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Farmers and researchers are aware of spatial variation in grain yield within farms or fields. Fertilizer management may be improved if techniques can be developed to identify grain yield variations in wheat fields. Aerial color infrared (CIR) photography was used to identify winter wheat (*Triticum aestivum* L.) canopy biomass variability in the Spring of the growing season. Low yielding areas identified from CIR photography were associated with shallow soil profiles consistent with soil forming factors of the region, and were significantly different from average and high yielding areas. The high yielding areas were located within a few meters of a drainage way, and were not significantly different than the average yielding areas except in one field with a deep soil profile and low variance. Fields with heterogeneous CIR photographs had high variances because of many dissimilar inclusions. CIR photography, although useful to distinguish vegetational differences, requires complex timing,

ground verification, and correction to estimate yield variability. A geographic information system (GIS) was used to overlay photo interpreted biomass and soil map units. The overlay analysis allowed construction of a higher (first) order soil map indicating inclusions. Area calculation of the inclusions and map units using a GIS function combined with estimated yield (no variance estimates or confidence intervals associated with the estimated yield) data suggests fertilizer management with a first order soil map to increase fertilizer efficiency by up to six percent. Future research combining remotely-sensed subsidiary variables correlated with moisture supply capacity estimates from soil survey methods may assess, using relatively new spatially dependent interpolation methods, the local and regional variation in wheat grain yield.

Remote-sensing and Geographic Information System Techniques to Map Spatial Variation of Wheat Grain Yield.

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INTRODUCTION

Cereal farmers are aware that grain yields differ from one area to another within a field or farm. Even though they realize that such variability exists, they commonly apply fertilizer uniformly. The uniform rate means some areas will be over-fertilized and some under-fertilized. Over-fertilizing as well as under-fertilizing, may reduce yields -- especially in dryland regions -- and money spent over-fertilizing is wasted.

No economically feasible methods are currently available to determine different grain yield potential in cereal fields and to map areas for nonuniform fertilizer application.

Recent advances have been made in remote-sensing technology for geologic surveys, military surveillance, and determining crop-yield potential for large regions or entire countries (Myers, 1983). The development of computer-aided geographic analysis and mapping technology has significantly accelerated map production. Stastical design and analysis methods for identifying geologic spatial variability have recently been adapted to soil survey methods. Some of this technology could be adapted to identify, analyze, and map gradients in yield potential in a field or farm. After these areas are delineated, the next step would be to develop technology to apply fertilizers nonuniformly based on need rather than uniformly.

This study was undertaken to (a) evaluate a remote-sensing technique to identify spatial variability of grain yield within a field in the Columbia Plateau region, and (b) map the grain yield variability for fertilizer application on an area (spatial) need basis rather than on a uniform blanket application.

Remote-sensing

By definition remote-sensing is detection, identification, and analysis of objects or features using sensors at remote positions from the objects studied. The distance may range from a few meters to kilometers (Avery and Berlin, 1985). Remote-sensing applications to agriculture involve measuring the elecrtromagnetic spectrum (EMS) as it interacts with crop canopies and soil. The most often sensed portion of the spectrum is visible light (0.4 to 0.7 um), near or reflected- infrared (0.7 to 1.1 um) and thermal or emitted-infrared (8 to 14 um). Sometimes active or passive microwave (0.1 to 1.0 meter wavelength) radiation is used for soil moisture studies (Myers, 1983). Some sensors are photographic, producing a picture (the visible light and reflected infrared) others are analog devices producing an image of the sensed object or features. Advanced sensors record the electromagnetic spectrum in numerical or digital format, later to be converted to image form.

Many factors influence the reflectance of light or other portions of the spectrum from leaves. Some of the more important factors are clorophyll, water content, and internal leaf structure. One of the leading factors contributing to reflectance is the air-cell wall interface.

As energy (EMS) impinges on the leaf, it is reflected, absorbed, or transmitted by the epidermis. The transmitted energy is then scattered primarily by the air-cell wall interfaces of the pallisade parenchyma of the mesophyll. At this point much of the visible light is absorbed by chlorophyll and other plant pigments in the chloroplasts (Knipling, 1970). The plant leaf has low reflection in the visible portion of the spectrum. In the near-infrared portion of the spectrum plants exhibit high reflectance and transmission, with little absorption because of internal leaf scattering (Knipling, 1970).

Opposed to reflected-infrared or near-infrared energy, plants emit energy in the thermal-infrared portion of the spectrum as heat. The heat emitted is a function of plant temperature and is regulated by convection, reflection of incident energy, and transpiration (Myers, 1983).

Remote-sensors primarily record reflected energy from crop canopies instead of individual leaves, although, individual leaves make up the canopy. The canopy variables that influence the reflected energy are leaf angle-leaf geometry, leaf area index (LAI), total biomass, percent ground cover, and background reflection from the soil (Knipling, 1983; Gates, Keegan, Schleter, and Weidner, 1965; Myers and Allen, 1968; Myers, 1983; Daughtry, Bauer, Crecelius, and Hixon, 1980). Of important interest are leaf area index (LAI), total above-ground biomass and soil background reflection-percent soil cover. Other factors are important, and many enviromental interactions influence crop spectral reflectance, but recording data in as near similar conditions as possible helps keep the interactions constant. For example, taking readings at solar noon, on days with similar weather conditions, at the same time of year, will help negate the effects of environmental interactions such as solar angle, or water-vapor absorption of energy.

Leaf area index (LAI), total biomass, and percent ground cover influence reflectance primarily because the more leaves reflecting energy the higher the reflectance. This is particularly the case in the reflected- or near-infrared portion of the spectrum. As near-infrared energy enters the canopy approximately one-half the energy is reflected by the upper leaves, with the remaining near-infrared energy transmitted to lower leaves. The lower leaves, likewise, reflect about one-half the near-infrared energy toward the upper leaves. Depending on leaf area index (LAI), biomass, and percent ground cover, the lower leaves transmit one-half the near-infrared energy to still lower leaves, or to the ground. As the infrared energy reaches the ground, soil conditions determine what percentage is reflected up through the canopy. As the infrared energy is reflected up through the canopy, internal leaf scattering again reflects some energy back to the lower leaves and ground, and transmits some energy back up through the canopy to the sensors. Thus, the higher the total biomass, leaf area index (LAI), and percent soil cover the greater the sum of all possible increments of infrared reflection from a crop canopy. This is known as the infrared-enhancement effect (Knipling, 1970).

