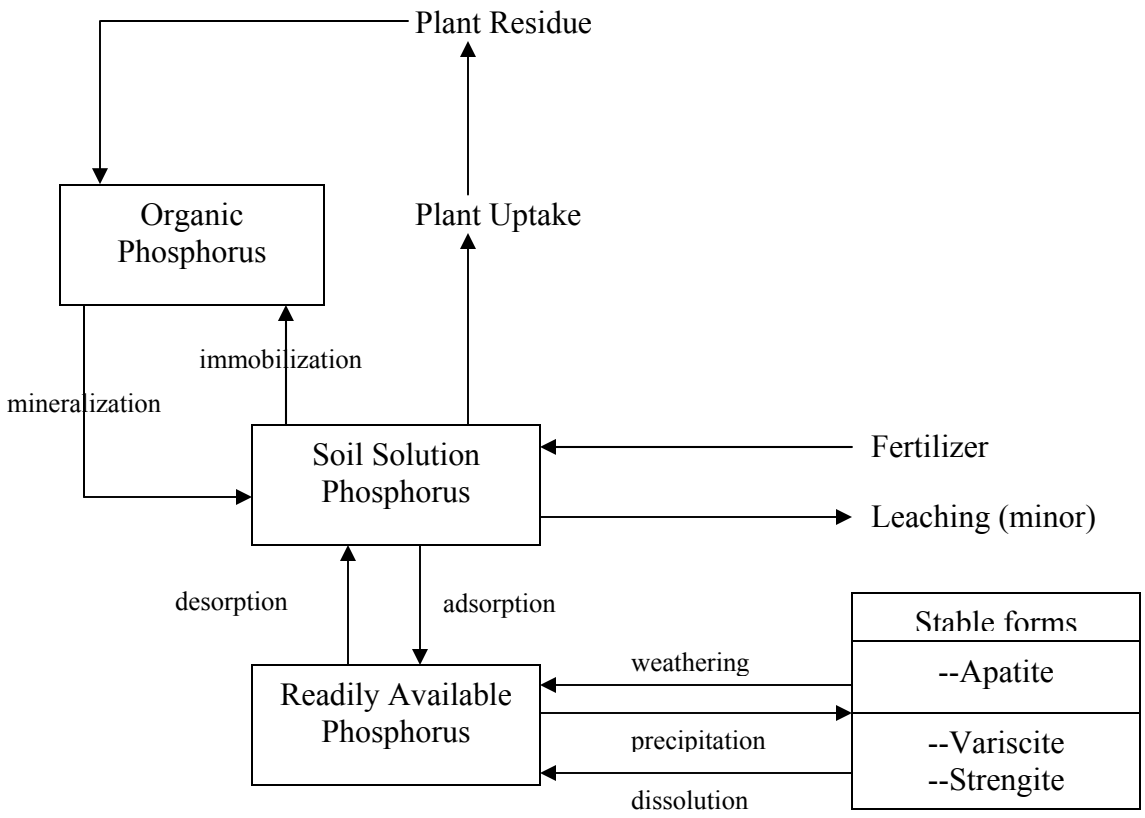


Figure 1-1. Pools of phosphorus in the soil and relationships between soil and plant phosphorus

CHAPTER 2
STATISTICAL ANALYSIS OF FIELD EXPERIMENT FOR TESTING THE MODEL

Introduction

Assessing plant response to phosphorus (P) is an important step towards understanding its behavior in agricultural systems. Plant response to P can be evaluated using different soils with P levels ranging from low to high (Colomb et al., 2000) or by testing different applications of a P fertilizer on the same P deficient soil (Fofana et al., 2005). In both situations initial soil testing for P is essential to determine the P status of the soil of interest.

The diagnosis of P level in soils is complicated by the complex chemistry of the nutrient. This complexity is the basis for assessing soil P content using extractants for their effectiveness to solubilize P tied up in different forms. The quantity of P extracted will vary with the reagent used. However, many P extraction methods are widely accepted and used because they adequately distinguish between soils on the basis of the responsiveness of crops to P supply. Soil P test does not provide information about the available P that can be actually taken up by crops but relates to that quantity of P which is correlated with plant response. This implies that soil analytical data allow the classification of soils descriptively in terms of P availability (e.g. deficient, sufficient, high) but these classes are only related to the probable response of a crop to an appropriate supply of P (Johnston, 2000). The relationship between soil P test and plant response cannot be established as necessarily deterministic. For example, if a soil tests very low in P, a 75% probability exists that plant response will be observed. If the soil test is low in P, there is a 50% chance that plants will respond to P applications. If the soil P level is medium, the response probability of plants is only 25%. Plants will not be responsive to P if the soil test indicates a high P level (Havlin et al., 1999).

Inorganic and organic fertilizers can be used as P sources in experimenting with P-deficient soils. The amount of P provided by the decomposition of organic materials over a cropping season can be small and relatively slow however, but continuous over several years. Inorganic fertilizers on the contrary can supply more P to the plants at a higher rate and over a relatively short period of time, a cropping season for instance. However, a big portion of the fertilizer applied to plants in cropping systems is retained in the soil, which constitutes the cause of long term accumulation of P in soils with a history of continuous P fertilization. The fraction of P applied in the form of inorganic fertilizer that is actually taken up by plants is about 0.2. This fraction is termed apparent recovery of the fertilizer. An appropriate art of managing P in cropping systems would be to integrate the use of organic resources with inorganic fertilizers so that soil organic matter can play its role of improving physical and biological properties of soils while immediate nutrients needs are satisfied by inorganic fertilizers (Janssen, 1993).

Plant response to P has been described as increasing the leaf area therefore allowing a higher interception of photosynthetically active radiation and resulting in a higher biomass accumulation and grain yield (Pellerin et al., 2000; Colomb et al., 2000; Plenet et al., 2000b). Other studies reported that the rate of leaf appearance was slowed down and the final leaf number was reduced in P-stressed plants (Plenet et al, 2000a; Singh and al., 1999).

The present chapter describes two field experiments conducted in Ghana in 2004 and 2006 on soils that tested low in available P and therefore considered P-deficient. Statistical procedures are used to summarize the data collected and understand the plant response observed.

Materials and Methods

Field experiments were conducted in Kpeve and Wa, Ghana in order to measure growth and development of maize as affected by P fertilizer. These experiments are described next with the statistical methods used to analyze them.

Field Experiments in Ghana

The experiments were carried out in two different agro-ecological zones of maize production in Ghana. The Kpeve site is located in the south in the Transitional zone with two distinct rainy seasons and annual rainfall ranging from 1100 to 1400 mm. The Wa site is located in the North in the Guinea Savannah with one rainy season and annual rainfall ranging from 800 to 1200 mm (FAO, 2005).

Experiment in Kpeve, Ghana

The experiment in Kpeve measured the effect of different levels of phosphorus fertilizer on the growth and development of the maize cultivar Obatanpa (Table 2-1).

Site description

The experiment was conducted in 2006 during the major rainy season (March to July) on a sandy loam soil at the experimental site of the Ministry of Food and Agriculture research station at Kpeve in southern Ghana (6^o 40.80' N, 0^o 19.20' E). The site is characterized by an altitude of 67 m above sea level, an average annual temperature of 28 degrees C and an average annual rainfall of 1300 mm falling in two rainy seasons, March to July and September to October (FAO, 2005) (Figure 2-1). The landscape is highly uneven with chains of hills surrounding the experimental station. Although the topography of the experimental site was almost flat, small micro-topography differences may have important water and nutrient management consequences in this type of terrain. This topography reinforced the need for treating the experimental plots individually regarding all data collected. The soil is classified as Haplic Lixisol which has a dark grayish brown topsoil and grayish brown to brown subsoil (Adiku, 2006). An automatic weather station to monitor maximum temperature, minimum temperature, and solar radiation and an automatic rainfall datalogger to record daily rainfall were located respectively at 1 km and 200 m from the experimental field.

Experiment design and management

Maize (*Zea mays* L. cultivar Obatanpa "a good nursing mother", Table 2-1), was planted on May 27. Seven days prior to planting, 5206 kg ha^{-1} of vegetation of a two-year natural bush fallow dominated by elephant grass (*Pennisetum purpureum*) and guinea grass (*Panicum maximum*) was plowed into the soil to a depth of 30 cm. The field was hand-harrowed to a depth of 10 cm and leveled three days before planting. Three levels of P and a control treatment were explored: low (10 kg P ha^{-1}), medium (30 kg P ha^{-1}) and high (80 kg P ha^{-1}).

A total of 30 kg K ha^{-1} was applied as Potassium Nitrate two times during the growing season, at planting and two weeks after planting. A total of 150 kg N ha^{-1} was applied at the rate of 50 kg ha^{-1}, at planting, four weeks after planting and six weeks after planting as Ammonium Sulfate. The Potassium Nitrate provided 10 kg ha^{-1} of the total 150 kg ha^{-1} of the nitrogen applied. The application methods varied with the growth stage (Table 2-2).

The existence of a slope gradient on the experimental field motivated the arrangement of the treatments in a Randomized Complete Blocks design with four replications. Each plot or experimental unit was composed of 14 rows 80 cm apart. Each row contained 30 hills 40 cm apart making up a total of 420 hills per plot. The total area of a plot was 134.4 m^2. At planting and emergence, the plant population was 9.38 plants m^{-2}. The field was thinned 10 days after planting to reduce the plant population to 6.25 plants m^{-2}. The application of sufficient rates of nitrogen (150 kg ha^{-1}) and potassium (30 kg ha^{-1}) and the control of soil variability through blocking were expected to highlight the effect of P deficiency in the crop.

Soil sampling

Soil samples were taken at three depths, 0-10, 10-20 and 20-30 cm on all 16 plots before planting, at silking and at final harvest. Texture, organic matter content, phosphorus content, exchange complex and acidity were determined on the samples in the soil testing laboratory at

the University of Ghana. A modified Hedley approach for P fractionation was used to quantify inorganic labile, microbial and stable, and organic P in the samples. The P fractions (Table 2-17) were performed in the Wetland Biogeochemistry Laboratory at the University of Florida following a four-step sequential extraction described by Reddy et al. (1998) (Figure 2-2). The extractants in order were: 1, 1.0 M KCl; 2, 0.1 M NaOH; 3, 0.5 M HCl; 4, Residual P. The extraction with reagent 1, potassium chloride removed that portion of P readily available to plants. The alkaline reagent (NaOH) extracted P associated with iron and aluminum while that extracted by reagent 3 (HCl) is probably associated with calcium (Figure 2-2). In the solution extracted by the alkaline reagent, both organic (Po) and inorganic P (Pi) were determined. The residual P in the soil was recovered after combustion at 550 ^{o}C for 4 h and dissolution in 6.0 *M* HCl (Reddy et al., 1998).

Soil moisture measurements

Soil moisture is generally determined from oven-dried soil samples at 105 ^{o}C until constant weight. The moisture difference between the fresh and the dried soil relative to the dried soil is established as the gravimetric soil water content. The gravimetric soil water content can be further converted into volumetric soil water content by multiplying it by the bulk density of the soil.

Monitoring soil water using gravimetric sampling can be tedious and not practical especially when the desired frequency is two to three-day intervals. Time domain reflectometry (TDR) technology is one of the best methods to quickly and accurately measure soil moisture. The technique is based on generating and remotely sensing a return energy signal that travels down and back through the soil. The travel time measured is dependent on the quantity of water present in the soil. This information is then converted into volumetric water content. Because soils have different properties that can influence the way TDRs “capture and read” the moisture

status of the soil, the calibration of the meter to field conditions is an important step towards its use for extensive applications.

In the present study, soil moisture was monitored during the entire course of the experiment at four GPS-referenced prelocated points on each plot in the top 12 and 20 cm using a portable soil moisture meter (FieldScout TDR 300) manufactured by Spectrum Technologies, Inc. The TDR readings were taken at 2 to 6-day intervals.

In order to calibrate the TDR, 67 pairs of TDR readings and gravimetric soil samples were separately taken at anthesis at three soil moisture conditions, low, medium and high. Fresh weight and soil volume were determined on the samples prior to drying. After oven-drying at 105 ^{o}C until constant weight, the fraction of the gravel was determined on each sample. The data were used to correct the bulk density of the soil using the following formula (Vincent and Chadwick, 1994):

$$\text{Corrected Bulk Density (g cm}^{-3}) = \frac{(1 - G_f) \times BD_m}{(1 - G_v)} \quad (2\text{-}1)$$

Where G_f is the fraction of gravel in the soil sample, on a mass basis;
BD_m is the uncorrected bulk density in g cm^{-3};
G_v is the volume of gravel in the sample, expressed as a fraction of the total volume and calculated as follow: $\frac{(BD_m \times G_f)}{2.65}$.
2.65 is the density of solid particles in the soil expressed in g cm^{-3}.

Plant sampling and growth measurements

Detailed measurements of leaf area, plant height, dates of tasseling, anthesis, and silking were made throughout the growing season.

Aboveground biomass samples were taken four times during the season, 17 days after planting (dap), 31 dap, 52 dap (anthesis), and 108 dap (final harvest).

After emergence 6 plants were randomly selected and tagged within three rows on each individual plot. Length and width of each expanding leaf were measured at 7-day intervals until

maximum values were reached or 50% leaf senescence observed (Colomb et al., 2000). At any time during the season, total area of leaves produced by the plant was computed as the sum of individual leaves' areas. The area of a single growing leaf was calculated as the product of length and width multiplied by 0.75 (Colomb et al., 2000). Visible leaf numbers, plant height and phenology events (tasseling, anthesis and silking) were recorded from emergence to silking for the six tagged plants on each plot.

Plant height was taken from the base of the plant to the tip of the most recent leaf. Tasseling, anthesis, and silking dates were established as the date when 50% (three out of the six) of the tagged plants tasseled (panicle visible, tasseling), showed some pollens or anthers (anthesis), or showed some silks (silking).

The samples taken for aboveground biomass determination consisted of randomly prelocated 12 plants from two continuous rows corresponding to a sampling area of 1.92 m^2. The dry weights of each plant part, stem plus petiole, leaves, fruit and grains, were determined on each sample by oven drying at 60 degrees C for 48 hours or until constant weight was reached. Biomass accumulation from week six to maturity was so high that for ease of handling, only fresh weights were determined on the 12 plants. A subsample of 6 plants (17 dap, 31 dap and anthesis) and 5 plants (final harvest) was used for dry weight measurements of each plant component. The samples were analyzed at the University of Ghana for total N, P and K content in each plant part.

An area of 6 m x 1.6 m = 9.6 m^2 was used for final harvest on each plot, 108 days after planting (September 12th). The two innermost rows harvested were bordered by two rows on each side. Grain yield, total aboveground biomass, stover biomass, grain number per m^2, unit grain weight, and N, P and K content of grain and stalk were determined.

Experiment in Wa, Ghana

The experiment in Wa measured the effect of combinations of nitrogen and phosphorus fertilizers on the growth and development of the maize cultivar Obatanpa (Table 2-1).

Site and experiment set up

The experiment was carried out in 2004 at the Savannah Agricultural Research Institute (SARI)'s experimental station in Wa, Ghana ($10^{o}3'$ N, $2^{o}30'$ W, altitude 320 m above sea level) by Naab (2005). The average annual rainfall is 1100 mm falling mainly between April and September (Figure 2-3). The mean annual temperature is 27 ^{o}C.

The experimental field was cleared of native vegetation that was plowed in. The field was harrowed and laid out in a Randomized Complete Block Design with four replications. Treatment plots measured 6 m x 8 m. The factors tested were: nitrogen at three levels, 0, 60 and 120 kg N ha^{-1} (N0, N60, and N120 respectively); and P also at three levels, 0, 60 and 90 kg P_2O_5 ha^{-1} (P0, P60, and P120 respectively). Initial P content of the soil was measured on soil samples taken at planting.

Maize was sown on June 17th at a spacing of 70 cm x 40 cm. A pre-emergence herbicide (Roundup or glyphosphate) was applied a few days after sowing.

All of the phosphorus was broadcast as Single Super Phosphate and incorporated by hand hoeing to a depth of 5 cm in all treatments, two days before sowing. Nitrogen was split-applied as urea at the bottom of 5-cm holes near the maize stands, 2 and 6 weeks after planting.

Field and laboratory measurements

Phenological observations on the number of days to emergence, tasseling, silking, blister stage, milk stage, dough stage, dent stage and physiological maturity were made on the middle four rows of each plot. The dates were established as corresponding to the time when 50% of the four rows sampled on each plot reached the different stages of interest.

Plant samples were taken five times randomly on the plots during the growing season. Each sample was obtained from a 0.8 m x 1.7 m = 1.12 m^2 area (two rows) that yielded about 8 plants. A sub-sample of 2-3 plants was taken from each sample for an oven-drying dry matter determination at 70^oC for 48 hours.

Leaf area index was directly measured on randomly selected plants using a Delta-T SunScan Canopy Analyzer.

Maturity total biomass and number of cobs were determined on the four middle rows (12 m^2) used for phenological observations. Sub-samples were taken for dry matter estimation of stover, grain yield and components, and 100-seed weight.

Statistical Analysis

Statistical analysis of the data obtained from the experiments in Kpeve and Wa was conducted using the SAS (SAS, 2002). A regression analysis was used to analyze soil moisture data collected at Kpeve and analysis of variance was used to summarize and understand the growth and development data from both experiments.

Regression analysis (soil moisture)

A regression analysis was carried out using the SAS software (SAS, 2002) to verify how well a linear regression model can be fitted to the dataset composed of the 67 pairs of TDR readings and soil moisture values obtained from the gravimetric samples. The purpose of the regression analysis was to derive an equation that can be used to convert TDR readings into volumetric water content of the soil. Tests of slope and intercept were carried out and a regression equation was set up that allowed the estimation of volumetric soil moisture values from specific TDR readings.

Analysis of variance at individual time points

Analysis of Variance (ANOVA) F-test was used to test the effect of P fertilizer application on crop phenology, grain yield, aboveground biomass, height, green leaf area, and soil moisture readings using TDR. This analysis was carried out at specific time points when the data were obtained. Hypotheses that were tested are described here.

Crop phenology. Inadequate supply of P has been reported to delay silking in maize resulting in an increase in anthesis to silking interval. It was hypothesized that increasing P fertilizer levels will result in early tasseling, anthesis and silking. These events should be delayed in no and low P treatments.

Green Leaf Area. Maize grown on low P soils has been reported to have access to a limited amount of Photosynthetically Absorbed Radiation (PAR), which reduces the area of expanding leaves (Pellerin et al., 2000). The green leaf area in the Kpeve experiment and the leaf area index in the Wa experiment were hypothesized to increase with higher levels of P fertilizer.

Aboveground biomass. The accumulation of aboveground biomass is directly related to the amount of PAR intercepted by the crop canopy and should be affected by P deficiency in the same way as green leaf area or leaf area index.

Grain yield. An increase of anthesis to silking interval or a delayed silking will result in a low grain number per square meter and a low grain yield (Plenet et al., 2000b). Growth deficit due to insufficient biomass accumulation can also affect negatively grain formation.

Height. Lack of adequate biomass accumulation and energy for physiological processes can result in stunted plants. Higher values of plant height are expected in P fertilized plots.

Aboveground biomass, height, green leaf area, leaf area index and soil moisture data were collected on the same plots, plants, and locations on the plots over time and were considered repeated measurements. Preliminary analyses of these data were first carried out at

individual time points. The individual time point analysis was used to examine treatment effects at specific sampling dates only. However, these analyses were one way ANOVAs considering each time point separately, as independent from each other, and did not make comparisons among different sampling dates.

Analysis of variance considering the effect of time on the repeated measurements

The individual time point analysis was extended using a repeated measures technique to account for the effects of time on the response variables taken in sequence over time during the growing season. More information can be derived from repeated measures than revealed by individual time point analysis ANOVAs: comparisons of treatments averaged over time and comparisons of times within a treatment are also informative.

When measurements (of height e.g.) are repeated on the same subject (e.g. plant) at specific time intervals (e.g. every 2 weeks, during the growth of the plant), the data are generally viewed as coming from a factorial experiment with treatments and time as the factors, and analyzed as if they came from a split-plot design because most statistical packages do not provide users with the capability of accounting properly for the effects of time. In this example, the plant would be considered as the whole-plot unit, and plants at specific times as the sub-plot unit. This method is known as the split-plot in time approach to analyzing repeated measurements (Littell et al., 1998). The assumptions supporting this split-plot in time approach are that variances of measurements taken at different times are equal and that pairs of measures coming from the same plant are equally correlated. This means that the correlation pattern among the measurements taken on the same plant is not affected by time. The split-plot in time analysis would have been optimal if the assumptions could be fully met in all circumstances. The peculiar property of repeating the measurement on the same plant means that sets of data from the same plant, though taken at different time points, are not independent. They include a

covariance structure resulting from differences between plants (between plants variation) and differences between times on the same plant (within plant variation). The covariance structure refers to two things: 1) variances in the data collected on the same plant at individual time points and 2) correlation between measurements taken on the same plant at different times. Littell et al. (1998) underlined the two aspects that are important to the correlation. First, two measures taken on the plant are correlated simply because they share common contributions from the same plant. Second, measures on the same plant close in time are often more correlated than measures far apart in time.

This covariance structure is not captured by the common ANOVA implemented in SAS with the general linear model PROC GLM.

In order to model the covariance structure related to the effect of time in this study, we used the PROC MIXED procedure now available in SAS since 1992 (Littell et al., 1998).

For comparison purposes we present results of the split-plot in time method (also called univariate ANOVA) and two covariance structures, summarized with their specifications in Table 2-3. The Akaike Information Criterion (AIC) was used as goodness of fit criterion to select the appropriate covariance structure for this study. The AIC is presented with the SAS output when PROC MIXED is run. The smaller the value of AIC, the better the structure.

The repeated measures analysis technique was applied only to green leaf area and height measurements taken from day 17 to day 52 after planting. Biomass and soil moisture were not analyzed using this technique because their measurements were taken at variable time intervals.

Results and Discussion

Response of maize biomass and grain yield to P fertilizer was not observed at Kpeve. At Wa, the plant response was measured not only on biomass and grain yield but also on phenology.

The analysis of the soil moisture data at Kpeve yielded an equation for prediction volumetric soil moisture from TDR readings.

Calibration of the TDR Meter

The soil moisture readings taken with the TDR meter appeared to be linearly related to the gravimetric sampling moisture determinations (Figure 2-4).

There is sufficient evidence to suggest that the relationship between the two methods of soil moisture determination is linear: an analysis of variance of the simple linear regression model was highly significant and the mean squared error was very low (Table 2-4). Seventy three percent of the variation in the meter readings was accounted for by the gravimetric samplings (coefficient of determination $R^2 = 0.73$). The regression equation model relating the volumetric soil moisture to the TDR reading is:

$$volumetric = 4.90 + 0.72 \times tdr \qquad (2\text{-}2)$$

Where *volumetric* is the volumetric soil moisture measured using gravimetric sampling;
tdr is the volumetric soil moisture read by the TDR meter;
The coefficient 0.72 (slope in the regression equation) is an estimate of the rate of increase in gravimetric soil moisture for each unit increase in TDR readings. Gravimetric soil moisture increases by 0.72% for each 1% reading by the TDR.

This equation can serve the purpose of predicting the volumetric soil moisture using the gravimetric method (considered as the true measurement) from any single or population of TDR readings. Tests of the slope and the intercept in this equation (H_0: slope = intercept = 0) lead to highly significant p values for rejecting H_0 (Table 2-5).

The regression line plotted on Figure 2-4 would be parallel to the 1:1 line ideally, but it is slightly more horizontal, thus crossing the perfect agreement line. This illustrates a tendency of the TDR meter to overestimate soil moisture at high soil moisture status. A possible explanation is that the meter would continue to read high soil moisture values as long as the rods are inserted into the soil with a steady, non wiggling downward pressure even if a high percentage of gravel

is present in the profile. The gravel content in the profile (0-30 cm) as measured for correction of the soil bulk density was between 25 and 45%. Gravel (soil solid particles with size greater than 2 mm) cannot hold water and would reduce the available water for the plant when they are present in relatively high quantities. The corrected bulk density used in this experiment to control the effect of the presence of stones on the soil moisture status helped to obtain lower values of soil moisture using the gravimetric sampling method. The equation established from this regression analysis is only valid for the type of soil used in the experiment.

Crop Response Results at Kpeve Using Individual Time Points Analysis

The individual time point analysis revealed no significant difference in phenology and growth at Kpeve except for the height (during the mid-season).

Phenology

The expected trend of P effect on tasseling, anthesis and silking was not observed. There was no consistent trend depicting the phenological response of the plant to P (Figure 2-5). The data collected in this experiment did not provide enough evidence to suggest an effect of P fertilizer on the phenology of maize (Table 2-6). On average, tasseling and anthesis dates differed among the P treatments by only one day. At silking however, the treatment receiving 80 kg P ha^{-1} was delayed by 4-6 days compared to the other treatments. The anthesis to silking interval (ASI) was 9 days on average and higher for the 80P treatment (13 days).

Grain yield and yield components

Both grain yield and stover weight were not affected by the P levels. Grain yield of about 3000 kg ha^{-1} was attained in all treatments and the average stover yield was 6500 kg ha^{-1} (Figure 2-6). The grain and stover yields were stable but the grain yield was more variable than the stover yield (overall coefficient of variation of 27% for grain yield and 15% for stover yield). This lack of response to P resulted in no statistical significance (Table 2-7).

The grain yield components were also stable between treatments (Figure 2-7). The average unit grain weight was 0.24 g and the average grain number per m^2 was 1500.

Aboveground biomass

Differences between P treatments were not significant at the individual time points analyzed, but the p-values decreased consistently over time (Table 2-8). The treatment mean squares increased with time corresponding to increased biomass accumulation with plant growth. The aboveground biomass as a combination of stover and grain yield, likewise did not respond to the P fertilizer. The coefficient of variation between treatments varied from 8 to 27% at 17 dap, 7 to 22% at 31 dap, 9 to 15% at 52 dap, and 10 to 19% at 108 dap. However, this variability in biomass and standard deviations (Figure 2-8) did not result in any statistical significance.

Plant height

Significant differences in plant height were observed mostly during mid-season (Pr = 0.03 at 31 dap, and Pr = 0.01 at 45 dap, Table 2-9). A least significant difference discrimination test showed that the treatment receiving 30 kg P ha^{-1} produced the tallest plants, not only at 31, 38 and 45 dap but also throughout the season (Table 2-10 and Figure 2-9). A maximum height of 250 cm was reached after anthesis.

Green leaf area

No statistical significant difference was generally observed among the treatments (Table 2-11) at the 0.05 level. At anthesis however, the treatments receiving 10 and 30 kg P ha^{-1} produced the highest green leaf area (6000 cm^2 per plant or a leaf area index of 3.75 using a plant population of 6.25 plants m^{-2}) (Figure 2-10) and were statistically different from the treatments receiving 0 and 80 kg P ha^{-1} at the threshold of $\alpha = 0.07$.

Soil moisture

The mean differences in soil moisture across the 4 treatment plots as shown on Figure 2-11 were not significant until after the drought spell (i.e. after 58 dap) when the soil started to be rewetted. There were significant soil moisture variations between blocks at the commencement of the trial, which justified blocking (Table 2-12). These interblock moisture differences disappeared however, from 48 dap onwards, at the start of the droughtspell and were not detected again until final harvest (Figure 2-11). It is noteworthy that when the soil moisture started to go up again, the significance probabilities for differences between blocks maintained a decreasing trend.

Crop Response Results at Kpeve Using Repeated Measures Analysis Techniques

The analysis revealed that the autoregressive structure was suitable for the datasets analyzed. Days after planting had a significant effect on growth but interacted significantly only with height. Averaged over time, height was the only measured variable that was significantly affected by P.

Selection of a correlation structure using the AIC

The values of AIC were consistently smaller for the autoregressive structure regardless of the variable of concern (Table 2-13). This statistic essentially confirmed that the correlation between pairs of height and green leaf area measurements taken on the same plant and at the same location on the field decreased with the age of the crop. For example, the autoregressive structure means that measurements of heights taken at days 17 and 24 after planting are more correlated than heights obtained at 17 and 52 days after planting on the same plant and at the same location on the field. Thus, the autoregressive structure was used in this application.

Effect of time on repeated measurements of crop response variables

Days after planting had a highly significant effect on all the repeated measurements regardless of the covariance structure. (Table 2-14). For plant height for instance, this means that the height values reached by the plant averaged over the four treatments were statistically different for days 17, 24, 31, 38, 45, and 52 after planting. This is expected because of the plant growth and development processes that notably increased the height between the measurement times.

Phosphorus treatments by time interactions effects on repeated measurements

The interactions involving time and P treatments were not significant for green leaf area regardless of the structure. The green leaf area curves for treatment 10P and 30P crossed each other at dap 45 but generally the shapes of the curves were essentially the same for each treatment (Figure 2-10). There was not enough evidence to suggest that the change over time in the responses of maize green leaf area was affected by P application.

The interaction between day after planting and P treatment was significant for maize height based on the autoregressive structure (Pr = 0.0354, Table 2-14). This statistical significance suggested that the height response curves that could be derived from Figure 2-9 were not the same. Differences between these responses curves came from the quantity of P applied in each treatment.

Effect on repeated measurements of phosphorus treatments averaged over time

The effect of P treatments on green leaf area averaged over sampling dates 17 through 52 days after planting was not significant (Pr = 0.3, Table 2-14) based on the autoregressive structure. This means that the overall effect of P treatments on maize green leaf area as tested in this study was not important at $\alpha = 0.05$. This finding is a confirmation of the results obtained

when the ANOVA was performed at individual time points: no statistical significance at $\alpha = 0.05$ was found at all sampling dates (Table 2-11).

Significant effects of P treatments on maize height averaged over sampling dates 17 through 52 days after planting were found using the autoregressive structure (Pr = 0.0228, Table 2-14). This suggested that plant height measurements taken at weekly intervals over the period 17 to 52 days after planting were significantly different between P treatments. This general conclusion on maize height response to P applications in this experiment was expected because the individual time point analysis showed significant differences between the P treatments at days 31 and 45 after planting and low probabilities for these differences at days 17, 24, 38 and 52 after planting (Table 2-9).

The importance of the choice of an appropriate correlation structure for the analysis of repeated measurements is highlighted by the contradictory results obtained with the univariate ANOVA and the compound symmetry structure (Table 2-14). For example, significance probability values produced by the univariate ANOVA were generally low for the effects of P (Table 2-14), suggesting strong evidence of differences in green leaf area between the four P treatments. We already knew that this was not true because most of the p-values obtained from analyses at individual time points were relatively high (Tables 2-9 and 2-11). The choice of a different correlation structure would lead to different conclusions about the effect of P on the green leaf area and height of maize averaged over six measurement dates.

