ABSTRACT

YUAN, XU. Evaluation of the Phosphorus Loss Assessment Tool (PLAT) and Revised Universal Soil Loss Equation (RUSLE) Using Geospatial Information. (Under the direction of Dr. John L. Havlin.)

Excessive agricultural phosphorus (P) has been a major contributor to non-point source pollution. North Carolina developed the Phosphorus Loss Assessment Tool (PLAT) to evaluate the potential P loss from agricultural fields to waterbodies via four components. Our overall goal was to evaluate the potential of using spatial data to estimate P loss without physically visiting fields since many PLAT required parameters occur in spatial formats. The objective of the first study was to assess the possibility of spatial implementation of PLAT and to compare the effect of scale on the PLAT numerical results and the associated categorical rankings. Since an important input parameter, the average annual soil loss determined by the Revised Universal Soil Loss Equation, is not directly available from field measurement, our objective in the second study was to assess the potential of obtaining RUSLE estimates, specifically the topography factor LS, through Digital Elevation Model data in a Geographic Information System environment. In the first study, two methods of whole field average (WFA) and grid average (GA) were used to compare the difference in modeling P loss at different scales. The same list of PLAT required parameters were prepared from soil test reports and spatial database at the coarse scale of whole agriculture field and the fine scale of 0.4-ha grid. Soil tolerance value was used to temporarily replace the soil loss data. In the second study, a widely used Arc Macro Language (AML) program for estimating RUSLE topographic factor LS was evaluated through two approaches of whole field (WF) and representative profile (RP) analysis on a North Carolina landscape. Watershed

delineation technique was adopted to select the representative profiles based on the references of slope distributions and field subdivisions from NRCS water quality specialists. Results from the first study indicated that soluble and particulate P loss, which occupied 59.3% and 26.3% of the total P loss through WFA method, and 56.1% and 39.0% through GA method, were the major pathways. Leaching P loss from PLAT was negligible. Particulate P loss was sensitive to scale as verified by the 12.7% increase of proportion in total P loss. The difference of particulate P loss through two methods was significant ($p < 0.05$), but no difference of soluble P loss and P source effect was found on a 95% confidence level. The overall P loss potential through two methods exhibited no significant difference due to the neutralization effect of individual pathways. Results from the second study showed that the AML program alone was not suitable for calculating RUSLE topographic factor on a North Carolina landscape because of the significant underestimation (~35% and ~20% through WF and RP approach, respectively). The concept of representative profile indeed improved the estimation accuracy (~15%), however, the linearity of the fitted line between field measured LS and GIS-aided LS estimate was not satisfactory. An adjustment factor was proposed rectifying the RUSLE-based AML program in order to approximate field measurements. This study demonstrated the potential of implementing PLAT model and the soil loss equation using spatial parameters derived from database instead of visiting the fields. The scale of modeling in estimating particulate P loss and RUSLE topographic factor LS was important and the adjustment factor was necessary to adapt the AML program application. The accuracy of model performance needed to be improved before claiming that GIS-aided PLAT modeling will provide a complete replacement for the field measurement.

EVALUATION OF THE PHOSPHORUS LOSS ASSESSMENT TOOL (PLAT) AND REVISED UNIVERSAL SOIL LOSS EQUATION (RUSLE) USING GEOSPATIAL INFORMATION

by

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BIOGRAPHY

Xu Yuan was born in March 16th, 1981, in a small village of Jilin Province, Northeast part of China. He received nine years of elementary and middle education and then moved to Liaoning province, where his high school study brought him to Nankai University in Tainjin. After completing the college with a BS degree in Environmental Science, he came to NC State University in 2003 to continue the graduate studies. His academic interests lie in environmental modeling, geospatial technology, and statistical analysis. He firmly believes that environmentalism is without the border and people from the globe should unite and fight against pollution.

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CHAPTER 1

BACKGROUND AND LITERATURE REVIEW

THE PHOSPHORUS PROBLEM

Phosphorus (P) is a naturally occurring element that is vital to agricultural production and aquatic ecosystems. However, excessive agricultural source of P presents a potential risk to water quality (USEPA, 1996). In the U.S. and many other regions around the world, P has contributed to non-point source pollution (NRC, 1992). The Clean Water Action Plan (USEPA-USDA, 1998) stated that “over-enrichment of waters by nutrients (nitrogen and phosphorus) is the biggest overall source of impairment of the nation’s rivers and streams, lakes and reservoirs, and estuaries.” The subsequent abiotic and biotic disturbance following excessive P loading in water bodies include accelerated eutrophication (Fluck et al., 1992; Carpenter et al., 1998; Correll, 1998; Daniel et al., 1998; Glasgow and Burkholder, 2000), dissolved oxygen depletion (Rosa et al., 1987; Axler et al., 1992; Bertram, 1993), toxic algal blooms (Paerl, 1988; Havens, 1994; Anderson et al., 2002), death of certain aquatic species (Ruello, 1976; Willemsen, 1980; Venugopalan et al., 1998; Jeppesen et al., 2002), and turbidity and bad odor (Sharpley et al., 1994). In the U.S, livestock and poultry manure are the key sources of excessive P. The revised Clean Water Act implemented in 2003 forced the producers or growers of large concentrated animal feeding operations to obtain a permit under the National Pollution Discharge Elimination System (NPDES) regulations and apply manure based on a nutrient management plan.

Phosphorus sources

P comes from multiple sources, including organic byproducts, agricultural fertilizers, biosolids from municipal and industrial waste, and domestic wastewater. However, in agriculture, P mainly comes from the use of conventional commercial inorganic fertilizer, and more dominantly animal waste, either spread as dry litter or sprayed as liquid waste (Edwards and Daniel, 1994; Williams et al., 1999). USDA-NRCS (1994) and USGS (1999) both identified agriculture P as a major contaminant of surface and ground water a cropland-dominated watershed. Considerable research has been conducted to study the environmental impact of agricultural P (Daniel et al., 1998; Parry, 1998; Sims et al., 1998; Sharpley and Tunney, 2000). In North Carolina, the agricultural P problem is critical because of massively industrialized livestock production in the form of Confined Animal Feedings Operations (CAFO), which is arguably a type of production that exceeds the assimilatory capacity for animal waste both locally and regionally that threatens downstream aquatic ecosystems (Austin, 1996; Sharpley, 1997; Martinez and Peu, 2000; Novak et al., 2000). Crouse et al. (2001) showed that P applied through animal waste exceeded P requirements of all agronomic crops in, representing about 85% of CAFO in the state..

Phosphorus modeling at different scales

Models were often developed to estimate the P loss potential based on the understanding of environmental, hydrologic, physical and chemical factors controlling P movement. This has been agreed to be an efficient approach considering the time and financial cost for the alternative field investigation. The general philosophy of modeling is to simulate the fate and behavior of P transport in soils, quantify the P export potential, select the most effective best management practices (BMPs), and apply them to critical source areas (CSA) where P loss potential is the most severe (Heathwaite et al., 2000; Weld et al., 2001; Sharpley et al., 2002; Page et al., 2005). Another advantage of modeling is the feasibility of prompt computer simulation under various hypothetical management scenarios through an integrated approach. Total Maximum Daily Loads (TMDLs), which specifies the maximum amount of a pollutant that a water body can receive and still meet water quality standards, is legislated by USEPA in Section 303(d) of the 1972 Clean Water Act. Phosphorus modeling, as part of the nutrient management plan, provides a reliable P loading estimate and thus serves as the basis of implementation of TMDLs and the evaluation of numerous management practices.

Popular process-based P loss assessment models include Agricultural Nonpoint Source model (AGNPS, Young et al., 1989) and AnnAGNPS (Croshley and Theurer., 1998), Soil and Water Assessment Tool (SWAT, Arnold et al., 1998), Areal Nonpoint Source Watershed Environment Response Simulation (ANSWERS, Beasley et al., 1985; Bouraoui and Dillaha, 1996), Guelph Model for Evaluating the Effects of Agricultural Management Systems on Erosion and Sedimentation (GAMES, Cook et al., 1985), Erosion-Productivity Impact Calculator (EPIC, Sharpley and Williams, 1990). In response to the revised USDA-NRCS Nutrient Management (590) Field Office Technical Guide, the P index, together with agronomic soil test P interpretation and environmental soil test P threshold, are the three approaches that can be used to assess agricultural fields in P loss potential (USDA-NRCS, 1999).

Due to the huge spatial variability of climate, cropping systems, soil types, hydrological condition, topography, and many other factors, a P index is expected to be the most efficient and robust approach because of the nature of site-specific assessment of P delivery, and therefore has been widely adopted by 49[†] states, with appropriate modifications, to target P management (Sharpley et al., 2003). A P index tool can provide references for field staffs, watershed planners, and land users to assess the various landforms and management practices for potential risk of P loading to water bodies (Sharpley et al., 2003).

Phosphorus reduction efforts

In addition to P loss modeling at the field, watershed and regional scale, several studies have been conducted to reduce the P loss by chemical approaches, including aluminum amendment into poultry litter (Hunger et al., 2004), immobilizing amendments for P sequestration (Zvomuya, 2006), use of dolomite phosphate rock (DPR) fertilizers to reduce P leaching (Chen et al., 2006), and utilization of municipal and industrial wastes to reduce excessive bioavailable soil P (Peters and Basta, 1996). Typically engineering efforts include wetland and sediment trapping pond construction. Kao and Wu (2001) found 59% of total P removal due to a mountainous natural wetland based on a major storm event study. Dunne et al. (2005) used soil/water column studies to determine the P release/retention rates. The study conducted by Liikanen et al. (2004) indicated that the processes taking place in the wetland diminished total P by 68% load and the dissolved reactive P load by 49%. It is expected that the efficiencies of management practices, when combined with the identification of critical source areas through P loss assessment and modeling efforts, could considerably reduce P delivery to water bodies and thus mitigate aquatic ecosystem degradation while maintaining economic agricultural production.

Sharpley et al. (2003) indicated 47 states in the published paper. As of now, it is 49.

PHOSPHORUS LOSS ASSESSMENT TOOL OF NORTH CAROLINA

In response to the revised USDA-NRCS nutrient management standard, 49 states in the U.S. have adopted the P index method to develop their own P risk assessment tool (Sharpley et al., 2003). This is because the P index method considers individual P loss pathways as affected by soil properties, climate, cropping system, management practices and other factors so that it can more comprehensively account for the between and within fields variations in P delivery potential compared with methods only using agronomic- or environmental-based soil test P thresholds. North Carolina is one of the leading states in livestock and poultry production and historically animal waste has been applied based on crop nitrogen (N) requirement, which caused significant surplus P accumulation in agricultural soils (Crouse et al., 2001; N.C. Dept. Agric. Consumer Services, 2002). Therefore, the Phosphorus Loss Assessment Tool (PLAT), a mechanistic model based on the P index concept was developed to evaluate the site-specific P loss potential from agricultural fields (The N.C. PLAT committee, 2005). PLAT rates the P loss potential from a field based on P transport pathways, P source effects, and management factors. Specifically, PLAT takes into account the processes involved with P transport to surface and groundwater and evaluates the potential P risk in sediment-bound or particulate P, soluble P in surface runoff, soluble P in leaching water, and source effect on P loss.

Particulate P loss

Particulate P refers to P attached or adsorbed to soil particles transported with surface runoff into lakes, streams, and rivers during or after storms events (Daniel et al., 1994; Sharpley et al., 1994; Pionke et al., 1997). Generally, this is the primary P loss pathway in cultivated cropland, especially when the soil has a high clay content. The major factors determining potential loss of particulate P include field erosion rate (ER, tons/ac/yr) and P concentration in soil particles or total P factor (lbs/ton). PLAT considers the annual erosion rate from average sheet and rill erosion due to the action of water. Gully erosion is currently not included. The soil erosion rate is based on a reliable estimated from the Revised Universal Soil Loss Equation (RUSLE) model (Wischmeier and Smith, 1965, 1978; USDA-NRCS, 1995; Renard et al., 1997). The parameter inputs for RUSLE include the rainfall erosivity factor (R, climate), soil erodibility factor (K, soil), slope length (L) and slope steepness (S) factors (topography), cover management (C) and supporting conservation practices (P). The P concentration in the eroded soil particles is critical because it greatly influences the amount of total particulate P loss at a given soil erosion rate. The current implementation of PLAT relies on the Mehlich-3 P (M3-P) soil test and average clay content to estimate the total P adsorbed to soil particles (Cox, 1994; Fig. 1.1). For North Carolina, the M3-P data (mg/kg) is converted from the Phosphorus Index (PI) value obtained from NCDA soil test information. The average clay content (%) for the surface horizon (0-20 cm) of each soil map unit is available through the NRCS National Map Unit Interpretation Record (MUIR) Database.

In addition to soil erosion rate and total P adsorbed, the net particulate P load to the nearby water bodies also depends on specific transport processes, during which P loss may be reduced due to natural or anthropogenic causes. Therefore, the potential of soil erosion and particulate P loss from the source areas are usually higher than the actual amount of sediment yield and final P export. A typical natural factor PLAT considers is the sediment delivery ratio (SDR). If the receiving slope becomes flat enough, the eroded soil particles partially redeposit in the foot slope area, and thus some particulate P only relocates within the same field instead of being delivered beyond the field edge. On the other hand, an enrichment factor is necessary to account for the increase of P concentration in fine-textured clay-enriched sediment due to particle selectivity during the deposition process (Wischmeier and Smith, 1978; Ongley, 1982; Foster et al., 1985). The overall effect of receiving slope on the reduction of particulate P loss is represented in the edge of field delivery ratio (EFDR). There are also many examples of effective sediment-control and P-reduction practices, including vegetative or tree/shrub riparian buffers (Peterjohn and Correll, 1984; Cooper and Gilliam, 1987; Daniels and Gilliam, 1996), sediment trapping ponds or basins (Bhaduri et al., 1995; Borden et al., 1998; Verstraeten and Poesen, 2002), as well as reduced tillage practices (Beasley et al., 1985; Gaynor and Findlay, 1995; Andraski et al., 2003). These optional practices, whether implemented in the field or beyond the field edge, can often efficiently control soil erosion and sediment yield, and therefore reduce particulate P loss (Thaxton, 2005). In PLAT, these factors are represented by the buffer delivery ratio (BDR) and sediment trap delivery ratio (STDR). In addition, PLAT also uses an Fe-P factor to account for the release of Fe-bound P as sediments are reduced in anaerobic environments (Shelton and Coleman, 1968). Other possible practices, but not evaluated in this component of PLAT, include crop rotation, contour cultivation, strip cropping, terraces, grass waterways, and diversion structures.

After calculating soil erosion rate, total P adsorbed to sediment, and individual reduction factors, the equation for calculating particulate P loss is:

$$\textit{Particulate P Loss (lbs/ac)} = \text{ER (t/ac/yr)} \times \text{Total P Factor (lbs P/ton)} \times \text{EFDR} \times \text{BDR} \times \text{STDR} \times \text{Fe-P Factor} \quad \text{[Eq. 1.1]}$$

Soluble P loss

Soluble P represents the dissolved fraction of P in surface runoff water, which occurs when the precipitation rate exceeds the soil infiltration capacity. Soluble P exists as orthophosphate, and can be readily taken up by aquatic plants and microorganisms. It is possible that soluble P is transformed into insoluble P through precipitation or adsorption as Al-P or Fe-P. Several researchers have concluded that drainage condition can influence the amount and form of soluble P transport because the pipes and ditches provide further pathways of water flow and place outlets in addition to the gravitational water flux (Armstrong et al., 1984; Hawkins and Scholefield, 1996). The two major factors for estimating soluble P loss are runoff volume and P concentration in runoff water. The release kinetics of both runoff and P concentrations are affected by several soil physical and chemical properties.

PLAT calculates the runoff volume differently for two situations, depending on the drainage condition of the field. For moderately or excessively well drained fields with no artificially drainage, the USDA modified curve number approach is used to estimate the runoff potential (USDA-SCS, 1985). Inputs data needed for computing the curve number include crop, qualitative hydrologic condition, and county-level long-term climate data. A runoff equation is developed for each county within North Carolina based on the long-term local weather data. For a field with a specific crop, soil, and hydrologic condition, the annual runoff is calculated from the exponential equation based on determined curve number.

For poorly drained fields with a shallow water table, whether artificial drainage exists or not, the drainage intensity (DI) method from DRAINMOD model is a reliable approach for estimating runoff volume. Input requirements for computing DI include estimated drain depth, width between drains, and the soil map unit specific transmissivity value (Skaggs, 1980, 2004). The P concentration in the surface runoff is estimated as a function of M3-P soil test level (Fig. 1.2) (Pote et al., 1996; Liu et al., 1997; Sharpley 1997; Sims et al., 1998; McDowell et al., 2001a, b). PLAT classifies soils into four groups based on texture (organic, sands, loams, and clay soils), and the relationship between soluble P concentration and soil test P is developed for each soil texture group. While the data are supported by substantial research when soluble P concentration is $\leq$ 1mg P/L, the relationship at > 1mg P/L are based on linear extrapolations that may underestimate soluble P and may need further field validation. (The N.C. PLAT Committee, 2005).

The practices that can effectively reduce particulate P loss, such as riparian buffers and receiving slopes, are not applicable to soluble P loss. However, some other practices that can reduce the runoff volume, such as conservation tillage or water control structures, or that can decrease the soluble P concentration, such as microbial additives or addition of municipal and industrial wastes could mitigate soluble P loss to some degree (Peters and Basta, 2000; Zhu, 2006). For example, studies by Maguire et al. (2006) indicated that adding $\geq$ 10% CaO reduced the water-soluble P in manures by over 90%, which greatly decreased soluble P loss potential. McGrath et al. (2005) and Maguire et al. (2004) also investigated the effect of dietary modification on P speciation in turkey and broiler litters and subsequent reduction in soluble P concentration. However, research on these practices in terms of soluble P reduction is still limited, so PLAT calculates the soluble P loss only based on the two determining factors (Eq. 1.2).

$$\textit{Soluble P in Runoff (lb/ac/yr)} = \text{Runoff Concentration (mg/L)} \times \text{Runoff Volume (ac-in)} / 4.415) \quad \text{[Eq. 1.2]}$$

Subsurface P loss

Dissolved P may also be lost from agricultural fields by subsurface drainage or leaching beyond the root zone. Significant P leaching usually occurs in sandy soils with moderately well to well drained hydrologic properties. However, some researchers also found considerable P leaching in clayey soils that exhibit substantial macropore water flow (Djodjic et al., 1999; Laubel et al., 1999). Usually, soils with high M3-P level, shallow water table, and low P retention capacity have great potential of P leaching. Similarly with surface soluble P, the amount of P loss through subsurface transport depends on mainly two factors: the leachate water volume and the dissolved P concentration. Skaggs et al. (2004) concluded that the relative proportions of water removed from poorly drained, high water table soils, as surface runoff, and through the profile as subsurface drainage, depend on precipitation, drain spacing and depth, soil hydraulic properties, crop, and surface depressional storage. The formulas for estimating leachate volume depend on the drainage condition of the fields. For well-drained soils, the leachate volume is estimated from the mass balance of annual precipitation, runoff volume, and evapotranspiration (Eq. 1.3). While for poorly-drained soils with a high water table, the average subsurface drainage is based on drainage intensity (DI) method from DRAINMOD model (Eq. 1.4).

$$\textit{Average subsurface drainage (in)} = \text{Annual PPT (in)} - \text{Runoff (in)} - \text{ET (in)} \quad \text{[Eq. 1.3]}$$

$$\textit{Average subsurface drainage (in)} = (a + b(DI)^c) / (d + DI)^c \quad \text{[Eq. 1.4]}$$

where DI is drainage intensity, and a, b, c, and d are regression coefficients characterized by crop, location, and annual precipitation.

PLAT uses subsoil M3-P soil test (76 cm in depth) as an indicator of P loss through subsurface leaching. For soils with high P retention capacity in the upper soil horizon, e.g., with high Fe and Al content, or soils with surface M3-P soil test (20 cm in depth) less than the threshold level of the corresponding soil group, leachate P concentration is treated as 0 mg/L. For soils with moderate or low P retention capacity, subsoil M3-P level is determined and the leachate P concentration is estimated through an empirical relationship (Fig. 1.3). When M3-P (76 cm) is > 50 mg/kg, which indicates the potential for P leaching, the P application rate is limited to crop removal.

Management practices to reduce leaching P loss are currently not considered in version of PLAT, and equations 1.5 and 1.6 are used to calculate total leachate P loss for naturally drained soils and artificially drained soils, respectively.