Relatively more near-infrared energy than visible light is reflected by canopies with high leaf area index (LAI); and relatively less near-infrared energy than visible light is reflected by canopies with low leaf area index (LAI). Near-infrared reflectance, then, results in more contrast between canopies of high and low biomass or leaf area index (LAI) than visible light reflectance.

Soil properties that influence the reflection of the electromagnetic spectrum (EMS) are primarily related to soil color. The visible and reflected portions of the spectrum are most useful to distinguish differences in color and, therefore, soil properties. Remote-sensing is useful to distinguish soil properties that influence the color of the soil surface, and the soil surface color influences the background, or soil, reflection component of crop canopies (Myers, 1983; Myers and Allen, 1968).

The Munsell color system is used in soil classification and soil surveys as a descriptive color system of hue, value, and chroma. Hue is the dominant spectral color (ie. green, red, or yellow,) and corresponds to the wavelength of the spectrum measured by sensors. Value is the relative brightness and refers to the total amount of light reflected. Chroma is the relative purtiy of the color, ie., the relative shades of a color. (Myers, 1983).

Some of the soil factors that influence color and reflection are moisture content, organic matter content, color of parent material, mineral content, particle size, and texture (Myers, 1983).

Past research estimating leaf area index (LAI) (Ahlrichs and Bauer, 1983; Wiegand, Richardson, and Kanemasu, 1979), above-ground phytomass (biomass) (Asrar, Kanemasu, Jackson, and Pinter, 1985), and dry matter production (Aase and Siddoway, 1981) of wheat by remote-sensing vegetation index methods (digital ratios of reflected red to near-infrared increments of the electromagnetic spectrum) report accuracies (R^2 values) of 0.70 to 0.95. This research reports almost a 1:1 relation for estimated to measured biomass, although some methods (vegetation indices) had higher standard errors than others.

Daughtry, Bauer, Crecelius, and Hixson, (1980) report that crop cultural practices influencing biomass, such as planting date, moisture stress, crop development, and in some instances fertility rate, can be identified by remote-sensing methods. The agronomic factors influencing canopy biomass the most, therefore, causing a greater spectral response, are stage of crop development and moisture stress. High grain yield was also correlated to high canopy biomass.

Asrar, Kanemasu, and Yoshida (1985) made estimates of leaf area index (LAI) from spectral reflectance measurements of red and near-infrared reflectance for wheat at three geographical locations. The actual measured LAI was not significantly different ($p = 0.01$) from an indirect LAI estimate or a regression method for estimating LAI (both estimates for LAI were made from digital vegetation index formulas: the indirect from an absorbed photosynthetically active radiation index, and the regression from a red to infrared ratio). The spectral reflectance measurements were recorded for different combinations of planting dates and irrigation frequencies. Standard errors ranged from 0.2 to 0.78 (units of LAI). The above results were from Phoenix, Az. and Manhattan, Ks. At Obregon, Mexico excessive standard error estimates attributed to experimental variance and high within field variation, caused estimated and measured LAI to be significantly different. Measurements were corrected for background reflection in some cases.

Dozier and Strahler, (1983) reviewed ground investigations supporting remote-sensing data collection. The purpose of the ground investigation is to correlate the remotely-sensed data with actual conditions found on the ground. This is sometimes referred to as ground-verification or ground-truthing. Ground investigations usually fall into four categories: calibration/ correction, interpretation of properties, training, and verification. Calibration/correction is essential to ensure correct data is obtained as well as account for variations because of uncontrollable interactions. For correct interpretation of properties ground investigations ensure that the relation between the reflected data and the property to be estimated are correct. For digital analysis of remotely-sensed data a training area is selected where the ground features are correlated with the digital data. Any interpretation procedure from remotely-sensed data must be verified by actual ground observations, as there are many anomalous interactions that may produce erroneous interpretations. The ground-verification should include examples of the entire range of the interpretation.

Aerial infrared photography was selected for this study to identify canopy biomass variation. Daughtry, Bauer, Crecelius, and Hixson (1980) report that high grain yield was also correlated to high canopy biomass. The subjective photo interpretation of the infrared photography used in this study may not be as accurate as the digital vegetation index used by Daughtry, Bauer, Crecelius, and Hixson (1980).

Color infrard photography measures both, the amount of infrared energy (0.7 - 1.1um), and the green and red visible light (0.5 - 0.7) reflected by a crop canopy (for photographic infrared review, see Lillisand and Kiefer, 1979). In general, areas of a crop canopy reflecting higher amounts of infrared energy have larger leaf area index (LAI), the canopy architecture is more erect, and the canopy has greater biomass. Of course, many interactions may contribute to anomalies. Reviews of canopy infrared reflectance are provided by Knipling (1983); Gates, Keegan, Schleter, and Weidner (1965); Myers and Allen (1968); and Myers (1983).

Infrared sensitive color photographic film records reflected infrared energy at the red sensitive dye layer. In final prints (there are many uncontrollable processing and printing variables) bright red areas are associated with large biomass areas in the field. Light or white areas on the print are associated with very low biomass, or bare spots in the field. Photo interpretation of color infrared photographs is subjective; the photo interpreter uses knowledge of all areas of crop culture, growing conditions, and soil characteristics to identify crop variations on the basis of biomass. Ground verification of photo interpretation is essential to the interpretation.

Geographic Information Systems

Remote-sensing systems characteristically collect volumes of data relating to large geographic areas. Extracting the relatively small amount of relevant data from the total data set presents a formidable task. The development of computer systems to handle large volumes of geographic or spatial (referring to geographic arrangement in space) data is essential for optimum use of remote-sensing systems (Marble and Peuquet, 1983).

Geographic information computer analysis systems (GIS) are designed to handle large volumes of spatial data, obtained from remote-sensing systems as well as ground derived data, such as, soil surveys, streams, or geological surveys, in either map or attribute (ie. stream flow volume) data format. The GIS provides an efficient means of storage, retrieval, manipulation, anlysis, and presentation of spatial data, usually in map form (Marble and Peuquet, 1983).

Unlike other data analysis systems, GIS systems handle and analyze spatial data as well as non-spatial attribute data associated with the spatial data. To preserve the data's spatial dependence, raster (a grid-like network of x-y coordinates), or vector (a series of points, line segments, line nodes, and polygons), formats (or a combination of both, raster and vector) are used for data management and analysis (Marble and Peuquet, 1983).

