Laboratory Investigation of Field Cropping Practices Resulting in Macropore Formation and Subsurface Nutrient Loss

Final Report

Submitted to the Corn Marketing Program of Michigan, Michigan Soybean Promotion Committee, and Michigan Wheat Program

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January 2, 2018

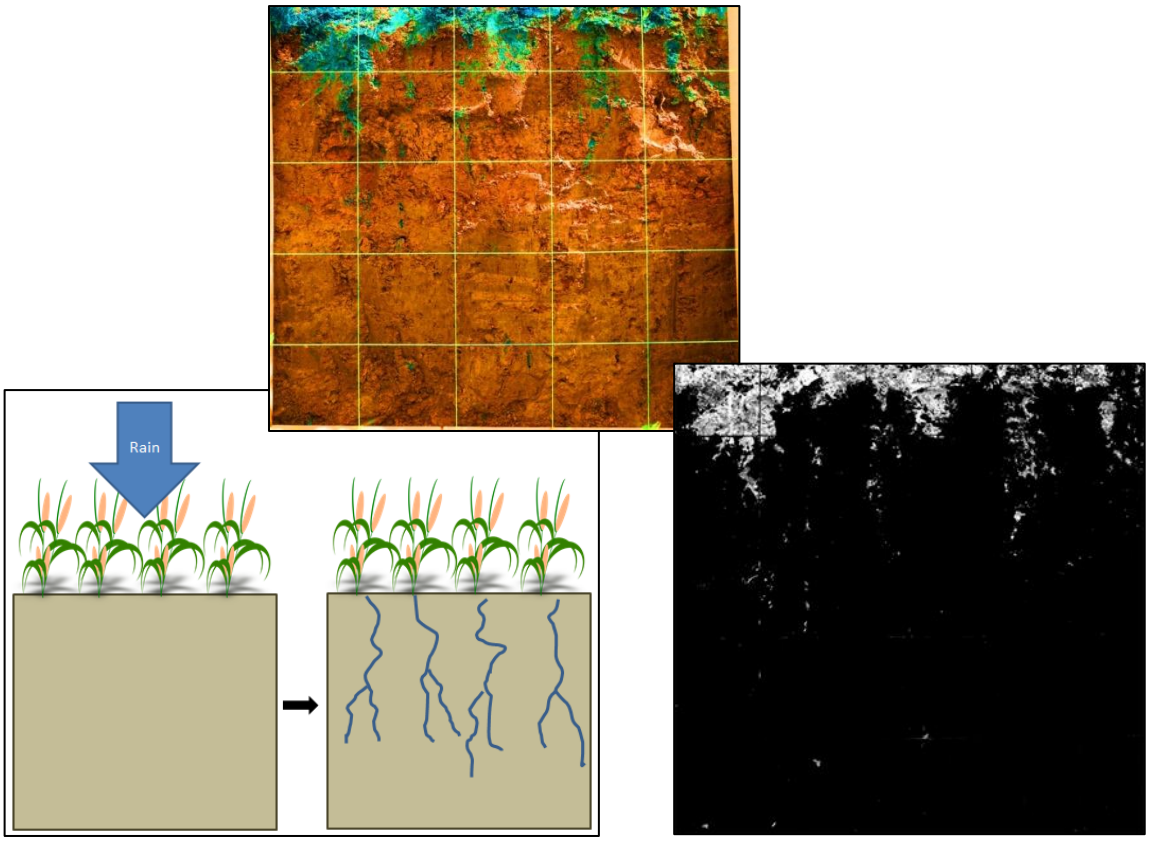


Table of Contents

1 Background & Problem Statement

Farm fields have been named by several studies as contributors to recent high profile surface water impacts caused, in part, by P (P) runoff. As non-point runoff from farm fields has been reduced, the assumption is that P is leaching through the soil, to tile drains, and then to surface water. This has led to discussions on more stringent winter manure management guidelines and limiting nutrient application rates, potentially resulting in lower crop yields. However, the science is not clear and research on a soil's site-specific dynamic phosphorus (P) holding capacity is a necessity to both maximize beneficial plant P uptake and minimize P transport to surface water through tile drains. This research program was designed to qualitatively estimate the dynamic P holding capacity by examining key factors influencing nutrient movement in soil systems and using exiting literature to generate models for common soil features in the state of Michigan.

2 Objectives

The purpose of these studies is to conduct field and laboratory activities to provide growers with information about the P holding capacity of their soil with respect to subsurface P losses. The information gathered is intended to be used in concert with existing best management practice and surface P loss indexes in order to provide producers with as much information as possible for selecting best management practices for their fields. In order to accomplish these objectives, the research team has conducted experimentation to determine the mobility of several different P sources commonly in use, developed and tested methodologies for assessing soil fractures and macropores, and used the information gathered in concert with soil modeling software to determine the relative risk of subsurface P loss for several common soil types using a risk index.

3 Methods

The three primary objectives of this study were investigated using the methods listed below.

3.1 Objective 1: Fertilizer Assessment – Column Studies

In accordance with suggestions made at the 2017 Michigan Corn Growers Association annual meeting, the research team investigated the effect of nutrient sources on the vertical migration of P in laboratory soil columns. Columns were constructed as detailed in Figure 1, and treated at random with one of the following fertilizers; mono-ammonium phosphate, di-ammonium phosphate, dairy manure, swine manure, or no fertilizer (control).

The columns were engineered using native Michigan soils found on MSU's campus. During construction, the columns were packed with soil to a density of 1.3 g/cm^3. The columns were then subjected to 2 simulated rainfall events in order to allow further settling of the soil structure and assure all columns possessed a similar hydrology prior to treatment with fertilizer. After the columns had finished draining, fertilizer was applied at a rate equivalent to 50 lb P/acre. This coincides with a moderate risk according to existing P indices used for crop production in Michigan.

After treatment the columns were subjected to simulated rain events mimicking typical Michigan weather patterns. Water reaching the subsurface drainage outlet has been collected and analyzed for

the presence of nitrogen and P. At the termination of the study, the columns were dis-assembled and the soil analyzed for vertical nutrient migration by taking representative samples at 10 cm intervals. Soil samples were analyzed by MSU Soil and Plant Nutrient Laboratory for Bray 1-P, Ammonia and Nitrate levels.