Leachate P (lb/ac) = P concentration (mg/L)x [drainage volume (ac-in)/4.415] [Eq. 1.5]

Leachate P (lb/ac) = P concentration (mg/L)

x [drainage volume (ac-in)/4.415]x (T_{30} /T_P) [Eq. 1.6]

where, T_P is the transmissivity of the entire profile and T_{30} is the transmissivity (12-30 in depth) that moves through the P-enriched soil zone (surface 30-in) and ultimately enters the drainage system.

P in waste sources

Animal waste characteristics and management, together with soil properties, cropping system and management factors, have important influences on P loss (Khaleel et al., 1980; Westerman et al., 1983; Edwards and Daniel, 1994). For example, total P concentration contained in different types of waste can vary greatly, such as 2.7 g P/L vs 1.2 g P/L in beef and dairy lagoon sludge, or 3.6 kg P/ton vs 17.3 kg P/ton in broiler fresh manure and house litter (Barker et al., 1994; USDA-NRCS, 1998; Dou et al., 2000; Sharpley and Moyer, 2000). Higher P loss through surface runoff would be expected if animal waste is surface applied instead of incorporated or injected.

The waste source characteristics that influence P delivery to a surface water body are P application rate and total P content, P solids percentage, and soluble P content. Due to high variability of manure composition, total P content largely depend on animal species, diet supplements, and type of waste handling and storage. The general trend of P content in common waste sources are poultry and turkey > beef > swine > dairy, and dry litter > liquid > slurry > sludge (Barker et al., 1994; Barnett, 1994; USDA-NRCS, 1998; Dou et al., 2000; Sharpley and Moyer, 2000). Animal wastes with low percentage of solids, characterized by high water content, will have more dissolved P that can infiltrate into soils and reduce soluble P loss (Westerman et al., 1983). Waste sources with high percentage of solids and low water content may contain low density waste particles that can float with water and increase P loss in surface runoff (Westerman et al., 1983).

In addition to waste source characteristics, application methods and timing also impact P loss. It has been well established that surface applications of animal wastes are more subject to runoff loss than incorporation or injection (Mueller et al., 1984; Daniel et al., 1993). Tarkalson and Mikkelsen (2004) found that incorporation of broiler litter decreased flow-weighted concentration of reactive P in runoff by 97% and mass loss of total P in runoff by 88% compared with surface application. Studies conducted by Eghball et al. (2002) suggested that manure added just before simulated rainfall (< 48 hours) resulted in significantly greater concentrations of dissolved P, bioavailable P, particulate P, and total P (Eghball et al., 2002). Therefore, it is beneficial to avoid the periods with high probability of rainfall events when waste materials are surface applied.

Soluble and non-soluble P loss through surface runoff and subsurface drainage are positively affected by rainfall intensity (Westerman et al., 1983). From previous studies, increased rainfall intensity caused elevated runoff volume but diluted P concentration, which may or may not result in increased amount of P loss (Edwards, and Daniel, 1993). Therefore, a runoff fraction is used to estimate the maximum fraction of total mobile P that is surface transported. Specific effect of rainfall intensity on P transport varied with waste types and characteristics.

In PLAT, soluble P is calculated as the multiplication of total P and soluble fraction, and non-soluble P is computed from P mass balance. PLAT estimates the total source P loss through soluble P and non-soluble P with corresponding adjustment factors (Eq. 1.7).

$$\begin{aligned}\text{Total Source P loss} &= \text{Soluble P} \times \text{SPAF} \times \text{RF} \times \text{AF} \times \text{AR} \\ &\quad + \text{Non-soluble P} \times \text{NSPAF} \times \text{RF} \times \text{BF} \times \text{AF} \times \text{AR} \qquad \text{[Eq. 1.7]}\end{aligned}$$

where, SPAF is the soluble P attenuation fraction, NSPAF is the non-soluble P attenuation fraction RF is the runoff fraction, AF is the application fraction, and AR is the application rate.

Overall P loss assessment rating

Although an individual P loss pathway is evaluated independently, interactions exist among the P loss pathways. For example, increased subsurface drainage may reduce surface runoff and, therefore, could result in overall decrease in net total P loss

(Baker and Johnson, 1976; Skaggs et al., 1982; Evans et al., 1995). Research by Vadas et al. (2002) reported a 20 fold overprediction of P concentration in runoff compared with measured value, and the discrepancy was attributed to the possible resorption of P from the runoff solution by eroded sediment.

Although the interactions among individual P loss pathways occur, PLAT calculates the potential P loss from each pathway independently, and evaluates the overall P loss assessment as the mathematical summation of the estimates from all four components (Eq. 1.8).. The equation for calculating the overall P loss is:

$$P\ Loss = \text{Particulate P} + \text{Soluble P} + \text{Leachate P} + \text{Source P} \qquad \text{[Eq. 1.8]}$$

This procedure generates a numerical value of potential P loss with the original unit of lbs P/ac/yr. PLAT as a P index tool, is not intended to represent the actual precise quantity of P loss off a field (Lemunyon and Gilbert, 1993). Rather, PLAT is developed to make comparative estimate of relative risk of P loss potential under numerous site characteristics and management practices. Therefore, PLAT numerical outputs of each field or management unit are converted into P loss index values and further classified into four qualitative categories. Each category is then assigned a relative P risk rating of “Low”, “Medium”, “High”, or “Very High”, which represents the relative field vulnerability to P loss. Based on the PLAT rating, a P management recommendation will be proposed from no necessary adjustment to starter P application only (Table 1.1).

PLAT links the waste source characteristics, P transport pathways, and management practices and eventually evaluates the risk of P loss on a site-specific basis. An advantage of PLAT (an index tool) over either agronomic- or environmental-oriented soil test P threshold strategy is that critical sources areas within a watershed can be identified aiding the selectivity and placement of efficient best management practices (Weld et al., 2001; Page et al., 2005). In addition, once some management practices have been adopted, such as switching manure application method or building buffers beyond the field edge, PLAT can be used to assess the impact of these practices on reducing P loss potential. Therefore, producers or growers can be protected and keep original agricultural production on non-critical source areas (Leytem et al., 2003).

SOIL EROSION AS AN ISSUE

The problem and its process

Soil erosion caused by water, wind and anthropogenic activities such as tillage, deforestation, overgrazing, and construction is a global issue. USDA-NRCS (2000) calculated the combined water sheet and rill and wind erosion for the U.S. was 1.9 billion tons in 1997. The overall erosion potential of a field or the spatial variability of erosion within a field is due to a combination of many factors, including the amount and the intensity of precipitation, soil type, topography, ground cover and land use. Generally there are three types of soil erosion: mass movement (natural process due to gravity), water erosion, and wind erosion. There are two steps involved in the water erosion process: detachment and transport of soil particles. From a temporal standpoint, the erosion process is a sequence of events from raindrop splash to the convergence of gully erosion. Therefore, water erosion can be further classified as splash erosion, sheet erosion, rill erosion, gully erosion, and tunnel erosion. It is necessary to understand the characteristics of each step in order to quantify soil erosion and propose appropriate management practices.

The adverse on-farm effect of erosion generates infertile soils and agricultural production is significantly disturbed, which is especially critical for many developing countries where agriculture occupies the predominately proportion of the country's economy. Currently, 97% of the world's food supply comes from land with only 3% coming from aquatic system. The topsoil, which contains the richest nutrient and organic matter for plant growth, is nearly irreplaceable, while it can be eroded in a short time period. Only when soil erosion is effectively controlled by proper farming and land management practices and its adverse environmental impacts are minimized can agriculture be implemented in a sustainable matter.

Although soil erosion on U.S. cropland decreased 43% between 1982 and 2003 (NRCS, 2006), erosion is still the focus of many natural resource managers and soil conservationists because of its off-farm impacts. The fraction of soil particles eroded that is finally delivered into water bodies represents non-point source pollution and negatively affects water turbidity in forms of either suspended particles or sediment (Uri, 2001). In addition, sediment serves as the transporting vehicle of agchemicals such as pesticide and nutrients (especially P), which will impair water quality.

Quantification of soil erosion

Although precise quantification of soil erosion is still challenging (Dudal, 1982; Lal, 1990), many field and lab studies have been conducted to calculate the overall soil erosion and sediment yield using radioactive ^{137}Cs (Walling and Quine, 1990; Martz and Jong, 1991; Chappell et al., 1998; Collins et al., 2001). Another popular approach to estimate erosion rate is through empirical and process-based modeling using high resolution spatial data combined with field measurements (Khan and Islam, 2003;

Martinez-Casasnovas, 2003; Mathys et al., 2003). The input data usually includes climate, soil, terrain features, and land use. Soil erosion modeling, based on the understanding of soil detachment and transport process, is a convenient diagnostic tool and can provide reasonable estimates that support land use planning and effective application of BMPs by resource managers and policy makers

The RUSLE (Revised Universal Soil Loss Equation) is a set of mathematical equations that estimate average annual soil loss and sediment yield resulting from interrill and rill erosion. It is derived from the theory of erosion processes, supported by more than 10,000 plot-years of data from natural rainfall plots, and numerous rainfall-simulation plots. RUSLE is an exceptionally well-validated and documented equation. A strength of RUSLE is that it was developed by a group of nationally-recognized scientists and soil conservationists who had considerable experience with erosional processes. RUSLE retains the structure of its predecessor, the USLE (Wischmeier and Smith 1965, 1978). WEPP (Water Erosion Prediction Project). It also includes simulation of hydrologic and erosion processes at small watershed scales (Alberts et al., 1987; Laflen et al., 1987; Nearing et al., 1990; Laflen et al., 2004).

Another method, AGNPS (AGricultural Non-Point Source), is an event-based distributed parameter model developed by USDA-ARS for prediction of soil erosion and sediment yield at the agricultural watersheds scale for real or hypothetical storms (Grunwald and Norton, 1999; Perrone and Madramootoo, 1999; Bhuyan et al., 2002). It was built upon the USLE algorithm but applied on a storm basis instead of annual average rainfall.

USPED (Unit Stream Power-based Erosion Deposition) is a simple model which predicts the spatial distribution of erosion and deposition patterns and rates for steady state overland flow with uniform excessive rainfall conditions for sediment transport capacity. The model is based on the theory originally outlined by Moore and Burch (1986) with numerous modifications (Mcisaac et al., 1992). One challenge for all these models is the generation of spatial and tabular parameters that can reflect the site characteristics the best possible yet not too memory-intensive and time-consuming to cause computing problems.

Scale issue as a spatial concern

Erosion potential and sediment yield have been studied at various spatial scales including plot (Wainwright et al., 2000; Bagarello and Ferro., 2004; Mathys et al., 2005; Boix-Fayos et al., 2005; Parsons et al., 2006), field (Jetten et al., 1999; Barthes et al., 2000; Issa et al., 2006), watershed (Harden, 1992; Aksoy and Kavvas, 2005; Fu et al., 2005; Cohen et al., 2005), and national levels (Brazier et al., 2001). Currently there is no universally successful method to transfer the soil erosion estimation algorithm or results between different scales. At the small scale (plot and field), environmental factors tend to be uniform, which reduces the difficulty of defining underlying erosion processes and, thus, improve the estimate accuracy. However, at large scales (watershed and national), the environmental factors become complex and spatially heterogeneous, forcing the final algorithm, if feasible, to be limited to the study area from which it was developed or other similar sites with identical characteristics. As illustrated by Renard et al. (1997) and Yitayew et al. (1999), current quantitative soil prediction efforts at the watershed or regional scale are all based on numerical modeling due to the difficulties in the field measurement of soil loss. Some studies have been conducted to compare the performance of different models at different scales (Amore et al., 2004; Reyes et al., 2004; Stolpe, 2005).

REVISED UNIVERSAL SOIL LOSS EQUATION MODELING

The Universal Soil Loss Equation (USLE) was first developed by Wischmeier and Smith and described in agricultural handbook (1965 and 1978). For many decades, USLE was the primary model used to assess soil loss potential in cropland at the field scale through rill and interrill erosions and was used as a regulatory and conservation planning tool for government agencies in U.S. and many other countries. The Revised Universal Soil Loss Equation (RUSLE) is an upgrade of USLE that extends the application to mined lands, construction sites, and reclaimed lands.

As a one dimensional field-scale model, RULSE uses inputs of six factors that contribute to soil erosion. The basic equation is:

$$A = R * K * L * S * C * P \qquad \text{[Eq. 1.8]}$$

where, A is the average annual sheet and rill soil erosion in ton/ac-yr; The climate factor (R) is the rainfall erosivity, and is the product of rainfall energy and maximum 30-min intensity (EI_{30}), often called Erosion Index. The soil factor (K) represents soil erodibility, or the soil loss rate per EI unit on a 22.13-m length and 9% standard fallow plot. The slope length factor (L) is a dimensionless ratio of soil loss from the field slope length to that from a 22.13-meter plot under identical conditions. The slope steepness factor (S) is a dimensionless ratio of soil loss from the field slope to that from a 9% plot under identical conditions. Often L and S are multiplied and considered as one overall terrain factor. The cropping factor C is the cover management factor, or the ratio of soil loss from an area with specified crop cover to that from an identical area in tilled continuous fallow. The management factor (P) represents supporting practices, or the ratio of soil loss with a conservation practice to that with straight-row farming up and down slope. Among the factors, cover management is the most variable in that the type and amount of surface residues and crop cover change during the year and between years. Natural events such as fire or human activities such as tillage can significantly increase the erosion rate. The type and intensity of vegetative cover greatly influences erosion rate through the effects on aggregate stability and the control of runoff velocity. One source of error in the RUSLE estimate is the determination of the slope steepness (S) and slope length (L). Traditionally, these values come from field measurements by a specialist as described in the NRCS Field Technical Guide. As information technologies have evolved, many researchers have been trying to estimate the soil erosion rate in an entirely digital environment based on the RUSLE algorithm combined with geospatial information (Hickey, 1994, 2000; Desmet and Govers, 1996; Dunn and Hickey, 1998; Van Remortel et al., 2001).

Connections of P Loss and Soil Erosion

The studies of P loss and soil erosion are not isolated. Instead, soil loss is a very important component for estimating particulate P transported beyond the field edge as sediment. Some models such as RULSE focus on soil loss potential, while other models such as Soil and Water Assessment Tool (SWAT) also consider the sediment delivery ratio (SDR) that calculates the sediment yield in a specified watershed. P loss models, as an important aspect of the nutrient management tool, are usually linked with soil erosions models. AGricultural Non-Point Source model (AGNPS) is a good example (Croshley and Theurer, 1998; Bhuyan et al., 2002). Recent research has been advanced in modeling non-point source pollution which includes agricultural P and sediment yield at the watershed scale (Heathwaite et al., 2000; Weld et al., 2001; Sharpley et al., 2002; Fu et al., 2005). In PLAT, soil loss data on an annual basis comes from a RUSLE calculation that is based on field-measured factors. It may be possible to combine the environmental modeling of P loss and soil erosion using only spatial data without actually visiting the field.

Table 1.1: PLAT overall rating of P loss potential and corresponding management recommendations

P Loss Estimate (kg/ha/yr)	P Loss Index	Ranking	P Management Recommendation
0.0 to 1.1	0 - 25	Low	No adjustment needed; N based application
>1.1 to 2.2	26 – 50	Medium	No adjustment needed; N based application
>2.2 to 4.5	51-100	High	Application limited to crop P removal
>4.5	> 100	Very High	Starter P application only

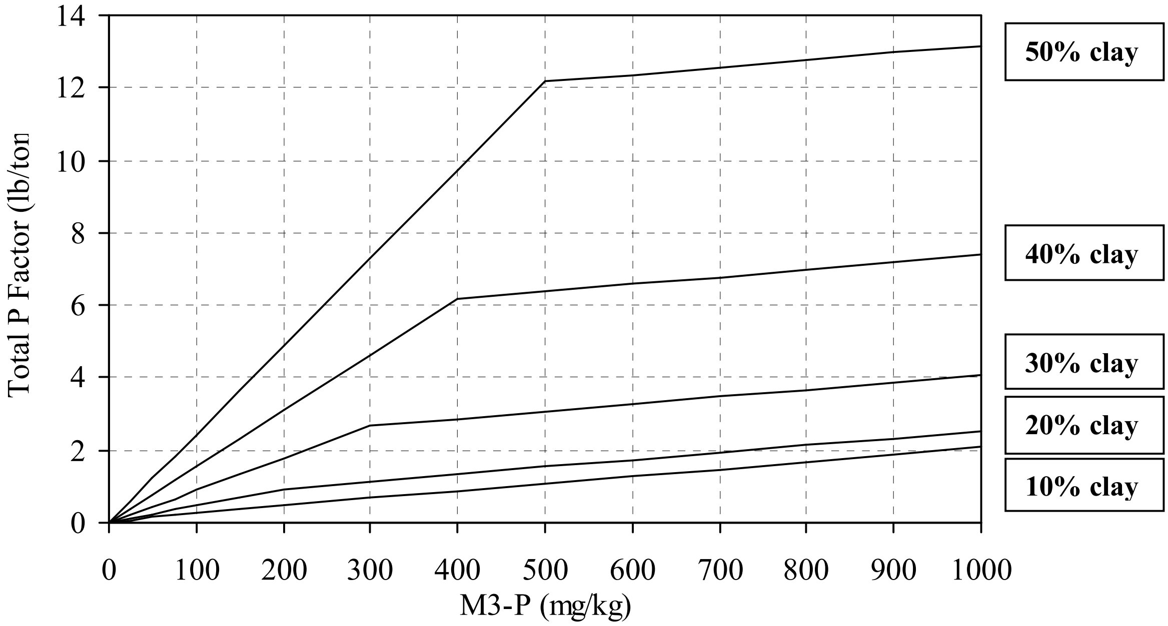

Fig. 1.1: Total P content of sediment as affected by clay content and M3-P. Lines represent example relationships. Inflection point represents threshold M3-P that results in 1 mg P/L solution P. (From PLAT model description.)

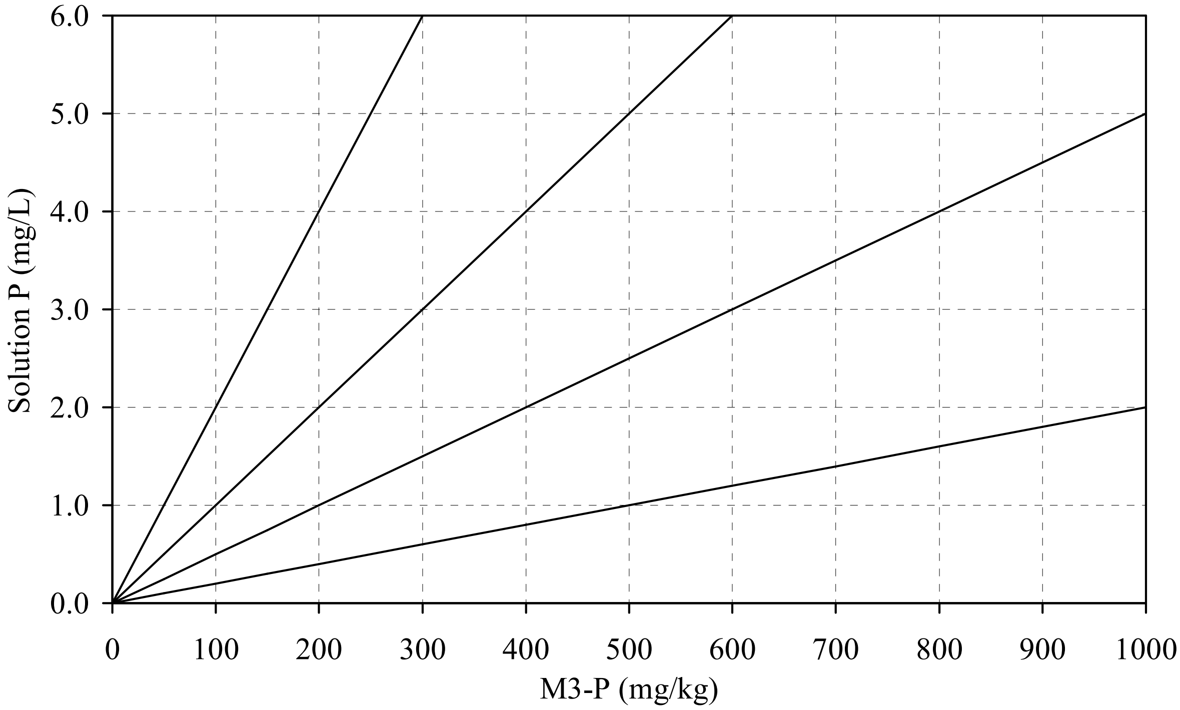

Fig. 1.2: Runoff P concentrations supported by soil groups as a function of M3-P. (From PLAT model description.)