Discussion of Results Obtained at Kpeve

The lack of response of phenology, biomass, yield and yield components of maize to P fertilizer in the Kpeve experiment was because P did not limit plant growth and development in the experiment. Since all other major nutrients and water (at least until anthesis) were supplied in sufficient amounts, it is reasonable to suggest that the plants had access to and were able to take

up P from an adequate supply of indigenous P throughout the growing season. Although the soil P level (Bray 1) was apparently low (Tables 2-15 and 2-16), there are at least five problems associated with relying on the classification in Table 2-16 alone to draw conclusions about the P status of the soil:

- **Problem 1:** the Bray-1 P method does not measure P available for plant uptake but only that amount of P that would probably correlate with plant growth (Johnston, 2000);

- **Problem 2:** the P level in the soil top 20 cm used in this experiment is close to the sufficiency level of 16 ppm as defined by Shapiro et al. (2003) (Table 2-16). Since P exists in the soil in many forms that exchange P between each other, it is not clear how P would behave in the soil at the boundary between sufficiency and deficiency. Other studies (for example Adeoye and Agbola (1985)) found a critical range of Bray 1 P availability of 10-16 ppm for tropical soils. Measured Bray 1 P in or below this range would be considered low;

- **Problem 3:** Other forms of P that were not measured by the Bray-1 method could have become soluble. The inorganic active P (represented by NaOH-Pi, Table 2-17) is an important source of P that can become directly soluble during the growing season. The organic carbon content of the soil that was nearly 2% in the topsoil could have contributed P through mineralization especially under tropical conditions (Osiname et al., 2000). Current thinking envisages the different forms of P in the soil as existing in equilibrium. Field preparation disturbs the equilibrium and subsequent decomposition of soil organic may release additional P. Also, plant uptake can displace this equilibrium in such a way that replenishment of soluble P from other forms of P is continuous. Johnston (2000) showed that in addition to providing P through mineralization, soil organic matter provides sites with low bonding energy for P;

- **Problem 4:** The experimental field was left to natural bush fallow for about 2 years and P fertilizer at 7.5 kg P_2O_5 ha^{-1} was applied to maize grown on the field in 2004 prior to the 2-year fallow. Plant residues from the two-year natural bush fallow that preceded the experiment was mixed with the soil during plowing, seven days before maize planting. The 2004 P fertilizer and the decomposition of the maize and fallow residues could contribute significant amount to soil P build up that could have been made available when the soil was brought out of the fallow for the experiment;

- **Problem 5:** The soil had an ideal pH (6.5) for P transformations and availability (Table 2-15).

The delay in silking was due to the drought spell that occurred right after anthesis and lasted until after silking (Figure 2-11). Studies have shown that water stress delays silking in maize and results in an increase in the anthesis to silking interval (Balanos and Edmeades, 1993).

Similar findings on the positive effects of P on plant height were reported by Khan et al., 2005. In the Kpeve experiment, the significant differences in heights between the treatments did not result, however, in differences in biomass production. The LSD for height differences at 31, 38 and 45 days after planting were respectively 6, 11, and 16 cm. Compared to the respective height ranges of 75-84, 124-138, and 188-215 cm (Table 2-9), those height differences (LSD) corresponded to a part of the upper canopy that did not contribute much to the weight of the plant and was mostly leaf blade.

The significance of the effect of days after planting on measurements repeated over time has an agronomic meaning. It corresponds to an active period of growth for plant height and green leaf area as shown on Figures 2-9 and 2-10.

Results and Discussion for the Wa Experiment

The soil in Wa contained very little available P and organic matter (Table 2-18). Maize responded to nitrogen and phosphorus to the expected extent, confirming past and current findings by other researchers (Singh and al., 1999; Colomb et al, 2000; Khan et al., 2005). The results obtained in the Wa experiment are fully reported and discussed in Naab (2005). A summary of the responses observed are presented here.

Nitrogen and phosphorus had similar effects on the phenological development of maize. Tasseling was not affected by nutrient management. On the contrary, silking was delayed by about 1-3 days in treatments that did not receive nitrogen or phosphorus (Table 2-19). Statistical differences at silking were observed only between the no and medium or high nutrient application. Differences were not found between the medium (60 kg [N] ha^{-1} and 60 kg [P_2O_5] ha^{-1}) and high (120 kg [N] ha^{-1} and 90 kg [P_2O_5] ha^{-1}) nutrient applications. The overall effect of the nutrient deficiency on physiological maturity of the crop was small and not significant (Table 2-19). Grain filling duration was shortened in the no nutrient treatments in such a way that

physiological maturity did not differ among treatments. Similar results were obtained in Hawaii by Singh et al. (1999).

Significant leaf area index (LAI) differences due to nitrogen and phosphorus applications were observed throughout the season (Table 2-20). The effect of P on LAI disappeared at 90 dap and thereafter. These LAI differences were observed only between the no nutrient treatments and the 60 kg [N] or [P] ha^{-1} treatments, and LAI did not increase beyond the level of 60 kg [N] or [P] ha^{-1}. The maximum LAI advantage over P0, 50% in P60, was observed at 40 dap. Plenet et al. (2000a) found an LAI reduction of the same magnitude (60%) between the 7- and 14-visible leaves in a P response experiment in France.

Aboveground biomass responded consistently both to nitrogen and phosphorus fertilization at all sampling dates (28, 46, 61, 81, and 125 days after planting). Nitrogen applied at 120 kg ha^{-1} did not result in any significant biomass accumulation over the 60 kg ha^{-1} N level at days 28, 46, and 61 dap. At 81 and 125 dap however, the difference between N60 and N120 were amplified and were significant (Table 2-21). The N60 treatment resulted in biomass differences of 75 to 4500 kg ha^{-1} over N0, which represented 19 and 67% of the biomass obtained in N60. Response to P was less drastic but also significant. Differences were not found between P60 and P90 at all sampling dates. The biomass gain of P60 over P0 ranged from 130 to 3300 kg ha^{-1} corresponding to 31 to 56% of the biomass measured in P60. The highest biomass and LAI gains (over N0 or P0) were obtained at the same sampling periods (40-46 dap for nitrogen and 61-68 dap for phosphorus). This could be a confirmation of findings by Plenet et al. (2000b) according to which poor biomass accumulation in P deficient plants was mainly due to reduced photosynthetically active radiation absorbed by the canopy caused by reduced leaf area.

Fruit weight increased significantly between N0, N60, and N120. For phosphorus, differences were found only between P0 and P60, and P0 and P90. No significant differences in fruit weight were revealed between P60 and P90 (Table 2-22). Fruit growth was affected more severely by nitrogen than phosphorus (Table 2-22). For example, grain yield gains were 77% in N60 over N0 and only 42% in P60 over P0. The effect of P applications on seed weight was relatively small compared to the effect of nitrogen (Table 2-22). These ultimate effects on grain yield and yield components were probably associated with the consequences of nitrogen and phosphorus stress on photosynthesis (Singh et al., 1999).

Conclusions

The study at Kpeve did not result in the expected response to P fertilizer applications. No significant differences in plant phenology, aboveground biomass, green leaf area and grain yield were found between fertilized and unfertilized treatments. Significant differences in plant height observed at 31, 38, and 45 days after planting were not reflected in biomass accumulation or grain yield. Although the initial available P (Bray 1) was relatively low in all layers, other important P sources such as chemical contributions of organic matter not accounted for by the Bray 1 extraction could have been responsible for high indigenous P supply in the soil.

At Wa, soil P levels were sufficiently low to cause a P fertilizer response in the crop. Delay in silking of about 1 day was observed in the treatment that did not receive any P input. The delay in silking was 2 days in the no nitrogen treatments and 1 day in the no P treatments. Leaf area index and aboveground biomass were reduced in no nitrogen and no phosphorus treatments throughout the season. The highest reduction in leaf area index and biomass occurred at the same time period, which strengthens the idea that poor biomass accumulation in P deficient conditions is associated with reduced photosynthetically absorbed radiation by the plant, which is a

consequence of reduced leaf area. The reduction in grain yield could have been a result of nutrient stress on photosynthesis.

The contrasting results obtained at the two sites in terms of response to P would be useful in testing the ability of computer simulation models of soils and plants to capture and mimic the effect of variability in P management on crops. In Chapter 4, this attempt is made using the soil-plant phosphorus model in the Decision Support System for Agrotechnology Transfer.

Table 2-1. Growth and development genetic coefficients for the Obatanpa cultivar used at both sites, Kpeve and Wa (Ghana)

Definition	DSSAT ID	Obatanpa
Degree-days (base 8^{o}C) from emergence to end of juvenile phase	P1	300
Photoperiod sensitivity	P2	0.00
Degree-days (base 8^{o}C) from silking to physiological maturity	P5	830
Potential kernel number (/plant)	G2	900
Potential kernel growth rate (mg/day)	G3	6.50
Phyllochron interval (degree-days)	PHINT	38.90

Table 2-2. Summary of fertilizer application methods used in the experiment in Kpeve, Ghana

Days after planting	Ammonium Sulfate	Triple Superphosphate	Potassium Nitrate
0	Broadcast without incorporation	Side placement, bottom of hole	Broadcast without incorporation
13	Side placement, without incorporation	Side placement, bottom of hole	Side placement, without incorporation
30	Side placement, without incorporation	No Application	No application
44	Side placement, without incorporation	No Application	No application

Table 2-3. Specifications of two different covariance structures used for modeling the effect of time on repeated measures in PROC MIXED for the Kpeve dataset

Covariance structure	Specifications
Compound Symmetry	1. Measures at all times have the same variance; 2. Pairs of measures from the same subject have the same correlation;
Autoregressive	1. Measures at all times have the same variance; 2. Correlations between pairs of measures from the same subject decrease as the time lag between measures increases;

Source: Adapted from Littell et al. (1998).

Table 2-4. Analysis of Variance for simple linear regression between soil moisture measurements using TDR and gravimetric methods at Kpeve, Ghana

Source of variation	Degree of Freedom	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	805.45874	805.45874	178.19	<.0001
Error	65	293.82273	4.52035		
Total	66				

Table 2-5. Test of parameter estimates used to fit the linear regression model in the Kpeve experiment

Variable	Degree of Freedom	Parameter Estimate	Standard Error	T Value	Pr > | t |
Intercept	1	4.90191	0.68030	7.21	<.0001
tdr	1	0.71900	0.05386	13.35	<.0001

Table 2-6. Analysis of variance of phenological events, tasseling, anthesis and silking in the Kpeve experiment

Source of variation	Degree of Freedom	Sum of Squares	Mean Square	F Value	Pr > F
Tasseling					
Block	3	0.6875	0.2292	0.11	0.9496
Phosphorus	3	6.1875	2.0625	1.03	0.4254
Anthesis					
Block	3	1.2500	0.4167	0.88	0.4861
Phosphorus	3	2.2500	0.7500	1.59	0.2594
Silking					
Block	3	31.1875	10.3958	0.70	0.5737
Phosphorus	3	100.1875	33.3958	2.26	0.1506

Table 2-7. Analysis of variance for grain yield (measured in kg ha^{-1}) at Kpeve, Ghana

Source of variation	Degree of Freedom	Sum of Squares	Mean Square	F Value	Pr > F
Block	3	2447042	815681	1.12	0.39
Phosphorus	3	427698	142566	0.20	0.90
Error	9	6557203	728578		

Table 2-8. Summary of results from ANOVA (mean squares (p-values), n = 4) at individual time points for crop aboveground biomass measured in kg ha^{-1} in the Kpeve experiment

DAP	17	31	52	108
Block	394 (0.45)	9342 (0.78)	462057 (0.36)	3781140 (0.11)
Phosphorus	55 (0.94)	11257 (0.73)	366238 (0.45)	1189617 (0.50)
Error	410	25489	381818	1382973

Table 2-9. Summary of results from ANOVA (mean squares (p-values), n = 4) at individual time points for plant height measured in cm in the Kpeve experiment

DAP	17	24	31	38	45	52	68
Block	45.82	61.69	90.81	727.11	794.51	775.17	1079.05
	(0.20)	(0.46)	(0.54)	(0.15)	(0.40)	(0.52)	(0.45)
Phosphorus	54.87	106.03	388.72	978.82	3517.83	1882.73	2401.73
	(0.14)	(0.22)	(0.03)	(0.07)	(0.01)	(0.14)	(0.13)
Error	29.21	70.63	124.47	397.13	805.88	1020.16	1224.96

Table 2-10. Treatment means at each day for plant height measured in cm, with least significant difference (LSD) in the Kpeve experiment ($\alpha = 0.05$)

DAP	Treatment				LSD
	0P	10P	30P	80P	
17	25.91 ab	28.52 a	25.65 ab	25.14 b	3.10
24	42.43 b	44.85 ab	47.40 a	43.81 ab	4.82
31	76.06 b	75.858 b	84.05 a	81.22 ab	6.40
38	123.70 b	128.94 ab	138.15 a	125.75 b	11.43
45	194.80 bc	207.78 ab	214.59 a	187.93 c	16.28
52	235.90 a	250.15 a	249.94 a	233.67 a	18.32
68	240.29 a	258.60 a	256.45 a	240.24 a	20.08

Means with the same letter are not statistically different at $\alpha = 0.05$.

Table 2-11. Summary of results from ANOVA (mean squares (p-values), n = 4) at individual time points for green leaf area measured in cm^2 per plant at Kpeve

DAP	17	24	31	38	45	52	68
Block	33194	302147	1014051	2427809	5623424	2411939	5006509
	(0.03)	(0.03)	(0.08)	(0.07)	(0.002)	(0.12)	(0.004)
Phosphorus	13567	151693	647931	1742106	1022362	3016789	1860147
	(0.27)	(0.19)	(0.22)	(0.17)	(0.40)	(0.07)	(0.16)
Error	10192	94055	430784	1010465	1040870	1220628	1052365

Table 2-12. Summary of results from ANOVA (mean squares (p-values), n = 4) at individual time points for soil moisture readings (in %) using TDR at Kpeve

DAP	30	37	45	48	53	55	58	64	69	74
Block	19.62	11.01	12.25	3.02	1.15	1.67	4.90	14.96	34.92	17.08
	(0.07)	(0.04)	(0.02)	(0.39)	(0.76)	(0.53)	(0.11)	(0.37)	(0.18)	(0.16)
Phosphorus	9.01	4.72	6.72	2.37	2.02	0.49	3.31	39.14	54.51	23.48
	(0.34)	(0.31)	(0.14)	(0.49)	(0.56)	(0.88)	(0.25)	(0.05)	(0.06)	(0.07)
Error	7.93	3.83	3.51	2.93	2.90	2.23	2.35	14.05	20.94	9.63

Table 2-13. Akaike Information Criterion (AIC) test for two covariance structures in PROC MIXED for repeated measures analysis for the Kpeve experiment

Variable	AIC value	
	Compound Symmetric	Autoregressive + random
Height	4909.8	4846.6
G. Leaf Area	9015.5	8865.1

Table 2-14. *F*-values and significance probabilities using univariate ANOVA, and for test of fixed effect using two covariance structures in PROC MIXED for the Kpeve experiment

Source of variation	df	Univariate ANOVA	Compound Symmetric	AR(1) plus random effect
Height				
P	3	10.63 (< .0001)	1.79 (0.1822)	3.21 (0.0228)
DAP	5	2096.7 (< .0001)	2096.7 (< .0001)	1770.88 (< .0001)
P x DAP	15	1.88 (0.023)	1.88 (0.0343)	1.77 (0.0354)
G. Leaf area				
P	3	6.80 (0.0002)	1.35 (0.3)	1.35 (0.3)
DAP	5	5.03 (< .0001)	888.8 (< .0001)	823.53 (< .0001)
P x DAP	15	0.87 (0.6)	0.87 (0.6)	1.15 (0.3066)

Table 2-15. Physical and chemical characteristics of the soil at the experimental site in Kpeve, Ghana

Parameter	0-10 cm	10-20 cm	20-30 cm
Texture			
Clay (%)	18	20	18
Silt (%)	28	29	27
Sand (%)	54	51	55
Gravel (%)	40	40	35
Organic Matter			
Organic carbon, Walkley-Black (%)	1.84	1.8	1.55
Total nitrogen (%)	0.26	0.25	0.22
Phosphorus			
Total phosphorus (mg/kg)	294	299	229
Bray 1 (mg/kg)	11.69	10.4	7.43
Mehlich 1* (mg/kg)	90.44	46.12	50.19
Exchange Complex			
Potassium K (cmol/kg)	0.11	0.08	0.06
Calcium Ca (cmol/kg)	7.39	7.31	7.65
Magnesium Mg (cmol/kg)	2.61	2.40	2.38
Acidity			
pH-H20	6.45	6.56	6.48

*The Mehlich 1 analysis was done by the Wetland Biogeochemisty Laboratory at the University of Florida. All other tests were done in the soil testing laboratory at the University of Ghana.

Table 2-16. Classes of phosphorus availability according to the Bray 1 extraction method

Soil test, P Bray 1 (ppm)	Relative P level
0-5	Very Low
6-15	Low
16-24	Medium
25-30	High
> 30	Very High

Source: Shapiro et al. (2003).

Table 2-17. Characterization of the different forms of soil phosphorus at Kpeve, Ghana. Data are reported in mg/kg

P fraction	0-10 cm	10-20 cm	20-30 cm
Inorganic			
KCl Pi	3.3	1.7	3.6
NaOH Pi	56.4	40.8	40.9
HCl Pi	76.4	28.3	27.6
Organic			
NaOH Po	65.8	65.0	64.7
Residual P	153.6	120.2	140.1

Table 2-18. Physical and chemical characteristics of the soil at the experimental site in Wa, Ghana

Parameter	0-20 cm	20-40 cm	40-60 cm	60-90 cm
Texture				
Clay (%)	7.50	14.50	40.90	52.90
Silt (%)	8.30	8.20	10.70	16.90
Sand (%)	84.20	77.30	48.40	30.20
Gravel (%)	4.30	6.40	49.20	80.70
Organic Matter				
Organic carbon (%)	0.49	0.48	0.51	0.43
Total nitrogen (%)	0.06	0.06	0.04	0.04
Phosphorus				
Bray 1 (mg/kg)	2.50	Not	measured	
Exchange Complex				
Potassium K (cmol/kg)	0.06	0.08	0.11	0.13
Sodium Na (cmol/kg)	0.49	0.45	0.52	0.45
Calcium Ca (cmol/kg)	1.54	1.23	1.62	1.86
Magnesium Mg (cmol/kg)	0.32	0.51	0.74	0.86
Acidity				
pH-H20	6.34	6.25	5.94	6.02

Table 2-19. Main effects of nitrogen and phosphorus on phenological development in maize at Wa, Ghana

Treatment	Days to Phenological Stage (days)			
Nitrogen	Tasseling	Silking	Grain filling duration	Physiological maturity
N0	49	57 a	39	96 a
N60	48	55 b	40	95 ab
N120	48	54 b	41	95 b
Phosphorus				
P0	49	56 a	40	96 a
P60	48	55 b	40	95 a
P90	48	55 ab	40	95 b

Source: Adapted from Naab (2005). Means with the same letter are not statistically different at $\alpha = 0.05$ in each column.

Table 2-20. Main effects of nitrogen and phosphorus on leaf area indices of maize at Wa, Ghana

Treatment	Days After Planting (days)				
	28	40	68	81	90
Nitrogen					
N0	0.60 a	0.52 a	0.57 a	0.83 a	0.54 a
N60	0.88 b	1.03 b	1.32 b	1.46 b	1.03 b
N120	0.88 b	0.92 b	1.55 b	1.74 c	1.13 b
Phosphorus					
P0	0.52 a	0.51 a	0.83 a	1.01 a	0.75 a
P60	0.90 b	1.02 b	1.38 b	1.55 b	1.01 a
P90	0.93 b	0.95 b	1.23 b	1.47 b	0.94 a

Source: Naab (2005). Means with the same letter are not statistically different at $\alpha = 0.05$ in each column.

Table 2-21. Main effects of nitrogen and phosphorus on cumulative aboveground biomass (in kg ha^{-1}) of maize at Wa, Ghana

Treatment	Days After Planting				
	28	46	61	81	125
Nitrogen					
N0	334 a	1088 a	2289 a	2155 a	1740 a
N60	410 b	2435 b	6961 b	6473 b	5621 b
N120	403 b	2436 b	7811 b	8287 c	7502 c
Phosphorus					
P0	292 a	1069 a	3223 a	3520 a	3222 a
P60	426 b	2403 b	6549 b	6816 b	6025 b
P90	429 b	2486 b	7289 b	6580 b	5615 b

Source: Naab (2005). Means with the same letter are not statistically different at $\alpha = 0.05$ in each column.

Table 2-22. Main effects of nitrogen and phosphorus fruit yield components of maize at Wa, Ghana

Treatment	Fruit Yield		
	Cob weight (kg ha^{-1})	Grain yield (kg ha^{-1})	1000-seed weight (g)
Nitrogen			
N0	632 a	479 a	190 a
N60	2556 b	2063 b	226 b
N120	4042 c	3340 c	250 c
Phosphorus			
P0	1646 a	1320 a	203 a
P60	2833 b	2292 b	235 b
P90	2750 b	2271 b	228 b

Source: Adapted from Naab (2005). Means with the same letter are not statistically different at $\alpha = 0.05$ in each column.

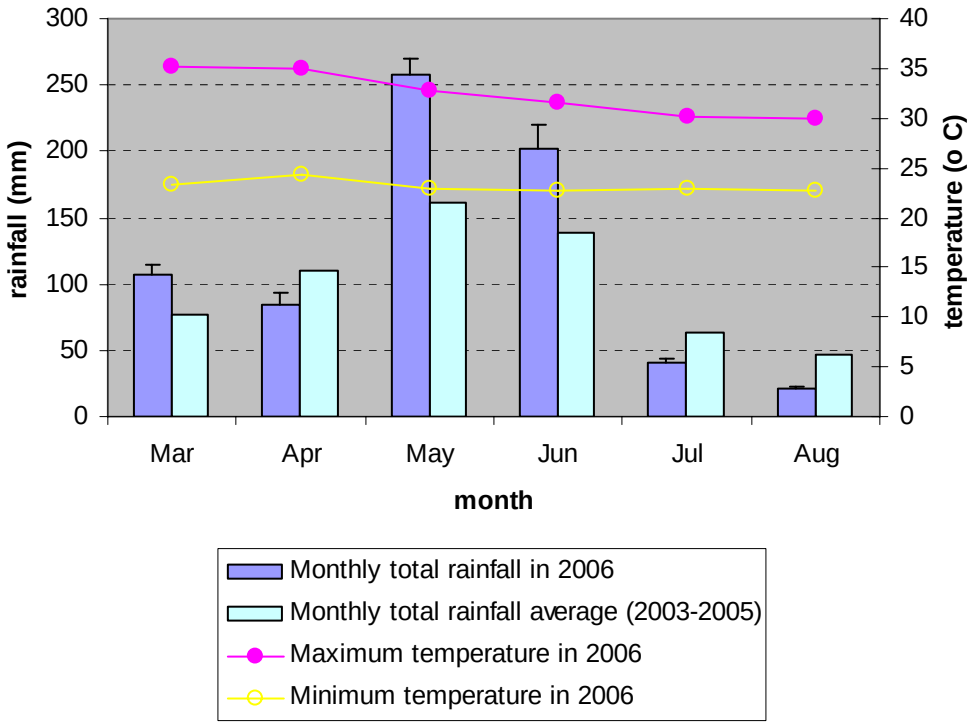


Figure 2-1. Monthly total rainfall in 2006 (mm) with error bars corresponding to one standard deviation of rainfall, monthly total rainfall average from 2003 to 2005, and monthly average daily temperature (^{o}C) in 2006 at Kpeve. 2006 data were collected during the experiment and 2003-2005 data taken from Adiku (2006)

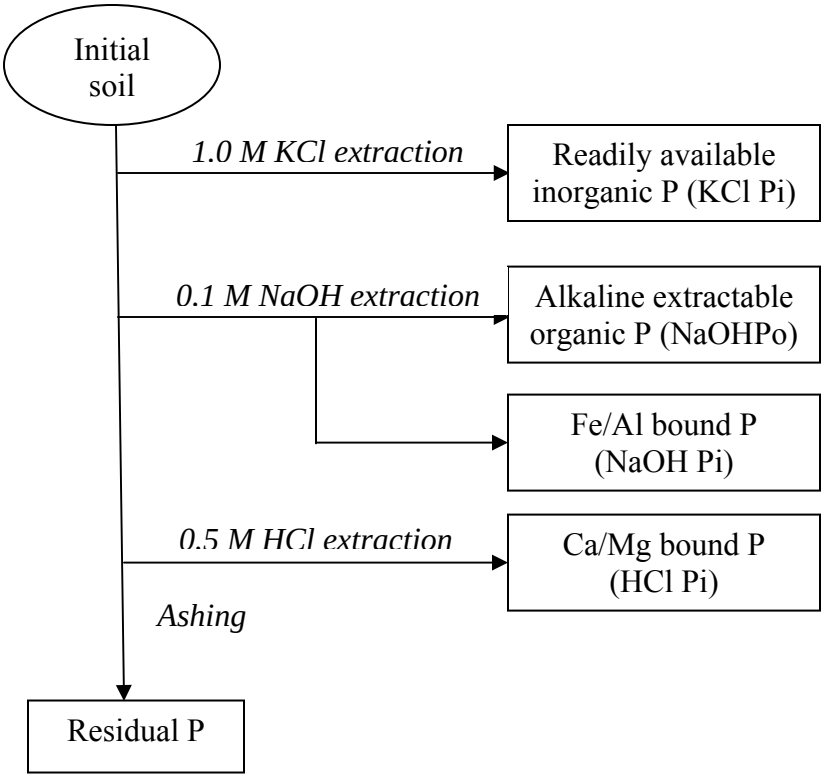


Figure 2-2. Sequential fractionation steps used for extracting the different forms of phosphorus from soil samples taken before planting of the Kpeve experiment. Samples analyzed by the Wetland Biogeochemistry Laboratory, University of Florida

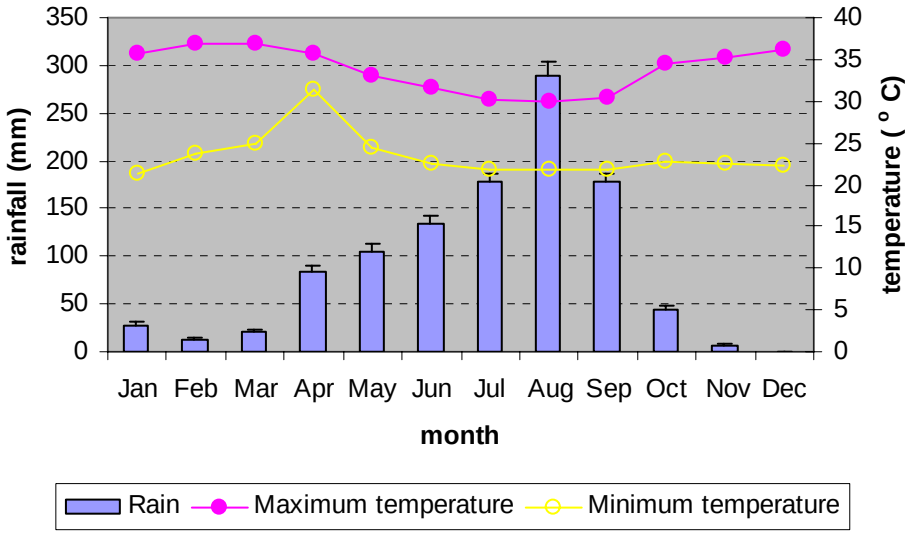


Figure 2-3. Monthly total rainfall (mm) with error bars corresponding to one standard deviation of rainfall and monthly average daily temperature (^{o}C) at Wa in 2004. Data from Naab (2005).