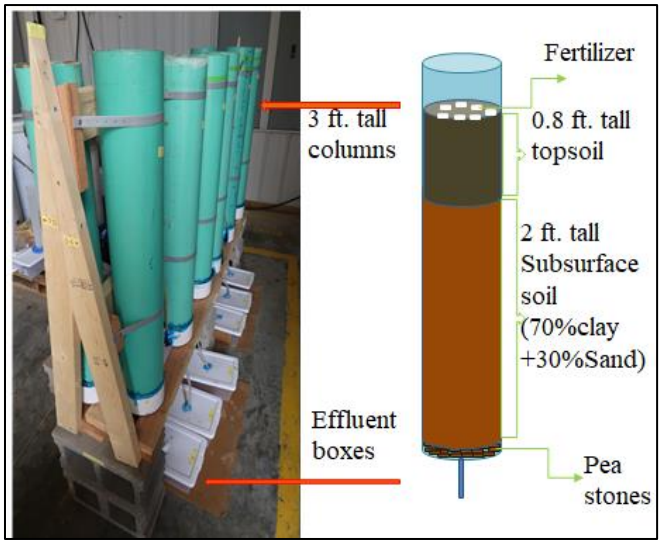


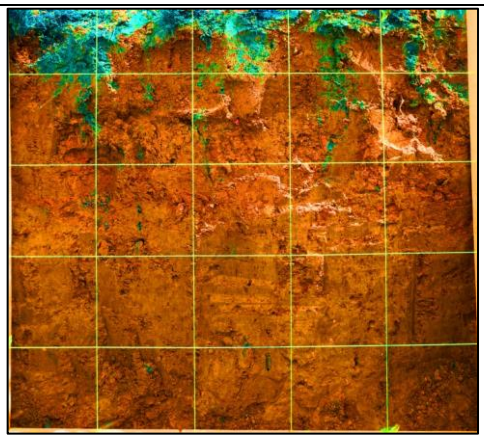
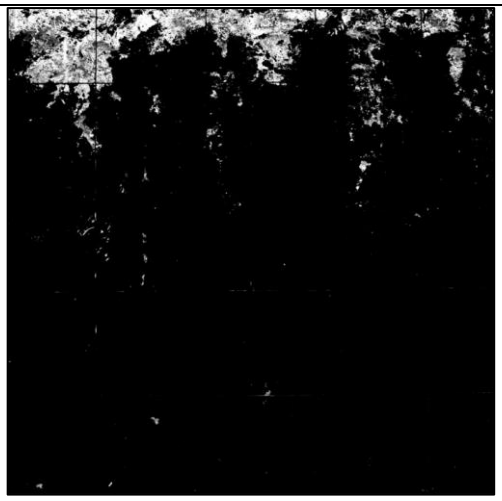
Figure 1: Soil Column Study Design

3.2 Objective 2: Assessment of Soil Fractures/Macropores – Dye Tracer Studies

Concurrently with the column studies, the research team arranged a series of in-field studies of macropore formation. To accomplish this, the researchers are adopted and modified a dye tracer study popularized be Cey & Rudolph[1] Dyes were applied in contained areas to fields that were representative to those across Michigan to investigate the effect of till/no-till practices as well as soil horizons on macropore formation. Sites subjected to dye were excavated and analyzed for depth & bulk density of macropores using MATLAB based imaging technologies. Figure 2 summarizes the protocol.

	Selected 1 m x 1 m field soil plots are treated with 7 mm of blue dye and irrigated overnight.

[1] Cey, Edwin E., and David L. Rudolph. "Field study of macropore flow processes using tension infiltration of a dye tracer in partially saturated soils." *Hydrological Processes* 23.12 (2009): 1768.

	After 12 hours, the test plot was excavated to a depth of 1 m and photographed. The grid seen here is 1 m x 1 m with 10 cm squares. No less than 3 excavations and pictures are performed for each plot.
	Using image processing software, the picture is first de-skewed in accordance with the grid pattern in order to avoid any issues with parallax induced error. Colors are then enhanced in order to optimize visibility of the blue dye.
	Finally, image processing software is again used to remove the gridlines, normalize the pixel ratios in the image (this image is now 1000 pixels by 1000 pixels), and convert all green and blue pixels to white, while all other pixels are converted to black, leaving a black and white image of dye infiltration patterns.

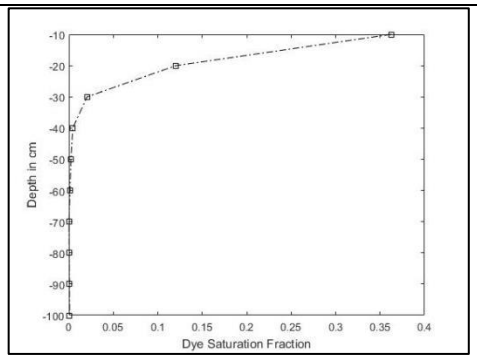
	MATLAB is used to count the white pixels found at various depths in the soil profile, allowing for quantifying what fraction of dye pictured is found at depths of 10 cm intervals.

Figure 2: Qualitative Macropore Field Study

3.3 Objective 3: P loss Risk Assessment for Common Soils - Modeling Activities

The results from the aforementioned studies were used to provide information for a finite difference model (Hydrus 1D) that estimated subsurface nutrient loss under various soil and climactic conditions. Hydrus was selected as the modeling tool due to its unique capability to account for fractures within the soil (macropores). Accounting for flow through macropores when calculating the potential for P loss is critical, as aqueous P closely binds with negatively charged particles when given the opportunity. As such, the ability of a soil to sorb mobile forms of P is largely a function of available binding sites and contact time with those sites. As displayed in Figures 3, matrix flow by definition maximizes contact time and area, while flow through macropores/fractures reduces soil contact time as well as the binding sites to sorb P. When modeling, assuming pure matrix flow could severely underestimate the amount of holding capacity a soil functionally has.

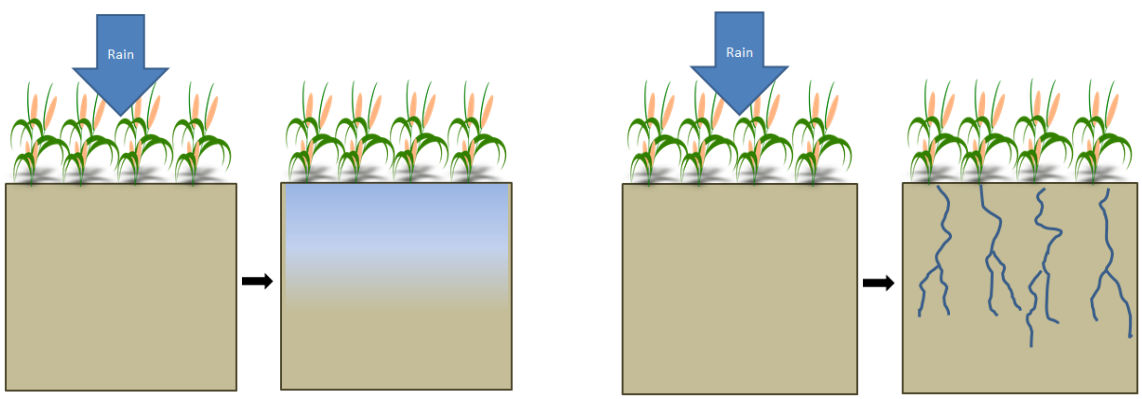


Figure 2: Visualization of Matrix (left) and Macropore Flow (right)

In order to account for this, when modeling subsurface flow Hydrus has a sub-module called dual perm that models water and solute transport as 2 different pools. The first pool is assumed to move according to pure matrix flow, while the second is assumed to move through the fractures. Movement between the matrix and the pores is also allowed (Figure 4). The soil matrix and macropores are each assigned their own hydrologic parameters using the Van Genuchtin equation for water and solute transport and the fraction of soil assigned to each of these conditions (i.e. what fraction of the soil is taken up by macropores).