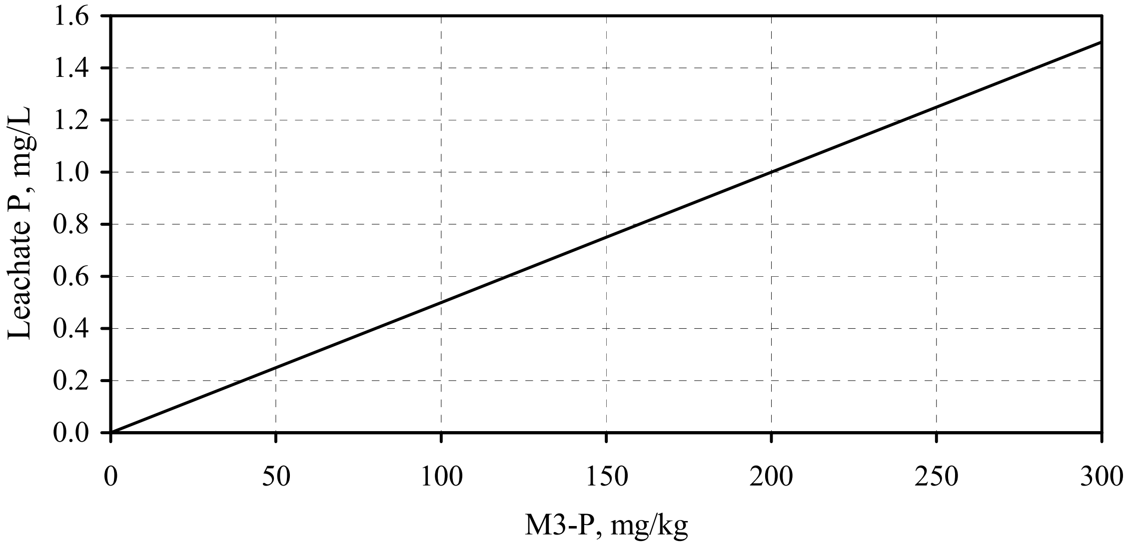

Fig. 1.3: Leachate P concentrations as a function of M3-P levels at 30-in depth. (From PLAT model description.)

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CHAPTER 2

EVALUATION OF PHOSPHORUS LOSS ASSESSMENT TOOL (PLAT) USING SPATIAL PARAMETERS

INTRODUCTION

Soil test P (STP) is an indicator of environmental risk of agricultural P because of its recognized relationships to particulate, dissolved, and subsurface P transport (Ohalloran et al., 1985; Sharpley, 1995; Mallarino et al., 2002; Sims et al., 2002; Cahoon and Ensign, 2004; Page et al., 2005). However, a single soil test P threshold cannot fully assess the P loss risk due to wide variability in environmental conditions, soil properties, landforms or topography, and numerous management factors. As a site-specific P index tool, PLAT is more sophisticated and accounts for more spatial variability by incorporating the waste sources, P transport pathways, and adjustment factors that may reduce P delivery (Sharpley, 1995; Pote et al., 1996; McDowell and Sharpley, 2001).

In environmental modeling, it is crucial that the modeling algorithms could well represent the underlying scientific processes of the phenomena being modeled. Therefore, research has been conducted to better understand the underlying principals of individual P transport processes to enhance PLAT risk assessment of P loss after the model was developed (Cahoon and Ensign, 2004; Skaggs et al., 2004; Bond et al., 2006). The potential influence of change in management practices predicted was also studied on North Carolina statewide farms receiving animal waste (Johnson et al., 2005).

The parameter inputs required by PLAT can be classified into seven classes: location, cropping system, best management practices (BMP), P application, soil properties, drainage, and hydrological condition. Typically many of the data come from government agencies or the specific growers, while other information such as soil loss, receiving slope, and BMPs, are from field measurements or modeling estimates based on field-measured factors. Many parameters involved in P delivery are spatial in nature and largely depend on the specific site characteristics, affecting the P distribution within the given field and the P loss potential beyond the field edge (Halbfass and Grunewald, 2003; Page et al., 2005). Studies have been conducted to evaluate the potential of modeling approach using existing database to mimic the fate and transport mechanisms of P loss so that the environmental risk can be assessed in a timely and cost-saving manner (Sharpley et al., 2002).

As a newly developed model, PLAT benefits from previous modeling efforts but still needs further research to increase the model accuracy and reliability. (Needelman et al., 2001; Veith et al., 2005; Srinivasan et al., 2005). One of the factors that usually affect the model performance is the scale of object unit being studied. Several researchers have concluded that the modeling scale can significantly affect the parameter derivations and subsequently the results of environmental modeling, especially when the modeling was carried out using Geographic Information System (GIS) for the benefits of computational speed and visualization output (Thieken et al., 1999). Vieux and Needham (1993) also reported that breaking down a watershed into equal-sized grid cells aid the model implementation but the parameters and uncertainties will depend on the resolution of the grid size. Modeling of P transport from agricultural fields to watershed outlets is no exception (Brazier et al., 2005). The research objectives of this part of the study are to evaluate the potential of spatial implementation of PLAT at the field scale based on spatially derived parameters alone with no physical site visits, and to compare the effectiveness of P loss estimates from two methods with respect of quantitative numerical values and qualitative ranking categories.

METHDOLOGY

Study Area

The field sites used in this study were the Strickland and Reggie Strickland farm of Sampson County located in the middle coastal plain region of North Carolina (35°N, -78.3° W). The two farms are located within Cape Fear river basin with two perennial streams, Railer Branch and Goshen Swamp, flowing along the edge areas the farms, which may contribute to P export off the agricultural watershed (Fig. 2.1). There are 24 agricultural fields in both farms with size ranging from 0.77 to 50.63 ha. Each field is composed of one or multiple management zones that respond similarly to agricultural management practices. A soil test report can be obtained from North Carolina Department of Agriculture & Consumer Services (NCDA&CS) at the management zone level. Eight fields (33.3%) were required additional P application, averaging 29.5 kg/ha (11.2 to 67.2 kg/ha). The topography of the study area is moderate with an average field slope of 9.8% and the maximum of 25.1%. At the center of both farms, terrain conditions are relatively flat, while near the farm boundaries and in the wooded buffer zone to stream water bodies, the slope increases rapidly. The cropping system is a cotton-tobacco rotation under conventional tillage. The annual mean temperature in this area is 16.33 ºC and the historical annual mean precipitation in this area is 124.9 cm with slightly more rainfall (125.4 cm) in our study year of 2004 (NC CRONOS). The evapotranspiration is estimated to be 83.8 cm for 2004. There are 13 soil map units, of which the Norfolk loamy sand (both 0-2% and 2-6%), and Wagram loamy sand (0-6%) are the most predominant. Average pH for all fields is 6.2, which is in accordance with the target pH range of 6.0-6.5 for NCDA classification of mineral soils based on humic matter percentage (%HM) and weight/volume ratio (W/V, g/cm^3). Clay percentage of the soils ranges from 5 to 16% with the average of 8.1 %.

Data Sources

The fields and management zone boundary data in ESRI shapefile format were supplied by Al Averitt of Protech Advisory Services Inc. The coordinate system was NAD1983 State Plane of North Carolina FIPS 3200. The management zone attribute variables required by PLAT, such as zone area, P recommendation rate, cropping system, soil test P index (PI) value, weight/volume ratio (W/V), and average slope, were obtained from NCDA soil test reports. U.S. Geological Survey (USGS) provides 10-m digital elevation model (DEM) data and the North Carolina Flood Mapping Program (http://www.ncfloodmaps.com) supplies 6-m bare-earth light detection and ranging (LIDAR) data, however, are not available at this moment for our study fields in Sampson County. Therefore, UTM grids of DEM data with 30-m sampling interval based on 7.5-minute topographic quadrangle maps were downloaded from USGS, as well as the color-infrared one-meter Digital Orthophoto Quarter-Quad (DOQQ) imagery data. The spatial and tabular soil map unit data were obtained from USDA-NRCS Soil Survey Geographic Database (SSURGO) with a scale of 1:24,000.

PLAT modeling at difference scales

Two methods, whole field average (WFA) and grid average (GA), are used on all fields to evaluate the potential spatial implementation of PLAT and to compare the scale effect on model performance on 24 fields. The same list of PLAT required parameters are prepared separately for each method so that PLAT output results could represent the estimates of potential P loss from two modeling scales. The WFA method refers to PLAT application at the whole field scale, regardless of the field sizes. This method is justified in that PLAT was originally developed as a field scale model and one of its important parameter, RUSLE estimated soil loss, is also based on whole field scale. When the scale of computer modeling matches with the traditional standard of field application, the efforts from WFA method could aid in addressing the potential of PLAT spatial implementation when field-monitored P loss data are available for validation in the future. While the whole field scale can be treated as irregular-shaped and extremely coarse experimental unit, the GA method breaks each field into equal-sized square grids and PLAT is run on each grid under the assumption of independence.

A third method, which is based on the GA method and referred as grid average with accumulation (GAA), is also used for the purpose of evaluating the P loss accumulation effects between neighboring grids. The principal and procedure of GAA method is basically identical to GA method except that the grids were treated as spatially correlated with P loss from one grid as additional P source flowing into the next downstream neighbor. This method was roughly tested on only one field adjacent to the streams.

Specifically, WFA method requires the input parameters at and only at the whole field scale; therefore only one value for each parameter category is required in the PLAT model. In our study fields, some spatial parameters, including P Index (PI), weight/volume (W/V) ratio, and average slope, existed at the management zone level from the NCDA soil test report. These parameters were weight averaged to develop the corresponding field-scale parameters with the aid of GIS and database spreadsheet (Table 2.1). For other parameters not in the soil test report, the parameter values that occupied the majority of the field were assigned to represent the whole field value. For example, the SSURGO soil map units were distributed independently with the management zone division and multiple soil map units commonly existed within the same field. To determine the field-scale parameter value, the predominant soil map unit with the largest overall portion of the field, whether scattered or clustered, was selected and other minor soil map units were disregarded. Parameters such as the hydrologic condition did not have a unique source but were correlated with soil map units, so the values were obtained from the soil survey database SSURGO based on its relationship with soil map units.

Continuous slope distribution map was derived from DEM data and the average field slopes were calculated for verification with the field records. If minor discrepancy was found between field measured and GIS-derived average slopes, the value from field measurement was used for the purpose of future field validation of PLAT modeling. If large discrepancy existed, however, the slope values derived from GIS were preferred because of the fact that the digital representation of a complex terrain in raster form provided dense regularly spaced elevation points, which would likely improved the slope estimate compared to the error-prone field measurements. High-resolution 1-m color-infrared DOQQ aerial photography has the advantage of distinguishing vegetation cover type and vigor. In our study, tree and shrub vegetation were successfully identified as the buffer zone that existed between the field boundary and the stream water bodies. The width of the buffer was estimated as the straight line distance between field edge and center of streams (blue line) using the Measure Tool in ESRI ArcGIS 9 desktop package. For each field located near the farm boundary and the streams, multiple segments were taken and measurements were averaged to reduce bias. For other fields in the central area of the farm that were not adjacent to streams, there were no BMP installed because no sediment trapping device or ponds existed.

The cropping system was either cotton or tobacco with conventional tillage, as documented in the soil test report for each management zone. Data for P application came from two sources. Firstly, a certain amount of P application was recommended in the soil test report for those fields with low or medium STP. It was assumed that the growers would follow the recommendation and applied the specified amount of P as inorganic fertilizer. Secondly, 336 kg /ha of inorganic fertilizer was hypothetically applied to increase P loss potential for convenient display and comparison of modeling results from the two methods. This was due to the fact that the soil test P level was high or very high for most of the fields and therefore no additional P nutrient was recommended for these fields. Although the P source influences P bioavailability and solubility, and therefore P loss potential (Nahm, 2003; Michaud and Laverdiere, 2004), it was not critical in this study because the objective was to compare results of two methods which exclude nutrient application. An important parameter required by PLAT is the field level average annual soil loss from the Revised Universal Soil Loss Equation

(RUSLE). Since RUSLE soil loss estimates were not available for this study area, soil tolerance values, which represent the average annual soil erosion rate that could occur without causing a decline in long term agricultural productivity, was used as a replacement of the soil loss data. Eventually, PLAT was run as the extracted field-scale parameters were input to the model.

For the GA method, each field was subdivided into 0.4-ha square grids in a GIS environment, except those partial grids that were intersected by field boundaries. The same list of PLAT required spatial parameters used by the WFA method was used again but at the finer grid scale. For example, many minor soil map units recognized at the whole field scale were used at the grid sale because they fully or mainly occupied the grid of interest. Eventually, PLAT was run through a batch mode with each grid as a modeling unit. One set of PLAT output, including particulate P loss, soluble P loss, leachate P loss, and source effects, for each grid unit was generated, as in the case for each field with the WFA method. The final potential P loss from individual pathways and overall summation at the field scale was extracted as weighted averages of the P loss at the grid scale using area as the weighting factor, which was calculated as the multiplication of the number of grids and the grid size plus the area of the partial grids, if any. In this approach, more detailed spatial heterogeneity was considered.

The GAA method addressed the concern of spatial autocorrelation in that P loss from one grid represented a P source into the neighboring downstream grid with the greatest elevation drop instead of exporting directly beyond field edge. The flow direction and flow path were visually estimated based on digital elevation distribution and the derived continuous slope map. The P loss predicted by PLAT in one grid was added as additional P source to the neighboring downstream grid before PLAT was run on that grid. In this study, the GAA method was tested on only one small field located near the stream because the subjectivity would inevitably introduce significant errors when the flow direction and path become more complex in large fields.

Statistical Analysis

PLAT generates both quantitative numerical results and qualitative ranking categories of potential P loss. The numeric data from individual pathways and overall summation from both WFA and GA methods were tested for spatial autocorrelation in the statistical computing package SAS (SAS Institute, 2003, Cary, NC). Since the variable of interest was the average P loss within an areal unit, a spatial adjacency matrix was created with a binary coding scheme which assigned a value of 1 if two fields were connected or shared a border and 0 otherwise. The widely used spatial test statistic Moran's I was calculated and spatial dependency was examined. The potential P loss data predicted by PLAT were tested for normality using Shapiro-Wilk test in UNIVARIATE procedure in SAS environment. Paired t-test Wilcoxon signed-rank test were carried out in SAS to evaluate the significance of difference between two methods, depending on whether the data normality was met. Pearson correlation was calculated to show the linear association between potential P loss from WFA and GA methods. The kappa statistic was computed to evaluate the agreement between the two methods in terms of the qualitative ranking categories.

RESULTS AND DISCUSSIONS

P loss characteristics predicted by PLAT

The average particulate P loss potential with the WFA method and GA method were 0.261 and 0.405 kg/ha, respectively, while the average soluble P loss were 0.665 and 0.582 kg/ha, respectively. Although some variation existed, it was clear that soluble P and particulate P were the dominant P loss pathways in the two methods. For WFA method, soluble P loss represented 68% of total P loss and particulate P loss contributed 27%; and for GA method, these two pathways contributed 56% and 39% of total P loss, respectively. Previous studies concluded that particulate P loss is the major pathway for cropland P loss (Heathwaite and Dils, 2000; Hansen et al., 2002). The seeming conflict in this study can be explained by the wide buffer zone which can effectively trap sediment particles and subsequently contained particulate P. The P source effect exhibited a less important role, yielding 0.054 and 0.053 kg/ha for WFA and GA methods, respectively. Treating the P loss from individual pathways independently, the overall P loss potential was 0.98 and 1.04 kg/ha for WFA and GA methods, respectively (Table 2.2 and 2.3).

With both methods, the P leaching loss was negligible in this study. Previous studies have shown that considerable P leaching occurs in either sandy soils with moderately well to well drained hydrologic properties, or in clayey soils that exhibit substantial macropone water flow (Djodjic et al., 1999; Laubel et al., 1999). Typically, soils with high M3-P level that exceeds the threshold value, shallow water table, and low P retention capacity have great potential of P leaching. In our study fields, a further investigation of mass balance found that the average leachate volume was 31.7 cm, based on 125.4 cm of precipitation, 83.8 cm of estimated evapotranspiration and average 9.9 cm of runoff. However, the leachate P concentration was zero. This was probably due to the fact that 21 out of 24 fields (87.5%) had soil test P threshold of 200 mg/kg, while the average M3-P concentration (125.4 mg/kg) in the surface soil failed to exceed this threshold, even though soil test report still documented high soil P level from agronomic perspective. The P retention capacity can further reduce the P leaching potential.

The potential P loss data with each pathway and the total P loss were treated as individual variables, and spatial autocorrelation test of Moran's I indicated that the data did not exhibit spatial dependency in either of the two methods (Table 2.4 and 2.5). For the WFA method, Shapiro-Wilk test from SAS UNIVARIATE procedure found the potential P loss data of each individual pathway and total P loss were not normally distributed ($p < 0.05$) (Table 2.6). For GA method, the P loss data for individual loss pathways were not normally distributed, although the total P loss was normally distributed (Table 2.6). Since the data represented the same variable obtained from two methods, the differences of potential P loss between the two methods were calculated and then were tested for normality. The normality of the differences was confirmed for particulate P, soluble P, and total P loss. The difference in the P source effects, however, was non-normal ($p = 0.0048$).

Comparison of WFA and GA methods

Both the quantitative estimates of potential P loss and the qualitative ranking categories of PLAT outputs were compared between the two methods of WFA and GA to investigate the scale effect. On average, the GA method yielded higher estimate of particulate P loss (0.14 kg/ha) but lower soluble P loss (-0.08 kg/ha) than the WFA method (Table 2.7; Fig. 2.2 and 2.3). The estimates of source effect were basically equivalent except for some outlier fields (Fig. 2.4). As a result, the GA method predicted slightly higher total P loss than the WFA method (Fig. 2.5). The differences in these individual pathways may be explained by the fact that the GA method investigated the P loss risk at a much finer scale compared with the WFA method and thus accounted for more variability in the contribution by multiple levels of parameter values (Brazier et al., 2005). For example, if 40% of the field exhibits a sandy soil texture and is very subject to water erosion, its effect would be suppressed in the WFA method because the dominant soil type may be a clay soil that occupies 45% of the field.

PLAT estimates through WFA and GA methods showed moderate correlation for particulate P loss and source effect with Pearson coefficient of 0.51 and 0.56, respectively. However, the correlations for soluble P and overall P loss between the two methods were very weak with Pearson correlation of 0.39 and 0.36, respectively. Scatter plots of P loss estimates from the two methods showed that a quadratic regression fit slightly better than linear regression, but the overall goodness of fit was not satisfactory (Fig. 2.6 to Fig. 2.9). One possible explanation is that the potential P loss predicted by WFA method tended to have much larger variability indicated by greater standard deviation and wider range than the GA method. For example, the error sum of square of particulate P loss is 1.32 for WFA method but only 0.25 for GA method. In WFA method, the predicted potential P loss distributed relatively uniform within the narrow range of 0.3 to 0.6 kg/ha for 21 fields (87.5%), while in the GA method P loss predictions were approximately 0.1 kg/ha for 13 fields (54.2%) but the rest fields ranged widely from 0.2 to 0.8 kg/ha. The lower variability in P loss with the GA method may be attributed to the contribution from minor parameter values, which diluted the tendency of severe P loss risk predicted by the dominant parameter values. This also explained the linear relationship between the differences of the two methods and the potential P loss from WFA method. The Pearson correlation was 0.90, 0.82, 0.72, and 0.88, respectively for particulate P loss, soluble P loss, source effect and overall P loss with R^2 of 0.81, 0.66, 0.52 and 0.78, respectively. (Fig 2.6 to 2.9). As WFA method predicted higher amount of P loss, the difference of P loss between WFA method and GA method tended to become larger. Generally, when the total P loss prediction from WFA method ranged from 0.5 to 1.5 kg/ha, the two methods were in good agreement (Fig. 2.9).

Since the paired differences of potential P loss data for particulate P, soluble, and total P loss met the assumption of normality, paired t-test was used to test the significance of the difference. On a 5% confidence level, the difference (0.14 kg/ha) between particulate P loss predicted by the two methods was significant. However, the difference between soluble P loss (-0.08 kg/ha) was not significant. Due to the non-normality of the source effect difference, non-parametric Wilcoxon signed-rank statistical test was used and the difference was insignificant ($p = 0.7083$).

The total P loss potential represents the overall effect of each individual P loss pathway, and no significant difference of total P loss between the two methods was found ($p = 0.3069$). This can be explained by the fact that the differences through the three loss pathways had different signs and their effects were partially neutralized when combined as total P loss. Since there are no P loss data directly available from field monitoring, the current study can only compare the two methods of PLAT modeling relatively with each other without field validation.