Future combinations of remote-sensing and GIS systems may provide efficient means where ground investigation derived GIS data can be imported into remote-sensing classification systems, thereby improving the accuracy of interpretation and classification. Presently, the remote-sensing information is transfered to the GIS, where, in combination with ground data, it is analyzed.

The GIS analysis is similar to overlaying one map onto another map, finding where areas of interest from both maps intersect, or where areas are spatially dependent, then producing a map of the areas of intersection, or the spatial dependence. In a sense, GIS analysis is a form of visual association of spatially dependent geographic areas, also allowing the analysis of non-spatial attribute data associated with the areal (refering to geographic area) data. For example, when combining a map of soil associations in which the soil types differ in sewage disposal attributes, with a map of utility services, the combination map may identify future sites for rural housing subdivisions. Marble, Calkins, and Peuquet (1985), and Marble and Peuquet (1983) present information, examples, and technical details of geographic information systems.

In this study, a GIS was used to overlay photo interpreted biomass strata onto soil survey map units. The soil survey map units differ in soil profile depth (attribute data) while the photo interpreted biomass strata differ in predicted (maps of the strata) and actual (sampled) grain yield (an additional attribute). The dependence of grain yield on soil profile depth (moisture supply capacity) can then be visually assessed.

Spatial Variability

For some time research has been concerned with the variability of soils influencing crop yields. Difficulty has been encountered in the actual assesment of the magnitude and the field area influenced by soil heterogeneity. Field plot design attempts to remove soil effects from treatment effects by blocking (Petersen, 1985). Sampling plans attempt to increase precision by stratifying homogeneous areas within heterogeneous fields to ensure adequate sampling coverage of all portions of the field (Petersen and Calvin, 1965). Soil survey personnel, involved in mapping soil variability over regions, are confronted with resolving the objectives of the survey (land use) with the accuracy and cost of the soil map. The soil map accuracy depends on how the description of a sampled site (pit or borehole) estimates the soil characteristics of the site neighborhood (Beckett and Webster, 1971).

The classical statistical methods assume that the population from which the samples are drawn is normally distributed, and that each sample is independent from all other samples. As soil characteristics are often related to landscape position, close samples as well as distant samples, may be correlated to each other, depending on the characteristic. The population from which each sample is drawn is not normally distributed and samples are spatially dependent.

A statistical analysis method, one that takes into account the interrelation of soil samples over landscape postition, has been adapted to soil variability studies from geology. This statistical approach is known as geostatisitcs. Geostatisitcs was developed by Matheron in a theory called the "Theory of Regionalized Variables" (Vieira, Hatfield, Nielsen, and Biggar, 1983).

The first step in geostatistical analysis of spatial variation involves assessing the variability over the region or area to be studied. Samples are obtained at a defined, regular interval along the length of a transect. Both, very closely spaced samples (approximately one meter), and widely spaced samples are obtained. If geomorphic landscape relations to soil genesis are known, such as fluvial, loessal, or erosional terrace features, transects are established and sampled both, normal and perpendicular to the geomorphic pattern. Multiple sample transects provide a measure of the variability of the soil characteristic as a function of distance and direction. Isotrophic variation (variation independent of the direction of measurement) and anisotropic variation (variation dependent on the direction of measurement) can be assessed by sampling transects established in different directions across the landscape.

The first step, or reconnaissance stage, of a geostatistical survey allows the graphical analysis of soil variability derived from the sampled transects. This graph is known as the semi-variogram (Burgess and Webster, 1980) and is a measure of variance among sample sites (dependent variable, or y-axis) as a function of distance (independent variable, or x-axis). Semi-variograms are constructed for each transect direction. The variance between very close samples is called the "nugget" variance, it is the point on the graph where the relation crosses the y-axis (Burgess and Webster, 1980b). The variance increases with distance (sometimes linearly or spherically) eventually reaching a maximum variance known as the "sill". Nugget and sill are terms adapted from geologic mining referring to mining related variance (ie. nugget variance is the ore variance associated with the size of a gold nugget within a sample, and sill variance is the ore variance associated with a block or area of the mine). The "range" is distance (actual measured distance on the transect) relating the distance between samples necessary to obtain an estimated variance, or spatial dependence of sampled points. The range is the distance along the transect, from the nugget variance to the sill variance.

Once the spatial dependence, or the variance increase with distance, has been accurately developed from intensive sampling to produce the semi-variogram, a sampling strategy is next developed. Depending on the objectives of the study with the desired level of precision defined, the density of sampling for the survey can be estimated from the semi-variogram by selecting the distance between samples needed to obtain the desired precision or variance estimate (Burgess, Webster, and McBratney, 1981). The most efficient sampling design will be one with the fewest samples, or maximum distance between samples, necessary to obtain the desired precision. Usually a square grid at a defined density is easiest to operate in the field.

After the survey is conducted, an interpolation procedure known as kriging is used to connect *infered* similar values together with isarithms, similar to topographic contour lines connecting points of equal elevation (Burgess and Webster, 1980). The kriging procedure is named for D.G. Krige who did much to develope the method for South African gold fields. Kriging is a form of weighted local averaging (Burgess and Webster, 1980). Kriging uses the spatial dependence from the semi-variogram to weight values at unrecorded or unsampled locations as a function of distance from recorded locations. Kriging provides an interpolated estimate at an unrecorded point that is unbiased, with known variance, and minimum variance, (Burgess and Webster, 1980) therefore, it is a statistically sound and optimal method.

If soil properties have large nugget variances (in other words, if the soil is very heterogeneous, if samples near each other have large variance) the punctual kriging isarithms (the contour-like lines on the map) are very erratic. In this case block kriging is described by Burgess and Webster (1980b) as a means of grouping areas together and averaging properties to produce a smoother map. The precision may necessarily be lower, however, the map may reveal a regional pattern.