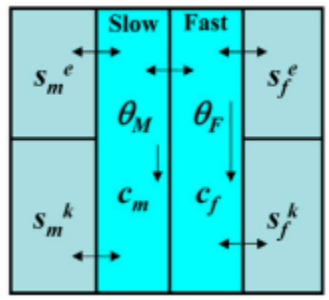


Figure 3: Hydrus Dual-Perm Model Visualization

In an effort to simplify the modeling process and test as many scenarios as possible, it is critical to reduce the number of variables. Based on information obtained in testing the first 2 objectives as well as information gained through literature searches, it has been determined that the primary factors effecting downward movement of mobile P are volume of macropore presence, existing soil P, and soil type. For the purposes of this study, it is assumed that other factors are either negligible in determining risk, or in some way contribute to the determination of the first two parameters. For example, no-till vs. conventional tillage cropping practices are often discussed as contributing factors to subsurface nutrient loss, however, this is only because it is assumed that these practices change the macrporosity of the soil. Thus, this factor is better expressed as the degree of soil macroporosity factor.

Modeling activities were performed in a forward manner, using literature values to determine kinetic parameters for both soil and macropore structures. Models were set to run over a period of 25 days following a simulated rain event to common soil structures. Variables were existing soil P, degree of macroporosity, and soil type. A range of values for each of these variables was selected (Figure 5) and investigated using the HYDRUS 1D model, with cumulative flux of P over the 25 day period being measured as well as the rate of P loss.

Clay		%Porosity of Macropores (w)			
	25-Day P Cum. Flux mg/cm2	1%	5%	10%	20%
Existing Top Soil P	75	?	?	?	?
	100	?	?	?	?
	200	?	?	?	?

Loam		%Porosity of Macropores (w)			
	25-Day P Cum. Flux mg/cm2	1%	5%	10%	20%
Existing Top Soil P	75	?	?	?	?
	100	?	?	?	?
	200	?	?	?	?

Clay Loam		%Porosity of Macropores (w)			
	25-Day P Cum. Flux mg/cm2	1%	5%	10%	20%
Existing Top Soil P	75	?	?	?	?
	100	?	?	?	?
	200	?	?	?	?

Silt Loam		%Porosity of Macropores (w)			
	25-Day P Cum. Flux mg/cm2	1%	5%	10%	20%
Existing Top Soil P	75	?	?	?	?
	100	?	?	?	?
	200	?	?	?	?

Figure 4: Layout of Scenarios Investigated using HYDRUS 1D Soil Model

4 Results

The results from each objective, described in Section 3, are presented below.

4.1 Column Studies

In initial meetings with growers and the commodity groups it was suggested that fertilizer source may partially explain the increases in tile drain P. This is in response to the observations by Dr. Baker (Ohio Lake Erie P Task Force, 2010) that the increase in the Lake Erie watershed of dissolved reactive phosphorus (DRP) temporally coincides with the change-over of farmers using monoammonium phosphate (MAP) to diammonium phosphate (DAP) as a primary P source. Engineered soil columns were used to investigate the difference in vertical P movement both through tile drain and through the soil profile using common fertilizer sources; dairy manure, swine manure, MAP, DAP and triple super phosphate (TS).

4.1.1 Column Soil Comparison

Columns were analyzed for P, nitrate, and ammonia prior to and after the weathering events described in the methods section. Samples were also collected of the effluent to measure P. The results from these tests are summarized in Table 1. For ease of viewing, tables are color coded with red colors denoting higher concentrations and greener colors denoting lower concentrations of nutrients.

Table 1: Final Soil P by Column and Depth (ppm Bray-P)

	Column											
	Dairy		Swine		MAP		DAP		TS		Blank	
	A	B	A	B	A	B	A	B	A	B	A	B
0-10 cm	145	140	132	136	136	140	132	145	136	132	94	117
10-20 cm	145	124	73	124	132	91	97	94	86	80	70	100
20-30 cm	97	75	14	12	11	10	9	9	4	10	10	9
30-40 cm	18	12	8	10	5	9	8	8	4	11	8	10
40-50 cm	10	11	9	11	6	10	9	7	5	9	11	12
50-60 cm	9	11	11	13	5	8	9	9	5	9	11	12
60-70 cm	10	11	10	10	6	6	7	6	4	10	10	9
70-80 cm	10	11	10	9	6	9	10	6	5	9	9	9
Total	443	393	265	323	305	281	278	283	247	268	222	276

No statistically significant difference was found between any of the mineral fertilizers with regard to P mobilization in the soil columns at any given depth interval. Amongst organic fertilizer sources, swine manure was also statistically similar to mineral sources, while dairy manure retained a significant amount of P at the 20-30 cm soil depth relative to all other samples. This is likely due to the increased presence of organically bound P in the dairy manure relative to other sources.

Nitrogen levels for each column were also tested as ammonia and nitrate (Tables 2 and 3, respectively).

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Table 2: Final Soil Ammonia by Column and Depth (ppm NH_4-N)

	Column											
	Dairy		Swine		MAP		DAP		TS		Blank	
	A	B	A	B	A	B	A	B	A	B	A	B
0-10 cm	1.4	2.0	1.9	1.9	1.2	1.2	0.2	1.2	1.2	0.0	0.6	0.5
10-20 cm	1.6	1.5	2.5	1.6	1.3	1.6	1.2	1.4	1.8	1.0	0.9	0.3
20-30 cm	1.4	1.5	4.4	1.9	1.4	1.1	2.1	2.1	1.9	3.4	2.6	0.2
30-40 cm	1.7	3.0	3.2	2.2	4.5	1.4	1.4	4.8	0.8	3.9	3.3	2.7
40-50 cm	4.3	3.9	2.7	1.8	1.1	0.1	0.8	2.9	0.0	4.4	3.8	3.5
50-60 cm	5.2	5.2	1.9	1.8	0.5	0.5	1.3	2.8	0.2	4.2	4.6	4.2
60-70 cm	5.0	3.9	1.7	0.8	0.1	0.3	0.6	1.0	0.1	4.4	3.3	4.2
70-80 cm	3.4	2.0	2.0	1.9	0.6	0.6	0.7	0.8	0.4	3.6	3.5	4.2
Total	24	23	20	14	11	7	8	17	6	25	23	20

Table 3: Soil Nitrate by Column and Depth (ppm NO_3-N)

	Column											
	Dairy		Swine		MAP		DAP		TS		Blank	
	A	B	A	B	A	B	A	B	A	B	A	B
0-10 cm	21.4	17.0	9.1	13.3	7.8	9.0	9.9	13.0	8.4	6.6	6.4	7.7
10-20 cm	19.6	3.3	1.8	2.0	2.0	2.3	1.3	1.9	1.6	1.6	1.6	2.9
20-30 cm	1.8	1.7	2.7	1.2	0.6	1.5	1.0	0.7	1.0	0.3	0.6	1.5
30-40 cm	1.6	1.6	2.5	4.9	0.2	0.7	1.2	0.6	2.0	0.4	0.3	0.8
40-50 cm	0.6	0.7	2.6	4.5	1.4	2.5	1.0	0.3	3.1	0.3	0.3	0.4
50-60 cm	0.4	0.5	2.4	5.0	2.4	2.6	2.9	2.0	2.7	0.2	0.4	0.4
60-70 cm	0.4	1.1	2.0	3.0	3.8	2.9	2.9	3.1	2.2	0.2	0.2	0.1
70-80 cm	1.9	2.0	0.8	1.1	4.2	2.2	1.2	1.7	2.0	0.2	0.2	0.2
Total	48	28	24	35	22	24	21	23	23	10	10	14

As anticipated, surface levels of ammonia were similar across all the treated columns through the aerobic nitrification process, while nitrate levels track closely with applied levels of total nitrogen across all fertilizer types. Interestingly, some columns experienced pockets of anaerobic conditions, marked by build-ups in ammonia and low levels of nitrate, particularly columns TS-A and Blank A & B. This was a function of drain clogging, as discussed below. In short, the soil nitrogen levels show variation in subsurface nitrogen concentration only due to drain clogging.