According to the PLAT ranking scheme, 18 fields (75%) in the WFA method and 17 fields (70.8%) in the GA method were ranked "Low" (Fig. 2.12). The percentages of "Medium" ranking were 5 fields (20.8%) and 7 fields (29.2%) for the WFA and GA methods, respectively. Only one field (4.2%) in WFA method was ranked "High" and no such field existed with the GA method (Fig. 2.10). The PLAT output was also compared in terms of categorical risk ranking. Of the 24 fields, 6 fields (25%) had different total P loss ranking. Specifically, three fields (16.7%) changed from "Low" to "Medium", two fields (40%) changed from "Medium" to "Low", and one field changed from "High" to "Medium" as the method changed from WFA to GA (Fig. 2.12). This qualitative comparison between the two methods indicated that the P loss potential of most fields were in good agreement between methods (84%). The statistical Kappa coefficient for comparison of ranking agreement between the two methods was 0.404, indicating fair to moderate agreement based on the criteria set by Landis and Koch (1977). The accuracy of the numeric prediction of potential P loss and the comparison of qualitative categories need further investigation when field monitored P loss data are available in the future.

Examination of the accumulation effect for one field

For the small field selected to test the P loss accumulation effect, the difference in particulate P loss (156.2%) between WFA method and GA method was significant by rough estimate even though no statistical test could be performed due to the sample size (n=1) (Table 2.8). In contrast, the potential soluble P loss decreased by 36.2% between WFA and GA methods. As before, the leaching P loss was negligible and P source effect was almost identical in all three methods. The total P loss risk decreased by 8.3% for GA method compared with the WFA method (Table 2.7).

The accumulation effect, which was expressed as the difference between GA and GAA methods, was not significant based on rough estimate because the changes were -1.49%, 0.75%, 2.33%, and -8.38% for particulate P, soluble P, source effect, and total P loss, respectively. Again, the differences between particulate P loss and soluble P loss were neutralized to some degree. Our interest was to assess the accumulation effect between the grids when P loss from one grid entered the downstream neighbor as a P source input. However, the accumulation effect in this case was negligible because the PLAT outputs were similar for GA and GAA methods. An examination of the nutrient application parameter showed that the net amount of P accumulation between two grids was too small compared with the fertilizer input (~1%). As a result, the ranking for this field by three methods remained unchanged. This study represented a preview of future work, when the calculated flow direction from high-resolution elevation and actual amount of P source are available and incorporated into the process.

CONCLUSIONS

This study successfully demonstrated the potential of using PLAT with spatial data, although the model accuracy needs further validation with field monitored P loss data. PLAT predictions from all three methods illustrated that soluble and particulate P loss were the most predominant P transport pathways from agricultural fields to water bodies. Leacheate P loss was negligible for all fields because surface soil test P were less than the threshold levels.

When evaluated on moderately complex topography, the scale effect was significant for particulate P loss but insignificant for soluble P loss and P source effect.

Due to the neutralization effect of individual P loss pathways, the overall scale effect was not significant. The discrepancy caused by the modeling scale, however, changed the final PLAT output ranking for 25% of the fields. The GA method, which accounted for more spatial variability by incorporating parameters at a finer scale, had a moderate impact on PLAT ranking.

There was no substantial evidence of P loss accumulation effect in this study. However, the current analysis was based on the visual estimated flow direction and the net P loss out of a grid cell was too small compared with the hypothetical P input source. Further work is needed to integrate quantitatively determined flow direction such as a flow direction grid derived from hydrologic modeling. In addition, studies with other P sources are needed to evaluate the effect of P accumulation between experiment units because P source can affect forms and solubility of P in soil and water (Maguire et al., 2004; Tarkalson and Mikkelsen, 2004; Akhter et al., 2005). In this study, soil loss tolerance value was used to temporarily replace the average soil loss because no RUSLE soil estimate was performed in this study area. However, soil loss tolerance values were relatively uniform across the small spatial scale, and therefore the actual difference of particulate P loss between the two methods was not fully reflected. Hence, average soil loss data on an annual basis from RUSLE is still needed. Hickey et al. (1994) and Van Remortel et al. (2001) have conducted research to integrate Geographic Information System (GIS) and RUSLE to estimate soil loss potential, which will be our second study.

Table 2.1: Summary of some field average parameter inputs of PLAT

Variable	N	Mean	S.D.	Minimum	Maximum
Area (ha)	24	9.43	13.48	0.77	50.63
P source type	8	54	-	-	-
P source amount	8	29.46	17.92	11.2	67.2
PI	24	134.9	43.5	46.5	220.8
W/V ratio (g/cm^3)	24	1.34	0.06	1.26	1.48
Average slope (%)	24	9.8	5.9	2.3	25.0

Table 2.2: Summary statistics of PLAT output in WFA method

Variable	N	Mean	S.D.	Minimum	Maximum
Particulate P (kg/ha)	24	0.261	0.240	0.030	0.813
Particulate PI	24	5.75	5.23	1	18
Soluble P (kg/ha)	24	0.665	0.313	0.180	1.656
Soluble PI	24	14.54	6.32	4	33
Leachate P (kg/ha)	24	0	0	0	0
Leachate PI	24	0	0	0	0
Source P (kg/ha)	24	0.054	0.018	0.027	0.110
Source PI	24	1.17	0.38	1	2
Overall P (kg/ha)	24	0.980	0.469	0.269	2.354
Overall PI	24	21.71	10.41	6	53

Table 2.3 Summary statistics of PLAT output in GA method

Variable	N	Mean	S.D.	Minimum	Maximum
Particulate P (kg/ha)	24	0.405	0.104	0.254	0.690
Particulate PI	24	9.1	2.3	6	15
Soluble P (kg/ha)	24	0.582	0.186	0.349	1.298
Soluble PI	24	12.7	4.6	5	29
Leachate P (kg/ha)	24	0	0	0	0
Leachate PI	24	0	0	0	0
Source P (kg/ha)	24	0.053	0.013	0.037	0.083
Source PI	24	1.1	0.3	1	2
Overall P (kg/ha)	24	1.039	0.222	0.644	1.712
Overall PI	24	23.3	5.0	14	38

Table 2.4: Test of spatial autocorrelation in WFA method

Pathways	Moran's I	Expected	S.D.	p-value	Spatial independent?
Particulate	-0.0066	-0.0435	0.2228	0.8237	Yes
Soluble	0.0090	-0.0435	0.3543	0.7231	Yes
Source	0.0001	-0.0435	0.2801	0.7794	Yes
Overall	0.0031	-0.0435	0.2952	0.7678	Yes

Table 2.5: Test of spatial autocorrelation in GA method

Pathways	Moran's I	Expected	S.D.	p-value	Spatial independent?
Particulate	-0.0093	-0.0435	0.2118	0.8323	Yes
Soluble	-0.0101	-0.0435	0.2548	0.7989	Yes
Source	0.0062	-0.0435	0.3069	0.7589	Yes
Overall	-0.0169	-0.0435	0.1696	0.8653	Yes

Table 2.6: Test of data normality of PLAT outputs in each individual P loss pathway and at combined overall matter. Method used is Shapiro-Wilk test.

P loss pathway	WFA				GA				Difference (GA- WFA)			
	Statistic	p-value	Skewness	Normality	Statistic	p-value	Skewness	Normality	Statistic	p-value	Skewness	Normality
Particulate	0.8097	0.0004	1.12	No	0.9087	0.0330	1.14	No	0.9312	0.1305	-0.61	Yes
Soluble	0.7643	< 0.0001	2.06	No	0.7663	< 0.0001	2.54	No	0.9268	0.0825	-0.97	Yes
Source	0.7290	< 0.0001	1.59	No	0.7338	< 0.0001	1.50	No	0.8679	0.0048	-0.25	No
Overall	0.8826	0.0094	1.41	No	0.9375	0.1437	0.91	Yes	0.9597	0.4325	-0.63	Yes

Table 2.7: Descriptive statistics and test of significance for the differences of P loss potential between two methods (GA-WFA).

P loss Pathway	Mean (kg/ha)	SD (kg/ha)	Lower CL of Mean (kg/ha)	Upper CL of Mean (kg/ha)	Test Statistic	p-value
Particulate	0.1448	0.2070	0.0560	0.2320	98.5	0.0027
Soluble	-0.0829	0.2940	-0.2072	0.0417	-41.5	0.2437
Source	-0.0020	0.0160	-0.0080	0.0050	-7	0.7083
Overall	0.0580	0.4410	-0.1280	0.2450	36.5	0.3069

Table 2.8: Comparison of P loss potential from each pathway of PLAT modeling and test for P loss accumulation effect based on one field analysis.

P loss Pathway	Whole Field Average	Grid Average	Grid Average with Accumulation
		kg/ha	
Particulate	0.118	0.301	0.297
Soluble	0.709	0.452	0.449
Leachate	0	0	0
Source	0.048	0.048	0.049
TOTAL	0.875	0.802	0.795

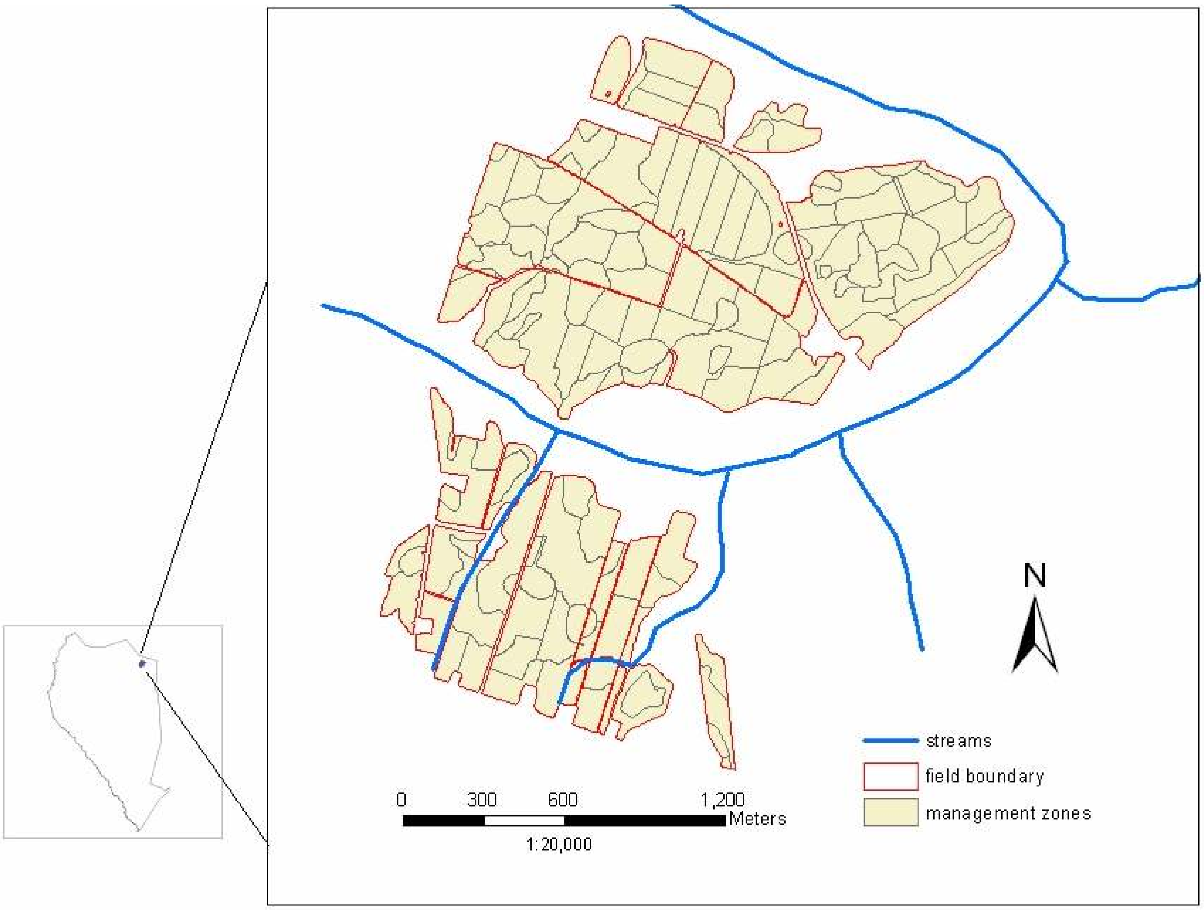


Fig. 2.1: Management zones and field boundaries of the study area map

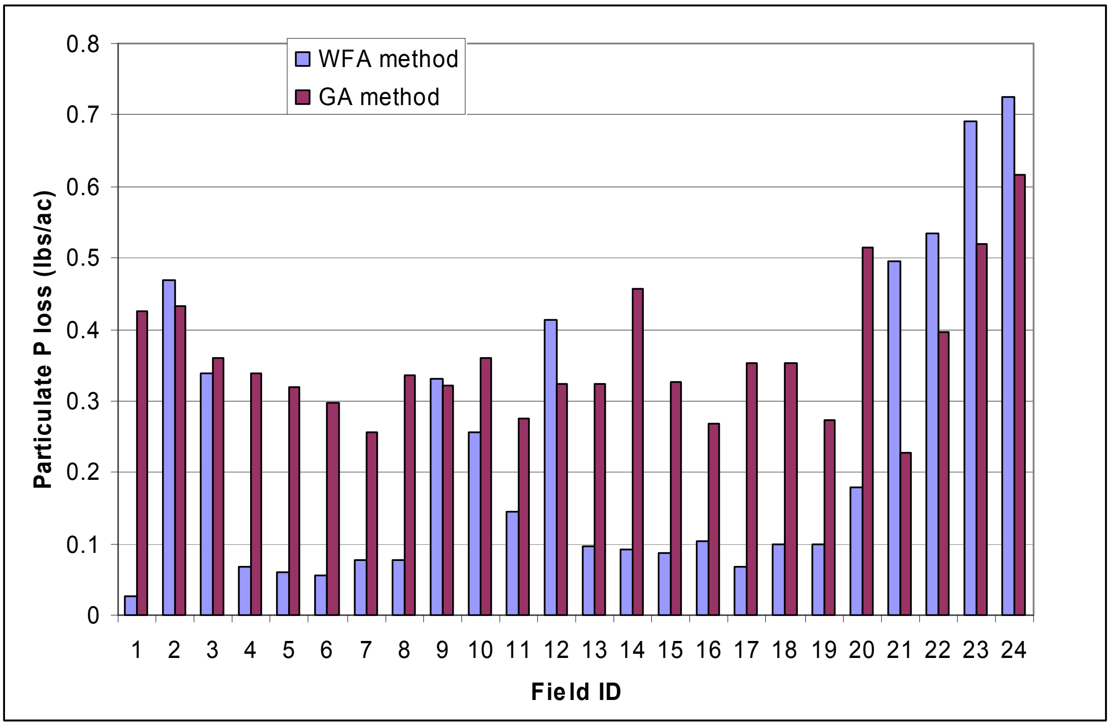


Fig. 2.2: Comparison of particulate P loss potential from PLAT by two methods: Whole Field Average (WFA) and Grid Average (GA) analysis.

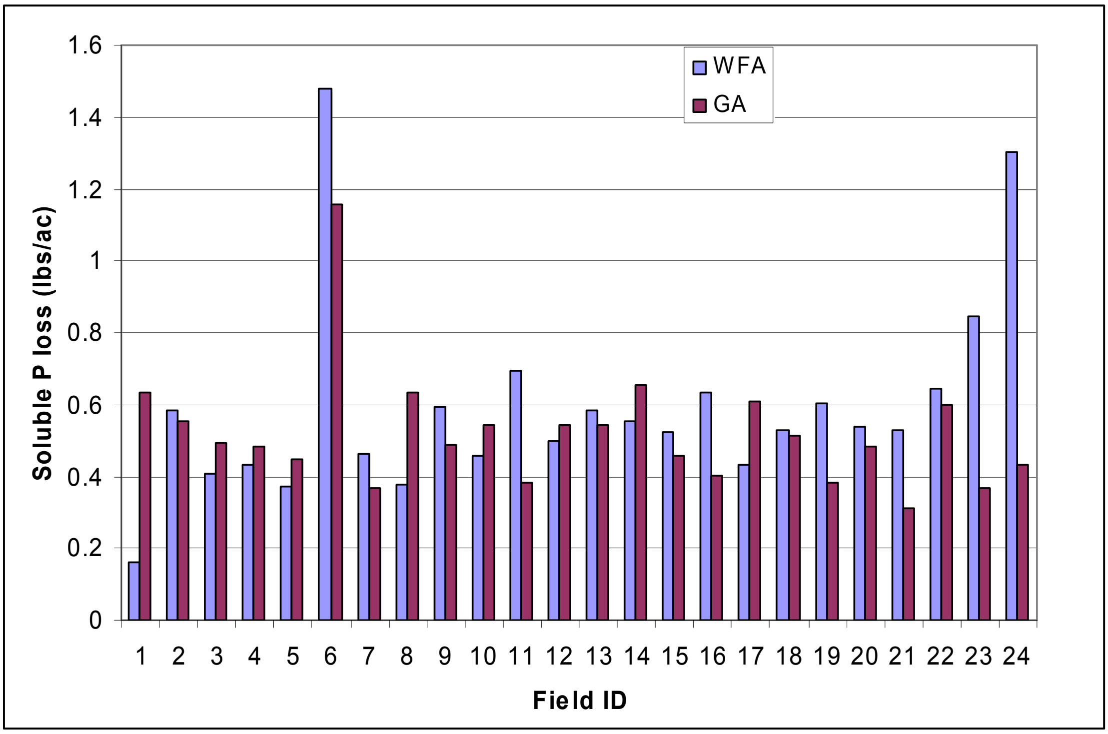


Fig. 2.3 Comparison of soluble P loss potential from PLAT by two methods: Whole Field Average analysis and Grid Average analysis.

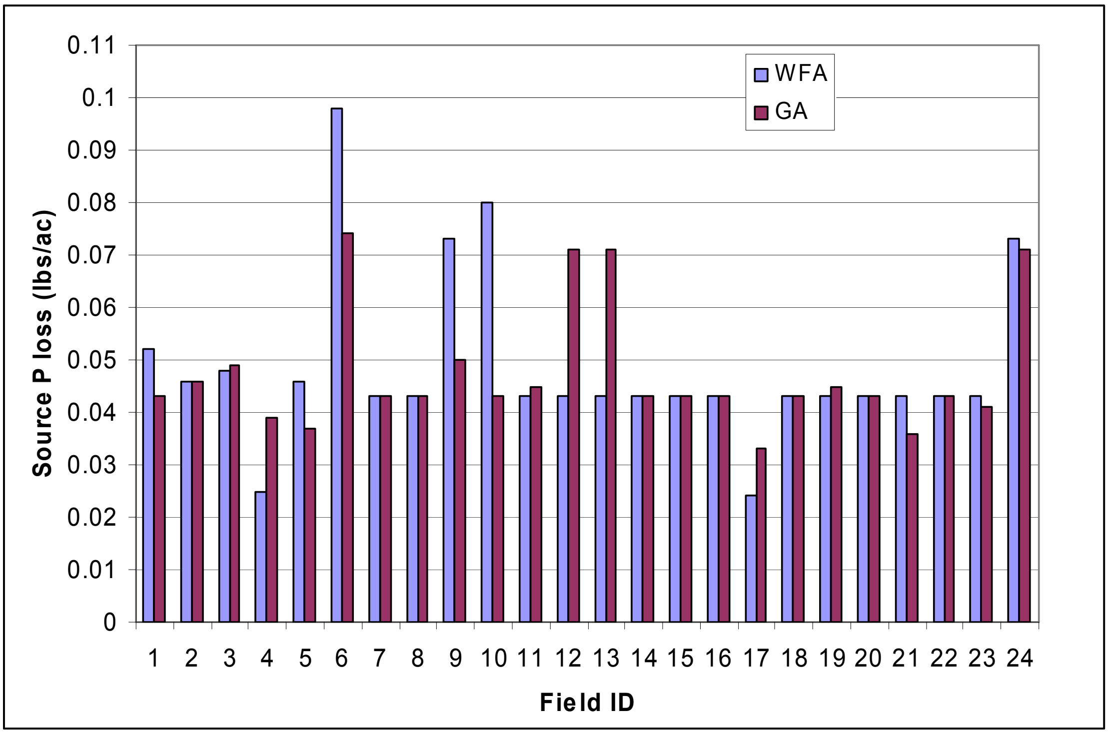


Fig. 2.4: Comparison of source P loss potential from PLAT by two methods: Whole Field Average analysis and Grid Average analysis.