Sometimes a soil property is very difficult to measure or may require large outlays of resources (time, labor, or money) to sample at an intensity required for the desired precision for interpolation methods. Another variable may be found to be highly correlated to the property of interest. If both variables are found to be spatially interdependent and exibit the same anisotrophy or isotrophy, McBratney and Webster (1983) provide a method of cross semi-variograms and co-kriging to interpolate one variable from measuring another. Actually, both variables are measured, the easiest to measure variable at a higher density or frequency than the more difficult to measure variable. Semi-variograms are made from intensive reconnaissance surveys for both variables, compared for anisotrophy or isotrophy, and spatial dependence. From the semi-variograms, survey method and sample density are determined for both variables. Spatially correlated and co-regionalized variables, one sampled intensively (the easiest and most economical to measure), the other sampled much less intensively, can produce a map of the spatial variability of the variable of interest much more economically than intensive sampling of the difficult to measure variable.

Remotely-sensed subsidiary variables are in many instances more economically measured than the primary variable of interest. The spatial variability of the remotely-sensed variable is often highly co-regionalized and has potential for co-kriging (McBratney and Webster, 1983). Examples provided by McBratney and Webster (1983) and Vieira, Hatfield, Nielsen, and Biggar (1983) include, temperature measured with remote-sensing techniques correlated to soil moisture, clay content, or organic matter content.

One assumption of the geostatistical interpolation method is that the boundaries of the soil parameter to be measured cannot be recognizable by distinct geomorphic breaks and must have very gradual gradients across the isarithm. In other words the interpolation techniques do not estimate soil properties across a cliff (Burgess and Webster, 1980).

Bouma (1985) points out the value of using traditional soil survey methods combined with reconnaissance geostatistical methods. First, the aerial photography and geomorphological associations used to identify preliminary soil boundaries could be used to identify subpopulations or homogeneous areas based on vegetation, landform position, or topography. Next, the subpopulations could be used for initial high intensity reconnaissance sampling transects to assess the variability within the subpopulation. A group of similar subpopulations could assess the variability within the region using the semi-variograms of the transects. Then, the estimate of the variance from the semi-variograms could provide the sampling density and method needed for both local and regional surveys at a desired precision.

Combining the ideas of Bouma (1985), Burgess and Webster (1980), McBratney and Webster (1983), and Vieira, Hatfield, Nielsen, and Biggar (1983) subpopulations, locally and regionally, could be identified based on remote-sensing subsidiary variables associated with grain yield. The variance of the subpopulation (estimated from the previously obtained reconnaissance semi-variogram for the region) could provide the grower with a sampling plan and density to assess the variability of grain yield within his farm. GIS systems could overlay several remotely-sensed subsidiary variables accelerating the identification of regional subpopulations and providing maps of the spatial variability of grain yield.

It should be pointed out that with the regionalized estimate of the variance of the soil property to be measured, geostatistical methods may increase precision over classical sampling designs, at a given cost, by reducing the total number of samples, even though the reconnaissance survey is sampled intensively.

By integrating the classical soil survey, remote-sensing, and geostatistical methods, an economical approach may be formulated for assessing the regional and local variation in grain yield for the Columbia Plateau in eastern Oregon.

Warrick and Gardner (1983) and Russo (1984, 1984b) provide papers dealing with assessing the spatial variabliliy of yield (a parameter with many interactions, therefore, hard to measure) and improved crop management by spatially varying irrigation. Bresler, Dasberg, Russo, and Dagan (1981) correlated crop yield of peas (total dry matter, pod, and hay) with soil water content.

Excellent reviews of geostatistical procedures of soils are provided in a five part series of papers by Burgess and Webster (1980, 1980b), Webster and Burgess (1980) Burgess, Webster and McBratney (1981) and McBratney and Webster (1983), including examples of analysis. Vieira, Hatfield, Nielsen, and Biggar (1983) include a review of geostatisitcal procedures, with examples and computer code. Neilsen and Bouma (1985) edit a workshop proceedings on various aspects of soil spatial variability.

METHODS

Aerial Photography

Field study areas were selected to represent the wheat yield, climatic, and geographic variability of the Columbia Plateau of eastern Oregon.

During the spring when the wheat canopy started to cover the rows, photographic flights were made to determine at what stage of development differences in wheat biomass could best be observed. Photographic flights were made weekly between 11:00 am and 1:00 pm on clear, sunny days from April 25 to May 23, 1985. In 1984 overcast weather delayed scheduled flights, and only one flight was made by a contractor on May 27. Flights were made with a 180 Cessna aircraft using a 35-mm single lens reflex camera hand-held in a near-vertical position from an open window. The film-filter used was 35-mm Kodak Ektachrome Infrared 2236 film with a Wratten 12 filter. Slides were processed with Kodak E-4 processing chemistry (Kodak Publication No. 17, 1981) in a hand-held tank. Flights by a contractor using a 70-mm aerial camera (vertical mount) with color infrared (CIR) film and filter of a similar type (70-mm format and roll length differences) were scheduled based on the growth-stage information obtained by the 35-mm CIR slides. The 70-mm photographic scale was nominally 1:5000.

Spatial Variability of Grain Yield

The winter wheat field photographs were manually interpreted for biomass variation based on red color value and chroma (see Munsell color description in introduction).

Within each field, three color intensity strata (white or light, pink to red, and dark-bright red) were identified and delineated on a transparent overlay placed on the 8- by 8- inch photograph of the field (70-mm format). Five locations in the field, each with the three color intensity strata, were then selected. A representative sampling site was selected for each color intensity stratum at each location in the field and marked on the overlay transparency-map. The sampling was based on a stratified clustered sampling design (Steele and Torrie, 1980).

Paired subsamples (1.0-m^{-2}) of above-ground biomass were harvested from the sampling sites marked on the overlay transparency-map. Ground-verification of anomalies was noted as sample sites were harvested. Biomass samples were air- dried, weighed, then threshed with a plot combine; grain samples were cleaned with an air-fractionating cleaner, and weighed. Harvest index (HI) was calculated as grain weight divided by above-ground biomass. The weight of 300 kernels was determined and multiplied by 3.33 to obtain 1000-kernel weight. Grain samples were ground with a Udy cyclone mill (0.5-mm screen) and the percentage of grain protein was measured with a Technicon 400 Infra-Analyzer. The Technicon was calibrated for percentage of grain protein by the micro-Kjeldahl procedure described by Nelson and Summers,

1973. The correlation coefficient of the percentage of grain protein measured by the Technicon as a function of micro-Kjeldahl measured percentage of grain protein was 0.97, and root mean square error (RMSE) of regression was 0.45 percentage point of grain protein. In other words, the standard error of the Technicon is about one-half a percentage point of grain protein; or the Technicon measured percentage of grain protein to an accuracy of plus or minus one-half percent of grain protein.