4.1.2 Drain Effluent

Figure 6 shows the cumulative releases of P collected from the drains of the soil columns. For ease of viewing, each pair of column results has been averaged before plotting. Because drain clogging was noted by the researchers, to reduce sources of variability only data is presented through day 50 of the trial, which is the point at which there was still no significant clogging.

The first thing to note is that there appear to be no spikes in discharge during the first few days when the initial rainfall treatments were added to the columns. This is consistent with a soil that is largely experiencing matrix and not macropore flow. This is expected, as the columns were artificially constructed and natural macropores did not have the chance to form. It is also worth noting that under these matrix flow conditions, the organic fertilizers appear to have reduced the risk of P release relative to soil that was left untreated with any fertilizer. The cumulative amount lost was similar until day 35 of

the test where a rain event of 4 cm was applied to the soil columns. This suggests that the manures may have dampened the effect of flash rain events. A statistical analysis of the data suggests that there is a statistically significant difference in cumulative losses between columns receiving organic fertilizers and columns receiving mineral fertilizers.

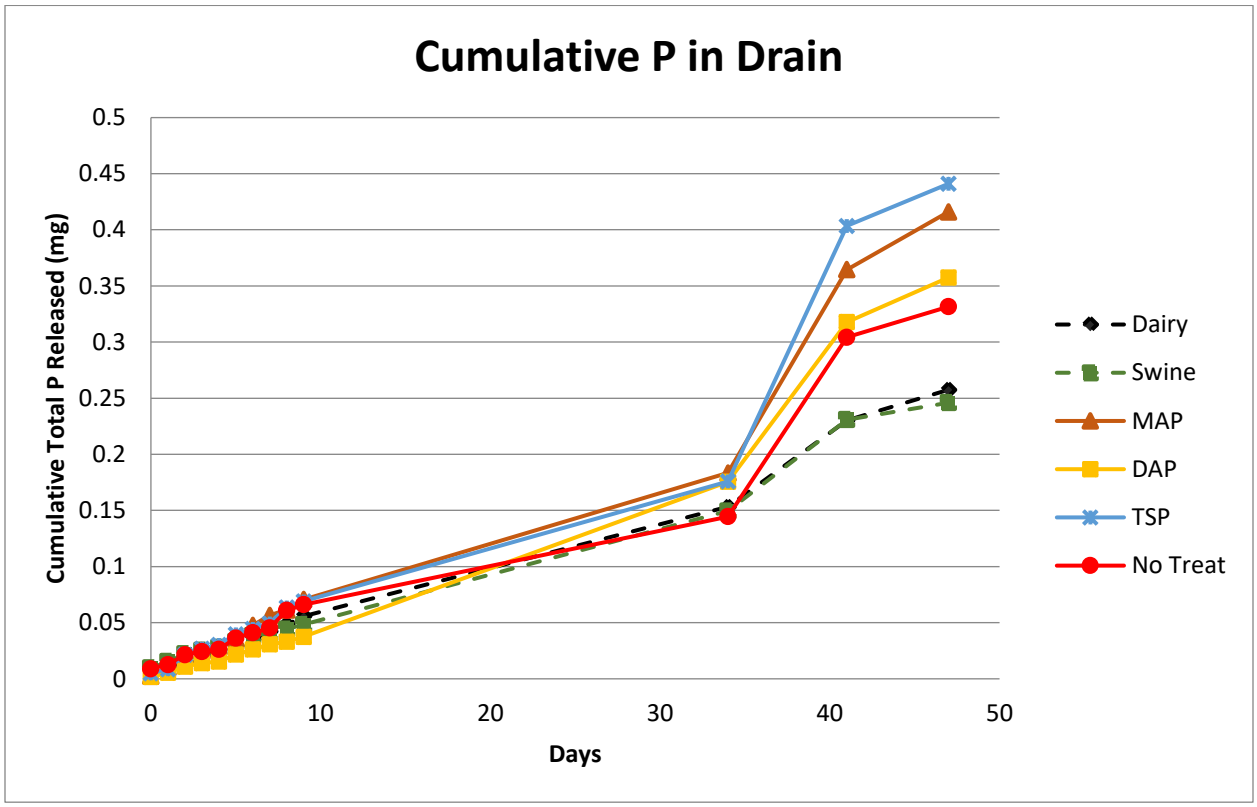


Figure 5: Cumulative P in Drain

4.1.3 Discussion of column study results

The original hypothesis of this work, which was that switching from MAP to DAP and TSP may be a contributing factor to subsurface P loss, is not supported by this study. Mineral fertilizers were statistically similar in both the degree of soil P retention and sub-surface P loss through simulated tile drains. However, it should be noted that there was a difference between organic fertilizers and mineral fertilizers with respect to the expected P in the tile drain. Dairy manure showed significant amounts of additional retention within the soil column, which is attributed to the amount of organically bound P that is present in the animal manure being less mobile than mineral P.

4.2 Dye Tracer Studies

Prior to discussing quantitative results, it can be instructive to identify known flow structures that can be observed within the soil matrix. Figure 7 shows a number of commonly understood forms of preferential flow that can be observed in 2 dimensions.

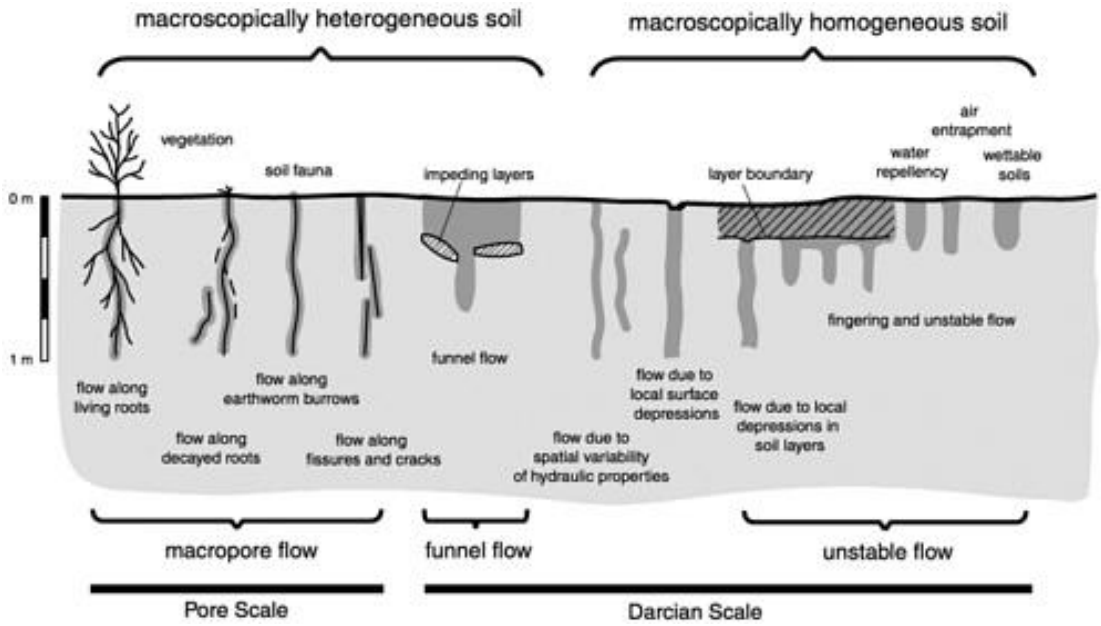


Figure 6: Common Methods of Preferential Flow Observed in 2 Dimensions[2]

Dye tracer experimentation was performed at 5 sites across the state of Michigan that varied in management practices and soil structure. A summary of key site properties is shown in Table 2. Sites investigated were on harvested wheat ground, and testing was conducted between the dates of July 1 and August 15 of 2017. Each image was processed as outlined in Figure 2.