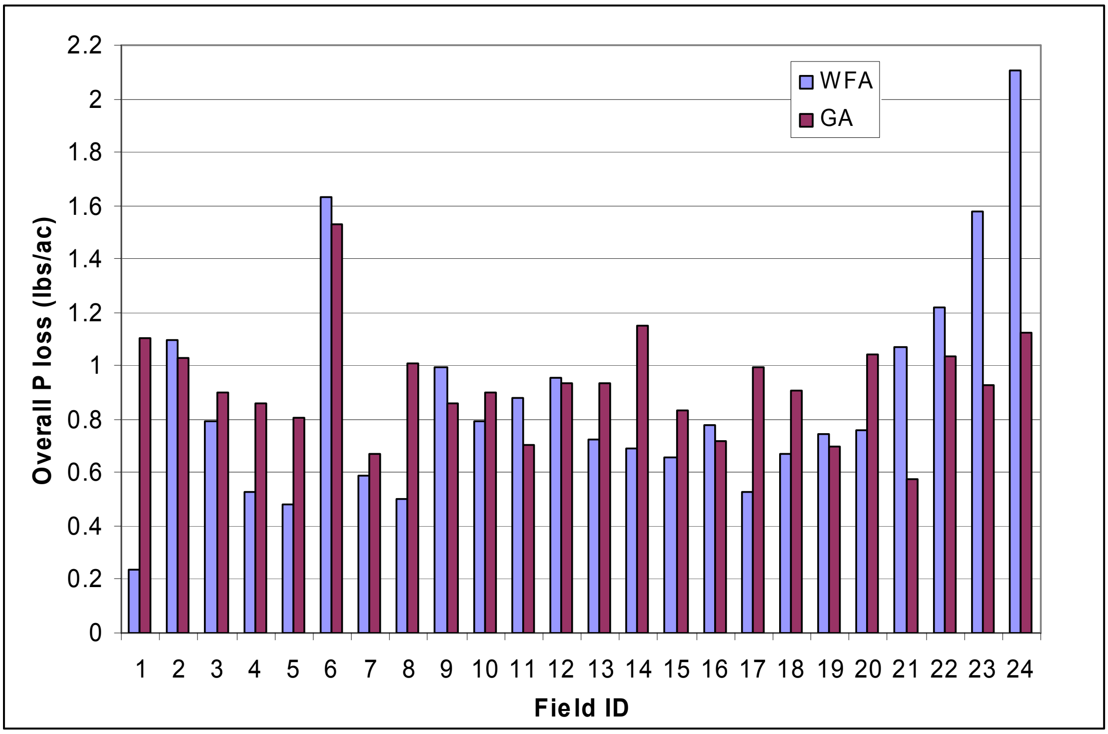


Fig. 2.5: Comparison of overall P loss potential from PLAT by two methods: Whole Field Average analysis and Grid Average analysis.

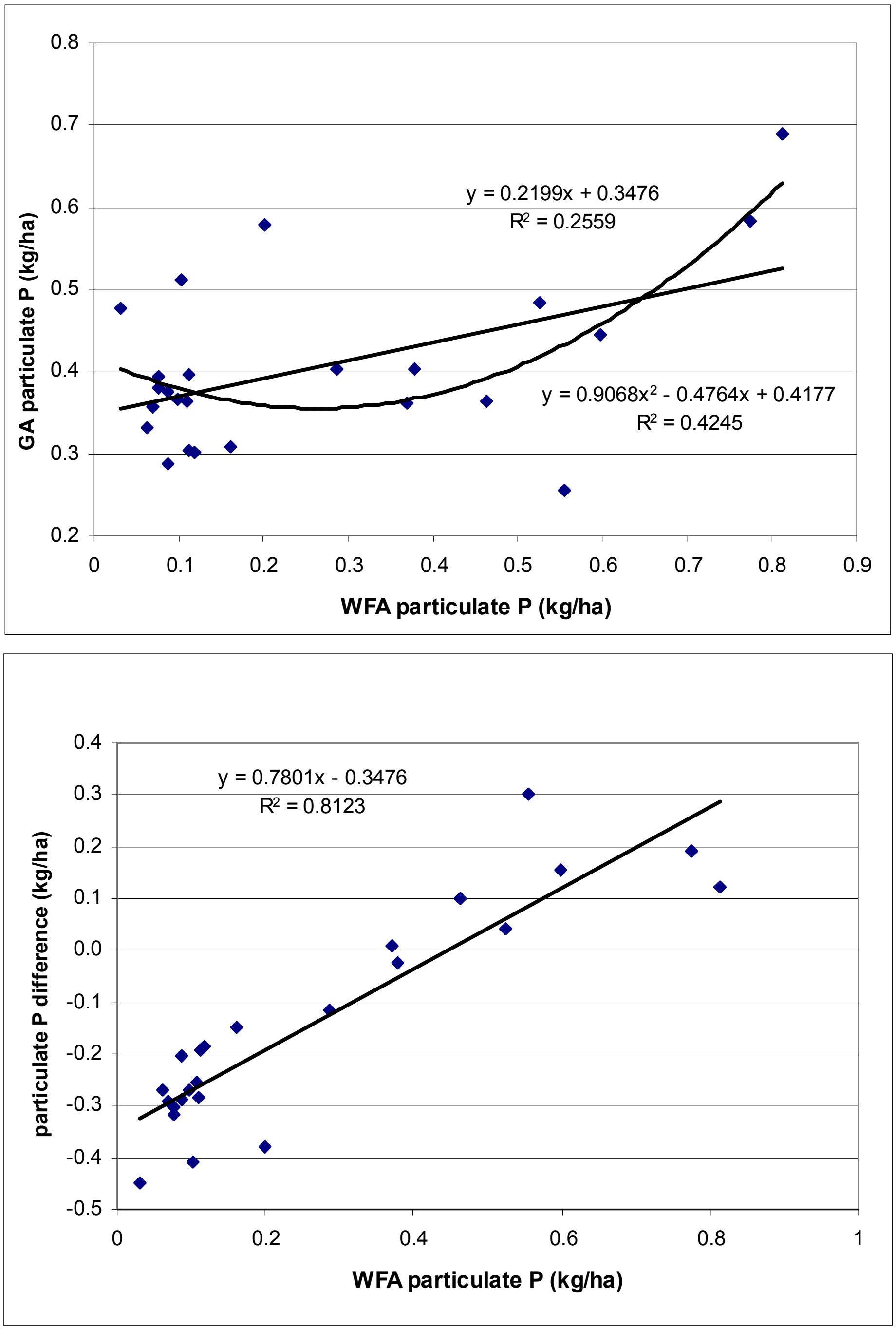


Fig. 2.6: Comparison of particulate P loss through WFA and GA methods

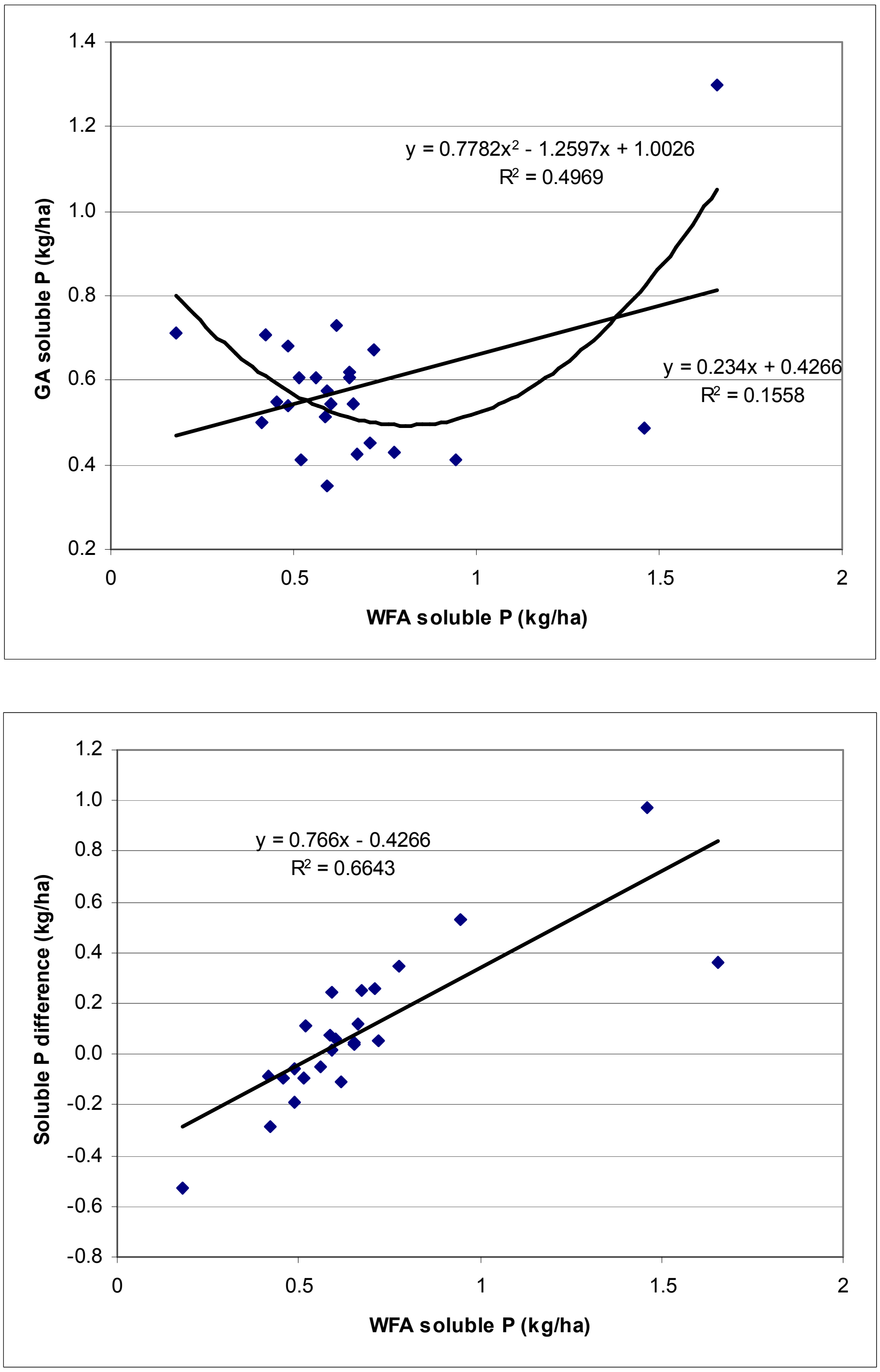


Fig. 2.7: Comparison of soluble P loss through WFA and GA methods

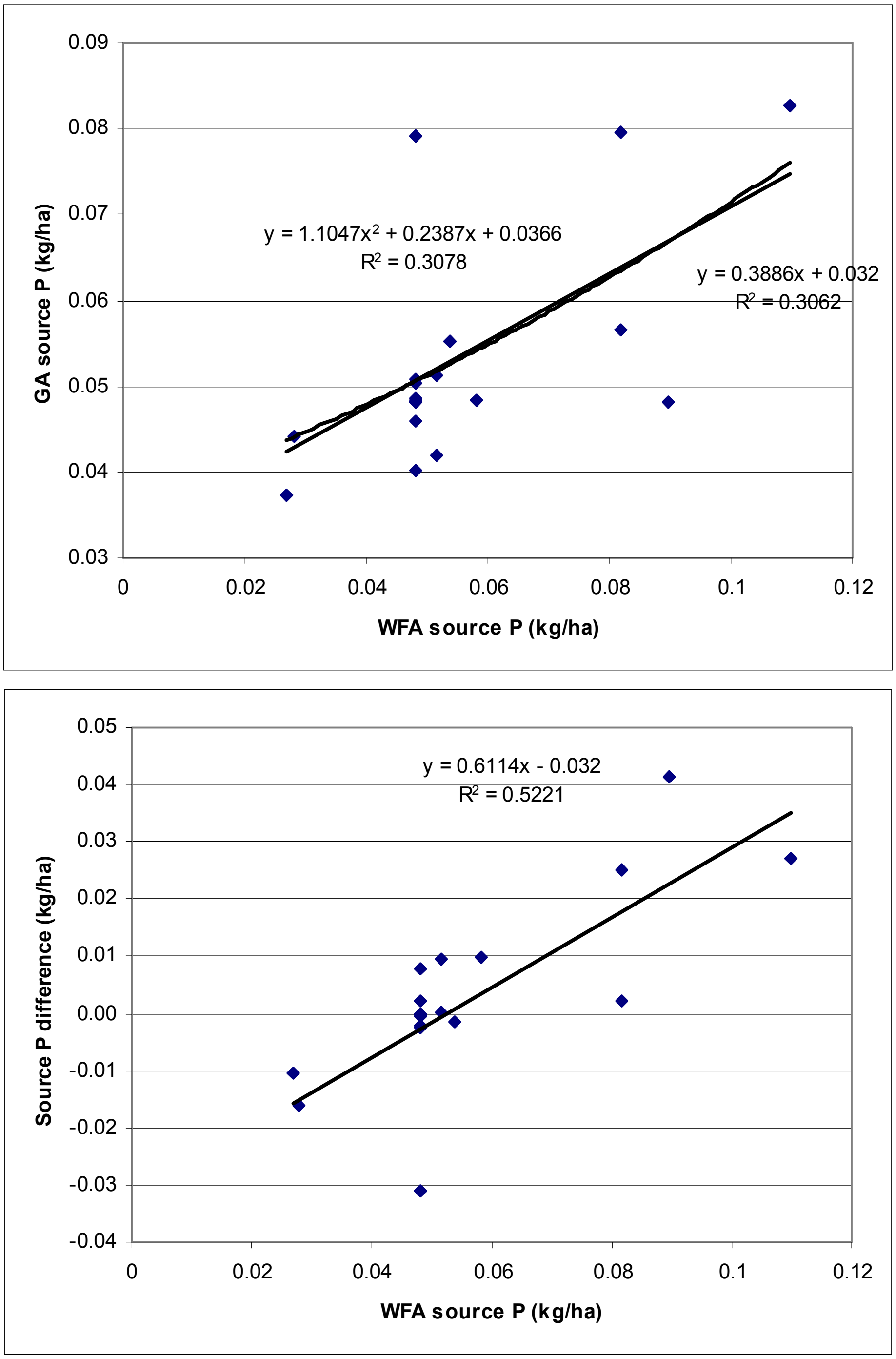
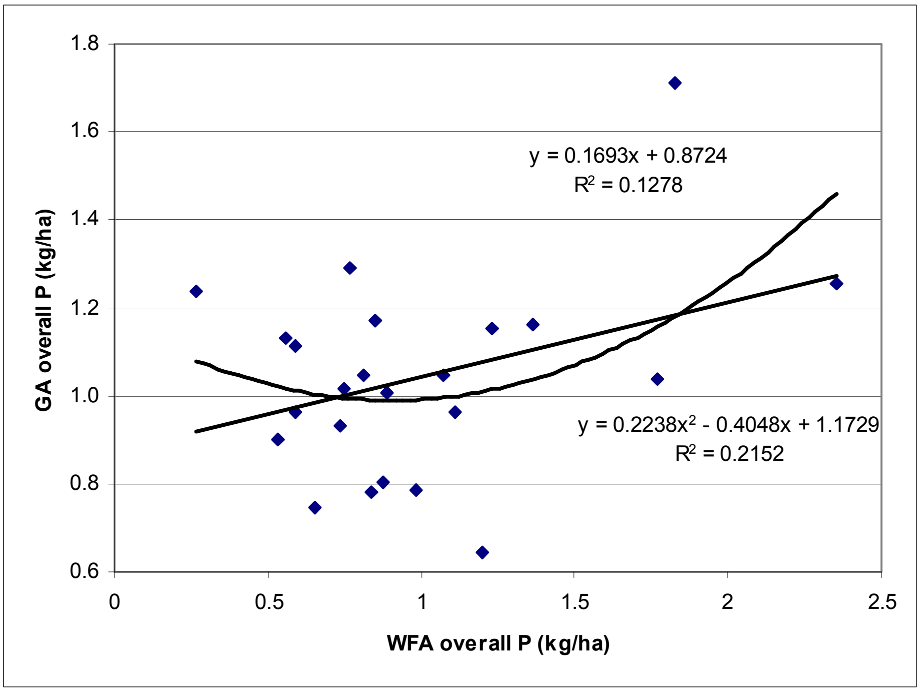


Fig. 2.8: Comparison of source P loss through WFA and GA methods



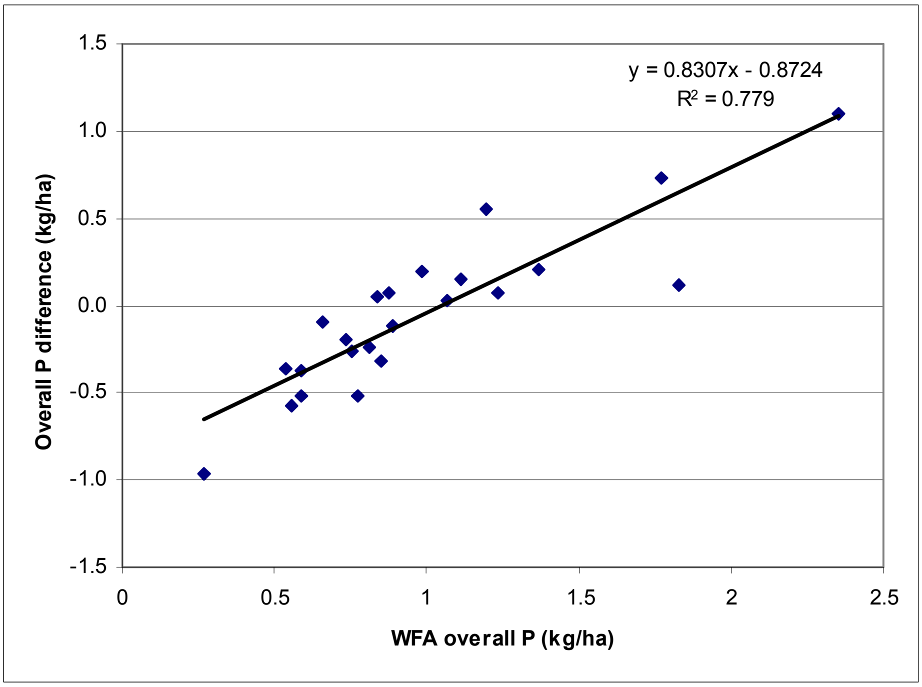


Fig. 2.9: Comparison of overall P loss through WFA and GA methods

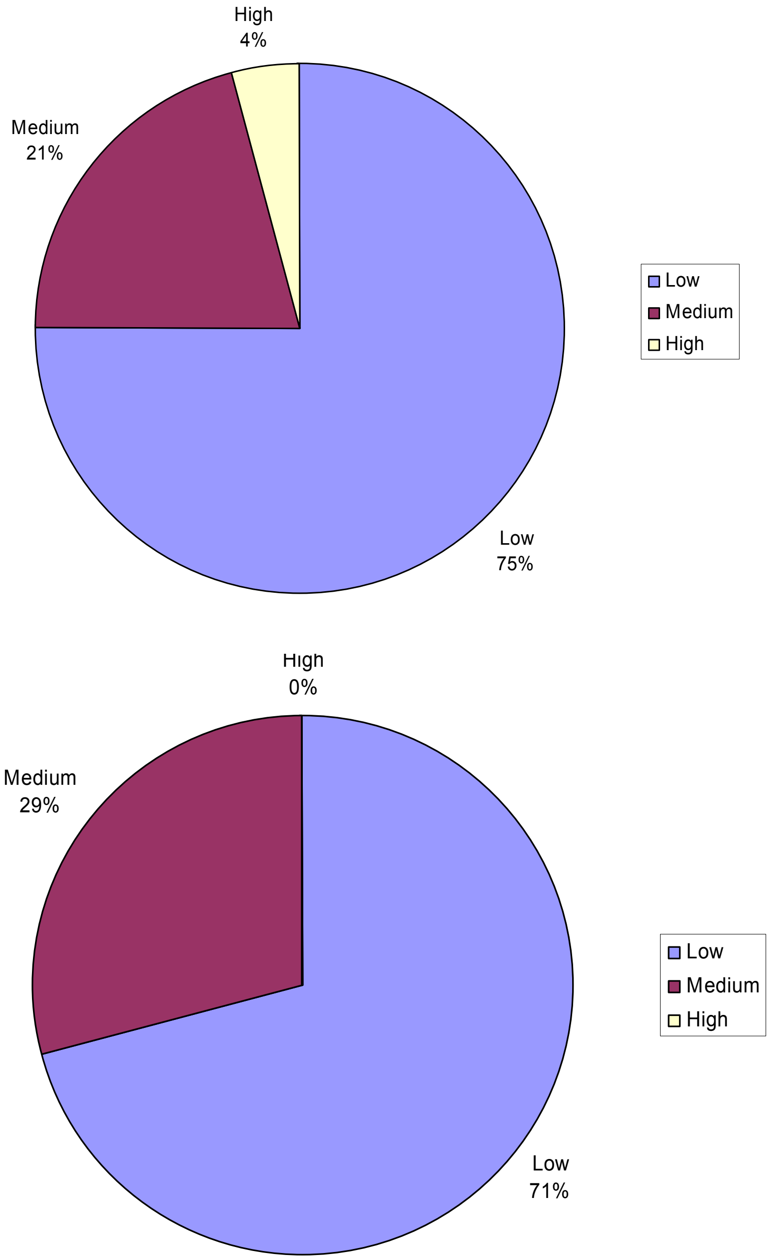


Fig. 2.10: Comparison of PLAT outputs through WFA (above) and GA (bottom) methods in terms of categorical ranking.