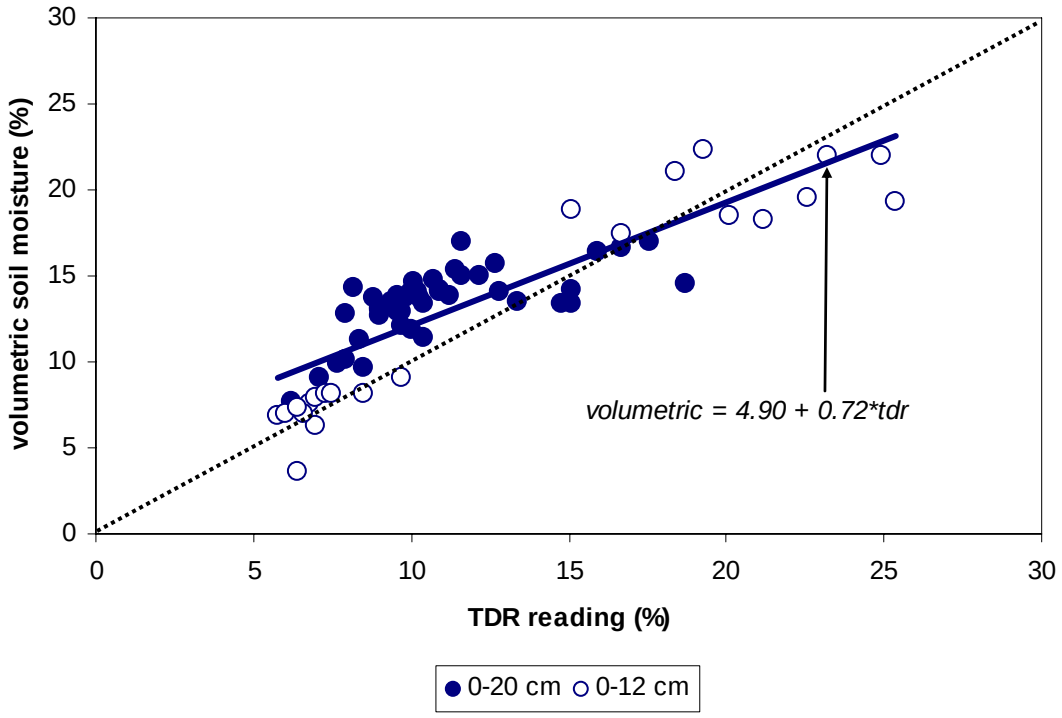


Figure 2-4. Simple linear regression of volumetric soil moisture (%) determined by using Time Domain Reflectrometry and gravimetric sampling at Kpeve

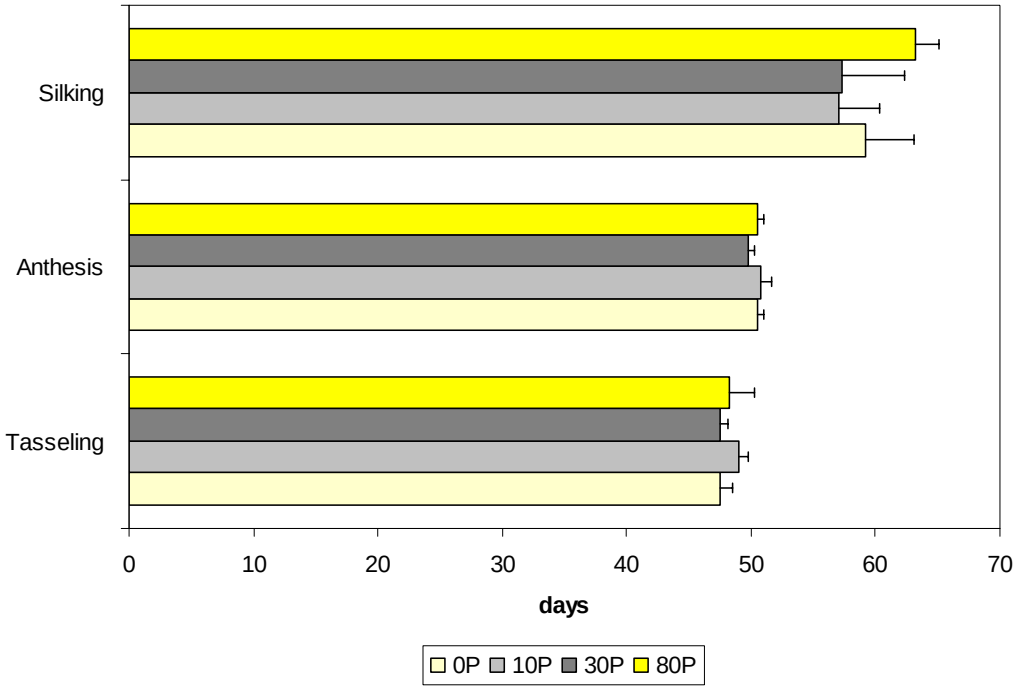


Figure 2-5. Phenology of maize as affected by phosphorus application at Kpeve. Error bars represent standard deviations of measurements taken from four replications

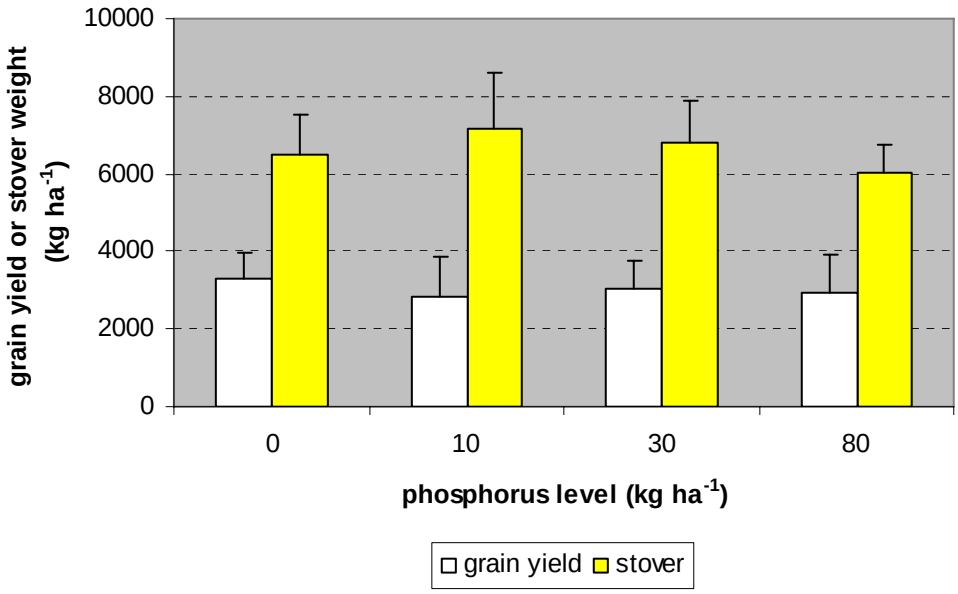


Figure 2-6. Stover and grain yield of maize as affected by phosphorus fertilizer at Kpeve. Error bars represent one standard deviation of measurements taken from four replications

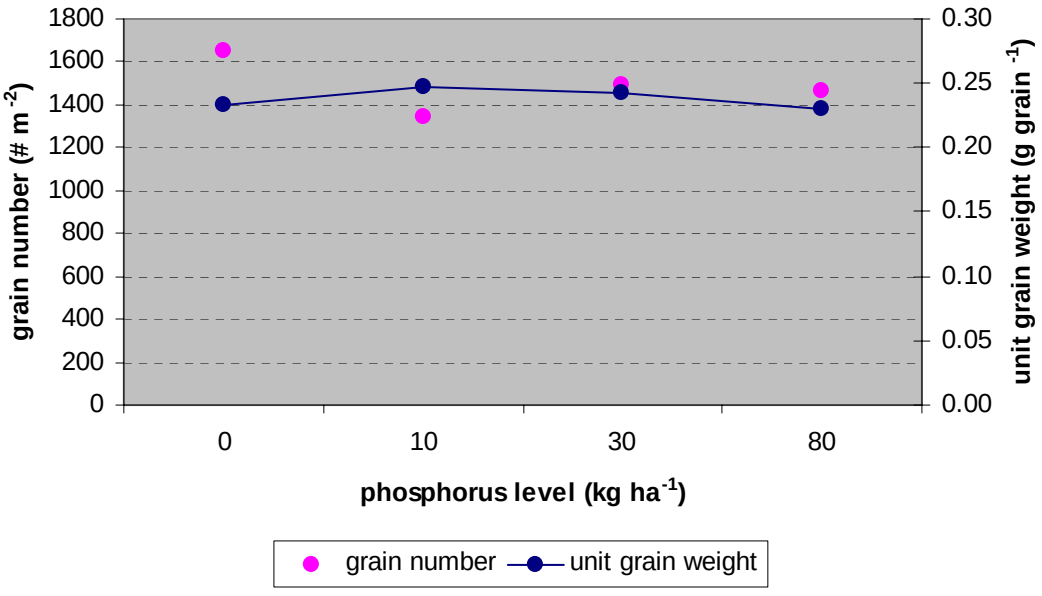


Figure 2-7. Grain number per m^2 and unit grain weight as affected by phosphorus fertilizer at Kpeve.

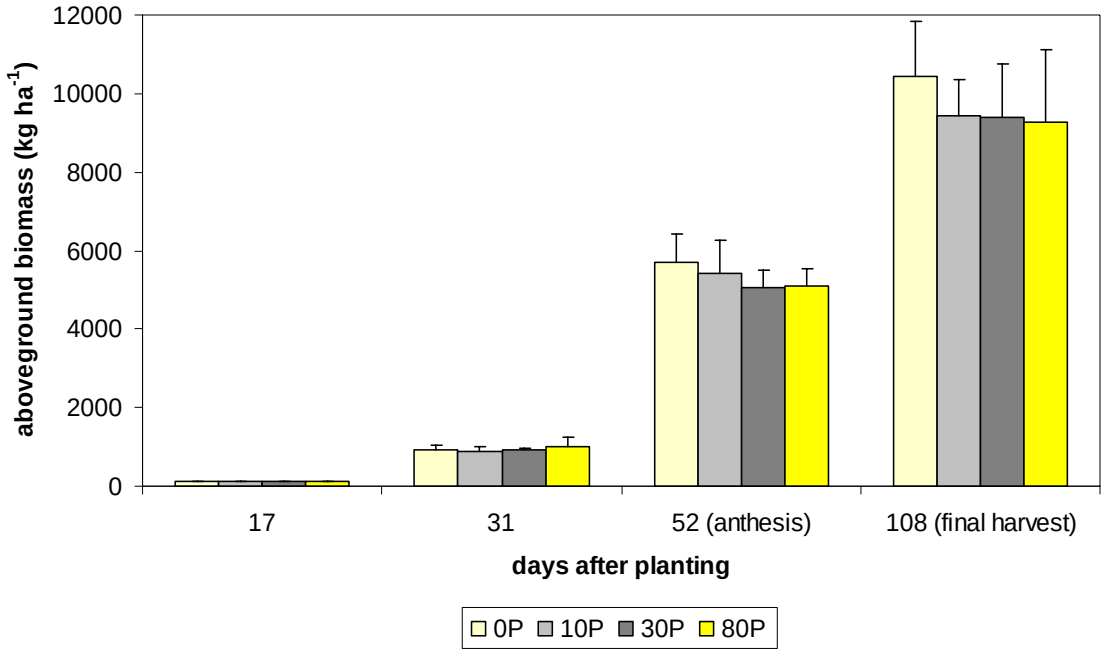


Figure 2-8. Aboveground biomass of maize as affected by phosphorus fertilizer application at Kpeve. Error bars represent one standard deviation of measurements taken from four replications.

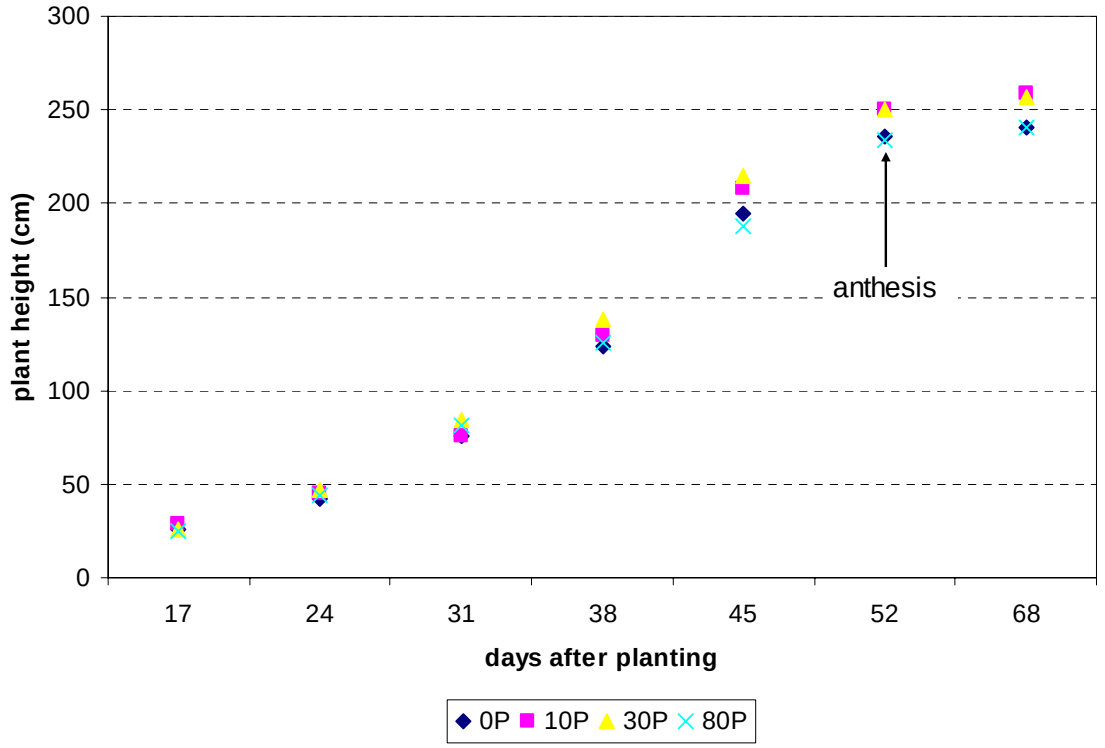


Figure 2-9. Height of maize as affected by phosphorus fertilizer in the Kpeve experiment

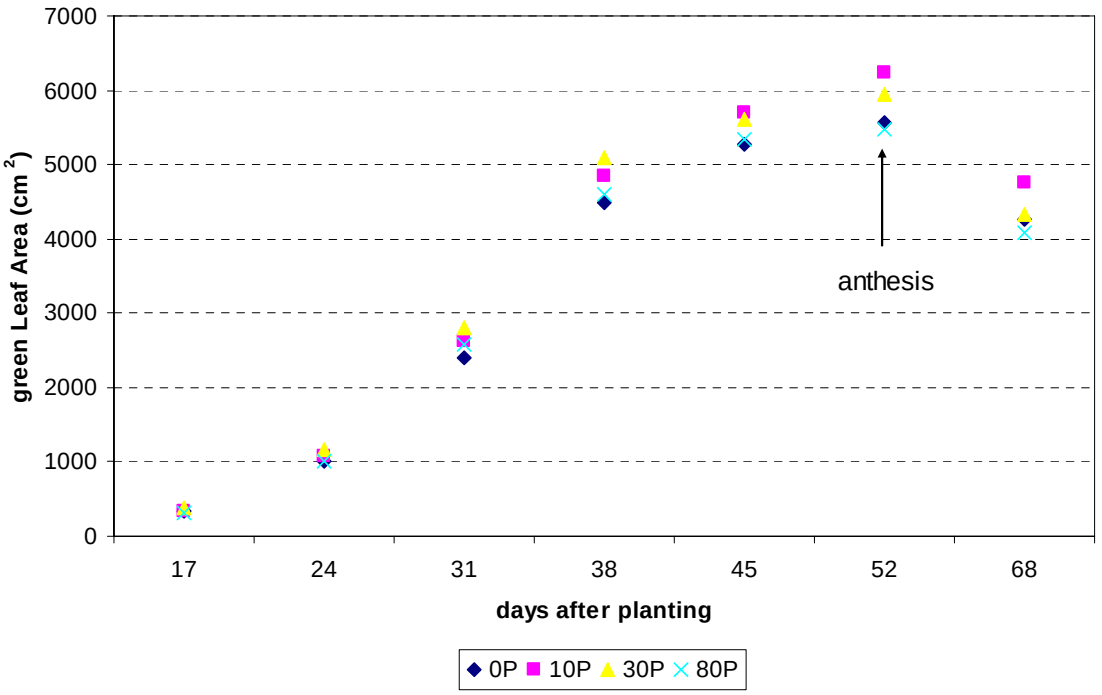


Figure 2-10. Green Leaf Area of maize in the phosphorus fertilizer experiment at Kpeve

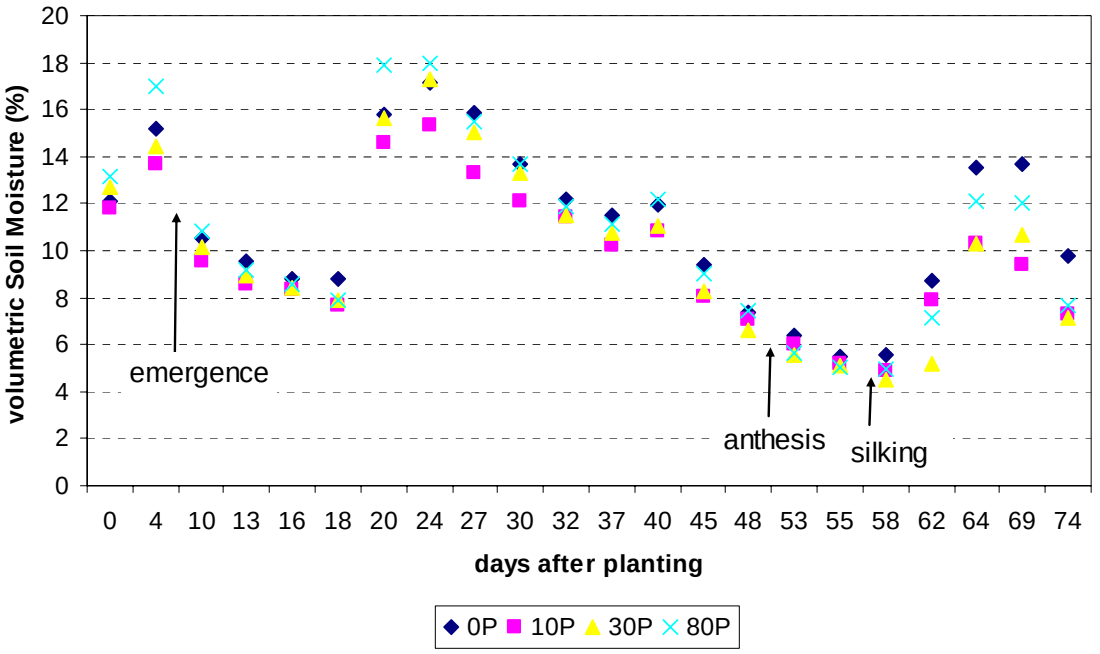


Figure 2-11. Variation in soil moisture measured using Time domain reflectometry in the Kpeve phosphorus experiment. The possible effects of the four phosphorus treatments on the soil moisture are analyzed and reported at individual time points in Table 2-12.

CHAPTER 3
THE SOIL-PLANT PHOSPHORUS MODEL IN DSSAT

Introduction

Biological, physical and chemical processes affecting phosphorus (P) transformations in soils and plants create dynamic soil P pools that interact with plants in a complex way. Phosphorus is present in the soil in two main forms: inorganic and organic. The inorganic forms represent mineral P in the soil solution, P bound to calcium, P retained by iron and aluminum oxides and by clay, and P occluded in iron and aluminum minerals. The organic forms correspond to P in fresh organic residues, P in soil organisms' biomass, and P in slowly decomposing soil organic matter. The forms of P in the soil are dependent on many soil properties but the most important are soil pH, organic carbon content, the quantity and type of clay, and the cation exchangeable capacity of the soil. For example, plant P nutrition is optimal at pH 6.5 because the available form of P for uptake by plants predominates at that pH.

Plants take up phosphorus from the soil solution that is replenished by the other forms of inorganic P and through mineralization of organic P. Several transformations between the different forms of P occur in the soil, but the contribution to the soil solution is very low. The amount of phosphorus available to plants from the soil solution at any one time would seldom exceed about 0.01% of the total phosphorus in most soils (Brady and Weil, 2002).

Description of phosphorus processes taking place in a soil-plant system therefore would deal with i) the different forms present in the soil; ii) the transformations that make insoluble forms soluble for plant uptake; iii) plant uptake mechanisms; and iv) conditions and mechanisms of P supply to plants.

The soil-plant phosphorus model in the Decision Support System for Agrotechnology Transfer (DSSAT) attempts to consider these aspects to simulate phosphorus transformations in

soils and plants and their effect on crop production. The soil inorganic P module of the model simulates phosphorus transformations between a labile, active and stable pool. The soil organic P module simulates phosphorus transformations between a surface litter, a microbial pool, and a stable pool. The model accounts for the mineralization of organic P to inorganic pools and the immobilization of P to organic pools. In phosphorus deficient soils where organic matter play an important role in the supply of nutrients, simulation of the release of phosphorus from organic matter accounts for an important source of P. Available phosphorus for uptake by plants is described as being provided by the labile pool within a short distance of plants' roots (2 mm).

Phosphorus taken up by the plant is partitioned to seeds, shells and vegetative tissues. During the reproductive phase, phosphorus accumulated in the vegetative tissues can be remobilized and translocated to seeds. Plant growth is limited by phosphorus between two thresholds that are species-specific optimum and minimum concentrations of P defined at different stages of plant growth. Phosphorus stress factors are computed to reduce photosynthesis, dry matter accumulation and partitioning.

The present chapter summarizes procedures used in the simulation of the phosphorus balance in the DSSAT cropping system models. The objectives of the chapter are to: i) present the phosphorus modeling framework in the DSSAT cropping system model; ii) present a description of the soil and plant phosphorus model in DSSAT; iii) present a sensitivity analysis of the model to selected key phosphorus-related parameters. The main question of interest in the sensitivity analysis was: how does the variability of six major phosphorus-related factors affect biomass and grain yield as simulated by the model?

Soil and Plant Phosphorus Modeling in DSSAT

The need for implementing a phosphorus model in DSSAT was already recognized as a limitation of the software at the release of its first version (Jones et al., 1998). It was clear that

the integration of a phosphorus component into DSSAT would considerably increase and extend its applicability not only to P deficient environments, but also to low input cropping systems receiving significant amounts of phosphorus from the decomposition of organic matter. The development of a phosphorus model in DSSAT presented at least two challenges: i) scientists need to improve their understanding of phosphorus behavior in soils and plants because of the complexity of P chemistry in soils and its interaction with other major nutrients that limit plant growth; ii) the design of the initial version of DSSAT was not suitable for maintenance of the software as new models were included and modifications were made. The software was a collection of independent models operating in the same framework to integrate information about soil, climate, crop and management. The models in the decision support system were operating in their own original programming settings.

For many years the models in DSSAT have been used to simulate potential, water and nitrogen limited production only, even in areas where phosphorus deficiency is widespread. Advances in modular programming techniques have enabled DSSAT developers to completely redesign the software (Jones et al., 2003); the crop models can now operate using the same soil module, the same climate module, and the same management module. Other modules could therefore be more easily included and connected to existing crop models with minimal modification to the system. The new programming technique also facilitates documentation and updating of the individual modules that were developed by specialists from different disciplines working together as a team.

The first version of a soil-plant phosphorus model linked to the DSSAT cropping system model (CSM) was developed and evaluated by Daroub et al. (2003) for calcareous and highly weathered soils. The model could have been plugged into any crop models within the DSSAT

CSM to simulate phosphorus-limited production, but was tested only for maize and soybean. Although the model predicted grain yield and plant uptake with a reasonable degree of accuracy (Daroub et al., 2003), two important modifications were necessary to make it satisfy the concern of extending the applicability of the CSM to low inputs cropping systems and to users having access to limited soil information: i) linking the model to the DSSAT-CENTURY model (Gijsman et al., 2002a) for simulation of organic P transformations; and ii) integrating a soil expert system that can allow the estimation of initial amounts of inorganic and organic soil phosphorus pools as influenced by major soil categories and using different methods of P extraction, pH and organic carbon.

The initial P model developed by Daroub et al. was thus updated with these two major modifications and is described here.

Description of the Soil Phosphorus Model

The soil phosphorus model is comprised of the soil inorganic module and the soil organic module. The two modules are linked in a way that soil phosphorus mineralized from organic matter is transferred to the inorganic module and phosphorus immobilized in the inorganic module is moved to the organic module. The initial sizes of the inorganic and organic pools can be derived directly from P fractionation data or indirectly from other P extraction methods. The initialization procedures, developed based on studies by Jones (1984), Singh (1985) and Sharpley (1984, 1989), are described in Appendix C.

Soil Inorganic Module

The soil inorganic module describes transformations that occur between the inorganic P pools to make P available for plant uptake.

Inorganic phosphorus pools

The soil inorganic module distinguishes three pools: labile (PiLabile), active (PiActive) and stable (PiStable). The three pools exist in two soil zones: the zone that is in direct contact with roots (within 2 mm) and the zone that is not in direct contact with roots (Figure 3-1). The labile inorganic P pool includes the P in the soil solution. Because roots do not develop at planting, the initial soil volume in direct contact with roots is assumed to be zero at the beginning of the simulation and the total amount of inorganic phosphorus available at that time is assigned to the no-root zone. If transplants are used, an initial soil root volume is estimated to initialize the simulation. As the roots develop, a proportional mass of P is added to the root zone pools and subtracted from the no-root pools in proportion to the soil volume adjacent to the new root growth.

Phosphorus transformations between the inorganic pools

Per day phosphorus transformations between the three pools occur according to the following first-order relationships:

$$\text{P flow from the labile pool to the active pool} = K_{LA} \times PiLabile \quad (3\text{-}1)$$

$$\text{P flow from the active pool to the labile pool} = K_{AL} \times PiActive \quad (3\text{-}2)$$

$$\text{P flow from the active pool to the stable pool} = K_{AS} \times PiActive \quad (3\text{-}3)$$

$$\text{P flow from the stable pool to the active pool} = K_{SA} \times PiStable \quad (3\text{-}4)$$

Where the P flows between the different pools are in units of mg [P] kg^{-1} [Soil] day^{-1}. The coefficients K_{LA}, K_{AL}, K_{AS}, and K_{SA} are the respective transformation rate constants, in unit of day^{-1}. The values of K_{LA}, K_{AL} and K_{AS} depend on the phosphorus availability index (Table 3-1) (Jones et al., 2005a; Jones et al., 1984a; Sharpley et al., 1984, 1989). K_{LA}, K_{AL} and K_{AS} are calculated as follow:

$$K_{LA} = 0.03 \times \left[\frac{(1 - PAvailIndex)}{PAvailIndex} \right]^{0.5} \quad (3\text{-}5)$$

$$K_{AL} = \frac{K_{LA}}{3} \times PAvailIndex \quad (3\text{-}6)$$

$$K_{AS} = e^{(-1.77 \times PAvailIndex) - 7.05} \quad (3\text{-}7)$$

$$K_{SA} = 0.0001$$

Where *PAvailIndex* = P availability index defined in Table 3-1.

K_{AS} = rate constant for transformation from active P to stable P.
K_{SA} = rate constant for transformation from stable P to active P.

Mineralization and immobilization of phosphorus from the organic matter are handled in the soil organic module. A net mineralized P amount is calculated and is added proportionally to the root and no-root zones when its value is positive and subtracted from the labile P pool if its value is negative.

Phosphorus uptake calculated in the plant model is subtracted directly from the PiLabile pool in the root zone.

P fertilizer applied is directly added to the labile and active pools. The amount of applied P that enters those pools depends on the soil category and the application method. Fertilizer applied in bands or hills is used more efficiently by the plant. When these application methods are used, all of the P is applied directly into the root soil volume. When broadcast or other application methods are used, the fertilizer is proportioned to the root and no-root zones to the depth of incorporation.

A P fertilizer availability function is computed using soil composition (Table 3-2) based on studies by Jones (1984) and Sharpley et al. (1984, 1989). The P fertilizer availability index is expressed as a fraction of fertilizer which enters the labile pool. The remaining P fertilizer is added to the active pool.

Phosphorus availability for uptake by plants

The available phosphorus for plant uptake is the soluble phosphorus that is in the root zone. A fraction of the root labile Pi is assumed to be soluble, and that fraction defines the portion of the root labile Pi in the soil solution that is "sensed" and is available for extraction by plant roots on a daily basis.

$$SoilPiAvail = FracPSol \times SoilPiLabileRoots \quad (3\text{-}8)$$

Where SoilPiAvail is the plant available inorganic phosphorus;

FracPSol is the fraction of root labile Pi that is soluble (i.e. enters the soil solution). SoilPiLabileRoots is the inorganic labile P that is in the root zone.

Soil Organic Module

The soil organic module describes transformations of organic materials that eventually contribute P to or extract P from the inorganic P pools through mineralization or immobilization.

Organic phosphorus pools

The soil organic P module has of four litter pools and two soil organic matter (SOM) pools (Gijsman et al., 2002a):

- Organic residues added to the surface of the soil become either surface litter or soil litter. The residue materials themselves are divided into easily decomposable or metabolic materials (i.e. sugars and proteins) and recalcitrant or structural materials (i.e. lignin and other fibers) (Figure 3-1). As a consequence, four litter pools can be defined: a surface structural litter pool, a surface metabolic litter pool, a soil structural litter pool, and a soil metabolic litter pool.
- Microbial activity creates two active pools, one on the surface and another in the soil (SOM1 pools).
- A stable pool exists in the soil only (SOM23) and is the combination of the slow SOM (SOM2) and passive SOM (SOM3) pools for carbon (Gijsman et al., 2002a).

The soil SOM1 and SOM23 are the main pools that control inorganic phosphorus dynamics in the soil. The surface litter pools generate flows of carbon and nutrients into the surface SOM1 and the soil litter pools through tillage (Figure 3-1), and the surface and soil litter pools eventually become part of the soil SOM1 pool.

Phosphorus movements between the different organic P pools follow carbon flows according to a carbon to phosphorus ratio at which phosphorus is allowed to enter a specific pool (Table 3-3). The different flows and their directions are summarized in the soil organic phosphorus processes section of Figure 3-1.

Phosphorus flows between the organic pools

Phosphorus flow from any organic pool A to any organic pool B (PflowAB) is proportional to the carbon flow between the same pools. The terms "pool A" and "pool B" as used in this section refer to any combination of the four litter pools and two soil organic phosphorus pools between which P flow can occur (Figure 3-1). A typical flow can be described by the following equation:

$$\text{P flow (from pool A to pool B in a specific layer) in kg [P] ha}^{-1} = P_A \times \frac{CFlowAB}{C_A} \quad (3\text{-}9)$$

Where P_A is the amount of phosphorus in pool A of that layer (kg [P] ha^{-1}). The amount of phosphorus in each of the five pools (3 inorganic and 2 organic) is defined at initialization.
C_A is the amount of carbon in pool A of that layer (kg [C] ha^{-1}). The partitioning of the measured total organic carbon defines the amount of carbon that belongs to the three different soil organic matter pools. The fractions of carbon in SOM1 (active), SOM2 (slow) and SOM3 (passive) are defined by the model user according the cultivation history of the soil. Typical partitioning of the total SOM respectively into SOM1, SOM2 and SOM3 for a previously cultivated, irrigated and highly fertilizer loamy soil is 2%, 39% and 59% (Parton et al., 1988, 1994), but this can be varied but the user.
CFlowAB is the carbon flow from pool A to pool B (kg [C] ha^{-1}) for that layer.

The flow of carbon out of a pool is calculated as follow (Gijsman et al., 2002a):

$$\text{C flow (out of pool A) in kg [C] ha}^{-1}\ \text{d}^{-1} = C_A \times DEC_A \times CUL_A \times DEFAC \times OTHER \quad (3\text{-}10)$$

Where C_A is the carbon content of pool A (kg [C] ha^{-1});
DEC_A is the maximum decomposition rate of pool A under optimal conditions and without increased decomposition due to soil disturbance (day^{-1}). The maximum decomposition rates of various pools are listed in Table 3-3.
CUL_A is the effect of cultivation on the decomposition rate of pool A. $CULT_A$ functions as a multiplier on the maximum decomposition rate (0 to 1);
DEFAC is the decomposition factor that represents the effect of temperature and low soil water conditions on the decomposition rate parameter. DEFAC functions as a multiplier on the maximum decomposition rate (0 to 1);
OTHER represents the effect of other factors on the maximum decomposition rate. These factors include the lignin content of the structural material and the clay content of the soil which are used to reduce the decomposition rate of the structural litter and the soil SOM1.

The lignin concentration of the structural litter is used to partition its total carbon flow to SOM1 and SOM23. The non-lignin portion enters SOM1 and the lignin portion flows into SOM23 with carbon and phosphorus.

Phosphorus mineralization and immobilization

The material flowing out of pool A is allowed to enter pool B only under a certain C:P ratio that is computed assuming a potential immobilization rate of phosphorus. This constraint is depicted by the following equation:

$$\text{CPB} = \frac{CFlowAB}{\left(PFlowAB + IMMOB\right)} \tag{3-11}$$

Where CPB is the C:P ratio of the material allowed to enter the receiving pool B;
IMMOB is the immobilization of P (kg [P] ha^{-1}) from the inorganic labile pool;
CFlowAB and PFlowAB are respectively the C flow and the P flow from pool A to pool B in (kg [C or P] ha^{-1}).