Table 2: Dye Tracer Study Site Comparison

	Site Properties				
Site #	1	2	3	4	5
Till or No-Till	No-Till	No-Till	No-Till	Till	Till
Predominate Soil Type	Clay-Loam	Clay-Loam	Loam	Heavy Clay	Organic

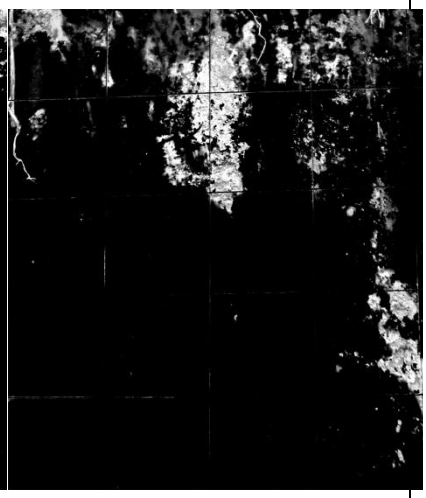
4.2.1 Visual Observation:

Table 3 presents a representative image (1 of 6) for each site that was studied. A complete set of processed images can be found in appendix A. Sites 1-3 all demonstrated classic signs of root and

[2] Hendrickx, Jan MH, and Markus Flury. "Uniform and preferential flow mechanisms in the vadose zone." *Conceptual models of flow and transport in the fractured vadose zone*(2001): 149-187.

earthworm style macropores that were well connected to the surface, allowing for easy infiltration and dye transport. In sites 1 & 2 there was also a degree of matrix flow in the first 10 cm of topsoil, though there appear to be funneling areas in this regard as well that may have formed due to more densely packed soils created in the absence of tillage. Qualitatively, it seems that assuming matrix flow in no-till soils is a poor assumption, regardless of soil type.

Table 3: Representative Images from 5 Sites for Qualitative Visual Observation

Site 1	Site 2	Site 3
		
Site 4	Site 5	
		

Sites 4 & 5 were both part of a conventional tillage regime though they differed in soil type. Site 4 was on a tiled heavy clay soil while site 5 was on a naturally well drained organic soil. While site 5 lacks the traditional look of protruding macropores, it should be noted that there is little or no visible matrix flow occurring. The “snowy” appearance here indicates that the water is following a series of fractures, while the lack of any discernable vertical pattern indicates that these fractures are highly tortuous and water

infiltration terminated after about 50 cm of depth in 12 hours. Site 5, on the other hand, experienced almost complete matrix flow with water being absorbed in the first 10-20 cm of soil depth in the first 12 hours.

4.2.2 Computer Program Quantification

A computer program in MATLAB was designed to quantify the presence of dye in different regions of the soil profile by automatically counting white pixels found at every 10 cm for each soil profile. The average pixel count for each site is shown in Table 4.

Table 4: Number of White Pixels Counted by Computer Program. Averages for Each Site.

	Site Properties				
Site #	1	2	3	4	5
Till or No-Till	No-Till	No-Till	No-Till	Till	Till
Predominate Soil Type	Clay-Loam	Clay-Loam	Loam	Heavy Clay	Organic
Depth	Dye Distribution				
0-10cm	40,998	58,317	24,829	12,504	33,169
10-20cm	9,880	28,659	12,642	4,471	5,093
20-30cm	1,646	5,403	8,553	1,950	264
30-40cm	511	2,343	3,679	1,376	36
40-50cm	232	770	871	992	4
50-60cm	58	486	780	458	-
60-70cm	27	567	780	373	-
70-80cm	12	439	982	95	-
80-90cm	15	413	485	57	-
90-100cm	16	284	116	4	-

This method found no statistically significant differences at an α of 0.05 between till vs. no till observations, thought it did find that dye distribution of the organic soil was significantly different than other soil systems below 50 cm as no dye was found below this level for any investigated sample. The lack of statistical differentiation is, in part, due to the site to site variability in dye infiltration generally and high degree of variability even amongst samples in the same subplot (see appendix A). It is possible that with more samples, we would begin to see statistical significance.

In an effort to reduce one of these sources of variability, the researchers also looked for patterns in dye distribution. This was accomplished by calculating (on average) what percentage of total dye was found at each investigated level of the soil profile (Table 5). Again, no statistical difference was found between the till and no-till conditions, but it was found that the organic soil was significantly different than the others in that the distribution of dye found was predominately in the top 0-20 cm of the soil profile.

Table 5: Percentage of total volume area dye is found in. Averages for each site sorted by depth of observation.

	Site Properties				
Site #	1	2	3	4	5
Till or No-Till	No-Till	No-Till	No-Till	Till	Till
Predominate Soil Type	Clay-Loam	Clay-Loam	Loam	Heavy Clay	Organic
Depth	Dye Distribution				
0-10cm	78%	62%	60%	56%	92%
10-20cm	18%	28%	21%	21%	8%
20-30cm	3%	5%	9%	9%	0%
30-40cm	1%	2%	5%	5%	0%
40-50cm	0%	1%	1%	4%	0%
50-60cm	0%	0%	1%	3%	0%
60-70cm	0%	0%	1%	2%	0%
70-80cm	0%	0%	1%	0%	0%
80-90cm	0%	0%	1%	0%	0%
90-100cm	0%	0%	0%	0%	0%

4.2.3 Continuing Work and Next Steps

The need for more robust computer programming in order to obtain the desired quantitative results for site differentiation is apparent. Visual observation can site macropores and determine their length. Therefore, as an educational tool and as a tool for professionals to determine and differentiate soil health, this method has significant value. However, efforts to quantify these observations using pixel counting appear to be inadequate to describe the nature of the issue. As such, future work will consider using more advanced visual imaging techniques to characterize the macropores formed by using more advanced image recognition techniques capable of shape recognition in order to identify, count, and quantify the structures identified in the manual visual analysis. It is also highly likely that the existing technique and the new efforts described above, would benefit from additional samples in order to improve overall statistical significance of the findings.

4.3 Modeling Activities

In order to generate the final risk analysis for P loss under various soil conditions, the research group applied lessons learned from the field and column studies to 1 dimensional modeling of common field conditions.