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CHAPTER 3

DERIVATION OF THE TOPOGRAPHIC FACTOR OF THE REVISED UNIVERSAL SOIL LOSS EQUATION (RUSLE)

INTRODUCTION

The RUSLE model requires four types of inputs related to climate, soil, topography, and management. These independent factor involve many physical, chemical and biological processes in the agricultural ecosystem. For example, areas within a field with lower elevation will typically have higher soil moisture and nutrient content due to runoff transport, which can subsequently stimulate crops growth. On the other hand, the cropping system and management practices such as terracing or strip cropping alter the field topography by reducing the effective slope length, decreasing runoff and variation soil erosion potential (Clarke and Rendell, 2000; Quine and Zhang, 2002; Havlin, 2004).

While holding other factors constant, soil erosion increases as slope steepness or length increases (Meyer and Wischmeier, 1969; Wischmeier and Smith, 1978; Desmet and Govers, 1996; Renard et al., 1997). Previous studies in many mountainous areas demonstrated that topography is the most critical factor when estimating soil erosion regardless of the scale (Millward and Mersey, 1999; Wang et al., 2005). In a geographic region where the landscape is relatively flat, topographic factors are still influential in determining the erosion rate, even though other factors such as cropping system may exert greater impact compared with steep slopes. Considering the topographic factor alone, soil erosion is more sensitive to slope steepness than slope length, which explain why all erosion models include a slope steepness factor as an input while only some models such as WEPP and AGNPS also incorporate the slope length. Although defined separately, these two topographic components are usually combined for computational purpose (Troeh et al., 1991), as is done in the RUSLE model.

Traditionally the slope steepness and slope length are obtained by simple field measurements by a conversation specialist, a process that can be very time-consuming and laborious. This has been a standard procedure over the past three decades both the precedent USLE model and currently updated RULSE for conservation planning. However, the values from these measurements are actually field average estimates (Hickey 2000), where the inherent within-person and between-person subjective measurement errors are common. With the increasing access to digital climatic, agricultural, and environmental data, RUSLE modeling performance has been greatly improved, resulting in more accuracy in soil erosion prediction and significant reduction in field visit. Particularly, the topographic factors of slope steepness and slope length, have benefited substantially where the geospatial technologies (Geographic Information System or GIS, Remote Sensing or RS) combined with the Digital Elevation Model (DEM) and Light Detection and Ranging (LIDAR) data enhance resolution and capabilities for spatial analysis (Revell et al., 2002; Thoma et al., 2005).

The geospatial approach for determining soil erosion in RUSLE involves processes of parameter derivation and themes overlay. Parameter derivation refers to the topographic parameter calculation for slope steepness (S) and slope length (L) from digital terrain surface such data (Wilson and Gallant, 1996; Wilson and Gallant, 2000; Ziadat, 2005). Theme overlay refers to the final multiplication of each parameter layer within the GIS framework. Recent studies showed the promising potential to integrate

RUSLE with geospatial technologies for estimating soil erosion, which also enables customized modification for unique climatic or topographic conditions of a study site (Millward and Mersey, 1999; Wang et al., 2005).

Although DEM data increased the model accuracy while reducing the labor and time required with traditional field measurement, some issues about slope calculation still remain. First, calculating of slope steepness in a raster format is not a complicated task, but the various existing algorithms produce different results, which are misleading without field verification. For example, maximum slope algorithm used by IDRISI usually overestimate slope angle because it only considers four cardinal directions in the 3x3 neighborhood. Dunn and Hickey (1998) and Srinivasan and Engel (1991) have provided detailed comparison of different slope calculation algorithms. Secondly, the slope length calculation exhibits bigger challenge because there is no universally recognized scientific method in the literature. Some researchers have suggested using theories of unit stream power (Moore and Burch, 1986a, 1986b) or upslope contributing area (Desmet and Govers, 1996) as a surrogate for slope length. However, the model efficiency depend largely on the field or watershed characteristics.

The objective of this study was to evaluate a widely used and recently updated RUSLE-based Arc Macro Language (AML) algorithm to estimate the topographic factor (LS) on a typical North Carolina landscape as a potential replacement of the traditional field measurement. If successful, the soil loss estimate can be used as a direct input into PLAT to evaluate the potential P loss from agricultural soils to water bodies.

RUSLE-Based AML program

The maximum downhill slope algorithm was introduced by Hickey et al. (1994) and a following USLE-based AML program was developed (Hickey et al., 1994; Dunn and Hickey, 1998). Recently, this AML program was updated with new assumptions made with respect to slope characteristics as USLE was replaced by RUSLE (Van Remortel et al., 2001). The program was also recoded using C++ language to solve the computer running speed problem caused by complex flow path processing and cumulative slope length calculations (Van Remortel et al., 2004). In the western U.S. area, this RUSLE-based AML program has been proved successful in estimating soil erosion rate (Van Remortel et al., 2001; Warren et al., 2004); however, no such study has been done in the eastern U.S.

As previously mentioned, various algorithms exist for slope calculation and the results may exhibit huge variability for the same study area, which would cause variability in model outcomes. In the raster spatial analysis environment, ESRI build-in slope calculation commands of uses a 3x3 moving window to compute the average slope of a cell based on its eight neighboring cells (Eq. 3.1; Fig. 3.1).

$$\text{slope of cell e} = \sqrt{\left(\frac{(z_a + 2z_d + z_g) - (z_c + 2z_f + z_i)}{8 \times resolution}\right)^2 + \left(\frac{(z_a + 2z_b + z_c) - (z_g + 2z_h + z_i)}{8 \times resolution}\right)^2} \qquad \text{[Eq. 3.1]}$$

where letters *a* to *i* represent the cell number and *z* represents the elevation in that cell. While the maximum downhill slope algorithm also utilizes 3x3 moving window for elevation comparison, only the maximum downhill elevation drop from the center cell to one neighbor is used to compute the slope (Hickey, 1994; Eq. 3.2).

$$\text{slope of cell e} = \frac{\max(z_e - z)}{L} \times 100 \qquad \text{[Eq. 3.2]}$$

where z represents the elevation of any one of its eight neighbors.

To accurately calculate the slope length, it is necessary that all sinks, which are group of cells surrounded on all sides by cells with higher elevation, are filled. Natural sinks are very rare (Hickey, 2000) and the artificial sinks were often caused by sampling effects during the DEM creation. Therefore sinks should be removed to generate a depressionless DEM before being used in further spatial analysis. The RUSLE-based AML program has the advantage over the ESRI standard build-in function in that all sinks in a DEM could be completely filled (Hickey, 1994), which reduced a source of error for calculating slope length.

In order to calculate slope length with the RUSLE-based AML program, a non-cumulative slope length (NCSL) is first calculated after the initial identification of high points, or cells with highest elevation. This is achieved by selecting those cells which have either no water flow entering them or in cases where both the cell of interest and its input cell have a slope angle of zero. Then, the non-cumulative slope length is defined as:

$$NCSL = 0.5*(cell\ resolution)*(atan\beta) \qquad \text{[Eq. 3.3]}$$

if the cell is a high point, and

$$NCSL = (cell\ resolution)*(atan\beta) \qquad \text{[Eq. 3.4]}$$

if the input cell is in a cardinal direction, and

$$NCSL = 1.4142*(cell\ resolution)*(atan\beta) \qquad \text{[Eq. 3.5]}$$

if the input cell is in a diagonal direction (β = slope angle). Finally the cumulative slope length (CSL) is created by summing the cell-based non-cumulative slope length segments along the flow direction. One important assumption adapted from Wilson (1986) and Griffin et al. (1988) is that when slope angle is decreased by 50%, referred as the slope cut-off factor, between adjacent cells along the flow direction (Fig 3.1), erosion potential decrease dramatically and deposition occurs. Therefore, the AML program not only constrains the slope angle calculations to one cell length in a downhill direction, but also considers the converging flows and areas of deposition.

METHODOLOGY

Study Area

The field site used in this study is the Beef Cattle Research Station near in Butner, North Carolina (36.1° N and -78.8° W, Table 3.1), located across the border of Durham and Granville counties. The farm is composed of 48 agricultural fields ranging from 0.9 to 19.8 ha. The Butner farm was chosen for this study because it has been traditionally used as a USDA-NRCS RUSLE conservation planning training site, and therefore site measured topographic factors, including slope steepness S (%) and slope length L (m), are available at the field scale. This enables the possibility of conducting field validation for GIS-based DEM-derived topographic factor estimates. No perennial streams or explicit surface water bodies exist around the farm, however, the tillage practices on these croplands result in substantial erosion potential within the agricultural watershed. Most fields are in permanent pasture or with woodlands in the non-cropped areas of the farm. The distribution of elevation is slightly skewed to the left with mean value of 138.3 m and range from 115.8 to 152.1 m. Based on NC CRONOS database, the average annual temperature and precipitation in this area are 14.4 °C and 115.8 cm, respectively. The most dominant soil map units are Chewacla and wehadkee soils (0-2 % slopes), Helena sandy loam (2-6 % slopes), Georgeville silt loam (2-6 % slopes), and Herndon silt loam (2-6 % slopes).

Data Sources

The farm and field boundary data were provided in an ESRI shapefile format by NRCS water quality specialist Roger Hansard. The coordinate system was reprojected to NAD1983 State Plane of North Carolina FIPS 3200. The field-based slope steepness (%) and slope length (m) at the profile level were originally measured by Roger Hansard and later processed by Josh Spencer. The high resolution light detection and ranging (LIDAR) data, which was generated through remote sensing technology with attributes of latitude, longitude and bare earth elevation above sea level, was downloaded from the North Carolina flood mapping program (http://www.ncfloodmaps.com) developed by the Federal Emergency Management Agency (FEMA). After being georeferenced and imported into ArcGIS software, LIDAR data was converted to dense point shapefile. Digital elevation model (DEM) based on LIDAR was created with 6-m sample interval or cell resolution. Compared with USGS 30-m and 10-m DEM data, the LIDAR-based digital elevation data represented substantially enhanced resolution.

AML program implementation from two approaches

A random number generator was used to select 25 of the 48 fields as test fields and two approaches were used to evaluate the AML program on the test fields. An important input is the slope cut-off factor, which is the threshold slope decrease between two neighboring cells along the downstream direction that indicates the occurrence of soil deposition. Every set of slope cut-off factor consisted of two values, one for fields with average slope > 5% and the other for fields with average slope ≤ 5%. For example, the default slope cut-off values in the AML program is 0.7 & 0.5, which means that 70% and 50% slope decrease along the flow direction was necessary for soil deposition to exceed erosion. Since the topography is less complex and the overall slope is relatively flat in our field sites compared to those in the western U.S. where the AML program was originally developed and tested, three sets of slope cut-off factors, 0.7 & 0.5 (default), 0.5 & 0.3, and 0.3 & 0.3, were evaluated on the test fields through two approaches. The additional two sets of cut-off factors were tested because it was hypothesized that in a relatively flat landscape, the decrease in slope gradient required for deposition is less than that required for a complex landscape with steep slopes. The estimated LS value from the RUSLE-based AML program through each approach was compared to field measurements.

Our first approach was to compute the average LS value at the whole field (WF) scale, which compares with the standard field measurement procedure in LS of RULSE. To do this, a 15-m buffer was created for each field to enlarge the field extent in order to avoid field edge effects (Van Remortel, et al., 2001). Then the 6-m DEM data generated from LIDAR points were clipped on the buffered field boundary. Based on the clipped DEM, the AML program was run and the process was repeated for all of the fields. In raster format, every 6 x 6 m^2 grid cell was treated as a uniform slope segment and the LS value calculated from the AML program was assigned to each grid. The number of grids with the same LS value was recorded and a weighted average based on grid area was computed as the final LS value for the entire field.

Our second approach was to evaluate the AML program at the subfield scale where representative profiles (RP) were selected, which are closed polygons that resemble the watershed characteristics. Although the RUSLE was developed at the field scale, the user's manual suggests that "the slope profile representing a significant portion of the field having the most severe erosion is often chosen" for conservation planning. This landscape profile is usually in the steep areas of the field. Within each representative profile, the previous procedure of calculating LS value in the WF approach was repeated for the representative profile. If a field was composed of multiple representative profiles, the process was repeated for all other representative profiles. Finally the LS values from all representative profiles were then averaged based on a weighting factor of profile area, resulting in a single LS value for the entire field. Specifically, the watershed boundary was delineated using DEM data in ArcGIS Hydro Extension, and the fields were subdivided when the original field boundary intersected the watershed boundary. In this way, each subfield was a locally hydrologically isolated area. Representative profiles are identified as those subfields that have the greatest soil erosion potential characterized by steep slope or long slope profile. The primary reference for the selection of representative profiles as opposed to other discarded subfields was a field subdivision map completed by NRCS water quality specialist, who visited the fields and estimate the subdivision based on visual investigation of topography. Additionally, the digital slope distribution produced by Spatial Analyst extension of ArcGIS package served as another reference of slope characteristics investigation. Only subfields that possess large soil erosion potential, i.e., steep slope gradient and long slope profile, were selected as representative profiles. Then the RUSLE-based AML program was performed on all representative profiles where a weighted average based on the profile area was computed to generate one LS value for the whole field. Finally, the GIS-based LS estimates from the 25 test fields were compared with field LS measurements and a relationship was derived. The remaining fields in the farm were used as validation for model accuracy in that LS were calculated without referencing the NRCS field subdivision map. The results were further adjusted to test the potential of replacing the field measurements.

Statistical Analysis

Treating the LS estimates as the variable of interest, the Moran's I spatial test statistic was used to test the spatial autocorrelation in SAS based on a spatial adjacency matrix with binary coding scheme which assigned a value of 1 if two fields were connected or shared a border and 0 otherwise (SAS Institute, 2003, Cary, NC). The LS value estimates from WF approach, RP approach, field measurement, together with the differences between WF approach and field measurement, and differences between RP approach and field measurement were tested for data normality using Shapiro-Wilk test in SAS environment. Pearson correlation was calculated to show the linear association between potential P loss from WF and RP approaches. Logarithm transformation was applied for data that did not meet the normality assumption. Paired t-test was carried out in SAS on original or transformed data to evaluate the significance of difference between two approaches.

RESULTS AND DISCUSSIONS

Whole field AML run

The LS values from field measurements and GIS-derived estimates using three sets of slope cut-off factors have no spatial autocorrelation as proved by Moran's I statistic ($p > 0.05$; Table 3.1). The Shapiro-Wilk test indicated that the LS estimates from the WF approach were not normally distributed ($p < 0.05$), therefore logarithm transformation was applied to the original data so that the normal assumption was met for further statistical analysis (Table 3.2). The RUSLE-based AML program, when implemented at the whole field scale, severely underestimates (~60%) the topographic factor LS for all three sets of slope cut-off values (Fig. 3.2 to 3.4). The average difference was 0.259, 0.235, and 0.231, respectively, for the slope cut-off factors of 0.7&0.5, 0.7&0.3, and 03&0.3 (Table 3.3).

The relationship between the field measured LS and the GIS-derived LS estimates at the whole field scale were investigated, and a linear regression line with moderate coefficient of variation was found (R^2=0.5). Pearson coefficients showed moderately strong linear correlation for the slope cut-off factors of 0.5&0.3 and 0.3&0.3 (ρ=0.7). There appeared to be an outlier when the 0.7 & 0.5 cut-off factor was used, which resulted in a small R^2 (0.24) and weak correlation (0.49) (Fig. 3.2).

The paired t-test was used on the log-transformed data to examine the difference between the LS values obtained from the AML program using the whole field (WF) approach and the field measurements. Highly significant differences were found ($p < 0.0001$) even though the data were moderately correlated. The standard deviation of the difference was relatively large compared to the mean. This may be due to each field being considered as a special irregularly shaped experimental unit with coarse resolution and variations in topography were not fully accounted for. The decrease in slope cut-off factor from 0.7&0.5 to 0.3&0.3 allowed deposition to be identified earlier because in the latter case only 30% slope decrease was enough to cause significant reduction of particles in runoff water. This may explain why the AML program had the smallest deviation from the field measured LS when slope cut-off factor of 0.3&0.3 was used. For fields with average slope > 5% and those ≤ 5%, the change in slope cut-off factor (from 0.5 to 0.3) did not to have significant influence on estimated LS.

Representative profiles for the AML analysis on test fields

Running the RUSLE-based AML program on representative profiles instead of the whole field may underestimate the slope length because the field was subdivided into hydrologically isolated areas and the depositional areas were relatively easier to identify in a GIS environment. However, the overall topographic factor calculation may be improved because on one hand, the slope steepness calculation may be more accurate due to the elimination of the unrepresentative portions of the field with low erosion potential (flat slopes), and on the other hand, the soil loss was less sensitive to slope length than slope steepness on most slopes profiles as documented in NRCS RUSLE handbook. The high resolution LIDAR and DEM data are essential to identify the upland high points and the ridge line divides for delineating the watershed boundaries. In this study, the stream definition was set as 20-30% of the upslope contributing drainage area, which was expressed in the number of upstream cells flowing into a certain cell of interest. This criterion enabled the relatively good agreement between subfield divisions by an NRCS specialist through site visits and the watershed boundary delineation from DEM in a GIS ArcHydro setting. Typically, the subfields created from GIS hydrological modeling showed more details than the field subdivision.

Compared to the whole field approach, using representative profiles on the test fields significantly improved the approximation of GIS-based LS calculation to the field measured values (Fig. 3.5-3.7). Although still underestimating LS, the average bias decreased to 0.152, 0.138, and 0.134, respectively for the three sets of cut-off factors in previously mentioned order. The linearity between field measured LS and GIS estimated LS has greatly improved ($R^2 \approx 0.75$ and $\rho \approx 0.86$; Fig. 3.5 to 3.7). It was also true that the quadratic relationship seems to fit the data slightly better ($R^2 \approx 0.78$). This reflected the small curvature from a pure linear relationship likely caused by measurement errors or unexplained uncertainty. Both types of regression lines were analyzed in the subsequent validation process.

Moran's I statistic showed spatial independency for the LS calculated from AML program in representative profiles (Table 3.1). Shapiro-Wilk test indicated that the data were not normally distributed when the slope cut-off factor 0.7&0.5 was used. Therefore, logarithm transformation was again applied. For the other two sets of slope cut-off factors, the LS data were normally distributed and paired t-test was conducted to examine the significance of the discrepancy. As expected, the difference was significant ($p < 0.0001$) although the standard deviation of the difference is relative small compared with the mean (Table 3.4). Similarly in the whole field approach, when the slope cut-off factor decreased, the difference also tended to be smaller. However, the improvement observed when the slope cut-off factor changed from 0.5&0.3 to 0.3&0.3 was not as significant as that when cut-off factor changed from 0.7&0.5 to 0.5&0.3.

Overall, the performance of the GIS-enabled RUSLE-based AML program significantly improved when implemented in hydrologically isolated areas, i.e., representative profiles. In retrospect, the unsatisfactory performance in the whole field approach can be attributed to the fact that a field boundary was defined for agronomic purposes and the fields were unlikely to be hydrologically isolated.