Analysis

The grain yield classes (low, average, and high) corresponding to strata (light, pink-red and dark-bright red) were analyzed for each parameter (yield, percentage of grain protein, 1000 kernel weight, and harvest index) by a one-way nested ANOVA (Steel and Torrie, 1980).

Percentage of grain protein and 1000-kernel weight were graphed as a function of grain yield to identify and correlate outlying observations with ground-verification notes collected during harvest.

In the process of correlating the ground-verification notes with the outlying observations some of the observations originally classified in one stratum were actually in a transition zone between strata. It was thought that ten strata may more accurately reflect the biomass or grain yield variability within the fields.

The data were reclassified into ten strata for the following reasons: 1) to place data into the correct strata after ground-verification, 2) to reflect more accurately the biomass and grain yield variability, and 3) to subjectively quantify the grain yield for each stratum by obtaining a grain yield as a function of photo interpreted biomass regression relation that would adequately represent not only the three original strata, but also the transition zones. The data were reclassified using a one-to-ten transformed scale (Little and Hills, 1978); with the addition of white color classified as zero, light color classified as one, and dark-bright red color classified as ten. The transformed scale (0 to 100) was used to eliminate subjective classification bais.

The area of the stratum was used for N_h (total number of possible sample units in each stratum) to estimate the total yield for the stratum; summing strata total yield provided an estimate of total yield for the field.

Grain yield (dependent variable in this case) was regressed against the color classification of the transformed scale, referred to as photo intrepreted biomass, (independent variable) and the relation plotted for each field. This regression relation provided an estimate of grain yield for each ten strata for the demonstration of a procedure for estimate fertilizer use efficiency. Grain yield was not sampled in all ten strata, therefore, variance estimates or confidence intervals for the estimates of yield cannot be obtained.

Geographic Information System Analysis

The three canopy biomass classes (original photo interpretation of grain yield classes) light, pink-red and dark-bright red polygons recorded on the transparent overlay were converted to digital format (digitized) for GIS analysis using digitizing processes outlined by Marble, Calkins, and Piquet (1984) for each field study area. The soil survey mapping unit polygons were digitized for each field study area from the county soil survey, (Mayers, 1959; Green, 1982; and Hosler, 1976). Topographic data were digitized from the USGS 7.5 minute quadrangle sheet for each field study area.

The USGS 7.5 minute quadrangle data was used for the base map, with common control points identified and calculated on the state plane coordinate system. A three level classification was assigned to photo intrepreted biomass; light, pink-red, and dark-bright red. The soil survey mapping unit code (see table 2) corresponding to soil profile depth was assigned a light brown-to-dark brown classification: with light representing shallow and dark-brown signifying deep soil profile classes. The USGS 7.5 minute quadrangle topographic data for the field study areas did not improve precision over the soil survey mapping unit slope gradient data, therefore, was eliminated from the analysis, except for the control points required to register maps.

The soil survey mapping units were overlaid on the photo intrepreted biomass polygons. GIS visual analysis identifying intersecting or spatially dependent areas of soil profile depth (an attribute associated to the soil map unit) and photo interpreted biomass polygons (with associated attributes of predicted and sampled grain yield) was performed. The outlying observations were located on photo interpreted biomass polygons. If soil profile depth, photo interpreted biomass predicted grain yield, and actual (sampled) grain yield were found to intersect (have common strata classifications) on the map, the representative (low, average, or high) grain yield polygons were mapped. If two of the attributes intersected common areas on the map, with one attribute not intersecting, the area of the map was examined for an outlying observation of actual grain yield (identified from the scatter graph of protein, 1000 kernel wt, vs. grain yield). If two attributes intersected, another attribute did not intersect, and an outlying observation (ie. moisture stress) supported the two intersecting attributes, the area was reclassified (if necessary) to reflect agreement.

The dark-bright red photo interpreted biomass polygons overlaying shallow soil profile mapping unit polygons were reclassified to pink-red. Polygon boundaries were redefined to indicate the increased precision of larger nominal map scale, approximately 1:5000, of the photography, opposed to 1:20 000, of the soil survey. A three class, low, average, and high, yield map was created.

The outlying observations, identified by ground verification of CIR photographs and probable moisture stressed-shallow soil profile, were corrected by the GIS analysis. Grain yield, corrected by GIS analysis (outlying observations removed) was again regressed on photo interpreted biomass. The GIS corrected grain yield-photo interpreted biomass regression relation was plotted on the initial grain yield-photo interpreted biomass regression analysis coordinates with the outlying observations indicated for comparison purposes.

Calculation of Fertilizer Use Efficiency

The estimated fertilizer use efficiency analysis is provided here for demonstration of a method only, as no variance estimate or confidence interval associated with the grain yield mean or total is provided.

The estimated yields (kg) of the polygons were obtained by entering the value of the photo intrepreted biomass of the polygon into the GIS corrected grain yield-photo intrepreted biomass regression relation. The estimated yield of the polygon was used to estimate nitrogen fertilizer application rates by using nitrogen requirement relations obtained from the fertilizer guide for winter wheat (non-irrigated--Columbia Plateau), (Gardner and Goetze, 1980).

The area of the polygons (ha) was calculated by a GIS function. The estimated yield of the polygon was multiplied by the polygon area (ha) to obtain the total estimated yield for the polygon. The total estimated yield for the field was calculated by summing the total estimated yield of the polygons.

The estimated applied nitrogen (nitrogen required to produce a given level of grain yield, minus the initial soil test nitrogen) of the polygon was multiplied by the polygon area (ha) to obtain the total estimated applied nitrogen for the polygon. The total estimated applied nitrogen for the field was calculated by summing the total estimated applied nitrogen for each polygon.

The applied nitrogen fertilizer use efficiency was calculated by dividing the total field estimated yield by the total field esimated applied nitrogen. Thus,

$$NFUE = \frac{E\ y_{ep}\ a_p}{E\ n_{ap}\ a_p}$$

where NFUE = Nitrogen fertilizer use efficiency (kg kg^{-1}),

E = Summation,

y_{ep} = Yield, total estimate of polygon (kg ha^{-1}), n_{ap} = Nitrogen, total applied per polygon (kg ha^{-1}),

a_p = Area of polygon (ha).