When the material flowing from pool A to pool B has a C:P ratio that is larger than the C:P ratio of the material that is allowed to enter pool B (CPB), an immobilization of phosphorus from the inorganic labile pool occurs to compensate for the deficit of P in the material flowing. The amount of phosphorus immobilized is derived from equation (3-11):

$$\text{IMMOB} = \frac{CFlowAB}{CPB} - PFlowAB \tag{3-12}$$

Mineralization (MINER_{AB}) occurs only when the actual flow (*PFlowAB*) exceeds the expected flow$\left(\frac{CFlowAB}{CPB}\right)$.

$$\text{MINER}_{AB} = PFlowAB - \left(\frac{CFlowAB}{CPB}\right) \tag{3-13}$$

Each carbon flow is accompanied by respiration losses in the form of carbon dioxide (CO2), which is a flow of carbon that does not enter the receiving pool. Phosphorus mineralization is also concomitant with this loss of carbon to CO_2. The amount of phosphorus that is mineralized during the respiration process (PFlowCO2) is calculated as:

$$\text{P flow CO2 (from A to B) in kg [P] ha}^{-1} = P_A \times \left(\frac{CO2FlowA}{C_A}\right) \tag{3-14}$$

Where CO2FlowA is the CO_2 flow out of pool A (kg [C] ha^{-1});
P_A and C_A are respectively the amount of phosphorus and carbon in pool A (kg[C or P] ha^{-1}).

The total P mineralization ($MINER_{TOT}$) resulting from the carbon flow and the respiration losses to CO_2 is therefore:

$$MINER_{TOT} = MINER_{AB} + PFlowCO2 \quad (3\text{-}15)$$

The net phosphorus mineralized

The flow of carbon or phosphorus from pool A to pool B generates an immobilization of phosphorus in the material flowing and a mineralization of phosphorus that does not enter pool B. Immobilization holds phosphorus and depletes the soil inorganic P but mineralization releases phosphorus that can be made available for plant uptake. Total P mineralized (SUMPMIN) and total P immobilized (SUMPIMM) are computed by summing up the mineralization and immobilization P from all the different flows. A net P mineralized corresponding to the difference (SUMPMIN – SUMPIMM) is calculated and added to the inorganic labile pool for plant uptake (Figure 3-1). However, if the total P immobilization and other P takeoff are greater than the amount of P available in the soil, the SOM and litter decomposition are reduced by a reduction factor, so that the amount of P needed for immobilization equals the amount of P available in the soil.

Description of the Plant Phosphorus Model

The plant phosphorus component models P taken up from the soil and stored in four different plant parts: roots, shoots (leaves plus stems), shells and seeds. Phosphorus supplied by the soil to meet the plant's demand and phosphorus exported by the crop at harvest are external to the plant P component.

Phosphorus in the Plant

The P accumulated in the whole plant is the sum of the P taken up into the different plant parts (Jones et al., 2005b; Daroub et al., 2003).

$$P_{Plant} = P_{Root} + P_{Shoot} + P_{Shell} + P_{Seed} \quad (3\text{-}16)$$

The P in the different parts of the plant is computed as P concentrations (g [P] g [shoot]$^{-1}$ for instance). The mass of P (in kg P ha^{-1}) is further calculated after its combination with growth data provided by the appropriate crop growth model.

Minimum and optimum concentrations of P for maize defined at three growth stages are derived from literature and stored in a species file (Table 3-4). The optimum shoot P concentration was calculated using growth stage dependent equations developed by Jones (1983). The minimum shoot P concentration was taken as 60% of the optimum values (Daroub et al., 2003). Initial P concentration values for the different plant parts are set to the optimum when the plant emerges from the soil. Because the model uses a daily time step to compute phosphorus in the plant and the optimum and minimum concentrations of P are available at discrete growth stages only, linear interpolation between the growth stages is used to determine the optimum and minimum P concentrations every day (Figure 3-2). These interpolations depend on the actual plant growth as influenced by cultivar characteristics, soil and weather conditions. The N:P ratio is handled in a similar way to constrain the uptake of P when nitrogen is limiting (Figure 3-3).

Actual phosphorus accumulated in the plant on any day is increased by uptake. Amount of P mobilized (from roots, shells and shoots only) and lost due to senescence, pest and disease is furthermore subtracted from the P in the plant part considered.

Uptake

The amount of phosphorus available for uptake by the whole plant is the minimum of demand and soil supply.

$$P_{Total\_Uptake} = MIN\left(P_{Total\_Demand}, P_{Soil\_Supply}\right) \quad (3\text{-}17)$$

The maximum and minimum N:P ratio computed daily by linear interpolation from Figure 3-3 is used to limit P uptake if on any day the actual N:P ratio is below the minimum.

$$P_{Total\_Uptake\_Nlimited} = P_{Total\_Uptake} \times P_{Uptake\_Reduction\_Factor} \quad (3\text{-}18)$$

The P uptake reduction factor utilized when the actual N:P ratio falls below the minimum value is calculated as follows:

$$P_{Uptake\_Reduction\_Factor} = MIN\left(\frac{N:P_{Actual}}{N:P_{Minimum}}, 1.0\right) \quad (3\text{-}19)$$

Where $N:P_{Actual}$ is the actual N:P ratio and
$N:P_{Minimum}$ is the minimum N:P ratio.

Soil Supply

Soil P supply is the amount of root zone labile P computed in the soil inorganic module. Only a fraction of the soil supply is considered available (soluble) to meet the plant demand on any day. That fraction is a parameter changeable by the user. The value currently used is 0.2 meaning that 20% of the labile inorganic P in the soil zone adjacent to roots on any one day can be taken up by the plant during that day. This value was obtained based on a best-fit compromise between simulated and measured biomass from the Wa experiment described in Chapter 2.

Plant Demand and P Mobilization Pools

Plant concentration of phosphorus at any one time during the growing cycle dropping below the optimum concentration (specified in the species file) is considered a deficit and induces stress (Figure 3-4). Demand is calculated for each plant part based on the amount of P

required to bring the P concentration in each of the plant parts up to the optimum, plus P required for new growth.

$$P_{Demand} = P_{Optimum} - P_{Actual} + P_{New\_growth} \quad (3\text{-}20)$$

Where P_{Demand} is the amount of P in kg ha^{-1} required to bring the actual concentration of P to the optimum;
$P_{Optimum}$ is the computed optimum P in kg ha^{-1} using linear interpolation;
P_{Actual} is the amount of P in kg ha^{-1} present in the plant part concerned;
P_{New_growth} is the amount of P in kg ha^{-1} needed for new growth.

High biomass accumulation can cause P_{Actual} to be greater than $P_{Optimum}$ resulting in a negative P_{Demand} for any plant part at any moment during the growth. The excess P accumulated is therefore stored in a mobilization pool for each plant part. There is no P mobilization pool for seeds.

Demand for each plant part is first met by P stored in the mobilization pools. P moves from root and shoot mobilization pools to satisfy P demand in shells and seeds. The P leftover stays in the respective mobilization pools. Total P demand is recalculated and is possibly met by the soil supply. If the soil supply is insufficient to meet this demand, uptake and subsequently P concentration in plant's parts are reduced and will increase P stress.

Partitioning and Translocation

During the reproductive phase, total phosphorus taken up by the plant (P_{Total_Uptake}) from the soil is first used to meet seed demand. If the seed demand is greater than the amount of phosphorus available to meet this demand, phosphorus translocation from roots, shoots and shells to the seeds occurs. The available P for translocation is calculated as follows:

$$P_{Translocation} = \left(P_{Roots\_Actual} - P_{Roots\_Min}\right) + \left(P_{Shoots\_Actual} - P_{Shoots\_Min}\right) + \left(P_{Shells\_Actual} - P_{Shells\_Min}\right) \quad (3\text{-}21)$$

The maximum amount of P that can be mined from the shells and the vegetative tissue in one day ($P_{Translocation\_Max}$) is a fraction of the available P for translocation.

$$P_{Translocation\_Max} = MAX\left(0.0, FracPMobil \times P_{Translocation}\right) \quad (3\text{-}22)$$

Where FracPMobil is the fraction of the translocated P that can be used by the seeds in one day. FracPMobil is defined as a parameter in the species file.

The P translocated is used to meet the seed demand if it is still positive after total P uptake from the soil has been used up. The remaining P after seed demand is fully met is used by shells. Vegetative tissues (roots and shoots) are supplied with P after reproductive organs' (seeds and shells) demand is met.

Stress Factors

Two stress factors are computed based on a P stress ratio when the actual shoot phosphorus concentration falls below the optimum. The stress ratio is computed as follows:

$$P_{Stress\_Ratio} = MIN\left[1.0, \left(\frac{P_{Shoots\_Actual\_Concentration} - P_{Shoots\_Min\_Concentration}}{P_{Shoots\_Optimum\_Concentration} - P_{Shoots\_Min\_Concentration}}\right)\right] \quad (3\text{-}23)$$

P_{Stress_Ratio} = 0 means maximum stress and
P_{Stress_Ratio} = 1 means no stress.

P stress effects on photosynthesis and P partitioning are modeled differently. Thresholds values are defined in the species file and are used to compute stress factors for photosynthesis and P partitioning:

$$P_{Stress\_Factor\_Photosynthesis} = MIN\left(\frac{P_{Stress\_Ratio}}{SRATPHOTO}, 1.0\right) \quad (3\text{-}24)$$

$$P_{Stress\_Factor\_Partitioning} = MIN\left(\frac{P_{Stress\_Ratio}}{SRATPART}, 1.0\right) \quad (3\text{-}25)$$

Where SRATPHOTO is the minimum value of the ratio of P in vegetative tissue to the optimum P, below which reduced photosynthesis will occur.
SRATPART is the minimum value of the ratio of P in vegetative tissue to the optimum P, below which vegetative partitioning will be affected.

The two P stress factors, which are given different weights, are used to reduce photosynthesis and P partitioning on any day during the growth of the plant when the actual shoot P concentration falls below the computed optimum shoot P concentration. Values of

SRATPHOTO and SRATPART as read from the species file are respectively 0.80 and 1.00 meaning that P deficits in shoot tissue will first affect root-shoot partitioning before it affects photosynthesis (Figure 3-4).

Model Inputs and Outputs

The soil-plant phosphorus model does not run as a standalone application but is intrinsically linked to DSSAT crop growth models. As a consequence the soil-plant P model also uses the basic inputs required to run the crop growth models. Additional inputs and parameters required to run the model are summarized in Tables 3-5 and 3-6. The model essentially modifies the crop growth model's outputs to allow them to be phosphorus-limited in P-limiting environments.

Sensitivity Analysis

Sensitivity analysis is an important assessment tool that assists with evaluating the uncertainty and variability associated with model structure and inputs during model development, calibration and validation.

Introduction

A simulation model of crop growth and development is the result of several cycles of fine tuning of model theory and structure, parameter estimations and adjustment of number of required input variables. The ultimate objective of the continuing model refinement is to obtain a model that is as close to the ideal model as possible, predicting measurable outputs with maximum accuracy. Scientists admit, however, that even the most carefully-built simulation model is not expected to give simulations that exactly equal observations. Uncertainty associated with model equations, measured model input variables and estimated model parameters will always remain an integrated part of the model and will contribute a great deal to simulation biases. The uncertainty is not an accident; it may be the substance of the scientific method itself

(Saltelli, 2002). More specifically, the role of sensitivity analyses is to help apportion the uncertainty in the model output to the different sources of uncertainty and variability in inputs (Saltelli, 2005).

Uncertainty and variability justifying the usefulness of sensitivity analysis can stem from various sources:

Choice of an appropriate complexity. Modeling agricultural and biological systems requires an appropriate choice of components that are meaningful for the system and will eventually form the structure of the model. The same real world system can be approached differently by various scientific communities although they may set the same objectives and have similar technical backgrounds. The main classical theories may be the same but the way scientists "see" the system can be influential in the way they "model" it. For example, modelers of phosphorus-limited production have used different P pools (Probert, 2004; Daroub et al., 2003). Because the components modeled and the structure used set the mathematical representation, the choice of the model complexity can be subjective and introduce some uncertainty with respect to the processes involved.

Parameter estimation. Uncertainty can also come from parameters estimated based on weak evidence or not-so-well established experimental results, especially during model development.

Measured model inputs. Another important source of variability is model input variables that may have been measured from field experiments or obtained from various data sources. Field measurements (even replicated) can include important precision errors, sometimes due to variability in natural processes. Errors of this kind can propagate to model outputs more than proportionally.

Expert systems. Parameters or input variable that cannot be easily measured are sometimes indirectly estimated using expert opinions or empirical relationships such as pedo-transfer functions (Gijsman et al., 2002b). When confidence limits are not provided for these methods, reliability on the indirect estimates may be questionable.

Modeling language and untrained model users. When the modeling language is not English-like, model users, sometimes performing calibration with no capability to read the programming language, may have to use it as a black box. It is not evident that members of interdisciplinary teams in which a model was developed are aware of the way inputs are mapped to outputs in the total model (Oberkampf et al., 2004). With complex models requiring hundreds of parameters and input variables to operate, it may become unclear how the model behaves independently of any evaluation with real world datasets.

Sensitivity analysis has become an ingredient of modeling (Saltelli et al., 2000) and been used in many studies at various stages of model development (Makowski et al., 2005; Ratto et al., 2001; Rahn et al., 2001). General objectives of a sensitivity analysis are (Monod et al., 2006): i) to verify that the model behaves as expected when inputs are changed; ii) to quantify the magnitude of the influence of parameters on outputs; iii) to identify the model parameters that require maximum accuracy in their estimation; iv) to identify input variables to the model that need to be measured accurately for the simulations to be correct; and v) to isolate possible parameter interactions effects on outputs.

This section describes and presents results of a sensitivity analysis performed on some major P-related parameters of the soil-plant phosphorus model in DSSAT. The overall objective of this sensitivity analysis was to assess the effect on maize biomass, grain yield and P uptake of

major inputs and parameters that are directly related to plant response to P and P stress. Specific questions for this sensitivity analysis were

- **Question 1:** Does the model respond to P fertilizer as expected?
- **Question 2:** How does biomass and grain yield react to changes in initial PiLabile where plant uptake occurs, initial organic P that add P to this uptake pool, and the fraction of this uptake pool that is soluble?
- **Question 3:** What is the magnitude of the effect of variability in initial PiLabile and initial organic P, two P pools that are estimated in the model with uncertainty, on biomass and grain yield in the model?
- **Question 4:** How does the model react to variability (as found in the literature), in parameters that are used to compute P stress, optimum and minimum shoot P concentration?
- **Question 5:** Would variability in optimum and minimum seed P concentration have any effect on biomass accumulation by the plant or crop grain yield?

Materials and Methods

The sensitivity analysis requires the specification of a computer experiment, a sensitivity analysis method and inputs factors. These three components of the sensitivity are described next.

Computer experiment

A sensitivity analysis can be regarded as a highly controlled experiment carried out using specific treatments applied to a specific crop growing in a specific environment under specific management conditions. The mention of "highly controlled" carries an important meaning for a sensitivity analysis because only the effects of the treatments are investigated and all other growing factors are fixed at constant values. While this kind of experiment can bear a high resemblance to a field station trial, some peculiar characteristics must be pointed out:

- The aim of a sensitivity analysis is to study the behavior of a model whereas the aim of a field station trial is to examine the behavior of nature. The sensitivity analysis of a crop model can be thought of as an experiment where nature is replaced by the simulated crop model (Monod et al., 2006);

- The experiment described through a sensitivity analysis can be hypothetical. Some conditions relevant to the experiment cannot be met in a station trial due to limits to control nature or ethical considerations. In the sensitivity analysis experiment, there is no limit to the achievement of conditions required to isolate treatments effects.

- A station trial examines the behavior of nature through independent factors usually external to the field but that are known or suspected to influence dependent variables. In a sensitivity analysis, the input factors are necessarily sampled or chosen from the input variables to the model or the model parameters.

- In a station trial, replications are key components to statistical analysis of the results of the experiment due to field variability that result in measurement error. When an analysis of variance is performed, the measurement error is used as a proxy to assess the amount of variation accounted for by each factor under study. In sensitivity analysis experiments, there is no need for repeating the same treatments as long as the model is deterministic. As a result, measurement error (actually simulation error) cannot be computed and formal hypothesis testing has no scientific meaning and cannot even be performed (Monod et al., 2006).

To differentiate the sensitivity analysis experiment from real world station trials, we will call it a "computer experiment". The treatments will be called "scenarios". Each scenario is the combination of levels of factors that will be named "input factors" (Monod et al., 2006).

Settings for the computer experiment

The computer experiment was performed using agro-ecological and modified management information from the phosphorus experiment conducted in Kpeve, Ghana (6^{o} 40.80' N, 0^{o} 19.20' E, altitude 67 m above sea level), in 2006 and described in Chapter 2.

The experiment was conducted during the main rainy season (April to August) on a loamy soil (Tables 3-7 and 2-15). Daily rainfall, solar radiation, and maximum and minimum temperatures were monitored using an automatic weather station located within the research station. A medium-duration cultivar, Obatampa (Table 2-1) was sown on May 27, 2006. The plant population at emergence was 6.25 plants m^{-2}. To remove any nitrogen stress, a total of 500

kg N ha^{-1} was applied in the form of urea and split as follow: 100 at planting; 150 at 14 days after planting; 150 at 27 days after planting; and 100 at 41 days after planting. Water stress was controlled by automatic irrigation when the available water in the first 50 cm dropped below 70% of the drained upper limit.

Input factors, scenarios and model outputs

Three input variables to the soil modules and three plant module parameters were selected and constituted two categories of input factors for the sensitivity analysis (Table 3-8). Each input factor had 3 levels. The factor levels were specified in a way that a low, a medium and a high setting of the factor were investigated through the sensitivity analysis. Wherever applicable the medium level reflected the default (or the nominal) values initially specified in the model and defined the control scenarios (Tables 3-8 and 3-9).

The input factor values were selected based on the knowledge of their uncertainty around a nominal value or the medium settings. To answer specific questions addressed in this sensitivity analysis, six input factors were selected. The input factors were selected from model parameters (Table 3-5) and inputs (Table 3-6). The six inputs factors for the sensitivity analysis are discussed next.

Initial Inorganic labile P and organic P. Although accurate knowledge of labile inorganic phosphorus and total organic phosphorus present in the soil at planting is crucial for good quality simulations of growth and development, it was anticipated that most model users will not have access to the data measured as needed. If an alternate method is not provided for indirect estimation, potential model users could possibly resort to indicative values found in literature or eventually conclude that the model is not of any practical use because required input data are not readily available. Access to heavy data requirement by the model user is a known constraint of model use in research and development in large parts of the world (Struif-Bontkes

and Wopereis, 2003; Matthews and Stephens, 2002; Walker, 2000). Since organic carbon, pH and available phosphorus are routinely measured in most traditional agronomic experiments, developing relationships that can make use of those data and provide reasonable estimates of inorganic labile P and organic P was thought to be helpful. Some soil properties are related to each other and may be estimated from selected measurements; however, indirect estimation of inorganic and organic phosphorus can pose serious uncertainty problems due to the complex chemistry of P in soils. In this specific situation, the uncertainty comes from two main sources: 1) measurement errors of the soil parameters; 2) regression errors associated with developing the equations for estimating indirectly the soil phosphorus. This was a strong motivation for studying the effect on variable initial inorganic labile P and total organic P on some key model outputs. Studies by Sharpley et al. (1984 and 1989) who developed linear relationships to predict inorganic labile P and organic P for different categories of soils provided a basis for the ranges of values used in the sensitivity analysis. Most soils considered in Sharpley (1984) have measured PiLabile in the range 0-15 ppm and total organic P in the range 50-200 ppm. The PiLabile in the first 20 cm was 6.5 ppm at Wa and 16 ppm at Kpeve. The estimated organic P (from Table C-5, Appendix C, Slightly weathered soils) in the top 20 cm was 37 ppm at Wa and 133 ppm at Kpeve. These two soils clearly have different P-supply capabilities in the ranges explored by Sharpley, and they present indicative starting points for the specific levels of the input factors initial PiLabile and organic P. Since some soils in Sharpley's survey would be more PiLabile-depleted than the Wa soil, the "low" level of the input factor PiLabile was set at 2.0 ppm. The medium level of the input factor Initial PiLabile was set at 8 ppm, around the middle of the range 0-15 ppm found in Sharpley (1984). The high level of the same input factor was set at the upper boundary of that range.

The organic P level in the Wa soil (37 ppm) seems representative of a very low level so the low level of the input factor Initial Organic P was set at 40 ppm. The medium level of the input factor Initial Organic P was set at 100 ppm, around the middle of the range 50-200 ppm found in Sharpley (1984). The upper limit of the range 50-200 ppm (that is 200 ppm) was considered as the high level of the input factor Initial Organic P.

The low, medium and high levels of the two input factors Initial PiLabile and Initial organic P were therefore respectively 2, 8 and 15 ppm for Initial PiLabile and 40, 100 and 200 ppm for Initial organic P. The original soil ratio between organic C and P (Table 3-7) was maintained for the soil used in the analysis meaning that the soil carbon input value was changed along with the organic P.

P fertilizer. Fertilizer application is one of the most important tactical management strategies used to balance nutrient requirements by crops. Studying and understanding a crop growth model's behavior to varying fertilizer levels is key to checking on the model's ability to simulate variable fertilizer input feasibilities. Small applications of phosphorus (20-40 kg [P] ha^{-1}) to degraded soils have been recommended to restore progressively the soil P status (Shapiro et al., 2003) and reported to increase inorganic soil labile P (Nziguheba et al., 2002) and improve grain yield in maize (Fofana et al., 2005). The levels of phosphorus fertilizer were set to 0, 30 and 60 kg P ha^{-1}. The P fertilizer was managed in the same way as in the Kpeve experiment to ensure efficient use by the plant, split-applied in bands, 50% at planting and 50% 14 days after planting.

Fraction of root labile P that is soluble. The maximum fraction of available phosphorus which can be taken up in a day has a value of 0.20 in the phosphorus model and is not allowed to vary regardless of growth stage, cultivar variation or differences in phosphorus uptake efficiency.

However, the uptake rate of phosphorus by cereal plants varies with plant age and intrinsic cultivar differences (Johnston, 2000). If there is a large supply of phosphorus in the soil, restricting the soluble P to 20% throughout the season could result in P shortage at the maximum uptake period. Phosphorus uptake can also be greatly increased in mychorizae-colonized environments, which will critically modify any parameter setting for P availability under normal conditions. These reasons may have motivated uptake of nutrients including phosphorus by biological systems to be modeled as a substrate saturation process with end-product inhibition using the Michaelis-Menten function (Wilson and Botkin, 1990; Lehman et al., 1975a). To quantify the effects on some model outputs of possible variations of the maximum fraction of available phosphorus which can be taken up in a day around the approximated average of 0.20, three uptake fraction levels 0.10, 0.20 and 0.80 were tested in the present sensitivity analysis.

Shoot P and seed P. Optimum and minimum values of shoot and seed phosphorus concentration used in the plant module were derived from literature (Daroub et al., 2003; Jones, 1983). Although those concentration limits are essentially associated with crop physiology, they can be subject to cultivar variability. In addition, P modelers have used different optimum shoot P concentrations. For example, Daroub et al. (2003) used an initial shoot P concentration of 0.7% whereas Probert (2004) used 0.5%, which is lower than the shoot P level of maize found by Jones (1983) in his survey. Other studies reported even lower initial shoot P concentration under non-limiting P conditions (e.g. 0.45, Ziadi et al., 2007). This sensitivity analysis was designed to cover the range of optimum shoot P variability found in literature. The optimum shoot P concentration was increased or decreased by 50% around the nominal to obtain the high and low levels of the input factor “shoot P concentration” (Table 3-9). The minimum shoot P concentration was taken as 60% of the optimum (Daroub et al., 2003). The optimum seed

concentration was also increased or decreased by 50% around the nominal value of 0.35% to obtain the high and low levels of the input factor "seed P concentration". The ratio of 2:1 between optimum and minimum seed P concentration was kept for all the input factor levels. The six input factors and their levels are summarized in Tables 3-8 and 3-9.

Model outputs. The effects of the total input space constituted of the six input factors were assessed on three model outputs: aboveground biomass, grain yield and total plant uptake.

Method and design of the sensitivity analysis

The analysis was conducted using a global approach where the input factors and their interactions were explored simultaneously (Saltelli, 2004). The six factors, each having 3 levels were combined in a complete factorial design yielding $3^6 = 729$ observations or simulation runs.

Sensitivity index

An analysis of variance was carried out on the model outputs using the SAS software (SAS, 2002). Since formal hypothesis testing cannot be performed due to the lack of a valid error term, the most useful assessment procedure was to compare the sum of squares contributions from each factor and interactions to the total sum of squares. This is denoted by the name "sensitivity index" and is calculated as follow:

$$\text{SI (Main effect of F)} = \frac{SS(FactorF)}{Total\_SS} \quad (3\text{-}26)$$

$$\text{SI (Interactions involving F)} = \frac{SS(InteractionsF)}{Total\_SS} \quad (3\text{-}27)$$

$$\text{SI (Total effect of F)} = \text{SI (Main effect of F)} + \text{SI (Interactions involving F)} \quad (3\text{-}28)$$

Where *SI* represents sensitivity index;
F represents factor F;
SS represents ANOVA Sum of Squares;
InteractionsF represents interactions involving factor F.

The sensitivity index was used to measure the effect of factors and their interactions on outputs. It has values between 0 and 1 with 0 indicating that the model is not sensitive at all to the factor for the particular output, and 1 indicative of maximum sensitivity.

Results and Discussion

Phosphorus fertilizer and initial PiLabile had the most influential effects on the output variables. In the absence of P fertilizer, the effect of the fraction of labile P in solution and the shoot P became also important.

Soil inputs effects

Figures 3-5A to C show the response of crop total aboveground biomass, grain yield and crop total phosphorus uptake to the three levels of the soil input factors (the levels low, medium and high along the abscissa have different meaning depending on the input factor considered and are explained in Table 3-9).

Among the soil input factors tested, initial PiLabile and P fertilizer had the most influential effects on the three output variables. Aboveground biomass, grain yield and total plant P uptake responded clearly to variable levels of initial PiLabile and P fertilizer application with the same pattern. Biomass, grain yield and uptake increased and their corresponding standard deviations decreased with increasing levels of initial PiLabile and P fertilizer (Figures 3-5A, 3-5B, and 3-5C).

The sensitivity indices of the response of initial PiLabile and P fertilizer to the three output variables were relatively high compared to the other input factors (Figure 3-7). These two input factors alone explained 54%, 47% and 41% of the total sum of squares respectively for aboveground biomass, grain yield and total plant P uptake (Tables 3-10 to 3-12).

The total sensitivity indices of P fertilizer and initial PiLabile were about two times their main effects showing that these two input factors were also influential in terms of interaction

with the other input factors. The total sensitivity index of P fertilizer was 0.73 for biomass (Table 3-10), 0.71 for grain yield (Table 3-11) and 0.52 for plant P uptake (Table 3-12). The total sensitivity index of initial PiLabile was 0.27 for biomass (Table 3-10), 0.31 for grain yield (Table 3-11) and 0.24 for P uptake (Table 3-12).

Organic phosphorus did not contribute much to the variation in any of the output variables over the range tested. This range that was derived from Sharpley's studies (1984) reflected approximately the variability in organic P in most P-depleted soils (Brady and Weil, 2002). The sensitivity indices for this factor were smaller than 0.01 (Tables 3-10 to 3-12).

The response to the input factors initial PiLabile and P fertilizer varied with the output variable and the level of the input factor. For example, when the six input factors are considered together, the response was more pronounced for the output variable total P uptake than for biomass and grain yield. Concerning the individual levels low, medium and high, of the input factors, the response of the output variables was especially marked at the low levels.

Variability in the input factors initial PiLabile and P fertilizer did not result in a proportional variability in the output variables. For example, a decrease in initial PiLabile of 75% relative to the nominal value resulted in 16% decrease in biomass and grain yield relative to the nominal values, and 24% decrease in total P uptake on average (Table 3-14). An increase in initial PiLabile of 88% resulted in only 8% increase in biomass and grain yield and 11% increase in total P uptake on average. Biomass increased by 37%, grain yield by 33% and total P uptake by 42% on average when P fertilizer was increased from 0 to 30 kg [P] ha^{-1} (Table 3-14). The increase in the output variables barely exceeded 5% when P fertilizer increased from 30 to 60 kg [P] ha^{-1}.

The reason initial PiLabile, P fertilizer and their interactions have so much effect on the output variables is that in the model, plants take up phosphorus directly from the labile pool. For slightly weathered soils with no base saturation measured, as the one used in this sensitivity analysis, 85% of the P fertilizer applied enters directly the labile pool making this pool the most important for plant uptake and productivity. The higher sensitivity of total P uptake is associated with the fact that the uptake is the primary process directly connected to phosphorus availability. The behavior of the model in terms of response of crop productivity and uptake to initial PiLabile and fertilizer is supported by numerous fertilizer studies (Colomb et al., 2000; Fofana et al., 2005; Nziguheba et al., 2002; Pellerin et al., 2000) and does not per se raise new issues.

Initial organic P had virtually no effect on the output variables suggesting that over a growing season, the organic matter contribution to phosphorus uptake may be more dependent on the rate constants controlling the mineralization and immobilization of organic P than the amount of organic P available at the beginning of the growing season. In fact in this sensitivity analysis, the total P mineralized from organic matter in the soil profile varied from 45 to 55 kg ha^{-1} at the end of the season, but the fraction that is actually contributing to plant uptake was small. This is because 1) the roots do not explore the whole soil profile and therefore cannot access all the P mineralized; 2) the portion of organic P mineralized that is soluble for plant uptake is only that amount that enters the volume of the soil where roots are present at the time of the mineralization. This means that mineralized P not "seen" by the plant at any one time in the season because the volume of roots is small is transformed over time into insoluble forms that cannot be used by the plant. The synchronization between the availability of the mineralized organic P and the accessibility of the plant to it was an influential factor of the small sensitivity observed of the input factor Initial organic P.

Plant parameters effects

The variability in plant parameters studied had less influence on the output variables than the soil parameters (Figures 3-6A to C). The graphs were scaled uniformly to Figures 3-5A to C to highlight the differences in response among the two groups of input factors (soil and plant). Aboveground biomass, grain yield and plant uptake varied over a smaller range, which resulted in main sensitivity indices between 0.02 and 0.15 (Tables 3-10 to 3-12). Shoot P had a higher influence on biomass (main SI of 0.04, Table 3-10), Fraction of labile P had a higher influence on grain yield (main SI of 0.03) and seed P had a higher influence on total P uptake (main SI of 0.15).

Increase in fraction of labile P from 0.2 to 0.8 resulted in about 7% increase on average in the output variables. Decrease in this fraction from 0.2 to 0.1 caused an 8% decrease on average in the output variables (Table 3-14).