4.3.1 Index Setup

Based on the results obtained from the laboratory studies and literature review, the factors effecting vertical P transport have been significantly reduced from the initial list produced for the exploratory phase of the project as presented in the original proposal (Table 6). For instance, the initial hypothesis that there was a significant difference between MAP, DAP, and TS fertilizer forms on nutrient movement was not supported by the evidence generated and therefore will not be considered as a variable in the index. Literature suggests that soil horizons and hydrologic group are less important than soil drainage rates and sportive capacity as expressed by soil type. For the purposes of this study, crop uptake was also not considered, as the primary goal was to gage soil P holding capacity in the period of time prior to crop root development.

Table 6: Theoretical Index Template Presented in Proposal

		Risk level & Coefficient			
Field Feature	Field Factor Coefficient	Very Low (1)	Low (2)	Medium (4)	High (8)
Soil Hydrologic Group	?	A	B	C	D
Soil Test P (lb/ac)	?	<79	80-149	150-300	300+
Nutirent Application Rate (lb/ac)	?	<30	31-60	131-200	200+
Crop uptake rate (lb/ac/yr)	?	?	?	?	?
Soil Horizon Group	?	Alfisols, Inceptisols, Spodosols			
Nutirent Application Method	?	Broadcast, Incorporation, Injection			
Nutrient Form	?	Manure, MAP, DAP, Tripple Super			

Index = $\sum(FieldFactorCoeff * Risk\ Coeff)$

After conducting sensitivity analysis on model parameters and investigating the literature it was determined that the most important parameters to consider in the model were soil type (used to populate the Van Genuchten water flow equation and Langmuir sorption isotherms), macroporosity (used to determine parameters for the dual-permeability portion of the model) and initial water extractible P in the soil matrix at the time of the rain event.

4.3.2 Modeling Results for Common Soils

Soil effluent was modeled in a series of 1 dimensional model runs for 4 common soil types; clay, clay loam, loam, and silt loam. Each had variable soil macroporosity (1%, 5%, 10% and 20%, respectively) and variable water soluble P levels (75, 100, and 200 ppm, respectively). It was assumed that the exiting P was distributed evenly in the first 20 cm of the soil, while the simulations tested how well each soil

retained this P by measuring the cumulative flux of nutrients exiting the bottom (100 cm) of a freely draining soil profile 25 days after a 5 cm rain event (Figure 8).

Clay		%Porosity of Macropores (w)			
	25-Day P Cum. Flux mg/cm2	1%	5%	10%	20%
Existing	75	16	31	41	59
Top Soil	100	21	41	55	79
P	200	43	83	109	157

Loam		%Porosity of Macropores (w)			
	25-Day P Cum. Flux mg/cm2	1%	5%	10%	20%
Existing	75	0.31	1.4	5.1	15
Top Soil	100	0.41	1.9	6.8	21
P	200	0.83	3.7	13.9	41

Clay Loam		%Porosity of Macropores (w)			
	25-Day P Cum. Flux mg/cm2	1%	5%	10%	20%
Existing	75	8.2	18	27.5	44
Top Soil	100	11	25.5	38	59
P	200	22.5	51	73	117

Silt Loam		%Porosity of Macropores (w)			
	25-Day P Cum. Flux mg/cm2	1%	5%	10%	20%
Existing	75	0.4	1.1	3.7	14
Top Soil	100	0.53	1.5	4.9	18.7
P	200	1.1	2.9	9.9	37.3

Figure 7: Cumulative bottom flux results for model simulations

Overall the results of this activity were quite surprising. It is commonly known that clay soils under matrix flow conditions have the highest affinity for P, and are thus considered the optimal soil for P retention. However, the result of these modeling activities showed that any semblance of macroporosity negated the advantage of clay soils in P retention and, in fact, showed that clay soils had a very high potential for nutrient flux out of the modeled area. This is attributable to clay's relatively inhibited ability to assimilate water into matrix flow. In this model, most flow was concentrated in the macropores and thus promoted more leaching in those areas than did the soils that could more easily assimilate water into the soil matrix. This mechanical observation is backed up by the dye tracer studies performed in the heavy clay soils (appendix A) which clearly show that relative to other soils, the heavy clay field investigated generated almost no matrix flow, and instead directed all water through fissures in the soil. Even with this explanation, the results are quite startling and bear further investigation via field studies to collaborate these findings.

4.3.3 Regression Analysis

Pursuant to the goals of this study, the results generated using the aforementioned modeling activities were used to perform a linear regression analysis in order to determine the relative risk of P loss from the investigated soil system. Traditional risk indexes use this method to generate the coefficients such as those denoted with question marks in Table 6. To accomplish this, results from the modeling analysis subjected to a simple linear regression analysis. In the regression analysis each investigated variable, macroporosity, soil group (scored 1-4), and soil P, was used in coordination with its resulting effluent level to solve the equation (Equation 1) in order to find the coefficients a, b and c. These coefficients would be similar to those denoted with question marks in Table 6.

$$Risk = a * SoilGroup + b * Macroporosity + c * SoilPhosphorus \quad \text{Equation 1}$$

While parameters were found successfully using this method (Table 7), the Regression analysis of simulation results show that this relationship is poorly predicted using a linear relationship such as those found in traditional indexes. This is seen in the wide variability in the confidence intervals for the coefficients. The r^2 value was also calculated for the regression analysis and was also found to be only 0.45.

Table 7: Parameter Estimation for Index

	Mean	Lower 95% CI	Upper 95% CI
a	8.40	3.10	13.69
b	1.38	0.39	2.38
c	0.01	-0.09	0.12

This does not however mean that this data is useless, only that it cannot be adequately described as a straight line approximation of factors. This means that a more practical route might be to generate look-up tables, decision support trees, or to derive a more complex risk assessment calculations that are non-linear. A look-up table for the Hydrus model derived values has been provided in Table 8. For ease of viewing the table is color coded such that highest values in each column are shown in red, and lowest column values are in green.

4.3.4 Incorporation into existing materials

Several indexes already exist to determine the relative risk of surface P loss based on estimates of runoff loss under numerous surface conditions. The data collected in these projects is meant to be used as a supplemental amendment to such indexes. Fields that are heavily drained and designed to reduce runoff risk may conversely experience an increased risk of subsurface P loss. This tool is designed to help producers recognize how and when such risks may exist and encourage

Table 8: Sorted Modeling Results

Soil Type	Macropore (%)	Soil P (ppm WEP)	Model Output Flux (mg/cm2)
Clay	20	200	157
Clay Loam	20	200	117
Clay	10	200	109
Clay	5	200	83
Clay	20	100	79
Clay Loam	10	200	73
Clay	20	75	59
Clay Loam	20	100	59
Clay	10	100	55
Clay Loam	5	200	51
Clay Loam	20	75	44
Clay	1	200	43
Clay	5	100	41
Clay	10	75	41
Loam	20	200	41
Clay Loam	10	100	38
Silt Loam	20	200	37.3
Clay	5	75	31
Clay Loam	10	75	27.5
Clay Loam	5	100	25.5
Clay Loam	1	200	22.5
Clay	1	100	21
Loam	20	100	21
Silt Loam	20	100	18.7
Clay Loam	5	75	18
Clay	1	75	16
Loam	20	75	15
Silt Loam	20	75	14
Loam	10	200	13.9
Clay Loam	1	100	11
Silt Loam	10	200	9.9
Clay Loam	1	75	8.2
Loam	10	100	6.8
Loam	10	75	5.1
Silt Loam	10	100	4.9
Loam	5	200	3.7
Silt Loam	10	75	3.7
Silt Loam	5	200	2.9
Loam	5	100	1.9
Silt Loam	5	100	1.5
Loam	5	75	1.4
Silt Loam	5	75	1.1
Silt Loam	1	200	1.1
Loam	1	200	0.83
Silt Loam	1	100	0.53
Loam	1	100	0.41
Silt Loam	1	75	0.4
Loam	1	75	0.31

them to take prudent measures to balance the risk of surface losses v. subsurface losses, and not to replace existing surface P indexes.