An estimated yield (kg) per unit of applied nitrogen (kg) analysis of nonuniform fertilizer application was determined for three fertilizer management strategies.

RESULTS and DISCUSSION

Identifying Inclusions by Color Infrared Photography

Low yielding areas identified by photo interpretation of color infrared photography were associated with shallow soil profiles in locations consistent with soil forming factors in the region (Mayers, 1959; Green, 1982; and Hosler, 1976). Loess mantle depth decreases with increasing distance from the Columbia River, and it is shallower on the leeward slope aspects (south-to-southwest, aspect is the direction the slope faces) at the time the loess mantle was deposited. Post-pleistocene climatic changes have resulted in the south-to-southwest aspect slopes presently (holocene) oriented in the windward position.

Photo interpreted color value and chroma classes, light (low yielding areas) and pink-red (average yielding areas), had significantly different grain yields (Table 1) across locations and years. The light and pink-red classes were linearly related to grain yield (Figure 1, 2, and 3).

All of the high yielding areas were located within a few meters of drainage ways. The grain yield of the photo intrepreted dark-bright red classes (high yielding areas) was significantly different from the grain yield of the pink-red classes (average yielding areas) in only one study site, Kaseberg 1985. The Kaseberg 1985 field study location has a relatively deep soil profile with few inclusions (Table 2), homogeneous soil map units (Figure 2b), and low variance (S.E.M., Table 1) compared with the Feist and Smouse locations.

Areas near drainage ways had more vegetative growth early in the spring than other areas in the field because of increased moisture. Areas with deep soil profiles can store adequate moisture to fill kernels while areas near drainage ways with shallow soil profiles cannot, resulting in shriveled kernels. In deep (Kaseberg 1985) soil profile areas, light, pink-red, and dark-bright red classes (low, average, and high yielding areas) were linearly related to grain yield (Figure 2). In shallow soil profile areas during dry years (1985), pink-red and dark-bright red (average and high yielding areas) classes were spherically (quadratically) related to grain yield (Figure 1 and 3). The spherical relation is thought to occur because of moisture stress during grain fill.

Moisture stress resulting in decreased yields fluctuates independently of the spatial variation of grain yield. In other words, having identified and mapped grain yield variation within a field, the grain yield of one area may be influenced more than another area with seasonal variation in the distribution and intensity of precipitation.

Table 1. Grain yield, percentage of grain protein, and one thousand kernel weight of light, pink-red, and dark-bright red classes within field study locations and years.

† Light (low yielding), pink-red (average yielding), and dark-bright red (high yielding) classes of wheat canopy biomass identified by photo interpretation of aerial color infrared photography value and chroma during late vegetative growth.

‡ S.E.M. = standard error of the mean, means comprising five paired observations for 1985 data, and 10 observations for 1984 data.

§ Light, pink-red, and dark-bright red class means within a parameter column followed by the same letter are not significantly different according to Fisher's Least Significant Difference (P = 0.05) test.

Table 1.

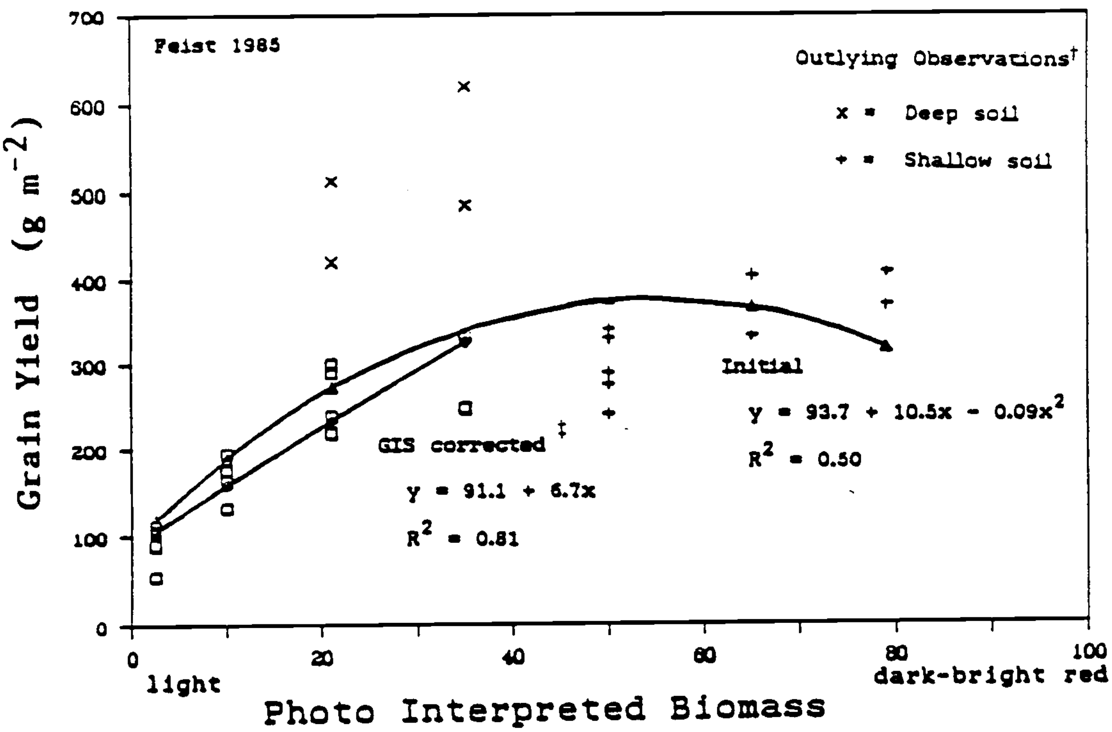
Location	Grain Yield ($g\ m^{-2}$)	Protein (%)	Kernel Wt (g^{-1000})
Canopy biomass classification from CIR photo interpretation			
Feist 85			
light †	124 a §	14.09 a	36.0
pink-red	307 b	11.20 b	37.0
dark-bright red	381 b	11.25 b	35.5
S.E.M. ‡	37	0.86	2.8
Kaseberg 85			
light	169 a	13.85 a	30.1
pink-red	304 b	10.44 b	30.4
dark-bright red	424 c	11.16 b	31.8
S.E.M.	14	0.33	1.2
Smouse 85			
light	76 a	13.01 a	37.6
pink-red	292 b	10.31 b	37.7
dark-bright red	386 b	11.76 ab	44.2
S.E.M.	32	0.55	2.2
Kaseberg 84			
light	207 a	7.52	46.04 a
pink-red	423 b	7.53	49.98 b
dark-bright red	530 b	7.55	50.44 b
S.E.M.	44	0.27	0.91
Smouse 84			
light	264 a	12.13 a	44.6 a
pink-red	392 b	10.61 b	47.5 ab
dark-bright red	423 b	13.11 a	35.6 b
S.E.M.	24	0.42	1.4

Figure 1. Wheat grain yield as a function of photo interpreted biomass (representing 10, subjective, relative value and chroma intensities -- light to dark-bright red) from color infrared photographs (CIR) obtained in late vegetative growth stages at the Feist 1985 study location.