Variation of the shoot P concentration from the medium to the low level (Table 3-9) caused the biomass to decrease by 13%, the grain by 3% on average. However, this decrease in shoot P concentration increased the total P uptake by 39%. When the shoot P levels were increased from medium to high, the biomass and the grain yield decreased by 10% but the total P uptake increased by 18% (Table 3-14).

Variation in seed P from medium to low decreased biomass and grain yield by about 4% on average. Increase in seed P from medium to high increased biomass and grain yield by only 1% on average. The total P uptake was more responsive to seed P variation. The uptake was reduced by 39% between the medium and the low seed P level and increased by 18% on average between the medium and high seed P levels (Table 3-14).

It is possible that higher effects could be detected at wider ranges of the three plant parameters. However, realistic motivations must support such analyses because the variability in

optimum phosphorus concentration in maize shoots and seed for instance is not of any huge magnitude (Jones, 1983).

Interactions

As might be expected from their high contributions to the total sum of squares Initial PiLabile and P fertilizer produced relatively high interactions with other factors. The interactions between Initial PiLabile and P fertilizer and P fertilizer and shoot P were the strongest (Tables 3-10 to 3-12).

The interaction plot (Figure 3-8) shows how the strong response to P fertilizer at low initial PiLabile disappeared very quickly as initial PiLabile increases. This has important implications when simulating a fertilizer trial: accurate measurements of initial PiLabile must be obtained in order to achieve good simulation of crop production. On the contrary, the response to Initial PiLabile did not seem to be affected by the fraction of labile P in solution. Increasing Initial PiLabile resulted in an increase of biomass at all fraction of labile P in solution levels. However, the rate of biomass increase did not depend on the level of fraction of labile P in solution (Figure 3-9).

Special case of zero P fertilizer

When the sensitivity indices were recalculated considering the 0P fertilizer level only, the effect on the relative order of importance of the input factors was small (Table 3-13). Initial PiLabile was the most influential factor (main SI of 0.47, Table 3-13). Shoot P had a much higher effect on the biomass (main SI of 0.25) than the case when P fertilizer was included. The Fraction of labile P in solution had also a much higher effect on the biomass (main SI of 0.15) than the case when P fertilizer was included. The effects of Initial organic P and Seed P remained relatively small (main and total SIs less 0.01, Table 3-13).

The sensitivity indices of Initial PiLabile, Shoot P and Fraction of labile P in solution increased because the dominant factor P fertilizer was removed from the input space. The main sensitivity index of Initial PiLabile and Fraction of labile P in solution increased by a factor of 4 and the main sensitivity index of Shoot P increased by a factor of 6 (Tables 3-10 and 3-13). The persistence of main sensitivity indices less than 0.01 for Initial organic P and Seed P suggested that the effects of these two factors on biomass were small per se and were not masked by the dominant effect of P fertilizer.

However, interactions between factors were weak (highest interaction SI for biomass was 0.04, Table 3-13, compared to highest interaction of 0.15 with P fertilizer, Table 3-10) showing that most of the interactions between factors were due to the presence of P fertilizer. In fact, the presence of P fertilizer as a factor had two effects: i) making all interactions involving P fertilizer relatively stronger than all other interactions between factors (Table 3-13); ii) decreasing interaction SIs between other factors by accounting for more variability. For example, the interaction SI between Initial PiLabile and Shoot P was 0.01 with P fertilizer (Table 3-10) and 0.04 without P fertilizer (Table 3-13).

Conclusion

While errors in observations tend to be the direct and most evident target when discrepancies between simulations and measurements are recorded, inaccurately-measured input variables and model parameters estimated based on weak evidences or regression analyses can contribute a great deal to simulation errors. The sensitivity analysis of some key model parameters and input variables help to learn the behavior of the model and to diagnose in advance sources of possible simulation errors. A sensitivity analysis on three of the model's parameters and three of the model's input variables revealed that i) initial PiLabile and P fertilizer had the greatest impact on grain yield, total plant biomass and total plant uptake of P; ii)

initial organic P had little effect on plant production in the range tested and over a single growing season; iii) the fraction of labile P in solution, the optimum shoot and seed P concentrations had smaller effect on grain yield, total plant biomass and uptake in the range of sensitivity used in this analysis; iv) the relative order of importance of the input factors was not affected by P fertilizer application but generally, interaction between the factors tested are strengthened in the presence of P fertilizer.

Accurate estimation of initial PiLabile present in the soil is crucial to simulating crop productivity in phosphorus deficient cropping systems especially when phosphorus fertilizer is simulated. Failure to estimate accurately cultivars' optimum shoot and seed P concentration by 50% around the nominal value used in the DSSAT soil-plant phosphorus model can result in biomass, grain yield and total P uptake variation of up to 39%. Inaccurate estimation of the fraction of labile P in solution can also become a cause of poor simulation results.

Summary and Conclusion

The soil-plant phosphorus model described in this chapter integrates soil and plant phosphorus processes that are linked using modular programming techniques to crop growth models in the DSSAT CSM. The model simulates phosphorus in plants and soils based on integrated processes between i) inorganic phosphorus present in the soil in three pools, labile, active and stable; ii) organic phosphorus present in two pools, active and stable; iii) plant phosphorus present in roots, shoots, shells and seeds. Phosphorus-limited production including plant biomass, grain yield and plant uptake can also be calculated thanks to the linkage to crop growth models in DSSAT.

A sensitivity analysis of the model limited to six input factors showed that initial PiLabile and P fertilizer were the most important forces driving simulations of plant production. The fraction of root labile P, the shoot and seed P appeared to have less impact on biomass, grain

yield and P uptake of maize. Accurate predictions require therefore that at least initial PiLabile be measured or estimated correctly. If PiLabile cannot be measured directly and has to be indirectly estimated based on available P like P-Bray1 or Olsen, careful attention needs to be paid to the relationships derived and their agronomic validity. Diagnosing causes of poor model predictions should not only focus on checking measurements compared to simulations but also verifying the validity of input data, initial PiLabile in this instance.

Table 3-1. Soil category-dependent calculation of P availability index

Soil category	P availability index
Calcareous	$(-0.0058 \times CaCO3) + 0.60$
Slightly weathered	$[(0.0043 \times TotalBaseSaturation) + (0.0034 \times PiLabile) + (0.11 \times pH)] - 0.70$
Highly weathered	$\left[0.30 \times \log\left(\frac{CLAY}{100}\right)\right] + 0.68$
Other soils	$0.40 + 0.00023^{PiLabile}$

Source: Singh, U. 1985. A crop growth model for predicting corn (*Zea mays* L.) performance in the tropics. PhD thesis, University of Hawaii, Honolulu.

Table 3-2. Soil category-dependent calculation of P Fertilizer Availability Index

Soil category	P Fertilizer Availability Index
Calcareous	$(-0.0042 \times CaCO3) + 0.72$
Slightly weathered	$(0.0043 \times TotalBaseSaturation) + (0.0034 \times PiLabile) + (0.11 \times pH) - 0.50$
Highly weathered	$\left[-0.19 \times \log\left(\frac{CLAY}{100}\right)\right] + 0.70$
Other soils	$0.60 + 0.0002^{PiLabile}$

Source: Singh, U. 1985. A crop growth model for predicting corn (*Zea mays* L.) performance in the tropics. PhD thesis, University of Hawaii, Honolulu.

Table 3-3. Summary of decomposition rates for the soil organic pools and C:P ratios at which phosphorus is allowed to enter the specific pools

Pool generating the flow	Pool location	Maximum rate at which flow occurs (d^{-1})	Pool C:P
Metabolic litter	Surface	0.040550	
	Soil	0.050680	
Structural litter	Surface	0.010680	
	Soil	0.013420	
SOM1	Surface	0.016440	50
	Soil	0.020000	50
SOM2	Soil	0.000548	
SOM3	Soil	0.000012	
SOM23	Soil		100

Source: Parton, W.J., Ojima, D.S., Cole, C.V., Schimel, D.S., 1994. A general model for soil organic matter dynamics: Sensitivity to litter chemistry, texture and management. In: Bryant, R.B., Arnold, R.W. (Eds), Quantitative modeling of soil forming processes. SSSA Spec. Publ. 39. SSSA, Madison, WI, pp 147-167.

Parton, W.J., Stewart, J.W.B., Cole, C.V., 1988. Dynamics of C, N, P and S in grassland soils: A model. Biogeochemistry 5:109–131.

Gijsman, A.J., Hoogenboom, G., Parton, W.J., Kerridge, P.C., 2002. Modifying DSSAT crop models for low-input agricultural systems using a soil organic matter-residue module from CENTURY. Agronomy Journal 94, 462-474.

Table 3-4. Optimum and minimum phosphorus content (%) in different plant parts and maximum and minimum plant N:P ratio at three growth stages, as used in the model for maize

Plant part		Emergence	Effective grain filling/ End of leaf growth*	Physiological maturity
Root	Optimum	0.041	0.041	0.041
	Minimum	0.020	0.020	0.020
Shoot	Optimum	0.700	0.250	0.200
	Minimum	0.400	0.150	0.100
Shell	Optimum	0.500	0.500	0.050
	Minimum	0.250	0.250	0.025
Seed	Optimum	0.350	0.350	0.350
	Minimum	0.175	0.175	0.175
Plant N:P ratio	Maximum	25.000	15.000	9.300
	Minimum	4.200	2.700	2.100

Source: Jones, C.A. 1983. A survey of the variability in tissue nitrogen and phosphorus concentrations in maize and grain sorghum. Field Crops Research 6, 133-147.

Daroub, S.H., Gerakis, A., Ritchie, J.T., Friesen, D.K., Ryan, J., 2003. Development of a soil-plant phosphorus simulation model for calcareous and weathered tropical soils. Agricultural Systems 76, 1157-1181.

*The end of leaf growth applies to shoots only.

Table 3-5. Summary of parameters in the soil-plant phosphorus model

Parameter	Unit
P transformations between pools and P availability	
Rate constant for transformation from labile P to active P	d^{-1}
Rate constant for transformation from active P to labile P	d^{-1}
Rate constant for transformation from active P to stable P	d^{-1}
Rate constant for transformation from stable P to active P	d^{-1}
P availability index	unitless
Fraction of root labile inorganic P that is soluble	unitless
Shoot P concentrations	
Optimum shoot P concentration at emergence	$g\ g^{-1}$
Optimum shoot P concentration at tasseling	$g\ g^{-1}$
Optimum shoot P concentration at physiological maturity	$g\ g^{-1}$
Minimum shoot P concentration at emergence	$g\ g^{-1}$
Minimum shoot P concentration at tasseling	$g\ g^{-1}$
Minimum shoot P concentration at physiological maturity	$g\ g^{-1}$
Root P concentrations	
Optimum root P concentration at emergence	$g\ g^{-1}$
Optimum root P concentration at effective grain filling	$g\ g^{-1}$
Optimum root P concentration at physiological maturity	$g\ g^{-1}$
Minimum root P concentration at emergence	$g\ g^{-1}$
Minimum root P concentration at effective grain filling	$g\ g^{-1}$
Minimum root P concentration at physiological maturity	$g\ g^{-1}$
Shell P concentrations	
Optimum shell P concentration at emergence	$g\ g^{-1}$
Optimum shell P concentration at effective grain filling	$g\ g^{-1}$
Optimum shell P concentration at physiological maturity	$g\ g^{-1}$
Minimum shell P concentration at emergence	$g\ g^{-1}$
Minimum shell P concentration at effective grain filling	$g\ g^{-1}$
Minimum shell P concentration at physiological maturity	$g\ g^{-1}$
Seed P concentrations	
Optimum seed P concentration at emergence	$g\ g^{-1}$
Optimum seed P concentration at effective grain filling	$g\ g^{-1}$
Optimum seed P concentration at physiological maturity	$g\ g^{-1}$
Minimum seed P concentration at emergence	$g\ g^{-1}$
Minimum seed P concentration at effective grain filling	$g\ g^{-1}$

Table 3-5. continued

Minimum seed P concentration at physiological maturity	g g^{-1}
N to P ratios	
Maximum vegetative N:P ratio at emergence	unitless
Maximum vegetative N:P ratio at effective grain filling	unitless
Maximum vegetative N:P ratio at physiological maturity	unitless
Minimum vegetative N:P ratio at emergence	unitless
Minimum vegetative N:P ratio at effective grain filling	unitless
Minimum vegetative N:P ratio at physiological maturity	unitless
P mobilization and stress	
Maximum fraction of P which can be mobilized from shoot per day	unitless
Minimum value of the ratio of P in vegetative tissue to the optimum P below which reduced photosynthesis will occur	unitless
Minimum value of the ratio of P in vegetative tissue to the optimum P below which vegetative partitioning will be affected	unitless

Table 3-6. Summary of additional inputs required to run the soil-plant phosphorus model in DSSAT

Input	Unit
Initial labile inorganic P	ppm
Initial active inorganic P	ppm
Initial stable inorganic P	ppm
Initial active organic P	ppm
Initial stable organic P	ppm
P in residue (if applied)	%
P fertilizer (if applied)	kg ha^{-1}
Soil CEC	cmolc kg^{-1}
Soil texture	%
Soil CaCO3 content	%

Table 3-7. Selected physical and chemical properties of the Kpeve soil used in the sensitivity analysis, as estimated from pedo-transfer functions in DSSAT

SLB	SLLL	SDUL	SSAT	SRGF	SBDM	SLCF	C:P
10	0.180	0.260	0.460	1.000	0.83	40.0	138
20	0.070	0.140	0.280	1.000	1.08	40.0	136
30	0.040	0.080	0.160	0.607	1.47	35.0	130
40	0.060	0.120	0.240	0.497	0.74	74.5	138
50	0.040	0.060	0.120	0.407	0.47	88.1	123
60	0.050	0.090	0.180	0.333	0.56	82.3	218
70	0.080	0.150	0.300	0.273	0.97	61.9	200
80	0.060	0.110	0.220	0.223	0.77	72.9	127
90	0.090	0.160	0.320	0.183	1.04	57.9	124

SLB, depth, base of soil layer (cm); SLLL, soil lower limit ($cm^3\ cm^{-3}$); SDUL, soil upper limit, drained ($cm^3\ cm^{-3}$); SSAT, soil upper limit, saturated ($cm^3\ cm^{-3}$); SRGF, soil root growth factor (unitless); SBDM, soil bulk density, moist ($g\ cm^3$), corrected for gravel content; SLCF, soil coarse fraction or gravel content (%); C:P, ratio of organic carbon to organic phosphorus (unitless).

Table 3-8. Summary of inputs factors and outputs for the sensitivity analysis of the P model

Input and output variable or parameter	Nominal value (medium value)	Variability limits Lower	Upper	Unit
Inputs				
Soil				
Initial inorganic labile P	8	2	15	ppm
Initial organic P	100	40	200	ppm
P Fertilizer	30	0	60	kg P ha^{-1}
Plant				
Maximum P uptake fraction	0.2	0.1	0.8	unitless
Shoot P concentration	Medium	low	high	g / g
Seed P concentration	Medium	low	high	g / g
Outputs				
Total plant aboveground biomass				kg ha^{-1}
Grain yield				kg ha^{-1}
Total plant uptake of P				kg ha^{-1}

Table 3-9. Specification of the different levels of the input factors “Shoot P” and “Seed P” for the sensitivity analysis of the P model

Shoot P concentration (g/g)		Emergence	End of leaf growth / Effective grain filling*	Physiological maturity
Low	Optimum	0.0035	0.0013	0.0010
	Minimum	0.0021	0.0008	0.0006
Medium	Optimum	0.0070	0.0025	0.0020
	Minimum	0.0040	0.0015	0.0010
High	Optimum	0.0105	0.0038	0.0030
	Minimum	0.0063	0.0023	0.0018
Seed P concentration (g/g)				
Low	Optimum	0.0018	0.0018	0.0018
	Minimum	0.0009	0.0009	0.0009
Medium	Optimum	0.0035	0.0035	0.0035
	Minimum	0.0018	0.0018	0.0018
High	Optimum	0.0053	0.0053	0.0053
	Minimum	0.0026	0.0026	0.0026

*End of leaf growth for shoot P and effective grain filling for seed P.

Table 3-10. Main, interactions, and total sensitivity indices (unitless) of biomass for factors used in the sensitivity analysis

	Main SI	Interactions SI						Total SI
		PiLabile	Organic P	P fertilizer	Frac LabileP	Shoot P	Seed P	
PiLabile	0.11		0.00	0.15	0.00	0.01	0.00	0.27
Organic P	0.00	0.00		0.00	0.00	0.00	0.00	0.00
P fertilizer	0.43	0.15	0.00		0.05	0.11	0.00	0.73
FracLabileP	0.04	0.00	0.00	0.05		0.00	0.00	0.09
Shoot P	0.04	0.01	0.00	0.11	0.00		0.00	0.15
Seed P	0.00	0.00	0.00	0.00	0.00	0.00		0.00

FracLabileP: Fraction of Labile P that is soluble

Table 3-11. Main, interactions, and total sensitivity indices (unitless) of grain yield for factors used in the sensitivity analysis

	Main SI	Interactions SI						Total SI
		PiLabile	Organic P	P fertilizer	Frac LabileP	Shoot P	Seed P	
PiLabile	0.11		0.00	0.19	0.00	0.01	0.00	0.31
Organic P	0.00	0.00		0.00	0.00	0.00	0.00	0.00
P fertilizer	0.36	0.19	0.00		0.04	0.12	0.00	0.71
FracLabileP	0.03	0.00	0.00	0.04		0.01	0.00	0.08
Shoot P	0.02	0.01	0.00	0.12	0.01		0.00	0.15
Seed P	0.00	0.00	0.00	0.00	0.00	0.00		0.01

FracLabileP: Fraction of Labile P that is soluble

Table 3-12. Main, interactions, and total sensitivity indices (unitless) of plant uptake of P for factors used in the sensitivity analysis

	Main SI	Interactions SI						Total SI
		PiLabile	Organic P	P fertilizer	Frac LabileP	Shoot P	Seed P	
PiLabile	0.11		0.00	0.09	0.00	0.01	0.02	0.24
Organic P	0.00	0.00		0.00	0.00	0.00	0.00	0.00
P fertilizer	0.30	0.09	0.00		0.02	0.10	0.01	0.52
FracLabileP	0.03	0.00	0.00	0.02		0.00	0.00	0.05
Shoot P	0.09	0.01	0.00	0.10	0.00		0.00	0.20
Seed P	0.15	0.02	0.00	0.01	0.00	0.00		0.18

FracLabileP: Fraction of Labile P that is soluble

Table 3-13. Main, interactions, and total sensitivity indices (unitless) of biomass for a special case of zero P fertilizer. The P fertilizer was also removed as a factor.

	Main SI	Interactions SI					Total SI
		PiLabile	Organic P	Frac LabileP	Shoot P	Seed P	
PiLabile	0.47		0.00	0.01	0.04	0.00	0.52
Organic P	0.00	0.00		0.00	0.00	0.00	0.00
FracLabileP	0.15	0.01	0.00		0.01	0.00	0.17
Shoot P	0.25	0.04	0.00	0.01		0.00	0.30
Seed P	0.00	0.00	0.00	0.00	0.00		0.00

FracLabileP: Fraction of Labile P that is soluble

Table 3-14. Mean aboveground biomass, grain yield and total P uptake corresponding to each level of the input factors used in the sensitivity analysis. Each mean contains 243 = 729/3 observations.

Input Factors	Output Variables (kg ha^{-1})		
	Biomass	Grain yield	Total P uptake
PiLabile (ppm)			
2	8282	3007	18
8	9885	3567	23
15	10704	3839	26
Organic P (ppm)			
40	9634	3474	22
100	9608	3465	22
200	9629	3474	22
P fertilizer (kg ha^{-1})			
0	6872	2604	15
30	10867	3885	25
60	11132	3925	27
Fraction of solution P (unitless)			
0.1	8886	3228	20
0.2	9643	3493	22
0.8	10342	3693	24
Shoot P (See Table 3-12)			
Low	9084	3494	26
Medium	10401	3621	19
High	9387	3299	22
Seed P (See Table 3-12)			
Low	9488	3403	27
Medium	9738	3530	17
High	9646	3481	23

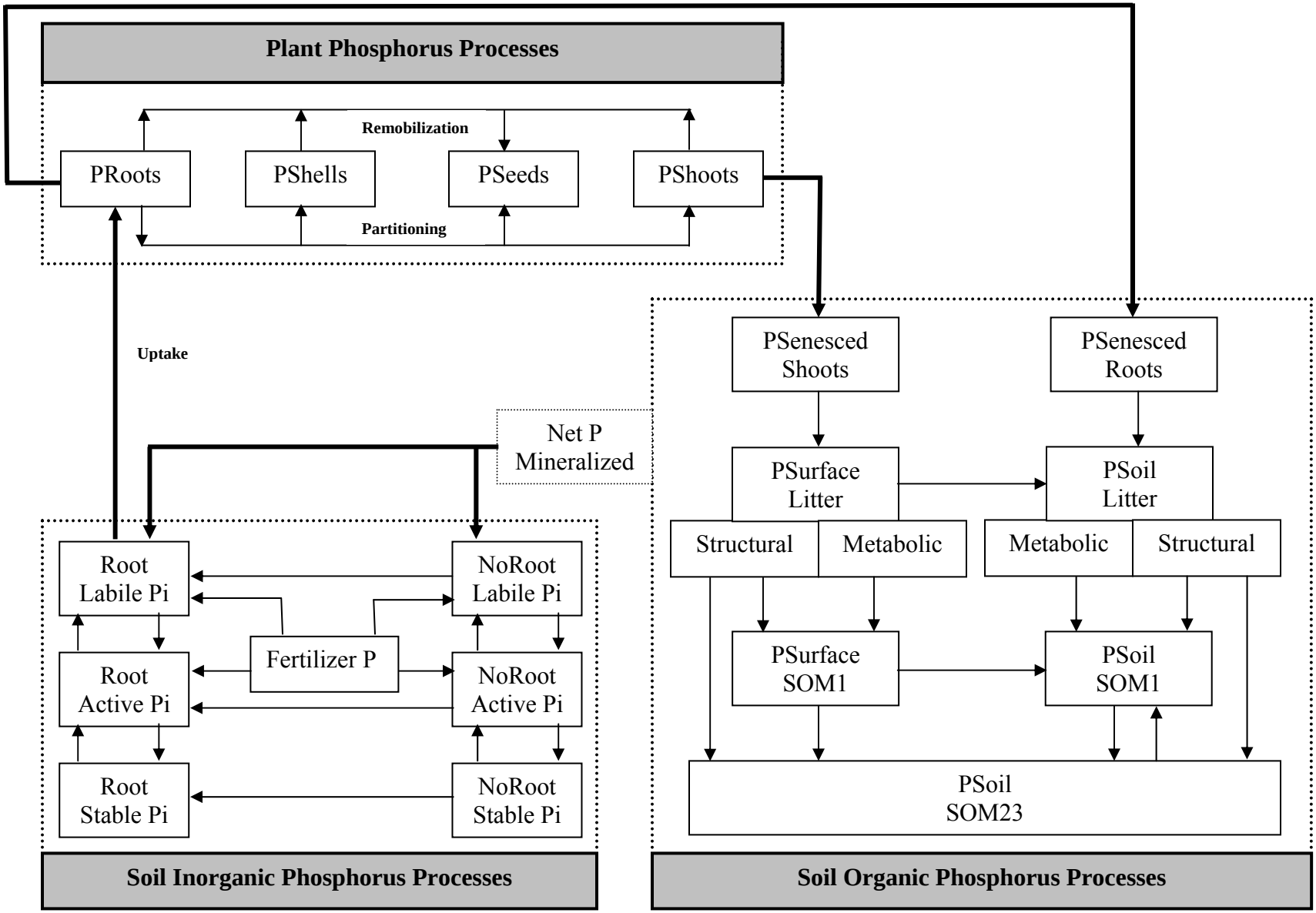


Figure 3-1. Processes in the integrated soil-plant phosphorus model in DSSAT

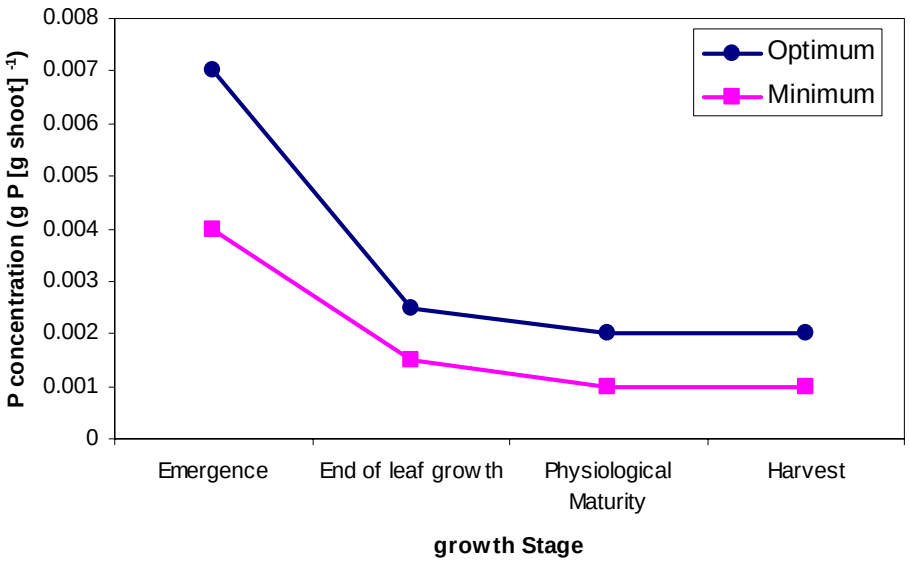


Figure 3-2. Optimum and minimum P concentration in maize shoots used in the plant P model

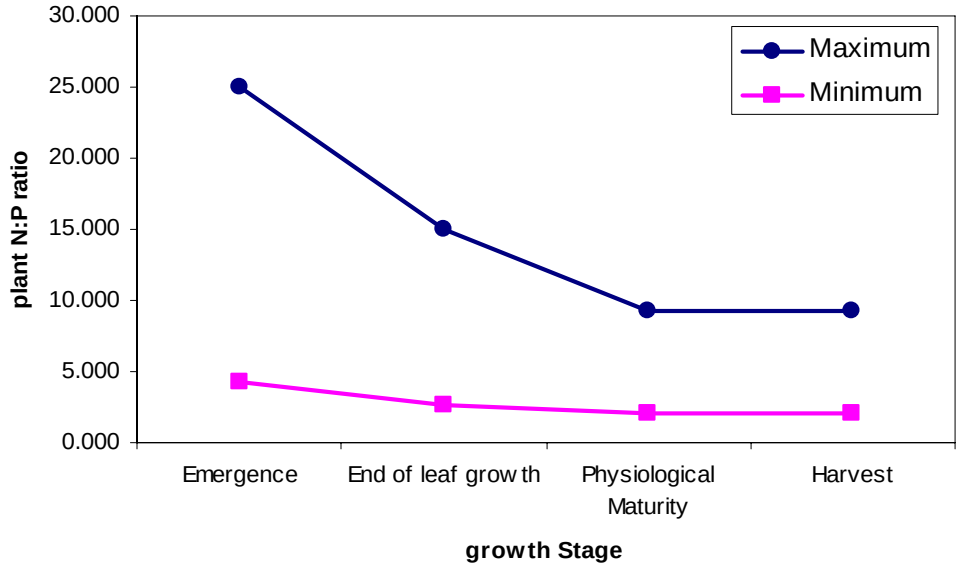


Figure 3-3. Maximum and minimum N:P ratios used in the plant module to limit uptake of P

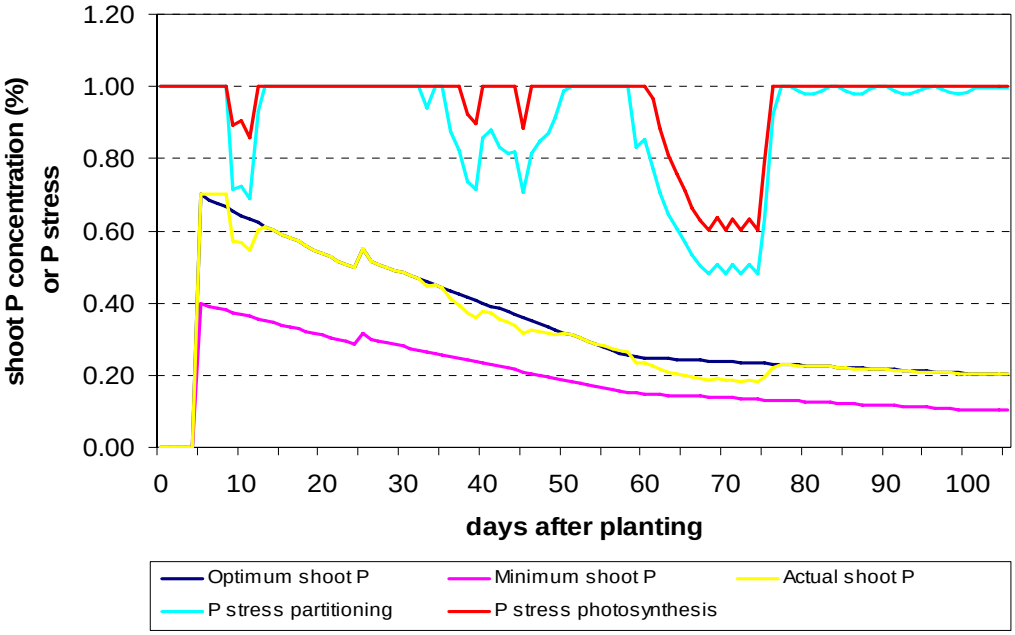
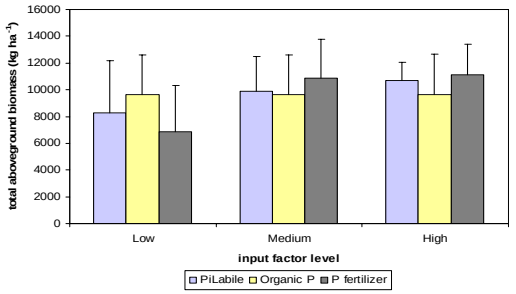
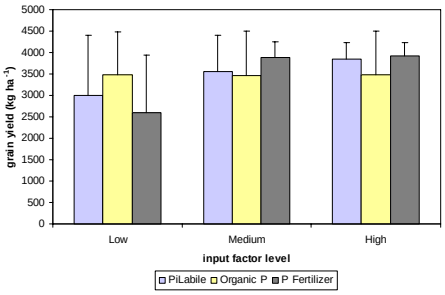


Figure 3-4. Relationship between maize shoot P concentrations and P stresses affecting vegetative partitioning and photosynthesis

A





B

C

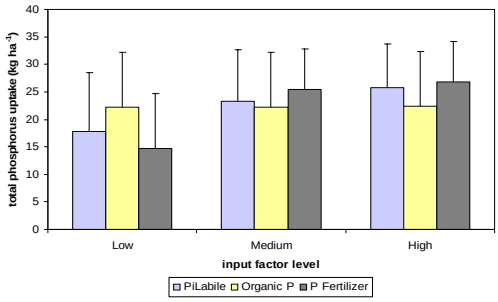


Figure 3-5. Simulated plant total aboveground biomass, grain yield and plant uptake of P at different levels of initial PiLabile, initial organic P and P fertilizer. Error bars shown represent one standard deviation. A) Aboveground biomass. B) Grain yield. C) Plant uptake of P.