4.3.5 Limitations of results

The model used in this analysis is highly sensitive to soil hydrologic parameters and is best used when these parameters are entered as the result of direct observation of the site to be analyzed. As these parameters can be highly variable from site to site and even within the field, it is important to remember that the simulations are based on approximations of common soil types, and thus are based upon a number of assumptions. The results found here-in are only estimates based on the assumptions of several key hydrological parameters derived from literature. Better understanding of an individual site can only be obtained through direct observation of soil hydrologic parameters as well as macropore structure.

5 Key Takeaways and Suggested Future Activities

A list of key takeaways from this research follows.

- Soil column studies found that there was no statistically significant difference between soil retention and effluent loss of P between mineral fertilizers (MAP, DAP and TSP) when applied at equal rates of P.
- Soil column studies also found that there was a statistically significant difference between effluent losses after a heavy rain event between organic and mineral fertilizers.
- Qualitative visual analysis of dye tracer studies resulted in a noticeable difference in macropore structure between management techniques (till vs no-till).
- Quantitative analysis techniques used for dye observation was unable to describe the differences between key site attributes at a statistically significant level.
    - However the trends appear to show deeper penetration of dye into the soil profile for no till soils and heavy clay soils.
    - Statistical significance would very likely be improved with additional sampling.
    - Additional and more statistically significant relationships may also be uncovered by using more advanced visual imaging techniques such as shape recognition.
- Modeling activities projected that heavy clay soils were projected to have greater losses of water extractible P relative to lighter soils. This was due to the lack of ability of these soils to incorporate any water into the soil matrix, creating a flushing effect within the fissures. Dye tracer studies backed this mechanism, but field testing should be used to validate the P loss results if possible.
- Linear regression calculations discovered that the relationship between risk and investigated parameters of soil type, macroporosity, and soil P, are not well described using linear relationships traditionally found in risk indexes.

- A look-up table was generated to describe P movement in common soil types as generated using the HYDRUS model that will be used in future investigative activities.
- Soluble phosphorus loss for some site-specific conditions is likely in modern agriculture to produce the high crop yields needed to feed a growing world population. Consequently, technologies to control and recover phosphorus at the edge of field should be examined, including the use of sorptive materials and controlled drainage structures.

Appendix A: Processed Soil Dye Photos:

Table A1: Site 1 Soil Photos

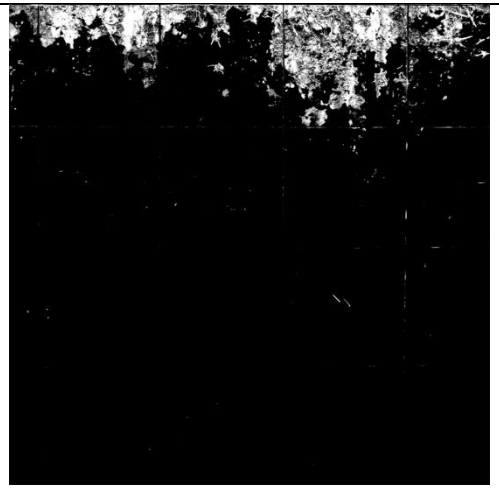
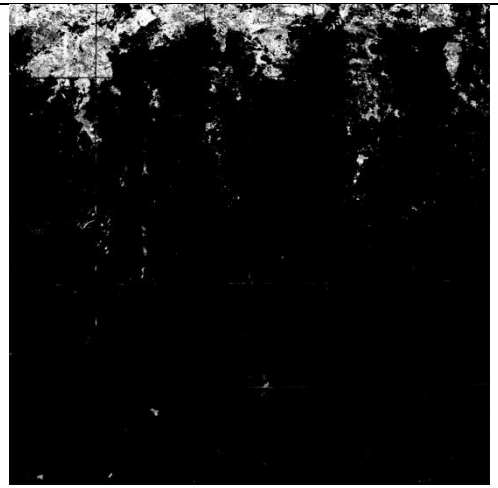
		
		

Table A2: Site 2 Soil Photos

Table A3: Site 3 Soil Photos

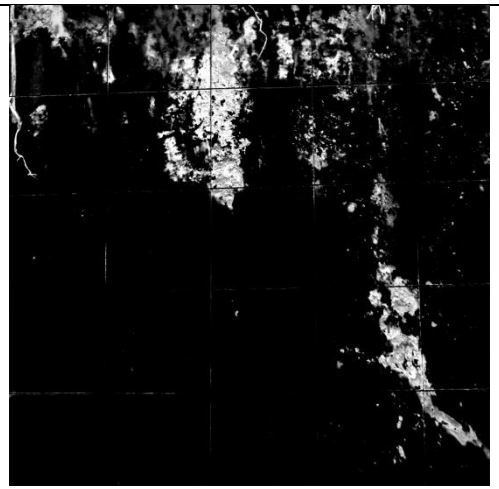
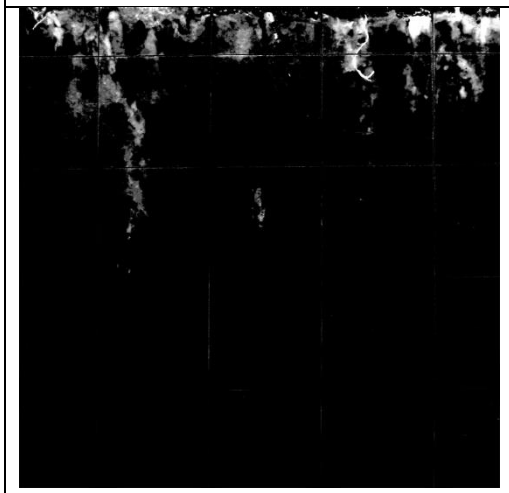
		
		