† Outlying Observations are caused by soil profile depth variation within the field. Moisture stress reduced yields in areas with shallow soil profiles. Deep soil profile areas on north-east aspect slopes had higher yields than predicted by photo interpreted biomass because of delayed development on cool north slopes. note: square symbols represent non-outlying observations, and other symbols not listed are for plotting lines only.

‡ The corrected regression relation was obtained by removing ground-verified outlying observations confirmed by overlaying maps of photo interpreted biomass and soil profile depth with geographic information system overlay analysis procedures.

Figure 1.



Feist 1985
Outlying Observations†
x = Deep soil
+ = Shallow soil
Grain Yield (g m-2)
700
600
500
400
300
200
100
0
GIS corrected
y = 91.1 + 6.7x
R2 = 0.81
Initial
y = 93.7 + 10.5x - 0.09x2
R2 = 0.50
‡
0
20
40
60
80
100
light
dark-bright red
Photo Interpreted Biomass

Figure 2. Wheat grain yield as a function of photo interpreted biomass (representing 10, subjective, relative value and chroma intensities -- light to dark-bright red) from color infrared photographs (CIR) obtained in late vegetative growth stages at the (a) Kaseberg 1985, and (b) Kaseberg 1984, study locations.

† Outlying observations are caused by lighter soil background reflection resulting from downslope movement of caleche (kqm, Table 2) fragments with tillage operations and downy brome (*bromus tectorum*) infestations. note: square symbols represent non-outlying observations, and other symbols not listed are for plotting lines only.

‡ The corrected regression relation was obtained by removing ground-verified outlying observations confirmed by overlaying maps of photo interpreted biomass and soil profile depth with geographic information system overlay analysis procedures. Other outlying observations (downy brome infestations) were identified with ground-verification notes.

Figure 2, (a) Kaseberg 1985, (b) Kaseberg 1984.