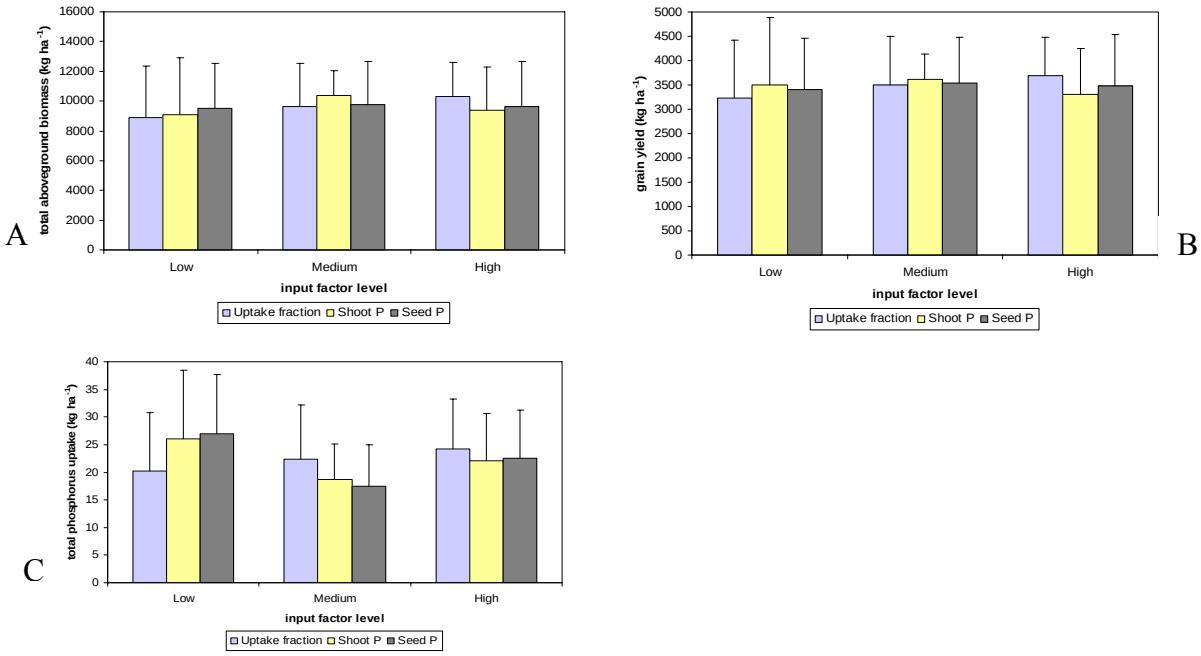


Figure 3-6. Simulated total plant aboveground biomass, grain yield and plant uptake of P at different levels of maximum uptake fraction, optimum shoot and seed P concentrations. Error bars shown represent one standard deviation. A) Aboveground biomass. B) Grain yield. C) Plant uptake of P.

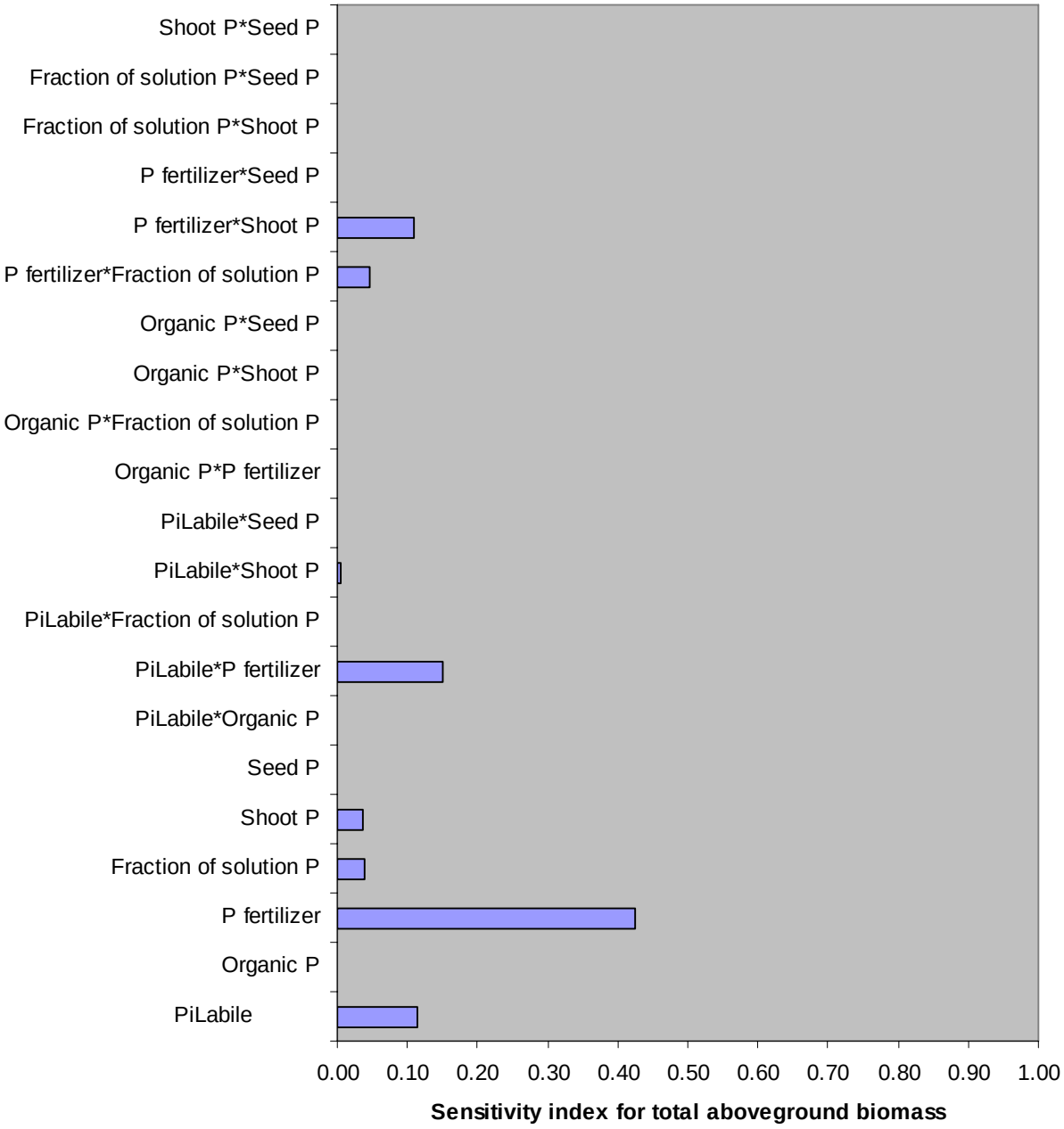


Figure 3-7. Sensitivity indices for the six input factors and their interactions

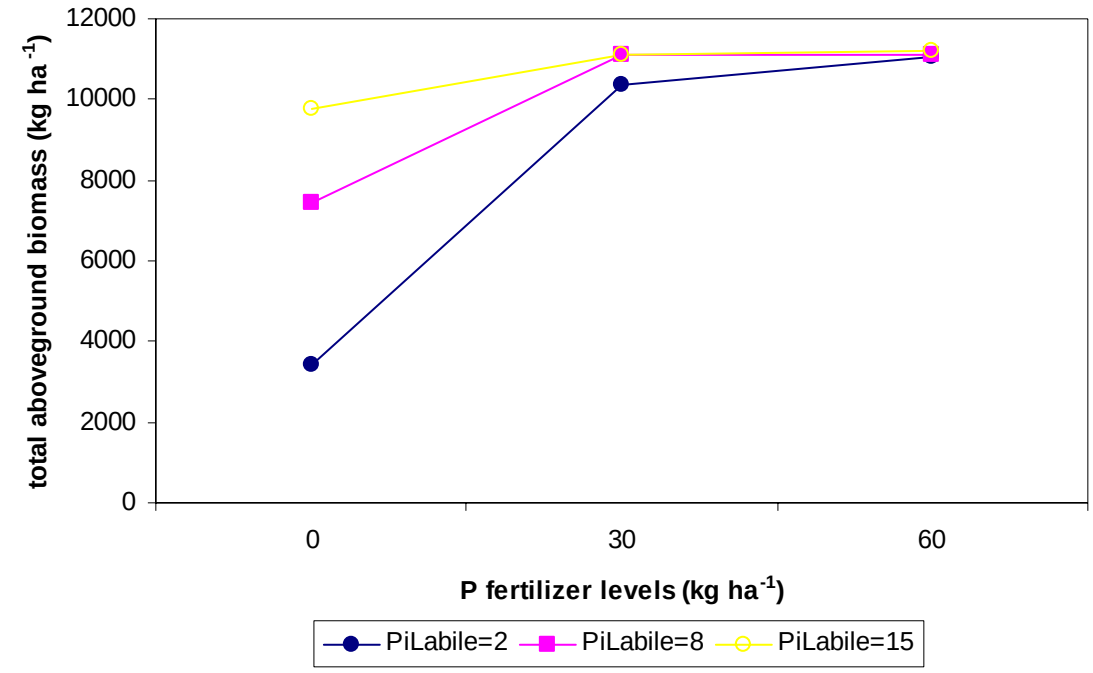


Figure 3-8. Simulated response of total plant aboveground biomass to phosphorus fertilizer at different levels of PiLabile

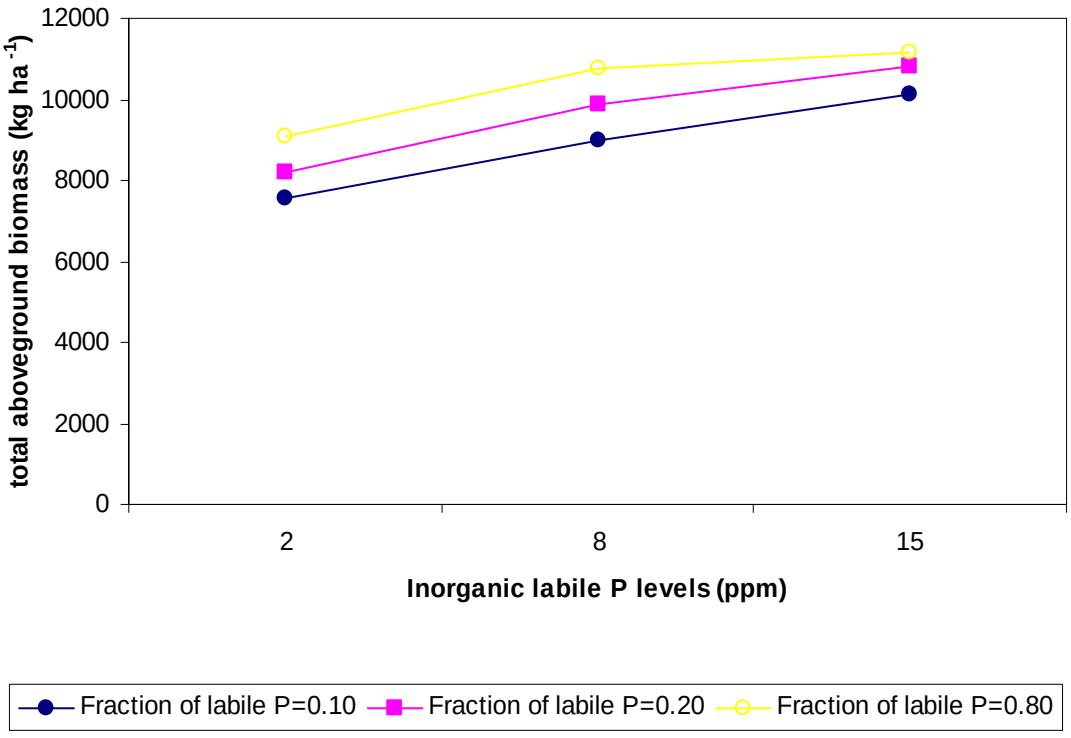


Figure 3-9. Simulated response of total plant aboveground biomass to PiLabile at different levels of fraction of labile P

CHAPT ER 4
FIELD TESTING OF THE DSSAT PHOSPHORUS MODEL

Introduction

The complex nature of relationships between components present in agricultural systems suggests the use of simulation techniques to study those systems rather than directly experimenting continuously on the systems themselves. Simulation models can assist with assessing alternatives and making decisions that would consume the entire career of an agronomist (Struif Bontkes and Wopereis, 2003; Matthews et al., 2000).

Because models developed in a certain environment can be adapted and applied in different agroecological conditions, the suitability of a model to simulate processes of interest is a major criterion in order to achieve meaningful inferences. Models have become so complex and been described with so many variables and parameters that their degrees of freedom have increased drastically. With an appropriate choice of input variable and parameter values they can be made to produce realistic outputs that can agree erroneously with real world measurements. Therefore, in addition to the suitability criterion, model testing or evaluation using the right combination of inputs and parameters is an important step that diagnoses the ability of the model to capture appropriately the essence of crop-environment interactions and their variability at the meso and micro scales. Annino and Russell (1981) underlined the risks associated with the application of simulation models that have not passed the test of a sound scientific assessment. They cited the use of an untested or invalid model as one of the seven most frequent causes of failure in many simulation modeling studies.

To enable crop models in DSSAT to simulate phosphorus dynamics in cropping systems, a soil-plant phosphorus model was modified from initial studies by Daroub et al. (2003) and implemented in the software. Modifications applied to the Daroub et al. version of the model

include: 1) linkage of the model to the CENTURY module to allow simulations of organic P transformations in soils; 2) implementation of a generic, modular crop P module that is usable by all crops in DSSAT, and 3) addition of algorithms for initialization of the different phosphorus pools using measured soil phosphorus data. Daroub et al. (2003) reported that the initial soil-plant phosphorus model simulated with good accuracy P uptake for maize grown under acidic conditions when linked to the DSSAT CSM. The redesigned soil-plant phosphorus model still operates as an experimental version and has not been tested yet. This chapter is centered on evaluating the soil-plant phosphorus model described in chapter 3. The datasets used for the evaluation of the model are two phosphorus experiments conducted in Ghana and described in Chapter 2. Results from these experiments are also discussed in Chapter 2.

The main question addressed in this chapter was: can the soil-plant phosphorus model simulate the responses of maize biomass and grain yield to different levels of phosphorus as observed in the field in Ghana?

The objectives of the present chapter are: 1) to describe selected methods for evaluating the performance of the soil-plant phosphorus model; 2) to present an assessment of the ability of the soil-plant phosphorus model to simulate soil and crop conditions in two locations in Ghana (Kpeve and Wa) using those tools.

To meet these objectives, some model parameters (genetic coefficients describing the cultivar used and the fraction of labile P in solution) were first calibrated using essentially the dataset from Wa and partially the dataset from Kpeve. The evaluation reported in this chapter focused on the following key outputs: grain yield, aboveground biomass and shoot P concentrations.

Materials and Methods

The Kpeve and Wa datasets described in Chapter 2 were used to evaluate the performance of the model.

The Soil-Plant Phosphorus Model

The model simulates phosphorus transformations between 1) three inorganic pools: labile, active and stable; 2) two organic pools: active and stable, and 3) four plant parts: roots, shoots, shells, and seeds. The model was implemented in DSSAT for CERES-Maize to enable the maize model to predict nitrogen and phosphorus-limited maize production as affected by cultivar, soil, weather, and management information.

The soil inorganic P module of the model simulates phosphorus transformations between a labile, active and stable pool. The soil organic P module simulates phosphorus transformations between a surface litter, a microbial pool, and a stable pool. The model accounts for the mineralization of organic P to inorganic pools and the immobilization of P to organic pools. Available phosphorus for uptake by plants is described as being provided by the labile pool within 2 mm of plants' roots.

Phosphorus taken up by the plant is partitioned to seeds, shells and vegetative tissues. During the reproductive phase, phosphorus accumulated in the vegetative tissues can be remobilized and translocated to seeds. Plant growth is limited by phosphorus between two thresholds that are species-specific optimum and minimum concentrations of P defined at three stages in the growth of the plant. Phosphorus stress factors are computed to reduce photosynthesis, dry matter accumulation and partitioning.

A sensitivity analysis of the model to some key phosphorus-related parameters established that the model responds well to phosphorus fertilizer applications on soils with low initial available phosphorus (Chapter 3). The analysis also isolated the initial soil inorganic labile

phosphorus and the fraction of P that is available for uptake per day as two important soil parameters that have significant influence on major model outputs.

Datasets for Testing the Model

The datasets used to evaluate the model came from two phosphorus experiments carried out in Ghana in 2004 and 2006. A description of the experiments is provided in Chapter 2. The treatments at Kpeve, 0P, 10P, 30P, 80P, received respectively 0, 10, 30, and 80 kg [P] ha^{-1}. At Wa, the treatments were combinations of levels of 2 factors: nitrogen fertilizer, 3 levels, 0, 60, and 120 kg [N] ha^{-1}; phosphorus fertilizer, 3 levels, 0, 60, and 90 kg [P] ha^{-1}. The experiment implemented in Kpeve in 2006 did not respond to phosphorus although available P measured as Bray-1 was low. It was found that the soil in Kpeve had relatively high organic matter content (1.8%) and other phosphorus forms that could have been made available to the plant during the growing season. This observation may help explain the lack of response to phosphorus observed at Kpeve. The second experiment conducted in Wa responded well to phosphorus and nitrogen fertilizer applications.

Parameters and Inputs for the Model Tests

The parameters for the model tests included genetic coefficients and phosphorus-related parameters. Inputs included soil and weather conditions. The parameters and inputs used are described next.

Weather conditions

The experiment in Kpeve, Southern Ghana (6^o 40.80' N, 0^o 19.20' E, altitude 67 m above sea level, Figures B-1 and B-2) was conducted in 2006 during the primary rainy season (March to July). The site has a bimodal rainfall pattern with an average annual rainfall of 1300 mm falling in two rainy seasons, March to July and September to October (Figure 2-1). The average annual temperature is 28 degrees C.

The experiment in Wa, Northern Ghana (10°3' N, 2°30' W, altitude 320 m above sea level, Figures B-1 and B-2) was carried out during the only rainy season in 2004. The rainfall pattern in Wa is unimodal. The average annual rainfall is 1100 mm falling mainly between April and September (Figure 2-3). The mean annual temperature in Wa is 27 °C.

Soil conditions

The soil in Kpeve has a sandy loam texture and is classified as Haplic Lixisol which has a dark grayish brown topsoil and grayish brown to brown subsoil (Adiku, 2006). Soil analysis (Table 2-15) showed that the soil has good organic carbon content and available phosphorus (Bray1) that is at the limit between sufficiency and deficiency (11.69 ppm). The relatively high Mehlich1 P (90.44 ppm) value obtained from a different soil testing laboratory suggested that this soil may not be severely P-deficient.

The soil in Wa has a loamy sand texture with very low levels of organic carbon, organic nitrogen, available P (Bray1) and exchangeable K (Table 2-18).

Genetic coefficients

The genetic coefficients for the cultivar used, Obatanpa were calibrated based on the growth and development data obtained essentially from Wa for the high N and P treatments. Because the experiment in Kpeve was affected by a drought spell starting at silking, the dataset from this location was not quantitatively involved in the calibration of the genetic coefficients for Obatanpa. However, qualitative comparisons were used to ensure that the model predicted well the anthesis date (that was not affected by the drought) at Kpeve as well.

Since the cultivar Obatanpa was described as a medium-maturing variety with a maturity period of 105-110 days (Anonymous, 1996), the calibration starting values of the genetic coefficients (Table 4-1) were from a medium-duration cultivar taken from the DSSAT database of cultivars. The coefficients were manually adjusted until an agreement between simulated and

measured days to anthesis and to physiological maturity, biomass and grain yield was obtained. The development coefficients (P1 and P5) were adjusted first using measured days to silking and physiological maturity from the Wa experiment. The growth coefficients G2 and G3 were calibrated next, using measured end-of-season biomass and grain yield from Wa. The coefficient PHINT for thermal time between the appearances of two successive leaf tips was not changed because leaf number data was not available. Since water stress affected the phenology and probably the biomass and grain yield in the Kpeve experiment, the data from this experiment was not used in any genetic coefficient calibration. The calibrated coefficients for Wa was used with no further altering for model evaluation purposes at Kpeve.

Phosphorus parameters

Optimum and minimum P concentrations in roots, shells, seeds as well as maximum and minimum N:P ratios were taken from the literature (Jones, 1983; Probert and Okalebo, 1992; Daroub et al., 2003; Probert, 2004). Optimum shoot P concentration at different stages of growth was estimated using the following equations (Jones, 1983):

At emergence and end of leaf growth: Optimum shoot P concentration (%) = $0.684 - 0.108X$

At physiological maturity: Optimum shoot P concentration (%) = $0.238 - 0.0056X$

Where:

X is the growth stage.

Emergence was defined as growth stage 0 ($X = 0$), end of leaf growth as growth stage 4, and physiological maturity as growth stage 10 (Jones, 1983). Minimum shoot P concentration was taken as 60% of the estimated optimum (Daroub et al., 2003).

For the soil parameters, the rate constants for inorganic P transformation from labile to active pools (K_{LA}), active to labile pools (K_{AL}), and active to stable pools (K_{AS}) were estimated from the value of the P availability index respectively using equations 3-5, 3-6 and 3-7. The P

availability index was approximated as 0.40 (Table 3-1, Other soils). The fraction of soluble P was adjusted until the lowest error between simulated and measured grain yield was obtained using the Wa dataset.

Initial conditions

Initial PiLabile was calculated from measured P Bray1 and exchangeable K (Table C-1) as (1.09*PBray1) + (10.59*ExchangeableK) + 2.71 for both sites, Kpeve and Wa. Initial PiActive and PiStable were calculated using equations 3-4 and 3-7.

Initial total organic P was calculated from the values of organic carbon and pH (Tables 2-15 and 2-18 as $900 \times e^{-1.5 \times \left(\frac{pH-10}{12} \right)^2} \times \left(1 - e^{-0.10 \times OrganicC}\right)$ (Singh, 1985). This total organic P was partitioned as 6% active and 94% stable (Parton et al., 1988, 1994; Gijsman et al., 2002).

Measured soil parameters that included soil organic carbon and nitrogen (Tables 2-15 and 2-18) were used as input to the crop model. Other soil parameters not measured but necessary to run all DSSAT models were estimated using pedotransfer functions in DSSAT. Soil's water lower limit (SLLL), drained upper (SDUL) and upper limit saturated (SSAT) for Kpeve were taken from Adiku (2006). The bulk density used at Kpeve was corrected for gravel content using equation 2-1. At Wa, the SLLL, SDUL, SSAT and bulk density values were estimated using pedotransfer functions in DSSAT.

Initial soil water at planting was set at the SDUL level for both sites. Initial nitrate-N and ammonium-N were not measured and assumed to be 0.01 ppm.

Model Evaluation

Simulation of exact real world values by models would not generally be expected because of the many simplifications with which the model approximates reality. The primary concern of model evaluation is comparing simulations and measurements and explaining possible

deviations. In this study, attention will be given to the analysis of these deviations to assess the model performance and gradually introduce modifications to get more understanding of the causes of simulation error. The evaluation presented here was a first step in testing the ability of the model to mimic the wide differences in responses to P.

Model evaluation tools

Simple scatter plots were used wherever appropriate to stimulate intuitive and preliminary evidence of model performance. The simulations and measurements were compared globally using a standardized mean deviation, the root mean square error (RMSE):

$$RMSE = \left[\frac{\sum (Simulation - Measurement)^2}{N} \right]^{0.5} \quad (4\text{-}1)$$

Where N is the number of pairs of measurements and simulations.

The RMSE estimates the dispersion between simulated and measured data (Du Toit et al., 1997).

The RMSE can be expressed relative to the mean of measurements to visualize how the deviation compares to the average observation:

$$RRMSE = \frac{RMSE}{\overline{M}} \times 100 \quad (4\text{-}2)$$

Where $RRMSE$ is the relative RMSE (in percent) and
$\overline{M}$ is the mean of measurements.

Deviations between simulations and measurements can be furthermore explored by partitioning the overall RMSE into components that relate to specific types of discrepancies (Kobayashi and Salam, 2000; Gauch et al., 2003). If the simulations and the measurements agreed perfectly, the (simulation, measurement) pairs of points would be aligned along the 1:1 line in a scatter plot and the RMSE would be equal to zero. This perfect agreement situation would mean the following: 1) the mean of simulations, S, equals the mean of measurements, M;

2) if a regression analysis was performed, the slope of the equation would be equal to 1; and 3) the coefficient of determination R^2 resulting from a simple linear regression analysis would be equal to 1. An RMSE different from zero can therefore be envisioned as the result of three potential problems:

- **Problem 1:** The model failed to simulate the mean of measurements, introducing a simulation bias: there is shift in the fitted regression line from the original perfect agreement line. This situation can be quantified by the Squared Bias: $SB = \left(S - M\right)^2$ (Kobayashi and Salam, 2000). *SB* reveals a possible trend of the model to overestimate or underestimate the measurements.
- **Problem 2:** The deviation is the result of the model failing to simulate correctly the magnitude of fluctuation among the measurements: there is rotation of the fitted regression line around the perfect agreement line with the axis of rotation passing through the origin. This condition can be measured by the Squared Difference between the Standard Deviations, SDSD,

  $$SDSD = \left(SD_s - SD_m\right)^2 \quad (4\text{-}3)$$

  Where SD_s is the standard deviation of simulations and

  SD_m is the standard deviation of measurements.
- **Problem 3:** The deviation is attributable to the failure of the model to simulate the pattern of the fluctuation across the measurements: the pairs of points would appear in a random pattern in a scatter plot. This situation can be quantified by the Lack of positive Correlation weighted by the standard deviations,

  $$LCS = 2SD_s SD_m\left(1 - r\right) \quad (4\text{-}4)$$

  Where r is the Pearson coefficient of correlation.

The LCS can also be interpreted as the residual error sum of squares after removing SB and SDSD. Kobayashi and Salam **(**2000) found that the three components SB, SDSD and LCS add up to the Mean Squared Error, MSE

$$MSE = SB + SDSD + LCS \quad (4\text{-}5)$$

Since $MSE = (RMSE)^2$, equation (4-5) can be rewritten to relate the RMSE to the components of the model error:

$$(RMSE)^2 = SB + SDSD + LCS \quad (4\text{-}6)$$

The advantage of using the partitioned MSE resides in the possibility to investigate what components of the overall model deviation were most important.

Results and Discussion

The soil-plant P model was able to capture the response of maize to P fertilizer as observed at both sites. Results of genetic coefficients calibration and P-related parameters estimation are also described next.

Weather

The crop in Kpeve experienced a drier than average July (2006) (Figure 2-1) that affected maize phenology and growth. The major season, which normally ends in late July, ended earlier (in June) at a critical stage during crop growth. The total rainfall in July was only 40.40 mm, which was below the calculated 2003-2005 average for that month (Figure 2-1). Although the total rainfall received in 2006 from planting to harvest was higher than the amount received during the same period in 2003-2005 (713 mm in 2006, 464 mm in 2005, 612 mm in 2004, and 526 mm in 2003), the rainfall received in the month of July 2006 was low: the July total rainfall was 60 mm in 2003, 105 mm in 2004 and 26 mm in 2005 compared to 40.40 mm during the year of the experiment.

As a response to this unexpected drought, the field was sprinkler-watered for three days from July 26th to July 28th (60 to 62 days after planting). Because irrigation equipment was not set up on the field at the commencement of the trial, the sprinkler-watering was improvised, which delayed the water application for about 10 days after drought symptoms were first observed, and provided only about 15 mm of water. The adverse effects of rainfall variability and unreliability at Kpeve in recent years were also pointed out by Adiku (2004 and 2006).

Genetic Coefficients

Thermal time related to days to anthesis (P1) was set (Table 4-1) so that the model could simulate correctly the measured anthesis dates at Kpeve and Wa. Thermal time related to days to physiological maturity (P5) was set (Table 4-1) so that the model could simulate correctly the measured physiological maturity dates at Wa. The potential kernel number per plant (G2) was increased from 700 to 900 and the potential kernel growth rate (G3) decreased from 8.50 to 6.50 mg/day to obtain the best fit to the measured grain yield at Wa.

Phosphorus Parameters

Optimum and minimum P concentrations in roots, shells, seeds and maximum and minimum N:P ratios taken from the literature (Jones, 1983; Probert and Okalebo, 1992; Daroub et al., 2003; Probert, 2004) are presented in Table 4-2. Estimated optimum and minimum shoot P concentrations using the equations developed by Jones (1983) are presented in Table 4-2. To reflect the fact that phosphorus stress should affect vegetative partitioning before photosynthesis, the minimum value of the ratio of P in vegetative tissue to the optimum P below which reduced photosynthesis occurs was set to 1.0, and the minimum value of the ratio of P in vegetative tissue to the optimum P below which vegetative partitioning will be affected was set to 0.8. It was assumed that the maximum fraction of P which can be mobilized from shoot per day cannot exceed 0.10.

The estimated soil P parameters were identical for both Kpeve and Wa (Table 4-3). This was because all of the soil P parameters (except the fraction of labile P in solution) depend on the value of P availability index. The dependency of P availability index on Initial PiLabile as shown in the equation $0.40 + 0.00023^{\text{Initial PiLabile}}$ is weak and the calculation essentially yields 0.40 for Initial PiLabile values ≥ 1 ppm (Initial PiLabile was 16.52 ppm at Kpeve and 6.49 ppm at Wa).

The adjustment to the fraction of labile P in solution was challenging. Specific studies were not conducted on this fraction in the way it is used in the soil-plant phosphorus model discussed here. Studies that suggested a value of 0.015-0.020 related the fraction directly to the total PiLabile pool (Daroub et al., 2003). Since in the present phosphorus model, the fraction applies to the part of PiLabile in the root zone only, it was certain that the calibrated value of this fraction would be higher than 0.020. Through calibration using the Wa dataset a value of 0.20 was obtained. This value was also used to evaluate the model at Kpeve. A sensitivity analysis on this fraction of labile P in solution showed that this parameter did not have as much influence on model outputs as the size of the initial PiLabile pool itself and the optimum shoot P concentration (Tables 3-10 and 3-13).