Model validation using remaining fields

Despite the improvement in estimating LS from the AML program implemented in representative profiles, the values were still significantly different from the field measurement. Therefore, instead of using the LS calculation directly from the AML program, an adjustment scheme was proposed. Specifically, the raw outputs from the RUSLE-based AML program was elevated using the linear or quadratic relationship developed from the test fields in previous study. The results were shown in Fig. 3.8 – 3.10. Clearly the adjustment did not perfectly approximate the field measurements. But paired t-test showed that the difference were insignificant in all three sets of slope cut-off factors (Table 3.5). Although the quadratic relationship fit slightly better in the test fields of representative approach, the polynomial adjustment did not show any advantage in the LS calculation with the validation fields. The differences between the field measured LS and GIS-calculated LS were slighted smaller with less variability (small standard deviation) when the linear adjustment scheme was used (Table 3.5). The three sets of cut-off factors exhibited some influence in the LS estimation; however, the effect need further study to be claimed significant or not. The Root Mean Square Error (RMSE, Eq. 3.7), an indicator of the model fitting accuracy, were 0.31, 0.21 and 0.30, respectively, for three sets of cut-off factors. However, outliers may damage the reliability of these criteria.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - t_i)^2}{n-1}} \qquad \text{[Eq. 3.7]}$$

where x_i is the observed value and t_i is the measured value using different methods. Additionally, the inherent errors with the field measurement may also cause discrepancy between field measurement and GIS-based calculation.

CONCLUSIONS

This study evaluated the RUSLE-based AML program for estimating the topographic factor LS, the product of slope length (L) and steepness (S), through two approaches using high-resolution DEM data in a GIS framework. In accordance to the RULSE model rationale the program should be implemented at the field scale, i.e., the calculation of one LS value for the entire field. However, in this study the LS calculation from extraction of reiterative modeling outputs on the small grids generated much better values that well approximated the field measurements. The AML program, though successfully verified in the western US region where topography is complex, did not directly work well in the agricultural fields, either in the whole field scale or in the representative profiles. In both cases, the program underestimated the LS values compared with field measurement. Creation of 15-m buffer to avoid the edge effect, and using watershed delineation technique to break the field into hydrologically isolated areas improved the estimates of LS.

After an adjustment process based on the linear or quadratic relationship developed from the test fields, the LS calculation for the remaining validation fields were in good agreement with field measurements. Potential sources of error and uncertainty in the AML program modeling include the appropriate buffer width (Kronvang et al., 2005;

Syversen and Borch, 2005), criteria of stream definition, DEM resolution (McMaster, 2002), and possibly slope cut-off factors. Overall, this study successfully demonstrated the use of GIS modeling to estimate LS with no site visiting; however, further studies are needed in similar landscape settings so that the data variability and adjustment scheme could be further tested. It is expected that the adjustment factor is sensitive to landscape characteristics, and therefore calibration maybe needed before direct application to other field sites.

Table 3.1: Moran's I test of spatial autocorrelation

	Moran's I	Expected	p-value	Spatial independent?
Test fields LS	-0.012	-0.067	0.8469	Yes
WF: computer LS (0.7 & 0.5)	-0.018	-0.067	0.8647	Yes
WF: computer LS (0.5 & 0.3)	-0.014	-0.067	0.8520	Yes
WF: computer LS (0.3 & 0.3)	-0.013	-0.067	0.8492	Yes
RP test fields: computer LS (0.7 & 0.5)	0.0086	-0.071	0.7866	Yes
RP test fields: computer LS (0.5 & 0.3)	0.0069	-0.071	0.7894	Yes
RP test fields: computer LS (0.3 & 0.3)	0.0076	-0.071	0.7873	Yes
Validation fields LS	-0.096	-0.063	0.9058	Yes
RP validation fields: computer LS (0.7 & 0.5)	-0.288	-0.063	0.4402	Yes
RP validation fields: computer LS (0.5 & 0.3)	-0.283	-0.063	0.4512	Yes
RP validation fields: computer LS (0.3 & 0.3)	-0.231	-0.063	0.5632	Yes

Table 3.2: Shapiro-Wilk test of data normality for the difference of LS values from field measurement and GIS-based calculation.

	WF				RP test fields				RP validation fields			
LS factor comparison	Statistics	p-value	Skewness	Normality?	Statistics	p-value	Skewness	Normality?	Statistics	p-value	Skewness	Normality?
field LS - computer LS (0.7 & 0.5)	0.8407	0.0012	1.7	No	0.9129	0.047	0.63	No	0.9241	0.0817	1.04	Yes
field LS - computer LS (0.5 & 0.3)	0.8872	0.0097	1.06	No	0.9174	0.0587	0.6	Yes	0.9222	0.0743	1.05	Yes
field LS - computer LS (0.3 & 0.3)	0.891	0.0117	1.04	No	0.9175	0.0588	0.57	Yes	0.9427	0.2056	0.86	Yes
log[field LS - computer LS (0.7 & 0.5)]	0.9569	0.3559	-0.38	Yes	0.9413	0.1919	-0.42	Yes	-	-	-	-
log[field LS - computer LS (0.5 & 0.3)]	0.9328	0.1011	-0.68	Yes	-	-	-	-	-	-	-	-
log[field LS - computer LS (0.3 & 0.3)]	0.9205	0.0527	-0.89	Yes	-	-	-	-	-	-	-	-

Table 3.3: Descriptive statistics and comparison of LS values estimated from GIS-aided RUSLE-based AML program and field measurements through whole field (WF) approach for test fields

LS factor Comparison	Mean	S.D.	Lower CL of Mean	Upper CL of mean	Test Statistic	p-value
field LS - computer LS (0.7 & 0.5)	0.2589	0.2153	0.1700	0.3477	7.88[¶]	< 0.0001[¶]
field LS - computer LS (0.5 & 0.3)	0.2345	0.1844	0.1584	0.3106	8.17[¶]	< 0.0001[¶]
field LS - computer LS (0.3 & 0.3)	0.2305	0.1845	0.1543	0.3066	7.95[¶]	< 0.0001[¶]

[¶]Statistical test was conducted based on log-transformed data

Table 3.4: Descriptive statistics and comparison of LS values estimated from GIS-aided RUSLE-based AML program and field measurements through representative profile (RP) approach for test fields

LS factor comparison	Mean	S.D.	Lower CL of Mean	Upper CL of Mean	Test Statistic	p-value
field LS - computer LS (0.7 & 0.5)	0.152	0.0941	0.1113	0.1927	8.35¶	< 0.0001¶
field LS - computer LS (0.7 & 0.5) with linear adjustment	0	0.0916	-0.04	0.0396	0	0.9983
field LS - computer LS (0.7 & 0.5) with quadratic adjustment	0	0.0843	-0.036	0.0365	0	0.9982
field LS - computer LS (0.5 & 0.3)	0.1377	0.0939	0.097	0.1783	7.03	< 0.0001
field LS - computer LS (0.5 & 0.3) with linear adjustment	0	0.0922	-0.04	0.0398	0	0.9981
field LS - computer LS (0.5 & 0.3) with quadratic adjustment	0	0.0857	-0.037	0.0371	0	0.9990
field LS - computer LS (0.3 & 0.3)	0.1344	0.0935	0.094	0.1749	6.89	< 0.0001
field LS - computer LS (0.3 & 0.3) with linear adjustment	0	0.0918	-0.04	0.0398	0	0.9980
field LS - computer LS (0.3 & 0.3) with quadratic adjustment	0	0.0853	-0.037	0.365	0	0.9991

¶Statistical test was conducted based on log-transformed data

Table 3.5: Descriptive statistics and comparison of LS values estimated from GIS-aided RUSLE-based AML program and field measurements through representative profile (RP) approach for validation fields.

LS factor comparison	Mean	S.D.	Lower CL of Mean	Upper CL of Mean	Test Statistic	p-value
field LS - computer LS (0.7 & 0.5) with linear adjustment	0.0702	0.1988	-0.016	0.1561	1.69	0.1046
field LS - computer LS (0.7 & 0.5) with quadratic adjustment	0.0783	0.1985	-0.008	0.1641	1.89	0.0718
field LS - computer LS (0.5 & 0.3) with linear adjustment	0.071	0.202	-0.016	0.1583	1.69	0.1061
field LS - computer LS (0.5 & 0.3) with quadratic adjustment	0.075	0.2989	-0.054	0.2043	1.20	0.2415
field LS - computer LS (0.3 & 0.3) with linear adjustment	0.061	0.2152	-0.032	0.1541	1.36	0.1874
field LS - computer LS (0.3 & 0.3) with quadratic adjustment	0.075	0.2996	-0.055	0.2406	1.20	0.2425

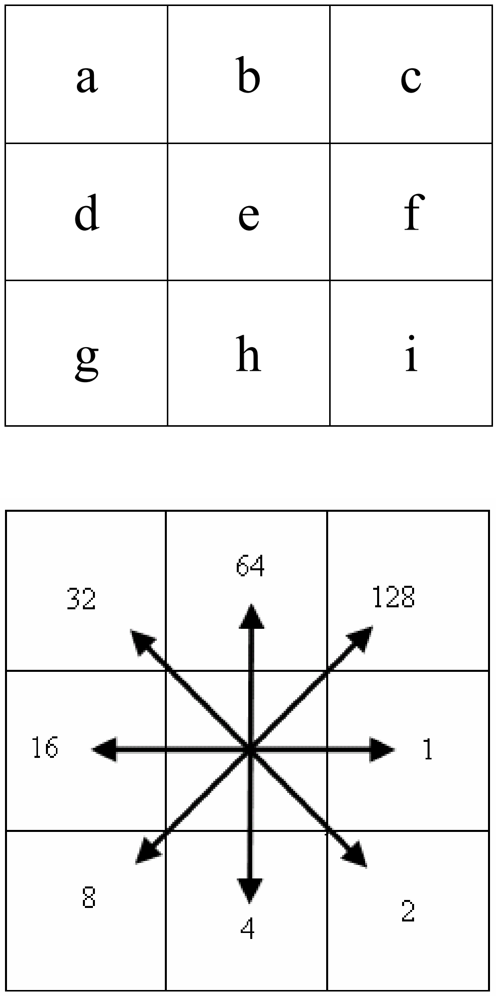


Fig. 3.1: (a). A conceptual 3 x 3 moving window explaining the position of the cells; (b). Scheme of assigning grid value for the flow direction derived in ArcGIS.

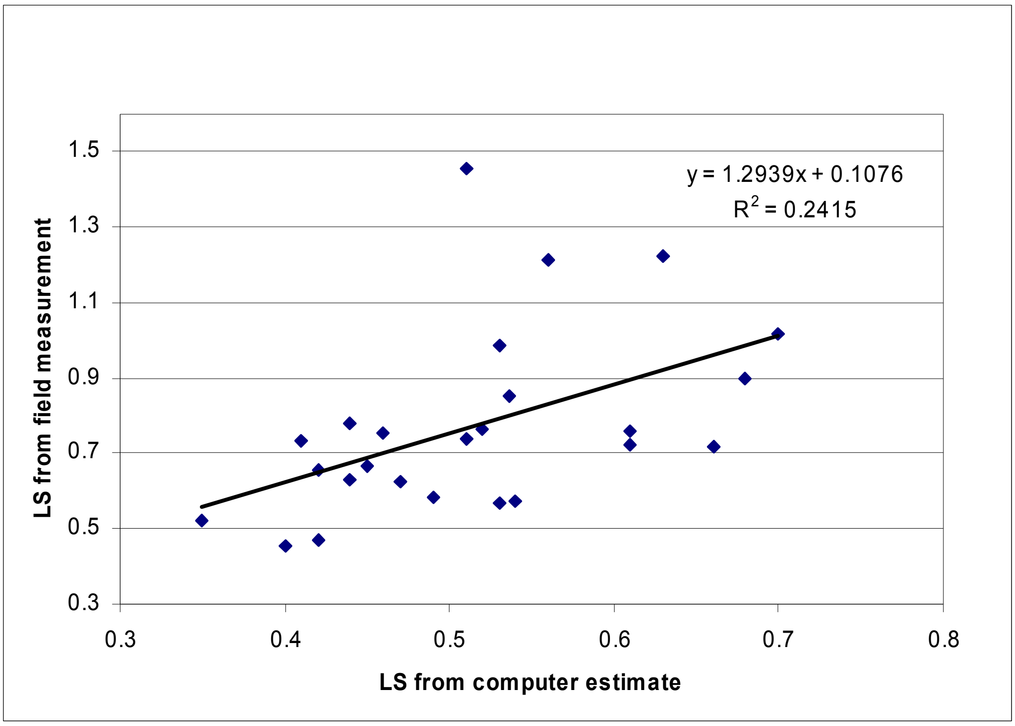


Fig 3.2. Whole average (WF) approach: comparisons of LS values from computer estimates and those calculated from field measurements for test fields: slope cut-off factors of 0.7 for the fields with average slope > 5% and 0.5 for the fields with average slope ≤ 5%

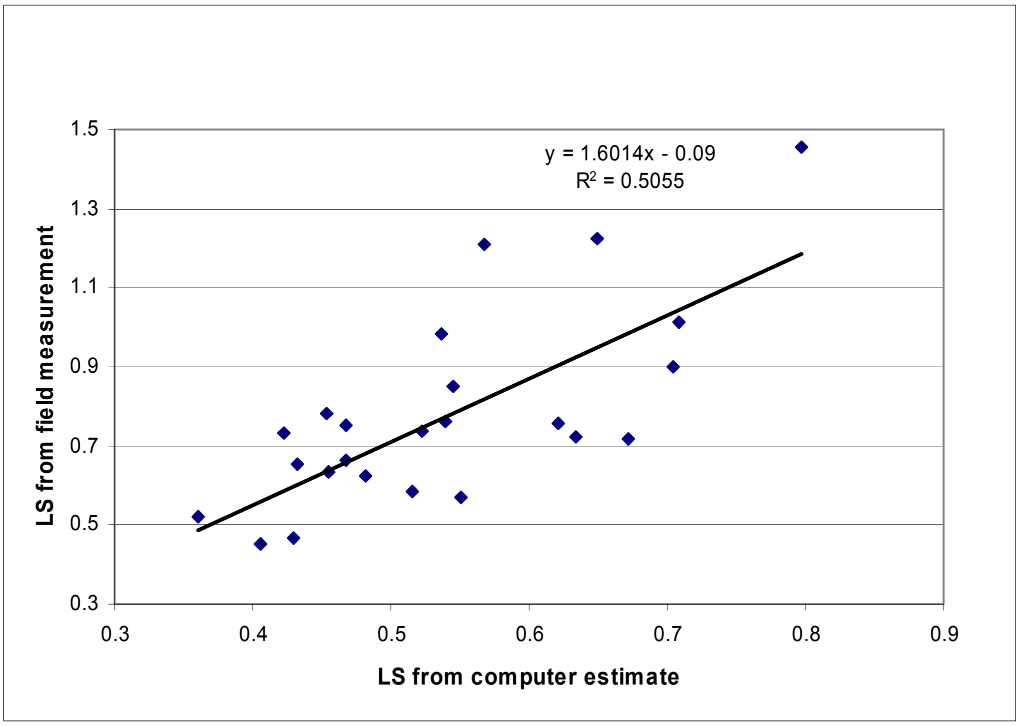


Fig 3.3. Whole average (WF) approach: comparisons of LS values from computer estimates and those calculated from field measurements for test fields: slope cut-off factors of 0.5 for the fields with average slope > 5% and 0.3 for the fields with average slope ≤ 5%

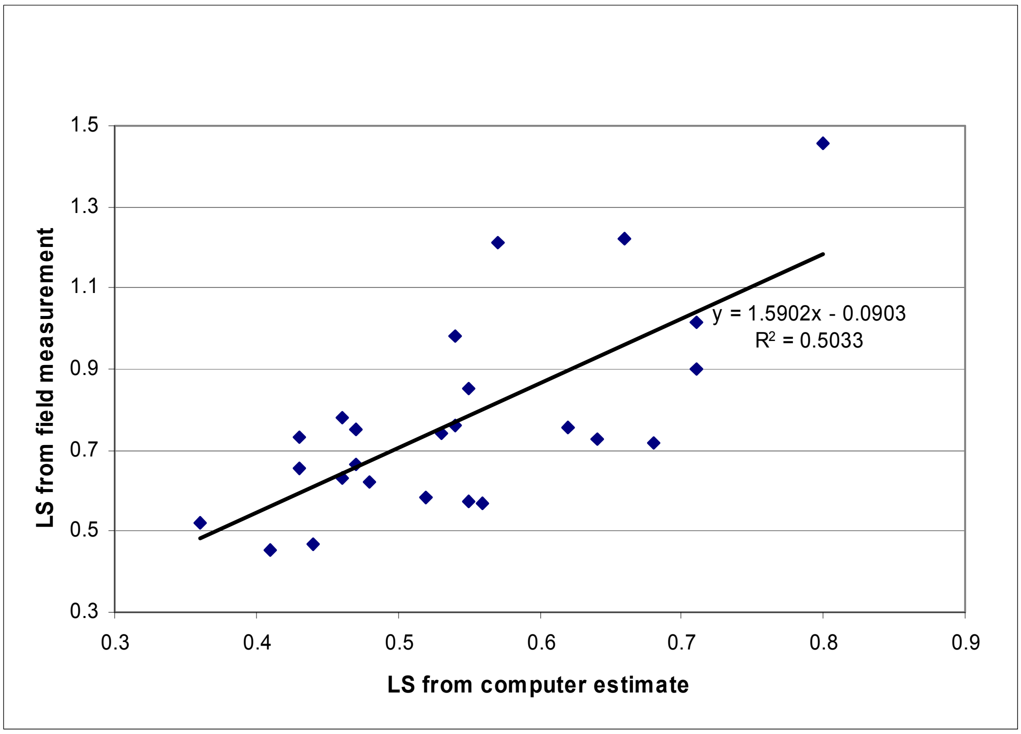
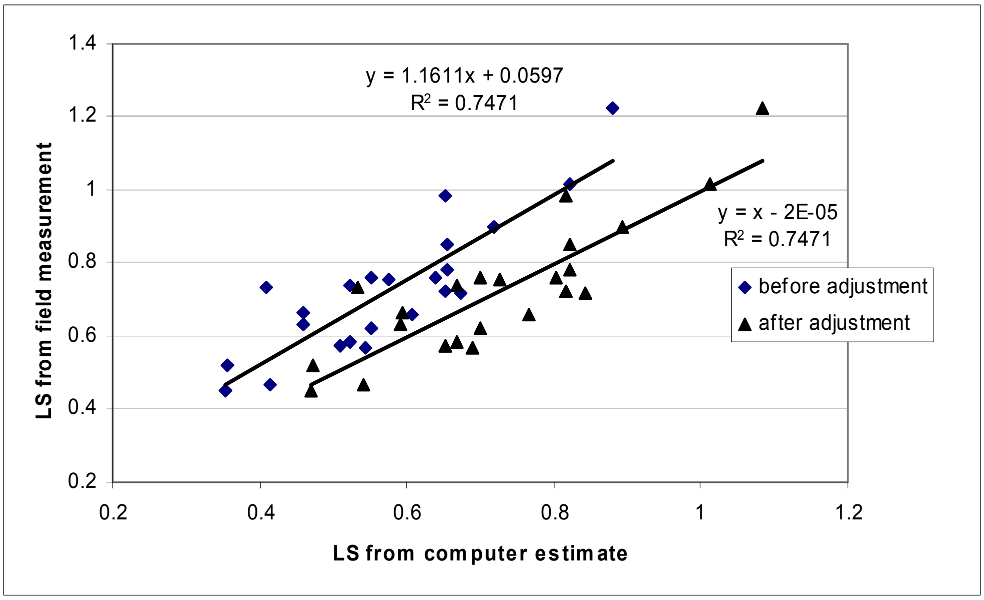


Fig 3.4. Whole average (WF) approach: comparisons of LS values from computer estimates and those calculated from field measurements for test fields: slope cut-off factors of 0.3 for the fields with average slope > 5% and 0.3 for the fields with average slope ≤ 5%



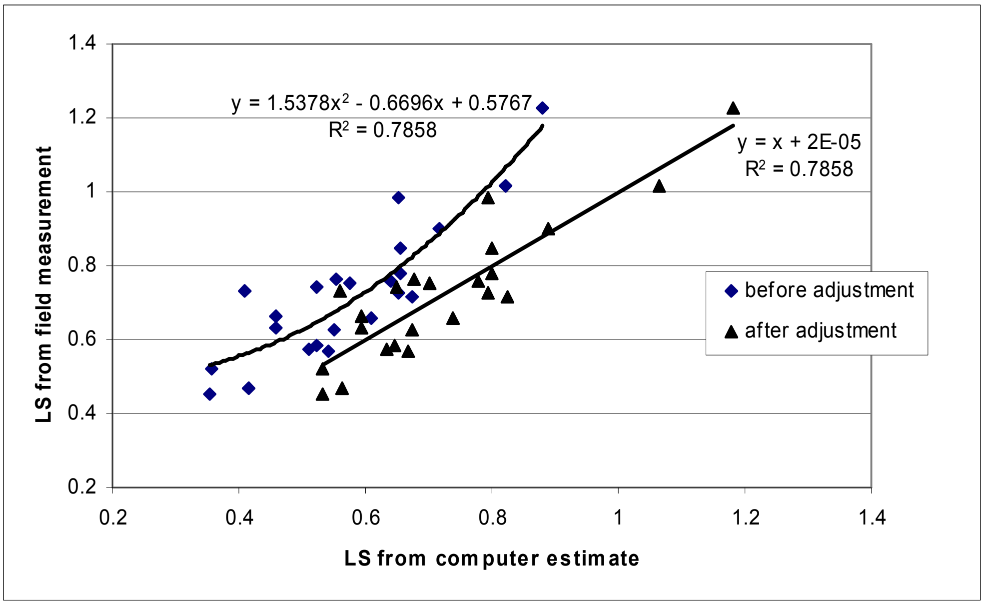
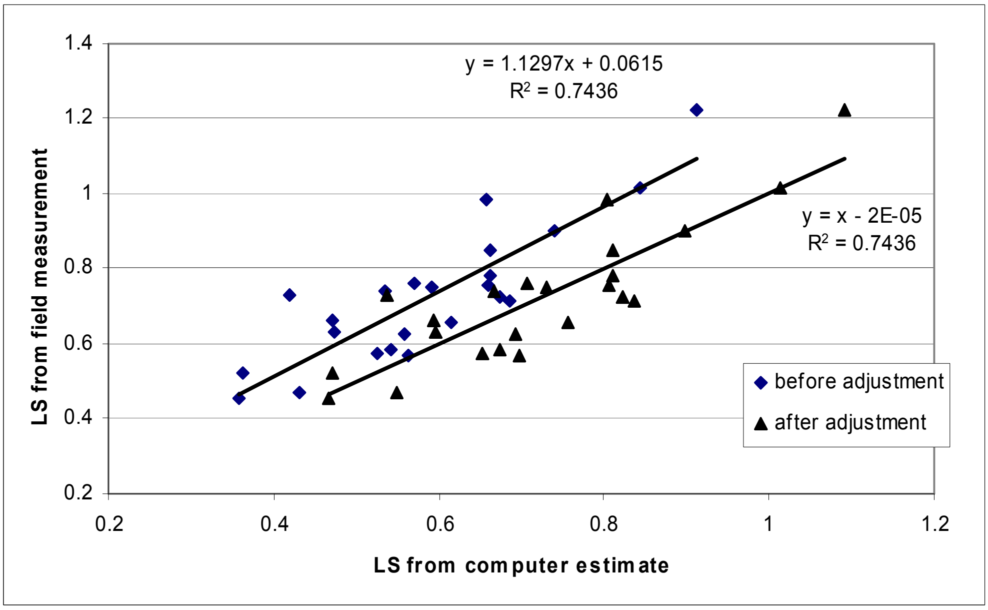


Fig 3.5: Representative profile approach: comparisons of LS values from computer estimates and those calculated from field measurements for test fields before and after adjustment: slope cut-off factors of 0.7 for the fields with average slope > 5% and 0.5 for the fields with average slope ≤ 5%.