Table A4: Site 4 Soil Photos

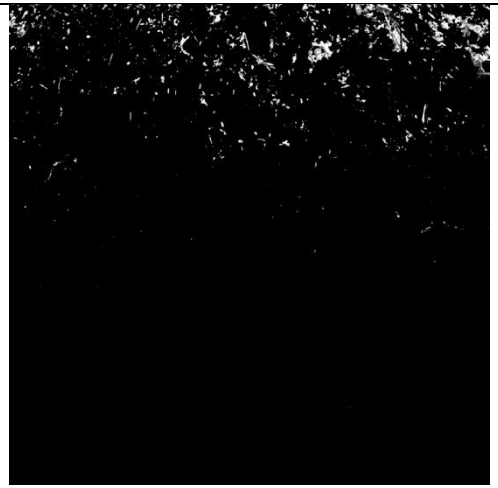
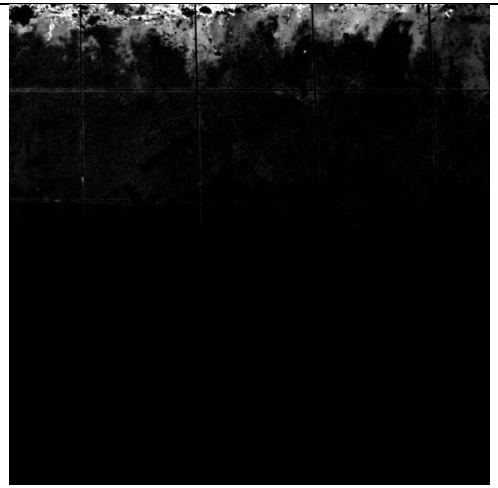
		
		

Table A5: Site 5 Soil Photos

Appendix B: MATLAB Code for Image Processing

```
function [ PercentTot2, FinalAns ] = PixelCounting( img_name )
% PercentTot2 returns the percentage of total pixels that are white at each
% 10 cm interval

% Final Ans Gives total White pixels at each level
%% Formatting
format short
format compact

%% Image Processing
Image = imread(img_name);
BW = im2bw(Image);
%BW1=double(image);

%% Initial conditions
xmax=1000;
ymax=1000;
White_pix_Tot=0;
Black_pix_Tot=0;
White_pix_0to10=0;
Black_pix_0to10=0;
White_pix_10to20=0;
Black_pix_10to20=0;
White_pix_20to30=0;
Black_pix_20to30=0;
White_pix_30to40=0;
Black_pix_30to40=0;
White_pix_40to50=0;
Black_pix_40to50=0;
White_pix_50to60=0;
Black_pix_50to60=0;
White_pix_60to70=0;
Black_pix_60to70=0;
White_pix_70to80=0;
Black_pix_70to80=0;
White_pix_80to90=0;
Black_pix_80to90=0;
White_pix_90to100=0;
Black_pix_90to100=0;

%% Final Array Setup
FinalAns= zeros(12,3);


%% Image Analysis

%% Total Image
for j=1:(xmax)-1
    for i=1:(ymax)-1
        if BW(i,j)==0
```

```
            Black_pix_Tot=Black_pix_Tot+1;
        else
            White_pix_Tot=White_pix_Tot+1;
        end
    end
end
FinalAns(12,2)= Black_pix_Tot;
FinalAns(12,3)= White_pix_Tot;
%% 0 to 10 cm
for j=1:(xmax)-1
    for i=1:(.1*ymax)-1
        if BW(i,j)==0
            Black_pix_0to10=Black_pix_0to10+1;
        else
            White_pix_0to10=White_pix_0to10+1;
        end
    end
end
FinalAns(2,2)= Black_pix_0to10;
FinalAns(2,3)= White_pix_0to10;
%% 10 to 20 cm
for j=1:(xmax)-1
    for i=(.1*ymax):(.2*ymax)-1
        if BW(i,j)==0
            Black_pix_10to20=Black_pix_10to20+1;
        else
            White_pix_10to20=White_pix_10to20+1;
        end
    end
end
FinalAns(3,2)= Black_pix_10to20;
FinalAns(3,3)= White_pix_10to20;
%% 20 to 30 cm
for j=1:(xmax)-1
    for i=(.2*ymax):(.3*ymax)-1
        if BW(i,j)==0
            Black_pix_20to30=Black_pix_20to30+1;
        else
            White_pix_20to30=White_pix_20to30+1;
        end
    end
end
FinalAns(4,2)= Black_pix_20to30;
FinalAns(4,3)= White_pix_20to30;
%% 30 to 40 cm
for j=1:(xmax)-1
    for i=(.3*ymax):(.4*ymax)-1
        if BW(i,j)==0
            Black_pix_30to40=Black_pix_30to40+1;
        else
            White_pix_30to40=White_pix_30to40+1;
        end
    end
end
FinalAns(5,2)= Black_pix_30to40;
FinalAns(5,3)= White_pix_30to40;
%% 40 to 50 cm
```

```
for j=1:(xmax)-1
    for i=(.4*ymax):(.5*ymax)-1
        if BW(i,j)==0
            Black_pix_40to50=Black_pix_40to50+1;
        else
            White_pix_40to50=White_pix_40to50+1;
        end
    end
end
FinalAns(6,2)= Black_pix_40to50;
FinalAns(6,3)= White_pix_40to50;
%% 50 to 60 cm
for j=1:(xmax)-1
    for i=(.5*ymax):(.6*ymax)-1
        if BW(i,j)==0
            Black_pix_50to60=Black_pix_50to60+1;
        else
            White_pix_50to60=White_pix_50to60+1;
        end
    end
end
FinalAns(7,2)= Black_pix_50to60;
FinalAns(7,3)= White_pix_50to60;
%% 60 to 70 cm
for j=1:(xmax)-1
    for i=(.6*ymax):(.7*ymax)-1
        if BW(i,j)==0
            Black_pix_60to70=Black_pix_60to70+1;
        else
            White_pix_60to70=White_pix_60to70+1;
        end
    end
end
FinalAns(8,2)= Black_pix_60to70;
FinalAns(8,3)= White_pix_60to70;
%% 70 to 80 cm
for j=1:(xmax)-1
    for i=(.7*ymax):(.8*ymax)-1
        if BW(i,j)==0
            Black_pix_70to80=Black_pix_70to80+1;
        else
            White_pix_70to80=White_pix_70to80+1;
        end
    end
end
FinalAns(9,2)= Black_pix_70to80;
FinalAns(9,3)= White_pix_70to80;
%% 80 to 90 cm
for j=1:(xmax)-1
    for i=(.8*ymax):(.9*ymax)-1
        if BW(i,j)==0
            Black_pix_80to90=Black_pix_80to90+1;
        else
            White_pix_80to90=White_pix_80to90+1;
        end
    end
end
```

```
FinalAns(10,2)= Black_pix_80to90;
FinalAns(10,3)= White_pix_80to90;
%% 90 to 100 cm
for j=1:(xmax)-1
    for i=(.9*ymax):(ymax)-1
        if BW(i,j)==0
            Black_pix_90to100=Black_pix_90to100+1;
        else
            White_pix_90to100=White_pix_90to100+1;
        end
    end
end
FinalAns(11,2)= Black_pix_90to100;
FinalAns(11,3)= White_pix_90to100;
%% Final Answers

FinalAns2=FinalAns(2:12, 2:3);
PercentSat=FinalAns2(:,2)./(FinalAns2(:,1)+FinalAns2(:,2));
PercentTot=FinalAns2(:,2)./(sum(FinalAns2(:,2))/2);

Depth=-10:-10:-100;
%
% plot(PercentSat(1:end-1), Depth, 'ks-.')
% ylabel 'Depth in cm'
% xlabel 'Dye Saturation Fraction'
%
% figure
% plot(PercentTot(1:end-1), Depth, 'ks-.')
% ylabel 'Depth in cm'
% xlabel 'Dye Saturation Fraction'
%
% hold on

PercentTot2=PercentTot(1:end-1);
FinalAns=FinalAns(2:end-1,3);

end
```