Initial Conditions

Initial sizes of the different phosphorus pools for both sites are given in Table 4-4. The initial PiLabile in the soil at Kpeve was nearly three times that of Wa (Table 4-4). Organic P was relatively high at Kpeve (Table 4-4). Other soil parameters are summarized for Kpeve in Table 4-5 and for Wa in Table 4-6.

Model Evaluation at Kpeve

The soil-plant P model was able to capture the lack of response to P as observed in the experiment at Kpeve.

In-season growth

Simulation of accumulated biomass over time was in good agreement with measurements (Figure 4-3). The RMSE of 87 kg ha^{-1} at 17 dap increased with biomass over time but remained at about 470 kg ha^{-1} between 31 dap and final harvest (108 dap). The RMSE increase during the season was due to increasing biomass values. In relative terms, the simulation actually improved over time. The RRMSE was only 5% at final harvest (Table 4-7).

The early season error was mostly due to an overprediction by the model that resulted in a high squared bias (Figures 4-4 and 4-3). At anthesis (52 dap) and final harvest (108 dap), the SB was less and the error due to the pattern of variation among the measurements (LCS) became the important component of MSE (Figure 4-4), but the overall errors were actually small (Table 4-7). The negative correlation coefficients observed at 17 dap and anthesis (52 dap) were caused by two opposite trends in the variation of the biomass: measured biomass decreased while simulated biomass increased at those periods with increasing P applications. The observed decreasing biomass with P additions was not significant.

Final grain yield

Predicted grain yields were in good agreement with measurements (Figure 4-1). The RMSE was 255 kg ha^{-1} representing 8% of the mean of measurements. The model captured well the lack of response to P at Kpeve as shown by the non significant differences among the measured grain yields (Figure 4-2) even though the growth data from Kpeve was not used in calibrating the genetic coefficients of the cultivar Obatanpa. The simulation error was mainly due to the pattern of variation of grain yield among the four treatments (Figure 4-2). This was also reflected in the low correlation coefficient observed between measurements and simulations (0.36). The statistical non significance of the grain yield means that the slight differences observed in grain yield among the four treatments were not determined by the phosphorus

applied but rather to other causes such as measurement error or field variability. Since a deterministic model does not account for such fluctuations, the low RMSE suggested good performance for final yield.

Wa

At Wa, the model predicted the response of maize to both nitrogen and phosphorus with higher error than Kpeve.

In-season growth

The aboveground biomass was underpredicted by the model at most planting dates in all treatments (Figure 4-9). The RMSE varied with sampling date between 216 and 2574 kg ha^{-1}, which corresponded to 19-57% RRMSE values (Table 4-7). However, the different components of the MSE showed that the general tendency of the model to underpredict the biomass did not actually affect its ability to effectively capture most of the responses of biomass to nitrogen or phosphorus fertilizer. The LCS or the SDSD, which correspond to the failure of the model to simulate correctly the pattern or the magnitude of fluctuation among the measurements, generally represented the smallest portion except for days after planting 46 (Figure 4-8).

The correlation coefficient between simulated and measured biomass at each sampling date can lead to misleading interpretations when used alone. For example, the correlation coefficient had the same value of 0.97 at days 46 and 61 after planting. However, the RRMSE doubled from 46 to 61 dap (from 24 to 45%) (Table 4-7). The increase in the RRMSE is an indicator of a progression towards a poorer performance of the model, but at the same time the persistence of a high correlation coefficient suggests that the strong linear association between simulations and measurements has not been lost. The problem with the use of correlation and linear regression alone for model evaluation is that when simulations and measurements are treated as dependent and explanatory variables, many assumptions of the analysis are violated (Mitchell, 1997).

In-season shoot P concentration

The performance of the simulation of shoot P concentration at Wa depended on N and P fertilization of the crop: 1) When neither nitrogen or phosphorus were applied (treatment 0N 0P, Figure 4-10), simulation of shoot P concentration followed a similar pattern as in phosphorus-fertilized treatments (Figure 4-10); 2) In the no phosphorus treatments that received nitrogen (treatments 60N 0P, 120N 0P, Figure 4-10), simulated shoot P concentration was less variable and remained closer to the minimum shoot P concentration than the measurements (Figure 4-10);

In treatments that received both nitrogen and phosphorus fertilizer, simulated and observed shoot P concentration were similar during the vegetative phase (Figure 4-10). After this phase, simulated shoot P concentration remained stable at a higher level than measured (Figure 4-10). These response patterns are summarized in Figure 4-11. At least three problems of incompatibility between simulations and measurements are highlighted in this figure: 1) Simulated shoot P concentration in the 0P treatment was lower than in the 60 and 90P treatments, which logically reflects low available soil P in the 0P treatment, low P uptake and low P status in the plant due to high P stress on biomass growth. This is the expected relationship between shoot P concentrations in plants grown on P-limiting and non P-limiting soils as found in several studies surveyed in Jones, 1983. In the experiment reported here, the shoot P concentrations did not show much variation between P-limiting and non P-limiting conditions (Figure 4-11). Shoot P concentration varied in the experiment between 0.58% and 0.05% on average regardless of the treatment considered. 2) The measured decrease in shoot P concentration from 0.57 at 28 dap to 0.05% at 125 dap was also in contrast to the simulated 0.50 to 0.20% during the same period in the well-supplied phosphorus treatments (Figure 4-11). In-season variability in shoot P concentration found in other studies under non P-limiting conditions is 0.50% - 0.25% (Plenet et al., 2000a) and 0.45% - 0.15% (Ziadi et al., 2007). The shoot P

concentration measured at maturity (125 dap) was lower than any of these values in the experiment reported here (0.05%).

Final grain yield

The grain yield in Wa was simulated with a low error. The RMSE of 266 kg ha^{-1} represented 13.6% of the mean measurement. The mean difference between simulations and observations (bias) was only 3 kg ha^{-1}. The simulations agreed well with the data (Figure 4-5). The model was able to capture the three yield ranges that are dependent on the amount of nitrogen applied with a correlation coefficient of 0.99 (Figure 4-5). The differential responses to nitrogen and phosphorus fertilizer were equally well simulated (Figure 4-6).

The decomposition of the error revealed that much of the overall MSE could essentially be partitioned among the SDSD and the LCS (Figure 4-7). The SB was very small because the mean measurement was well predicted (mean of measurements = 1961 kg ha^{-1}; mean of simulations = 1958 kg ha^{-1}).

The prediction of the measured variance of yield was also good (standard deviation of measurements = 1336 kg ha^{-1}; standard deviation of simulations = 1472 kg ha^{-1}). The variances of the grain yield themselves were generally high because of the wide range in fertilizer inputs (0, 60 and 120 kg ha^{-1} for nitrogen and 0, 60 and 90 kg ha^{-1} for phosphorus). These high grain yield variances reflected the low nitrogen and phosphorus status of the soil prior to the start of the experiment, which made the soil responsive to the application of either nutrient. The relatively high LCS (compared to the other model error components) does not mean, in this particular situation, that the model failed to simulate correctly the pattern of variation among the measurements because 1) the overall simulation error was low and 2) the LCS is a weighted product of the standard deviations which are inherently high in this experiment.

Conclusion

The assessment presented in this paper showed that the soil-plant phosphorus model simulated maize grain yield and biomass with a good degree of accuracy both under phosphorus-limiting (Wa) and non phosphorus-limiting (Kpeve) conditions in Ghana.

Grain yield was simulated with an RRMSE of 8% at Kpeve and 14% at Wa. Final biomass was simulated with an RRMSE of 5% at Kpeve and 30% at Wa. The higher errors at Wa were mostly due to more bias in biomass simulations, but the model actually simulated well the response to P fertilizer.

Simulation of shoot P concentration at Wa was generally good and in agreement with in-season shoot P variability found in the literature. However, the shoot P concentrations measured in the Wa experiment at 81 dap and harvest maturity (125 dap) were exceptionally low (0.05%).

The soil-plant P model captured the observed response to P fertilizer at Wa, and lack of response to P fertilizer at Kpeve. These results are promising because this is a first evaluation of the model across two contrasting conditions of P availability to plants.

However, the calibration of the fraction of labile P in solution was challenging mostly because it is difficult to measure directly and sufficient information was not available in the literature. Different values of this parameter might work better on other soil types. This parameter was found to be influential on plant P uptake, biomass and grain yield when P fertilizer was not applied.

Methods for indirect estimation the initial sizes of the inorganic and organic P pools that play an important role in the response of the model to P have uncertainties associated with them. Model performance can be expected to improve as refinements are introduced in these methods.

Table 4-1. Growth and development genetic coefficients for the Obatanpa cultivar used at both sites, Kpeve and Wa, for testing the phosphorus model

Definition	DSSAT ID	Starting Value	Obatanpa
Degree days (base 8^{o}C) from emergence to end of juvenile phase	P1	200	300
Photoperiod sensitivity	P2	0.00	0.00
Degree days (base 8^{o}C) from silking to physiological maturity	P5	800	830
Potential kernel number (/plant)	G2	700	900
Potential kernel growth rate (mg/day)	G3	8.50	6.50
Phyllochron	PHINT	38.90	38.90

Table 4-2. Plant parameters used for testing the phosphorus model at Kpeve and Wa

Parameter	Unit	Value
Shoot P concentrations		
Optimum shoot P concentration at emergence	%	0.70
Optimum shoot P concentration at tasseling	%	0.25
Optimum shoot P concentration at physiological maturity	%	0.20
Minimum shoot P concentration at emergence	%	0.40
Minimum shoot P concentration at tasseling	%	0.15
Minimum shoot P concentration at physiological maturity	%	0.10
Root P concentrations		
Optimum root P concentration at emergence	%	0.041
Optimum root P concentration at effective grain filling	%	0.041
Optimum root P concentration at physiological maturity	%	0.041
Minimum root P concentration at emergence	%	0.020
Minimum root P concentration at effective grain filling	%	0.020
Minimum root P concentration at physiological maturity	%	0.020
Shell P concentrations		
Optimum shell P concentration at emergence	%	0.50
Optimum shell P concentration at effective grain filling	%	0.50
Optimum shell P concentration at physiological maturity	%	0.050
Minimum shell P concentration at emergence	%	0.25
Minimum shell P concentration at effective grain filling	%	0.25
Minimum shell P concentration at physiological maturity	%	0.025
Seed P concentrations		
Optimum seed P concentration at emergence	%	0.35
Optimum seed P concentration at effective grain filling	%	0.35
Optimum seed P concentration at physiological maturity	%	0.35
Minimum seed P concentration at emergence	%	0.175
Minimum seed P concentration at effective grain filling	%	0.175
Minimum seed P concentration at physiological maturity	%	0.175
N to P ratios		
Maximum vegetative N:P ratio at emergence	unitless	28.0
Maximum vegetative N:P ratio at effective grain filling	unitless	15.0
Maximum vegetative N:P ratio at physiological maturity	unitless	9.3
Minimum vegetative N:P ratio at emergence	unitless	4.2
Minimum vegetative N:P ratio at effective grain filling	unitless	2.7

Table 4-2 continued

Minimum vegetative N:P ratio at physiological maturity	unitless	2.1
P mobilization and stress		
Maximum fraction of P which can be mobilized from shoot per day	unitless	0.10
Minimum value of the ratio of P in vegetative tissue to the optimum P below which reduced photosynthesis will occur	unitless	0.80
Minimum value of the ratio of P in vegetative tissue to the optimum P below which vegetative partitioning will be affected	unitless	1.00

Source: Jones, C.A. 1983. A survey of the variability in tissue nitrogen and phosphorus concentrations in maize and grain sorghum. Field Crops Research 6, 133-147.

Jones, C.A., Cole, C.V., Sharpley, A.N. Williams, J.R., 1984a. A simplified soil and plant phosphorus model: I. Documentation. Soil Science Society of America Journal 48, 800-805.

Daroub, S.H., Gerakis, A., Ritchie, J.T., Friesen, D.K., Ryan, J., 2003. Development of a soil-plant phosphorus simulation model for calcareous and weathered tropical soils. Agricultural Systems 76, 1157-1181.

Probert, M.E., 2004. A capability in APSIM to model phosphorus responses in crops. In: Delve, R.J. Probert, M.E. (Eds), Modelling Nutrient Management in Tropical Cropping Systems. ACIAR Proceedings No. 114. pp. 92-100.

Table 4-3. Soil parameters used for testing the phosphorus model at Kpeve and Wa. The values correspond to the top layer of the soils (0-10 cm for Kpeve and 0-20 cm for Wa)

Parameter	Unit	Kpeve	Wa
Rate constant for transformation from labile P to active P	d^{-1}	0.03674	0.03674
Rate constant for transformation from active P to labile P	d^{-1}	0.00490	0.00490
Rate constant for transformation from active P to stable P	d^{-1}	0.00043	0.00043
Rate constant for transformation from stable P to active P	d^{-1}	0.00010	0.00010
P availability index	unitless	0.40	0.40
Fraction of root labile inorganic P that is soluble	unitless	0.20	0.20

Table 4-4. Values of additional inputs required to run the soil-plant phosphorus model for the Kpeve and Wa experiments. Values correspond to the top layer of the soils (0-10 cm for Kpeve and 0-20 cm for Wa)

Input	Unit	Kpeve	Wa
Initial labile inorganic P	ppm	16.52	6.49
Initial active inorganic P	ppm	123.91	48.70
Initial stable inorganic P	ppm	495.66	194.82
Initial active organic P	ppm	7.99	2.22
Initial stable organic P	ppm	125.15	34.78
P in residue (if applied)	%	1.1	Not measured
P fertilizer (if applied)	kg ha^{-1}	0, 10, 30, and 80	0, 60, and 90
Soil CEC	cmol kg^{-1}	17.8	10.0
Soil Clay	%	18.3	7.5

Source: estimated from soil composition data from the experiments.

Table 4-5. Estimated initial condition soil parameters for Kpeve

SLB	SLLL	SDUL	SSAT	SRGF	SBDM	C:P	SLTX
10	0.180	0.260	0.460	1.000	0.83	138	Sandy Loam
20	0.070	0.140	0.280	1.000	1.08	136	Loam
30	0.040	0.080	0.160	0.607	1.47	130	Sandy Loam
40	0.060	0.120	0.240	0.497	0.74	138	Clay
50	0.040	0.060	0.120	0.407	0.47	123	Sandy Clay
60	0.050	0.090	0.180	0.333	0.56	218	Sandy Clay
70	0.080	0.150	0.300	0.273	0.97	200	Sandy Clay
80	0.060	0.110	0.220	0.223	0.77	127	Sandy Clay Loam
90	0.090	0.160	0.320	0.183	1.04	124	Sandy Clay

SLB, depth, base of soil layer (cm); SLLL, soil lower limit (cm3 cm-3); SDUL, soil upper limit, drained (cm3 cm-3); SSAT, soil upper limit, saturated (cm3 cm-3); SRGF, soil root growth factor (unitless); SBDM, soil bulk density, moist (g cm3), corrected for gravel content; C:P, ratio of organic carbon to organic phosphorus (unitless); SLTX, soil texture (unitless).

Table 4-6. Estimated initial condition soil parameters for Wa

SLB	SLLL	SDUL	SSAT	SRGF	SBDM	SSKS	SLTX
20	0.085	0.155	0.383	1.000	1.54	2.59	Loamy Sand
40	0.122	0.190	0.362	0.549	1.57	2.59	Sandy Loam
60	0.124	0.170	0.204	0.368	1.52	0.12	Sandy Clay
90	0.059	0.079	0.088	0.223	1.38	0.06	Clay

SLB, depth, base of soil layer (cm); SLLL, soil lower limit (cm^3 cm^{-3}); SDUL, soil upper limit, drained (cm^3 cm^{-3}); SSAT, soil upper limit, saturated (cm^3 cm^{-3}); SRGF, soil root growth factor (unitless); SBDM, soil bulk density, moist (g cm^3); SSKS, saturation hydraulic conductivity (cm h^{-1}); SLTX, soil texture (unitless).

Table 4-7. Summary of aboveground biomass error statistics for the Kpeve and Wa experiments

Kpeve					
Days after planting	17	31	52	108 (harvest)	
RMSE (kg ha^{-1})	87	475	470	470	
RRMSE (%)	83	51	9	5	
Correlation Coefficient	-0.63	0.88	-0.88	0.53	
Wa					
Days after planting	28	46	61	81	125 (harvest)
RMSE (kg ha^{-1})	216	481	2574	1048	1479
RRMSE (%)	57	24	45	19	30
Correlation Coefficient	0.74	0.97	0.97	0.99	0.99

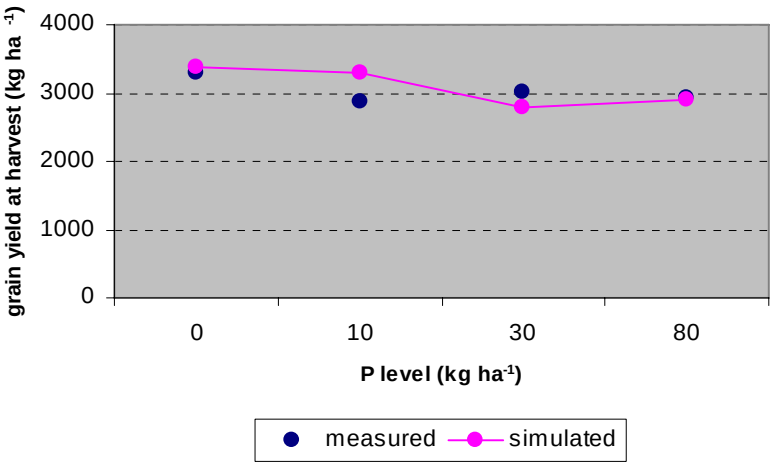


Figure 4-1. Comparison of simulated and measured grain for different phosphorus levels in the Kpeve experiment

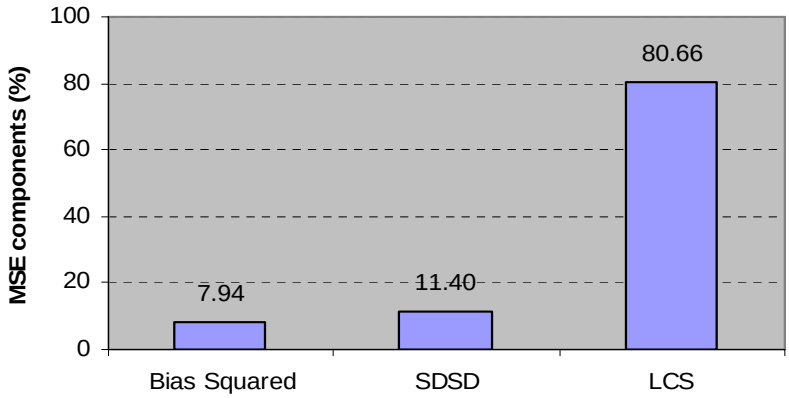


Figure 4-2. Decomposition of the grain yield MSE for the Kpeve experiment, using the method developed by Kobayashi and Salam (2000)

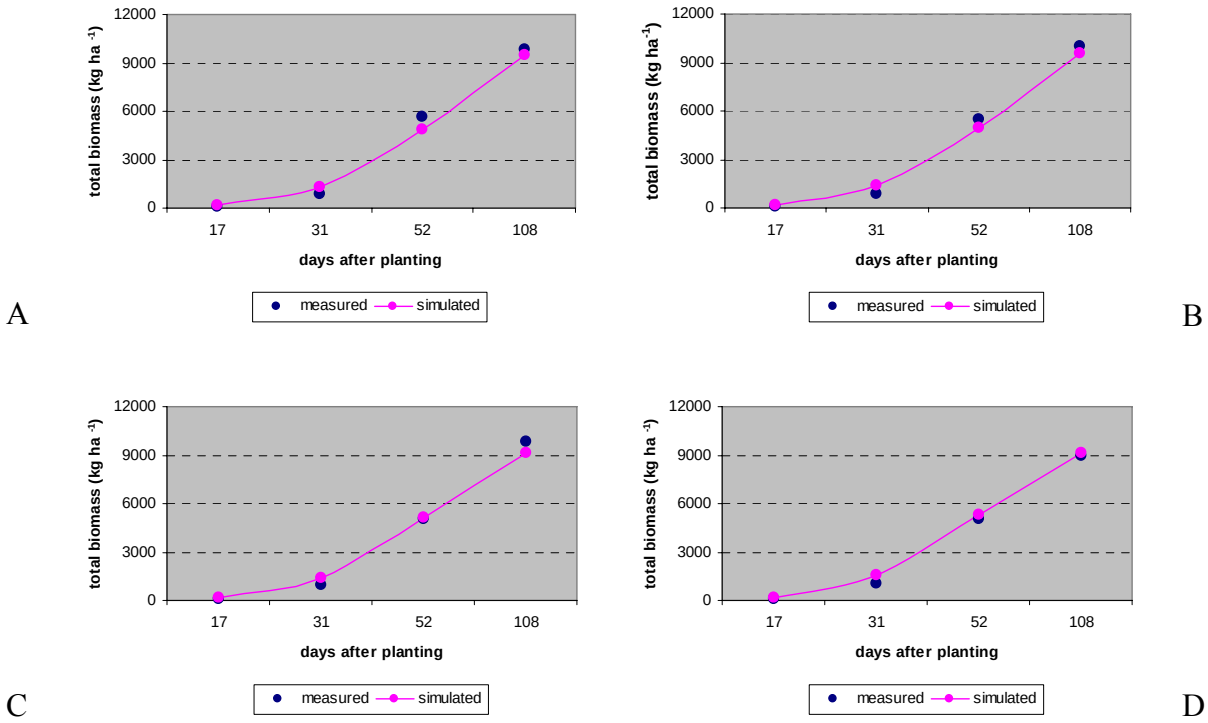


Figure 4-3. Comparison of simulated and measured biomass on four samples taken during the season for the four treatments tested in Kpeve. A) Treatment 0P. B) Treatment 10P. C) Treatment 30P. D) Treatment 80P.

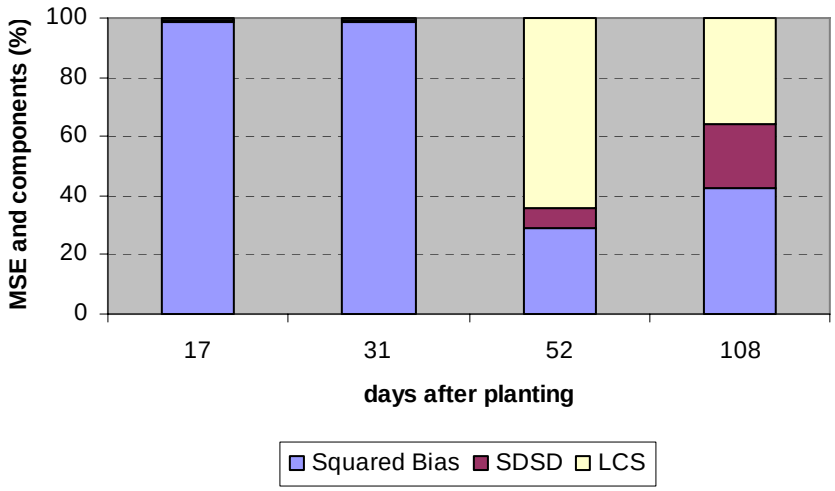


Figure 4-4. Decomposition of the in-season biomass MSE for the Kpeve experiment, using the method developed by Kobayashi and Salam (2000)

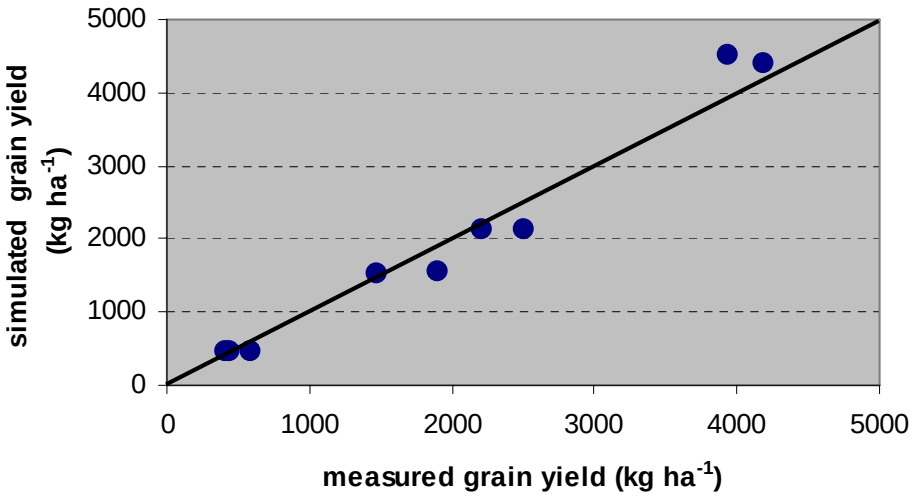


Figure 4-5. Comparison of measured and simulated maturity grain yield obtained in the Wa experiment using the 1:1 line

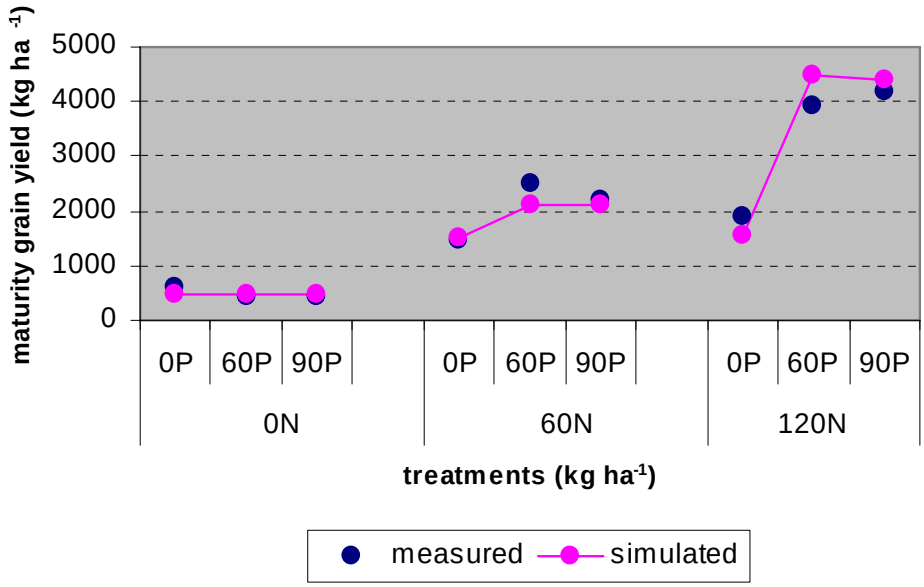


Figure 4-6. Measured and simulated responses of maturity grain yield to different combinations of nitrogen and phosphorus levels in the Wa experiment

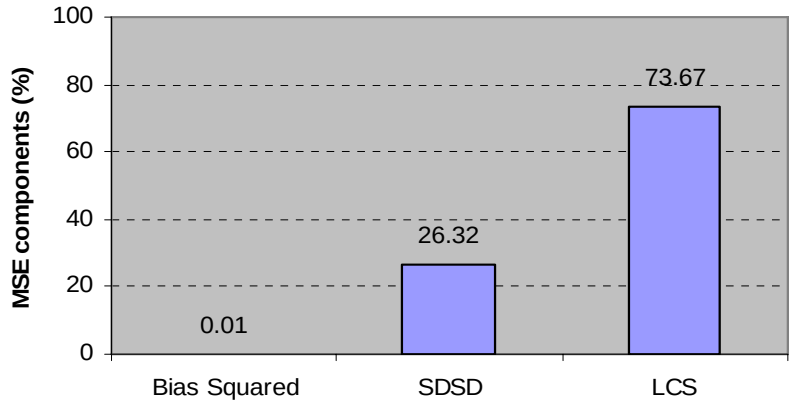


Figure 4-7. Decomposition of the grain yield MSE for the Wa experiment, using the method developed by Kobayashi and Salam (2000)

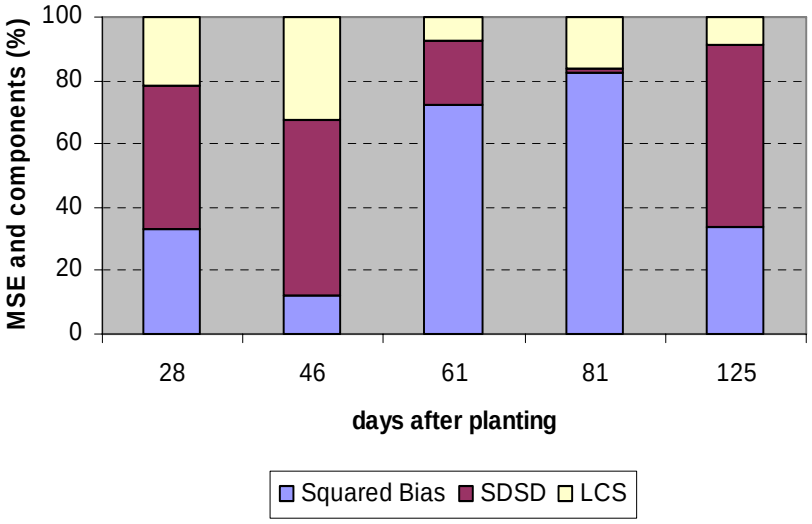


Figure 4-8. Components of the biomass MSE for the Wa experiment at five sampling times

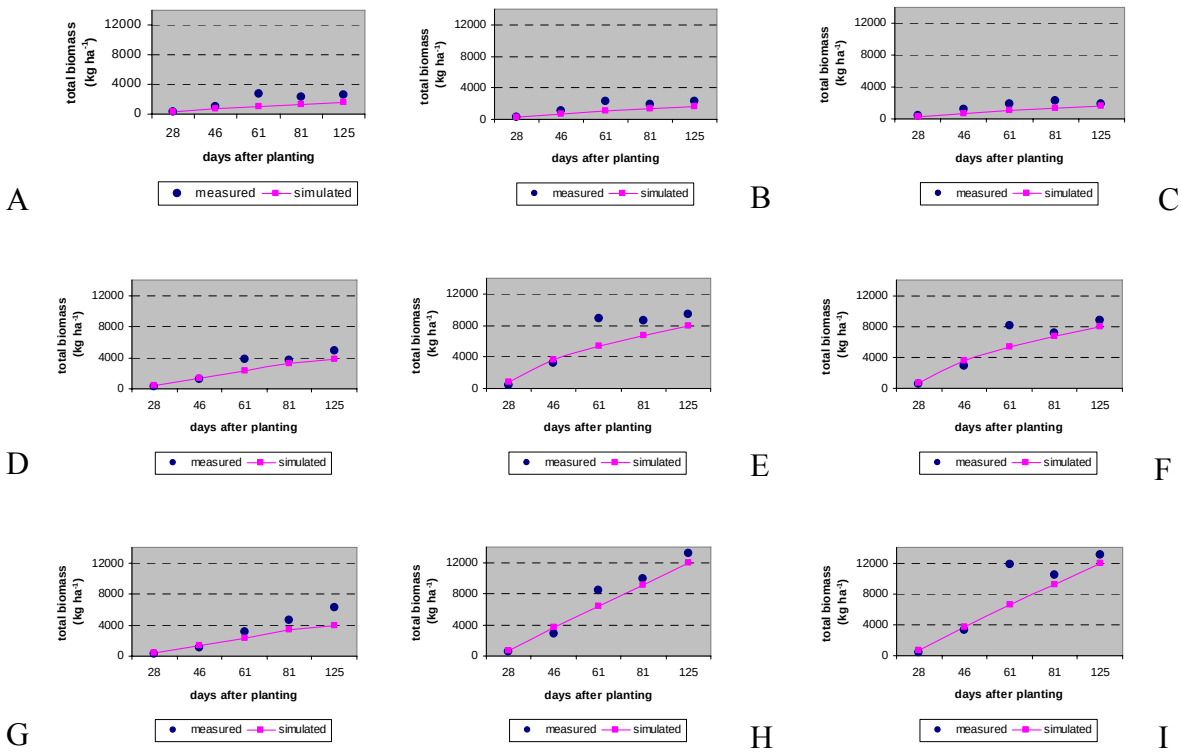


Figure 4-9. Measured and simulated responses of cumulative biomass to different combinations of nitrogen and phosphorus levels in the Wa experiment. A) Treatment 0N 0P. B) Treatment 0N 60P. C) Treatment 0N 90P. D) Treatment 60N 0P. E) Treatment 60N 60P. F) Treatment 60N 90P. G) Treatment 120N 0P. H) Treatment 120N 60P. I) Treatment 120N 90P.