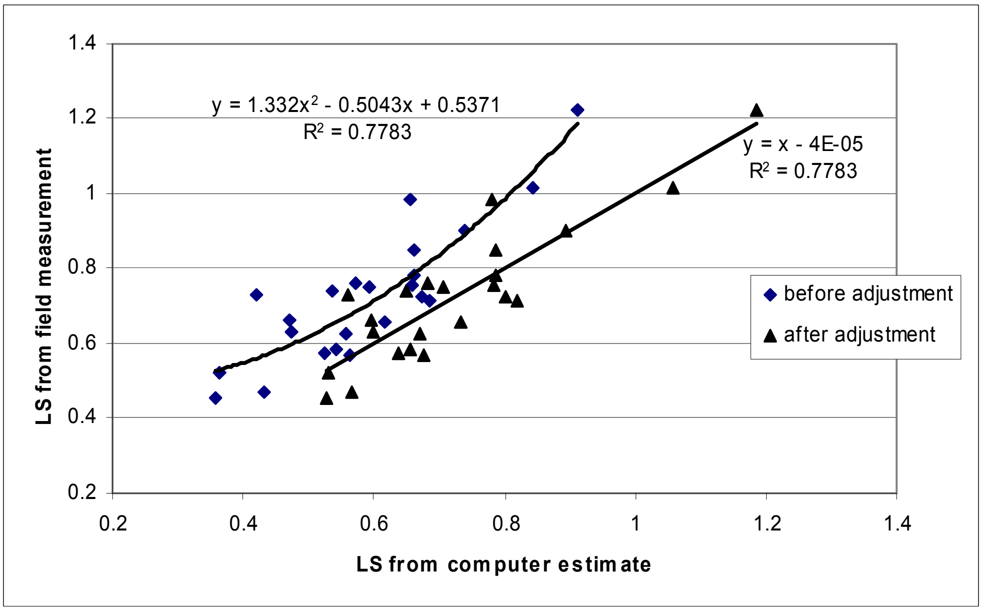
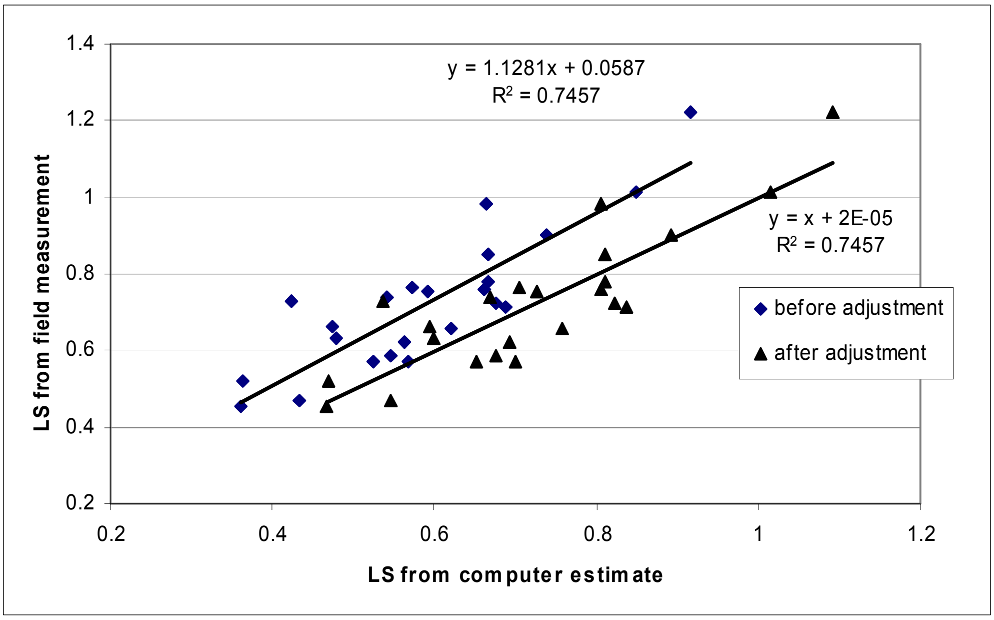


Fig 3.6: Representative profile approach: comparisons of LS values from computer estimates and those calculated from field measurements for test fields before and after adjustment: slope cut-off factors of 0.5 for the fields with average slope > 5% and 0.3 for the fields with average slope ≤ 5%.



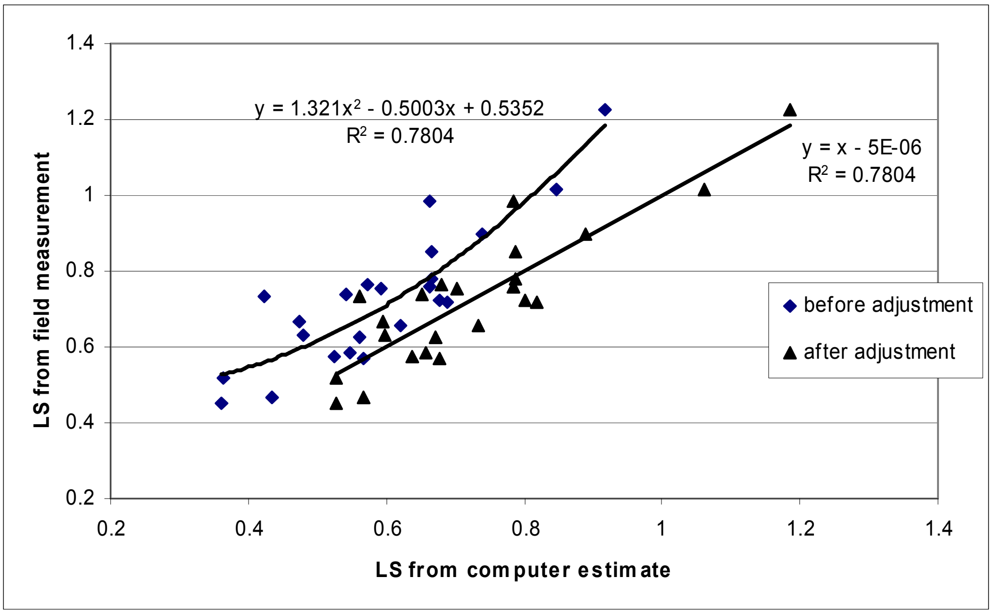
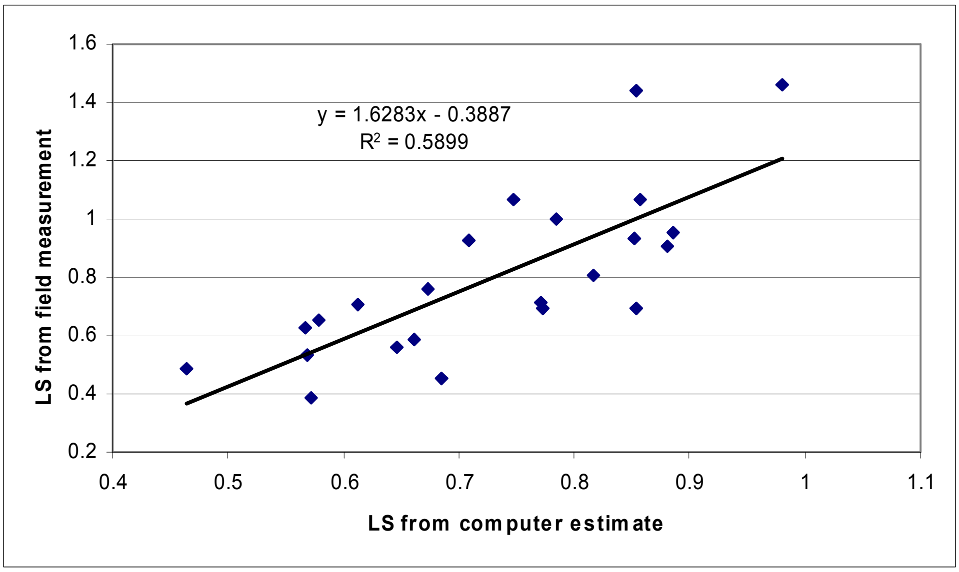


Fig 3.7: Representative profile approach: comparisons of LS values from computer estimates and those calculated from field measurements for test fields before and after adjustment: slope cut-off factors of 0.3 for the fields with average slope > 5% and 0.3 for the fields with average slope ≤ 5%.



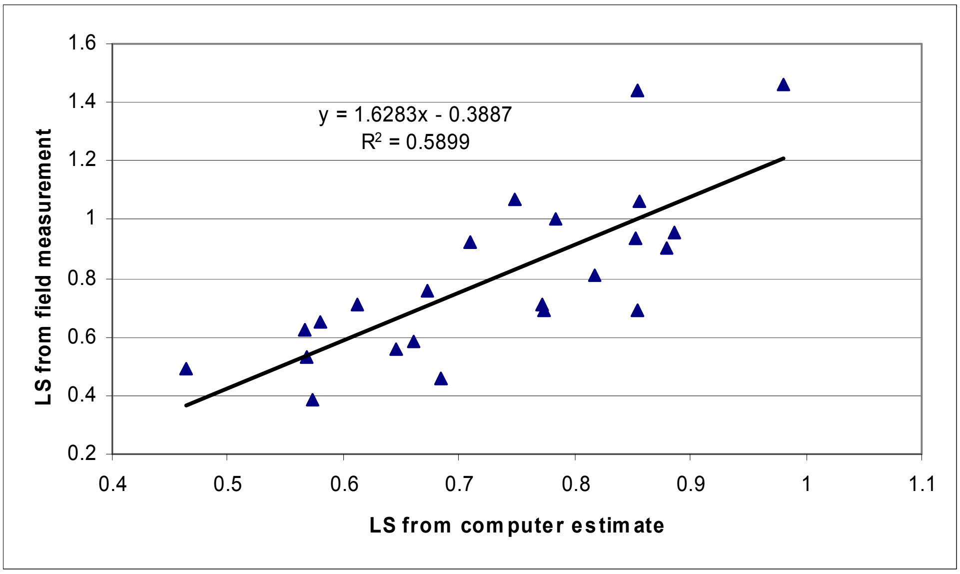
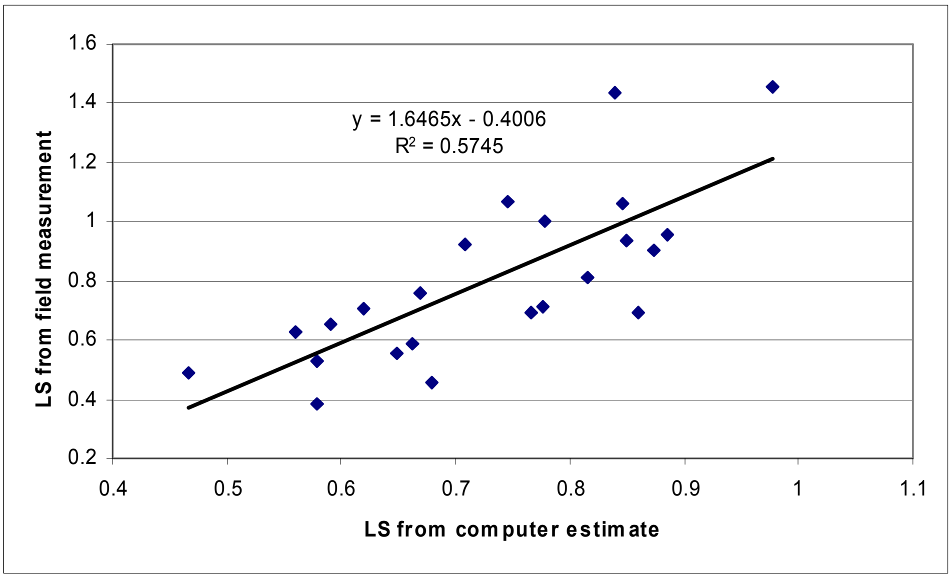


Fig. 3.8: Comparison of LS values calculated from field measurements and those estimated from AML program through representative profile (RP) approach with adjustment factor for validation fields: slope cut-off factors of 0.7 for the fields with average slope > 5% and 0.5 for the fields with average slope ≤ 5%.



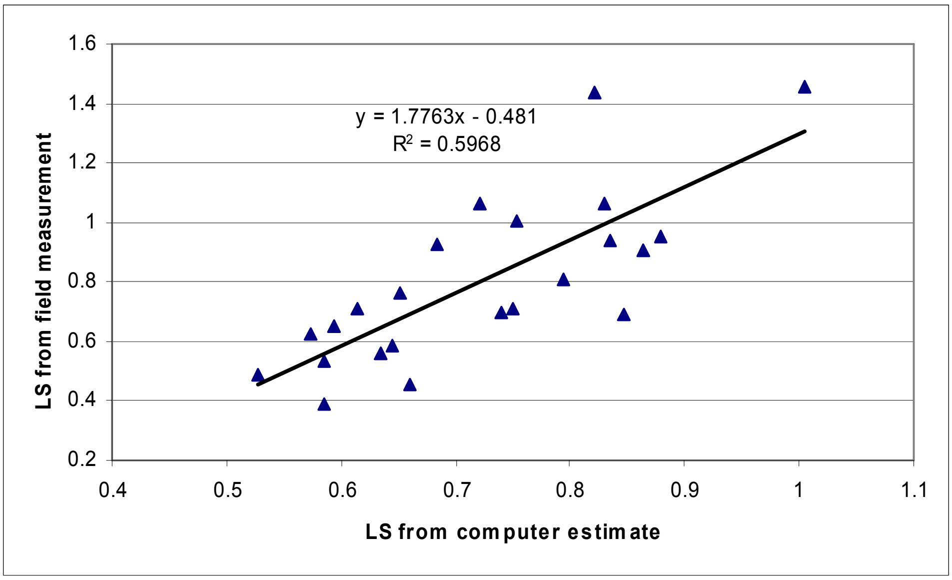
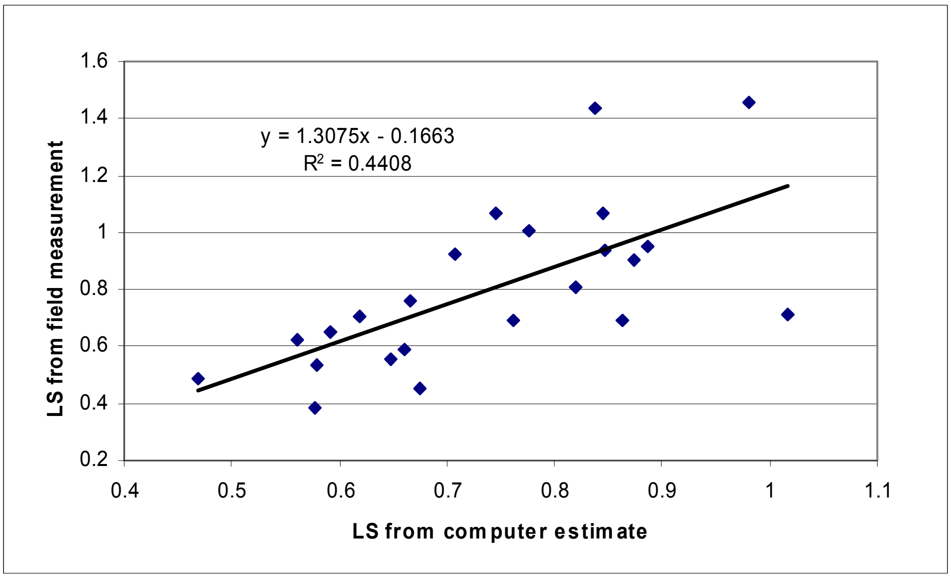


Fig. 3.9: Comparison of LS values calculated from field measurements and those estimated from AML program through representative profile (RP) approach with adjustment factor for validation fields: slope cut-off factors of 0.5 for the fields with average slope > 5% and 0.3 for the fields with average slope ≤ 5%.



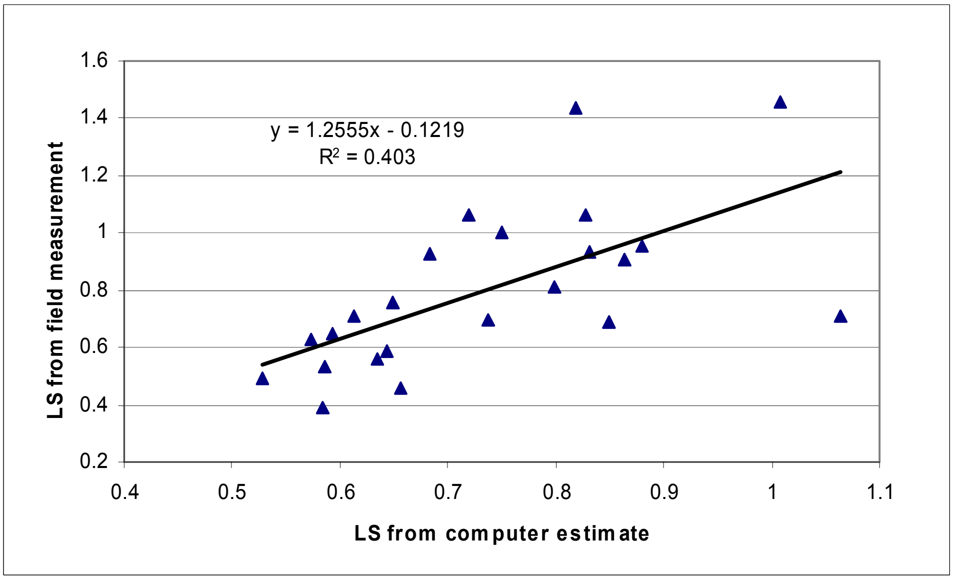


Fig. 3.10: Comparison of LS values calculated from field measurements and those estimated from AML program through representative profile (RP) approach with adjustment factor for validation fields: slope cut-off factors of 0.3 for the fields with average slope > 5% and 0.3 for the fields with average slope ≤ 5%.

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