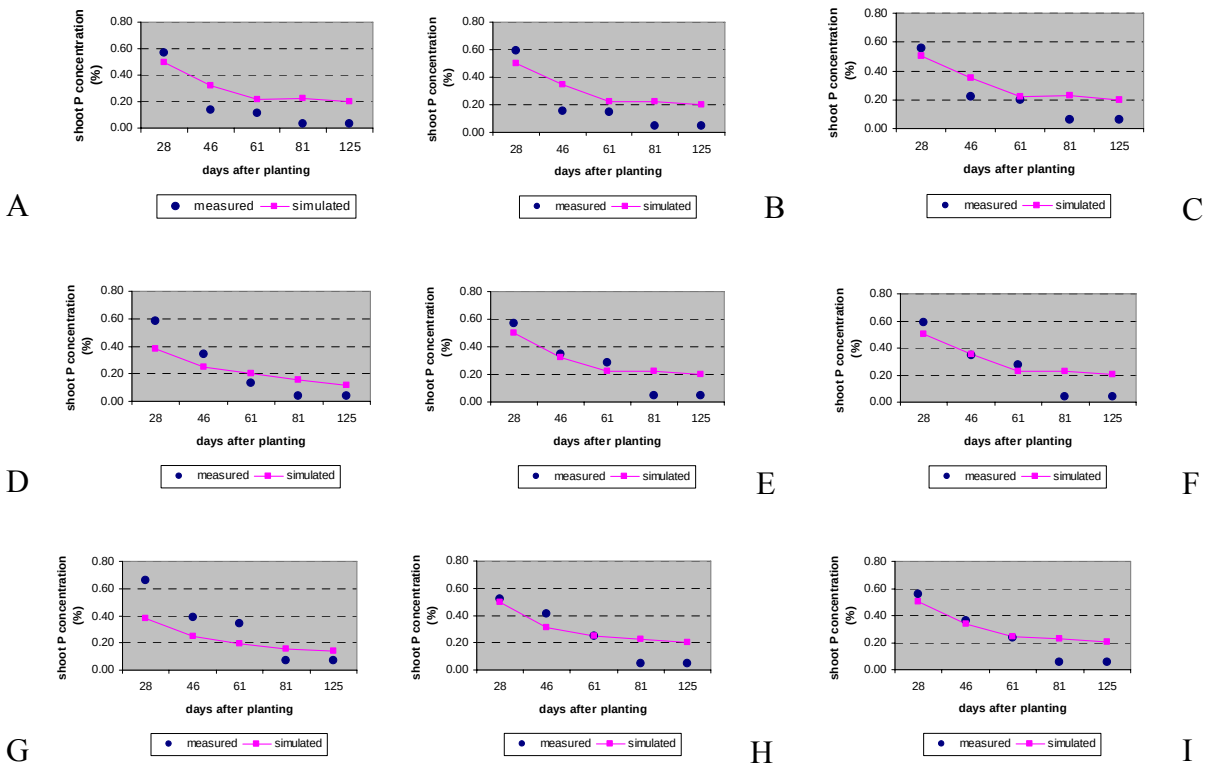


Figure 4-10. Measured and simulated responses of shoot P concentration to different combinations of nitrogen and phosphorus levels in the Wa experiment. A) Treatment 0N 0P. B) Treatment 0N 60P. C) Treatment 0N 90P. D) Treatment 60N 0P. E) Treatment 60N 60P. F) Treatment 60N 90P. G) Treatment 120N 0P. H) Treatment 120N 60P. I) Treatment 120N 90P.

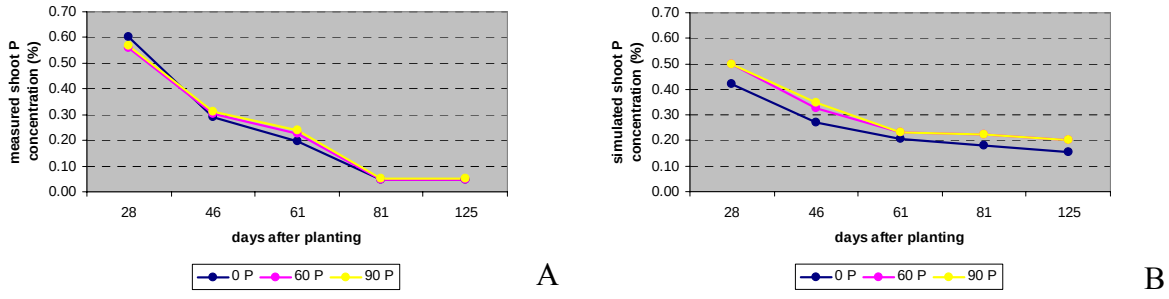


Figure 4-11. Variation of the shoot P concentration during plant growth as affected by three phosphorus levels in the Wa experiment. A) Measured. B) Simulated.

CHAPTER 5
SUMMARY AND CONCLUSIONS

The soil-plant phosphorus model in the DSSAT CSM integrates information on phosphorus in soils and plants to simulate phosphorus transformations in soils and their effects on plant production. Information on soil phosphorus includes the quantity of inorganic, readily-available phosphorus (labile P), slowly available phosphorus (active P), very slowly available phosphorus (stable P) and organic phosphorus. Transformation constants control the way phosphorus is moved among these pools. The model differentiates between soils with different P sorption capacities to partition fertilizer applied to the inorganic P pools. A fraction of the phosphorus in the readily-available pool becomes soluble and may be taken up on any day that a plant is growing on the soil. Information on the plant includes optimum and minimum phosphorus concentration in different plant parts (roots, shoots, shells and seeds). The plant's demand for phosphorus is estimated as the P deficit relative to a seasonally-varying optimum P concentration. This demand is satisfied by P uptake from the readily available inorganic P pool. If this uptake is not sufficient to meet the demand of seeds present, phosphorus can be removed from other vegetative organs. Phosphorus not removed with harvest constitutes a capital investment in the soil in the organic form.

A sensitivity analysis of the model, limited to six key factors, showed that P fertilizer application and the initial value of the readily available P were the most important P-related inputs affecting the predictability of plant biomass, yield and P uptake. The fraction of readily-available P that is soluble, the shoot and seed P were also influential but to a smaller extent. However, these parameters have more influence on the model outputs in the absence of P fertilizer. Accurate predictions require therefore that at least initial readily available P be measured or estimated correctly. In this regard, different names of readily available P have been

used in the literature and can be the source of model input error. In the DSSAT soil-plant phosphorus model, the readily available P that provides soluble P for plant uptake is approximately the inorganic labile P extracted with resin. If the resin P measurement is not available but any of the following extractants were used to measure available P, Bray1, Colwell, Mehlich1, Morgan, Olsen, Truog, and water, the model will use empirical relationships from an expert system to indirectly estimate the readily available inorganic P. The correct specification of the quantity of fertilizer applied can become another source of error. Although in many agronomic experiments, P fertilizer application is expressed as phosphate (P_2O_5), the amount of phosphorus applied is expressed as pure P in the model. There is a 2.29 factor for converting between the two.

The contrasting results obtained from the two experiments used to evaluate the phosphorus model provided an ideal situation for testing the robustness of the model under opposite conditions. The available phosphorus (Bray1) was relatively low at Kpeve (southern Ghana) but other important phosphorus sources such as chemical contributions of organic matter (organic matter content in the soil top 20 cm at Kpeve was 1.8%) not accounted for by the Bray1 extraction could have been responsible for high indigenous phosphorus supply in the soil. No significant difference in measured plant phenology, aboveground biomass, green leaf area and grain yield was found between fertilized and unfertilized treatments at this site.

The soil at Wa (Northern Ghana) was relatively low both in available P (2.5 ppm Bray-P in the top 20 cm) and organic carbon (0.49% in the top 20 cm). Maize responded well to phosphorus fertilizer application on this soil. Leaf area index and aboveground biomass were low in no nitrogen and no phosphorus treatments throughout the season. The highest reduction in leaf area index and biomass occurred at the same time, which supports the reported finding that poor

biomass accumulation in P deficient conditions is associated with reduced photosynthetically absorbed radiation by the plant, due to reduced leaf area. The reduction in grain yield could have been a result of indirect and direct effects of N and P stress on photosynthesis.

Testing of the phosphorus model under both P-limitation (Wa) and no P limitation (Kpeve) conditions showed that plant biomass and grain yield were quite predictable. Grain yield was simulated with an RRMSE of 8% at Kpeve and 14% at Wa. Final biomass was simulated with an RRMSE of 5% at Kpeve and 30% at Wa. Although the simulation skill was lower at Wa, the model reasonably captured the response of biomass and grain yield to P fertilizer at both sites.

The soil-plant phosphorus model described, analyzed and tested with field data performed acceptably well over specific and known soil phosphorus conditions. The potential exists for using the model as an application tool or in decision-support because model simulation of crop response to P fertilizer is promising. However, the current level of confidence in the model must be enhanced through further testing and validation studies. Some P model parameters are highly uncertain and must be estimated from other, more easily measurable variables. For example, the initial inorganic labile P that has a major influence on crop response need greater precision in its estimation. This confidence raising process includes: 1) verification or re-verification of the model; 2) more accurate estimation of the inorganic labile P from measured available P when new data become available for calibration of the expert system; 3) special study on the estimation of the fraction of inorganic labile P that is soluble for a specific soil and how this fraction changes with soil properties like the P-sorbing capacity.

APPENDIX A
MEASURED GROWTH DATA AT KPEVE

Table A-1. Monthly total rainfall in 2006 (one standard deviation of rainfall), mean daily solar radiation, and mean daily temperature collected during the Kpeve experiment in 2006

Month	Rain (mm)	Solar Radiation (MJ m^{-2} day^{-1})	Maximum Temperature (^oC)	Minimum Temperature (^oC)
March	107.6 (7.4)	14.8	35.2	23.4
April	84.0 (8.8)	14.0	35.0	24.3
May	257.4 (12.3)	14.4	32.7	22.8
June	202.4 (18.3)	14.5	31.5	22.7
July	40.4 (3.6)	11.6	30.2	22.9
August	21.0 (1.8)	10.5	30.0	22.7

Table A-2. Days to tasseling (one standard deviation of four replications), days to anthesis (one standard deviation of four replications), and days to silking (one standard deviation of four replications) for the experiment in Kpeve, Ghana

P level (kg ha^{-1})	Tasseling (day)	Anthesis (day)	Silking (day)
0	48 (1.0)	51 (0.6)	59 (3.9)
10	49 (0.8)	51 (1.0)	57 (3.3)
30	48 (0.6)	50 (0.5)	57 (5.1)
80	48 (2.1)	51 (0.6)	63 (1.9)

Table A-3. Measured mean aboveground biomass (one standard deviation of four replications) for four phosphorus treatments, sampled four times during the growing season in the Kpeve experiment

P level (kg ha^{-1})	17 dap	31 dap	52 dap	108 dap
0	110 (22)	913 (145)	5681 (739)	9802 (1572)
10	102 (18)	897 (91)	5436 (805)	10002 (949)
30	105 (13)	914 (106)	5047 (883)	9816 (706)
80	101 (9)	1013 (81)	5083 (680)	8926 (914)

dap = days after planting. Data are reported in kg ha^{-1}.

Table A-4. Mean green leaf area (one standard deviation of four replications) for four phosphorus treatments, measured seven times during the growing season in the Kpeve experiment

P level (kg ha^{-1})	17 dap	24 dap	31 dap	38 dap	45 dap	52 dap	68 dap
0	327 (47)	1010 (44)	2409 (176)	4495 (309)	5269 (481)	5554 (187)	4258 (470)
10	332 (77)	1078 (318)	2634 (656)	4842 (881)	5699 (1034)	6235 (1067)	4543 (1309)
30	373 (47)	1175 (189)	2807 (235)	5102 (454)	5612 (411)	5946 (454)	4330 (464)
80	320 (25)	1004 (78)	2576 (235)	4605 (315)	5345 (202)	5473 (278)	4090 (217)

dap = days after planting. Data are reported in cm^2 plant^{-1}.

Table A-5. Mean maize height (one standard deviation of four replications) for four phosphorus treatments, measured seven times during the growing season in the Kpeve experiment

P level (kg ha^{-1})	17 dap	24 dap	31 dap	38 dap	45 dap	52 dap	68 dap
0	26 (5)	42 (10)	76 (10)	124 (22)	195 (32)	236 (36)	240 (42)
10	29 (5)	45 (8)	76 (14)	129 (22)	208 (22)	250 (27)	259 (33)
30	26 (5)	47 (6)	84 (8)	138 (15)	215 (19)	250 (29)	256 (31)
80	25 (7)	44 (9)	81 (12)	126 (21)	188 (37)	234 (35)	240 (32)

dap = days after planting. Data are reported in cm plant^{-1}.

Table A-6. Mean soil moisture (one standard deviation of four replications) in four phosphorus treatments plots, measured using TDR eight times during the growing season in the Kpeve experiment

P level (kg ha^{-1})	0 dap	16 dap	24 dap	30 dap	37 dap	45 dap	53 dap	69 dap
0	12.1 (3.1)	8.8 (2.2)	17.1 (4.8)	13.7 (3.1)	11.5 (2.6)	9.4 (2.6)	6.4 (2.1)	13.7 (7.3)
10	11.8 (2.1)	8.3 (1.4)	15.3 (2.9)	12.1 (1.4)	10.2 (1.5)	8.0 (1.9)	6.0 (1.9)	9.4 (1.6)
30	12.7 (2.5)	8.4 (1.1)	17.3 (4.0)	13.3 (3.1)	10.8 (1.6)	8.3 (1.6)	5.6 (1.2)	10.6 (3.3)
80	13.2 (3.2)	8.6 (1.7)	17.9 (5.4)	13.7 (3.6)	11.1 (1.7)	9.0 (1.7)	5.7 (1.4)	12.0 (4.5)

dap = days after planting. Data are reported in %.

Table A-7. Measured mean grain yield (one standard deviation of four replications), unit grain weight (one standard deviation of four replications), and grain number (one standard deviation of four replications) for four phosphorus levels in the Kpeve experiment

P level ($kg\ ha^{-1}$)	Grain yield ($kg\ ha^{-1}$)	Unit grain weight ($g\ grain^{-1}$)	Grain number ($\#\ m^{-2}$)
0	3286 (683)	0.23 (0.04)	1655 (193)
10	2859 (384)	0.25 (0.03)	1344 (405)
30	3025 (358)	0.24 (0.02)	1492 (471)
80	2918 (411)	0.23 (0.04)	1467 (334)

APPENDIX B
MAPS OF THE EXPERIMENT SITES LOCATIONS

Figure B-1. Map of the African continent showing Ghana, the country where the field experiments were carried out

Figure B-2. Map of Ghana showing the location of the two study sites, Kpeve in the South and Wa in the North

APPENDIX C
INITIALIZATION OF SOIL INORGANIC AND ORGANIC PHOSPHORUS POOLS IN THE SOIL-PLANT PHOSPHORUS MODEL

Initial values of the three soil inorganic P pools (labile, active and stable) and two soil organic P pools (active and stable) described in Chapter 3 are needed to simulate phosphorus in soils and plants. These values would ideally come from P fractionation studies on the soil of interest following the procedure developed by Hedley et al. (1982), Tiessen et al. (1984), and Tiessen and Moir (1993). The Hedley/Tiessen fractionation procedure is a thorough phosphorus extraction method that treats a soil sample with increasingly aggressive chemicals. The soil is first shaken with water plus resin (to extract the most labile part of P), then treated with NaHCO3, NaOH, (and sometimes NaOH with sonication), diluted HCl and hot concentrated HCl. Each chemical extracts a more resistant form of phosphorus that escaped the previous extractant. The residual phosphorus still remaining in the soil is measured after digestion of the soil sample with perchloric or sulfuric acid. This procedure sequentially extracts both inorganic and organic forms of P. The data obtained from the P fractionation are used to determine directly the sizes of the inorganic and organic pools.

However, few researchers make use of the P fractionation method probably because it is expensive and also because simple and inexpensive extraction methods, such as resin and Bray1 methods, would generally answer phosphorus availability questions that arise in most agronomic experiments.

If an alternate method is not provided for indirect estimation of the pools sizes, potential model users could possibly resort to indicative values found in the literature or eventually conclude that the model is not of any practical use because required input data are not readily available. Since organic carbon, pH and available phosphorus are routinely measured in most

traditional agronomic experiments, developing relationships that can make use of those data and provide reasonable estimates of inorganic labile P and organic P was thought to be helpful.

The aim of this appendix was to present direct and indirect methods of estimation of initial inorganic labile, active and stable P, and initial organic active and stable P for use by the soil-plant phosphorus model in DSSAT. The relationships discussed in this appendix are based on studies by Singh (1985), Sharpley (1984, 1989).

Initialization of Inorganic Phosphorus Pools

From P Fractionation Data

The quantities of inorganic labile, active, and stable P (Table C-1) initially present in the soil can then be derived, in mg kg^{-1}, from the fractionation data for each soil layer as (Jones et al., 2005a):

$$\text{Initial PiLabile} = Pi\,\text{Resin} + PiNaHCO3 \quad \text{(C-1)}$$

$$\text{Initial PiActive} = 0.5 \times PiNaOH \quad \text{(C-2)}$$

$$\text{Initial PiStable} = \left(0.5 \times PiNaOH\right) + PiNaOHSonic + PiHCl + PiHClHot + \left(0.5 \times P\,\text{Residual}\right) \quad \text{(C-3)}$$

Where *PiResin* is inorganic P extracted with water and resin.
PiNaHCO3 is inorganic P extracted with bicarbonate of sodium.
PiNaOH is inorganic P extracted with sodium hydroxide.
PiNaOHSonic is inorganic P extracted with sodium hydroxide plus sonication.
PiHCl is inorganic P extracted with diluted HCl.
PiHClHot is inorganic P extracted with hot concentrated HCl.
PResidual is residual P measured after digestion of the remaining sample with perchloric or sulfuric acid.

From Measured Available P Using the Anion Exchange Resin Method

P extraction using this method can be approximated as a direct measurement of PiLabile in the soil. The anion exchange resin technique extracts phosphorus from the soil in the same manner as plants and has been reported as a reliable method for measuring plant available phosphorus (Myers, 2005; Abdu, 2006). PiActive and PiStable are assumed to be in equilibrium initially and are calculated based on the value of PiLabile as follow (Jones et al., 1984a):

$$\text{PiActive} = PiLabile \times \frac{K_{LA}}{K_{AL}} \quad \text{(C-4)}$$

Where K_{LA} = rate constant for transformation from labile P to active P
K_{AL} = rate constant for transformation from active P to labile P.

$$K_{LA} = 0.03 \times \left[\frac{(1 - PAvailIndex)}{PAvailIndex} \right]^{0.5} \quad \text{(C-5)}$$

$$K_{AL} = \frac{K_{LA}}{3} \times PAvailIndex \quad \text{(C-6)}$$

Where *PAvailIndex* is used as a measure of the activity level of P in the soil. The calculation of the PAvailIndex depends on soil category (Sharpley et al., 1984, Table C-2) and is provided in Table 3-1.

According to Jones et al. (1984a), PiStable is four times as large as PiActive:

$$\text{PiStable} = 4 \times PiActive \quad \text{(C-7).}$$

From Other Methods

If fractionation data are not available and resin measurements were not made, the initial PiLabile can be estimated from other P extraction methods based on regression equations between resin P and extractable P (such as Bray1 and Olsen P) that were used to build an expert system.

The equations that appear in the expert system are based on studies conducted by Sharpley et al. (1984, 1989) and Singh (1985). The expert system in its current version has not been tested independently for its ability to estimate accurately labile P from different available P extraction methods. It is used in the soil modules of the P model as an experimental version to estimate the initial inorganic and organic phosphorus pool sizes based on the method used for measuring available P and the soil category concerned. The criteria used for assigning soil categories are presented in Table C-2.

The inorganic labile P is computed first and the active Pi is derived from the labile Pi in such a way that the two pools remain in equilibrium (Equation C-4). The stable Pi is calculated using the size of PiActive (Equation C-7).

The following P extraction methods are used in the expert system proposed by Singh (1985) to compute initial PiLabile in the soil: water, Bray 1, Olsen, Mehlich 1, Truog, Morgan's solution and Colwell (Table C-3). In slightly weathered soils, measured exchangeable potassium is used in combination with Bray 1, Olsen, Mehlich 1 and Truog for a more accurate estimation of PiLabile (Table C-3). The soil-plant phosphorus model cannot be initialized if none of these measured P data is available.

Initialization of Soil Organic Phosphorus Pools

The division of the organic residues added to the surface of the soil into metabolic and structural components (Figure 3-1) is governed by the lignin to N ratio (lignin:N) of the residues. The metabolic fraction is estimated as equal to 0.85 – 0.013*(lignin:N ratio) (Gijsman et al., 2002a).

The procedures for estimating the initial sizes of the active and stable soil SOM (SOM1 and SOM23) from P fractionation data or from the expert system (using organic C and pH) are described next.

Initialization from P Fractionation Data

The initial values of the SOM1 and SOM23 pools can be obtained from Hedley/Tiessen soil P fractionation data (Table C-4) (Gijsman and Porter, unpublished):

$$\text{Initial PoActive (SOM1)} = PoNaHCO3 + PoNaOH \quad \text{(C-8)}$$

$$\text{Initial PoStable (SOM23)} = PoNaOHSonic + PoHCl + PoHClHot + (0.5 \times P\,\text{Re}\,sidual) \quad \text{(C-9)}$$

Where *PoNaHCO3* is organic P extracted with bicarbonate of sodium.
PoNaOH is organic P extracted with sodium hydroxide.

PoNaOHsonic is organic P extracted with sodium hydroxide plus sonication.
PoHCl is organic P extracted with diluted HCl.
PoHClhot is organic P extracted with hot concentrated HCl.
PResidual is P recovered after digestion with perchloric or sulfuric acid.

Initialization from Measured Organic P

If only a pooled total organic P value is known, the partitioning between active and stable P depends on the land and crop use history of the soil (previous crop in DSSAT). The initial active organic P is set to 3% and the initial stable P to 97% of the total organic P if the previous crop is bahia grass or grass weeds. For all other previous crops, the initial active and the initial stable organic P represent respectively 6% and 94% of the measured total organic P.

Initialization from Organic C and soil pH

Indirect estimation of the active and stable organic P (if total organic P was not measured) through the expert system uses measured soil organic C and pH (Table C-5). These soil properties are known to be correlated with soil organic P; equations relating them to total organic P in the soil have been developed based on studies by Sharpley et al. (1984, 1989) and Singh (1985). The distribution between active and stable P is exactly the same as if the total organic P was directly measured.

Table C-1. Relationship between inorganic P pools and P extracted using the Hedley procedure

Inorganic P pools	P fractionation methods						
	Resin	$NaHCO_3$	NaOH	NaOH and Sonication	HCl	Hot HCl	Residual
Labile	+	+					
Active			+1/2				
Stable			+1/2	+	+	+	+1/2

Source: Gijsman and Porter (2005)

Table C-2. Specification of soil categories

Soil Category	Criteria
Andisol	Soil description or taxonomy includes the terms "ANDOSOL" or "ANDISOL" or "VOLCAN" or "ANDEPT"
Calcareous	$CaCO_3$ content > 15%
Slightly Weathered	Ratio $\frac{CEC}{(CLAY/100)} > 16$
Highly Weathered	Ratio $\frac{CEC}{(CLAY/100)} \leq 16$
Other Soils	--Soil description or taxonomy does not include the terms "ANDOSOL" or "ANDISOL" or "VOLCAN" or "ANDEPT"; --$CaCO_3$ and CEC are not measured.

Singh, U. 1985. A crop growth model for predicting corn (*Zea mays* L.) performance in the tropics. PhD thesis, University of Hawaii, Honolulu.

Table C-3. Equations for calculating initial inorganic P labile from different extraction methods for different soil categories

Soil Category	P or K data available	PiLabile (mg kg^{-1})
Calcareous	Olsen	$(1.17 \times POlsen) + 0.18$
	Bray 1	$(1.81 \times PBray1) + 1.88$
	Mehlich 1 (double acid 1:5)	$(0.10 \times PMehlich1) + 10.20$
	Water	$(5.92 \times PWater) + 0.09$
Slightly Weathered	Olsen	$(0.76 \times POlsen) + 6.53$
	Olsen and Exchangeable K	$(0.62 \times POlsen) + (10.09 \times ExchK) + 2.62$
	Bray 1	$(1.37 \times PBray1) + 6.77$
	Bray 1 and Exchangeable K	$(1.09 \times PBray1) + (10.59 \times ExchK) + 2.71$
	Mehlich 1 (double acid 1:5)	$(2.71 \times PMehlich1) + 5.82$
	Mehlich 1 & Exchangeable K	$(2.16 \times PMehlich11) + (9.58 \times ExchK) + 2.42$
	Truog	$(0.34 \times PTruog) + 3.35$
	Truog and Exchangeable K	$(0.30 \times PTruog) + (5.85 \times ExchK) + 1.48$
	Morgan's Solution	$187.30 \times PMorgan \times 11.87$

Table C-3 continued

Highly Weathered	Olsen	$(2.50 \times POlsen) - 2.19$
	Bray 1	$(2.88 \times PBray1) - 0.30$
	Mehlich 1 (double acid 1:5)	$(5.97 \times PMehlich1) - 0.21$
	Truog	$(1.07 \times PTruog) - 1.49$
	Mehlich 1 (double acid 1:10)	$(0.64 \times PMehlich1) + 5.72$
	Colwell	$(0.43 \times PColwell) + 4.21$
Andisol	Olsen	$(1.41 \times POlsen) - 2.56$
	Bray 1	$(2.88 \times PBray1) - 2.11$
	Mehlich 1 (double acid 1:5)	$(4.52 \times PMehlich1) + 6.67$
	Truog	$(0.27 \times PTruog) - 0.73$
Unknown Or Not specified	Olsen	$(0.74 \times POlsen) - 11.39$
	Bray 1	$(1.35 \times PBray1) - 10.24$
	Mehlich 1 (double acid 1:5)	$(2.65 \times PMehlich1) + 9.39$
	Truog	$(0.28 \times PTruog) - 6.15$

Singh, U. 1985. A crop growth model for predicting corn (*Zea mays* L.) performance in the tropics. PhD thesis, University of Hawaii, Honolulu.

Table C-4. Relationship between organic P pools and P extracted using the Hedley procedure

Inorganic P pools	P fractionation method					
	$NaHCO_3$	NaOH	NaOH and Sonication	HCl	Hot HCl	Residual
Active	+	+				
Stable			+	+	+	+1/2

Source: Gijsman and Porter (2005)

Table C-5. Equations for calculating initial total organic P from soil organic carbon (OrgC) and pH for different soil categories

Soil Category	Organic P (mg kg^{-1})
Calcareous	$200 \times e^{-1.8 \times \left(\frac{pH-3}{6}\right)^2} \times \left(1 - e^{-0.55 \times OrgC}\right)$
Highly Weathered	$200 \times e^{-1.85 \times \left(\frac{pH-3}{6}\right)^2} \times \left(1 - e^{-0.35 \times OrgC}\right)$
Slightly Weathered	$900 \times e^{-1.5 \times \left(\frac{pH-10}{12}\right)^2} \times \left(1 - e^{-0.10 \times OrgC}\right)$
Other Soils	$520 \times e^{-1.5 \times \left(\frac{pH-7}{8}\right)^2} \times \left(1 - e^{-0.135 \times OrgC}\right)$

Singh, U. 1985. A crop growth model for predicting corn (*Zea mays* L.) performance in the tropics. PhD thesis, University of Hawaii, Honolulu.

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BIOGRAPHICAL SKETCH

Kofikuma Adzewoda Dzotsi was born in Lome, Togo (West Africa). He obtained his GED in 1996 and in fall 1996 entered the School of Agronomy at the University of Lome (UL), Togo. During his fifth and last year at the School of Agronomy (2001), Kofikuma participated in a training workshop on systems analysis and modeling organized by the African division of the International Center for Soil Fertility and Agricultural Development (IFDC). This program was his first exposure to systems analysis and simulation modeling applied to soils and crops and he decided to do his thesis research in this field. In March 2001, Kofikuma joined IFDC to carry out his thesis research on "Long-term assessment of variety and sowing time effects on grain yield of maize in southern Togo" that was defended in November 2002 and Kofikuma graduated as an "agronomy engineer" from the Department of Plant Productions, School of Agronomy, UL. Between September and December 2002, Kofikuma worked as a research assistant at IFDC's Systems Approach Unit in Lome. In January 2003, he took up the position of agronomist in IFDC's Natural Resource Management Program in Lome and worked on developing integrated soil fertility management (ISFM) options for basil. During his tenure in the program, he was responsible for evaluating and fine-tuning some ISFM-oriented decision support tools like DSSAT, QUEFTS, SIMFIS. He also supervised two "agronomy engineer" theses in 2004 and 2005. After spending almost 3 years in the program, he decided to pursue a graduate program at the University of Florida (UF). In fall 2005, Kofikuma joined the McNair Bostick Simulation Laboratory in the Agricultural and Biological Engineering department at UF as a master's student. Kofikuma married Pascaline Akitani-Bob in April 2005. They have one son, Eyram R. Dzotsi.