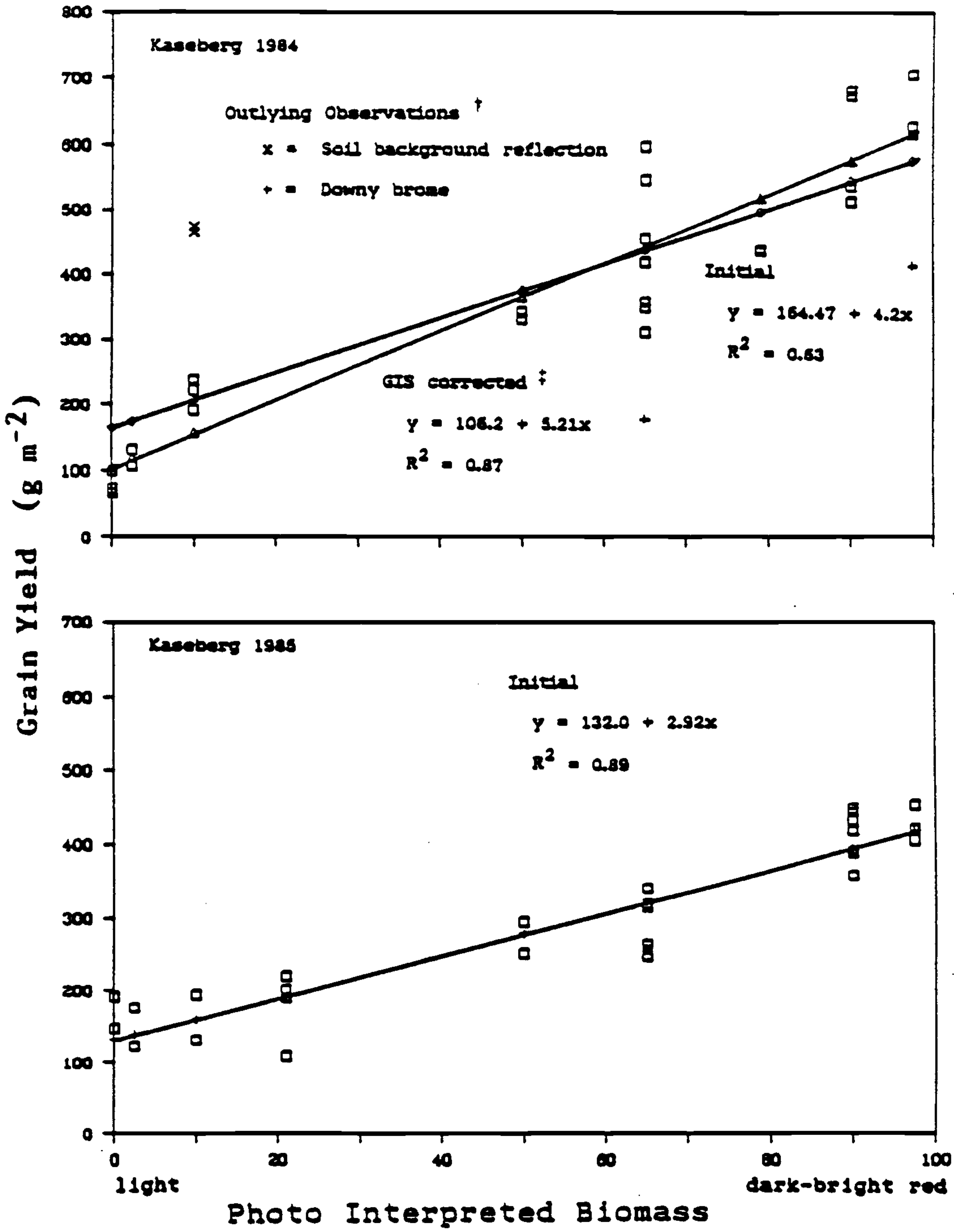
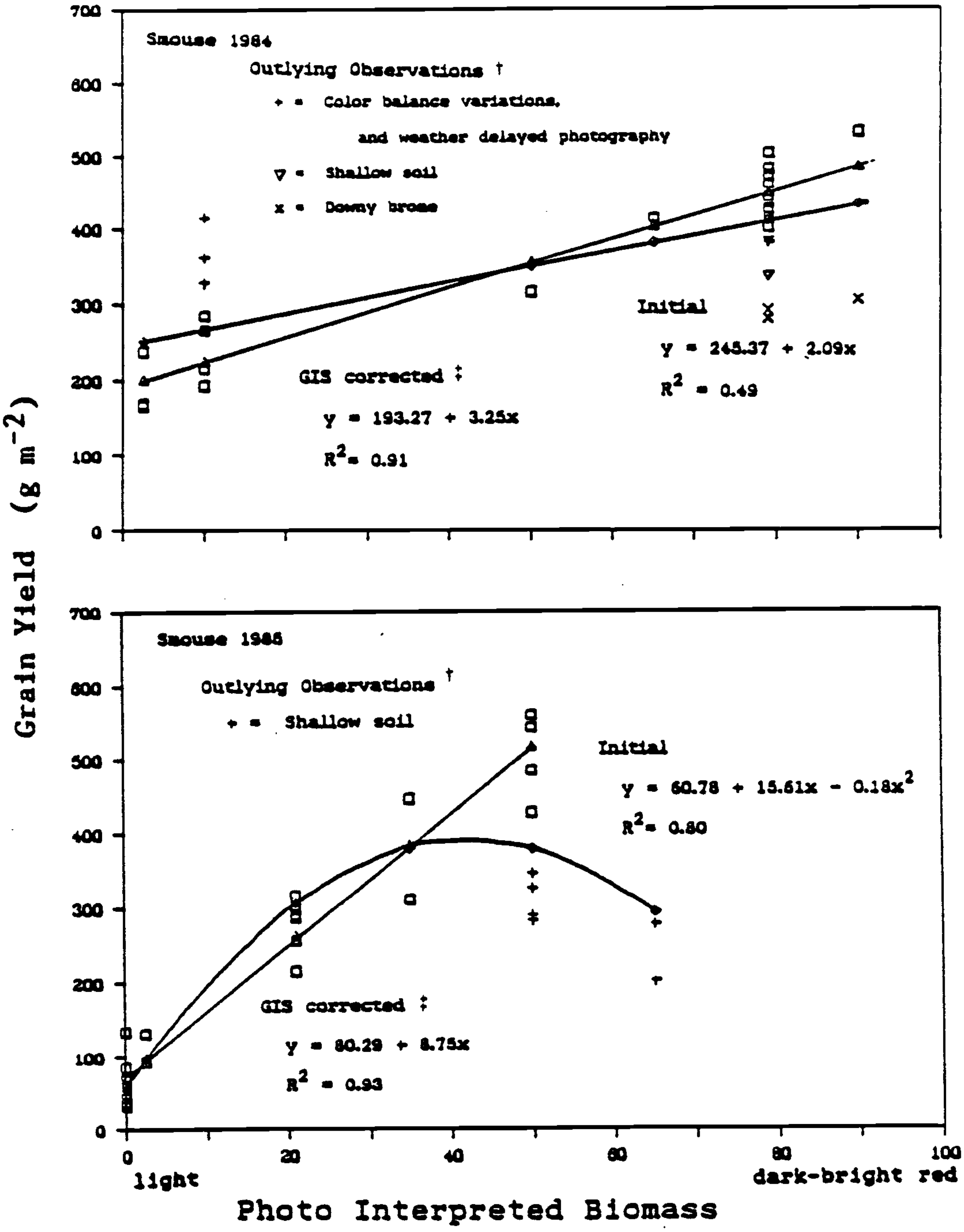


Figure 3. Wheat grain yield as a function of photo interpreted biomass (representing 10, subjective, relative value and chroma intensities -- light to dark-bright red) from color infrared photographs (CIR) obtained in late vegetative growth stages at the (a) Smouse 1985, and (b) Smouse 1984, study locations.

† Outlying observations are caused by overcast weather that delayed photography until the boot and heading growth stages, darker color balance variations, shallow soil profiles, and downy brome (*bromus tectorum*) infestations. Lighter photo interpretated biomass shifted curves to the left in 1985 because of 0.4 meter row spacings. note: square symbols represent non-outlying observations, and other symbols not listed are for plotting lines only.

‡ The corrected regression relation was obtained by removing ground-verified outlying observations confirmed by overlaying maps of photo interpreted biomass and soil profile depth with geographic information system overlay analysis procedures. Other outlying observations (downy brome infestations) were identified with ground-verification notes.

Figure 3, (a) Smouse 1985, (b) Smouse 1984.



Spring regrowth and development was not uniform in all areas within fields because south aspect areas warm before north aspect areas. At higher elevations (Feist 1985 study area, Figure 4, 5, & 6, elevation is 735 meters, about 305 meters higher than the other field study areas) the crop development on the north-to-east aspect slope was delayed, therefore, the field may need more than one photographic flight to record extended development within the field resulting from extreme elevation and aspect differences.

The optimum plant development stage to discriminate biomass variation occurs during the late vegetative growth stages (jointing) just prior to the boot stage.

Yield variations in adjacent fields from a wet crop year to a dry crop year (Figure 2 vs. Figure 3) were greater in the high yielding range. The perimeters of inclusions or map units are in a transition zone rather than an absolute boundary line, and may shift from crop season to crop season with precipitation changes.

The data from this study indicate that soil moisture and the ability of the soil to supply moisture to the crop through the grain fill period is a major limiting constraint to grain yield. The moisture supply to the crop is related to soil profile depth. Spatial variability of grain yield in the Columbia Plateau may be related to soil profile depth, limiting dissimilar inclusions, and landform position.

Color infrared photography, although useful for distinguishing vegetational differences, requires complex timing, ground verification, and correction to estimate yield variability.

Statistical Analyses

Removing ground verified outlying observations and performing an ANOVA with unequal sample numbers and unplanned comparisons (Sokal and Rolf, 1981) resulted in no change in significance between light, pink-red or dark-bright red means. The outlying observations did not increase the variance, thus, the photo interpreted (dark-bright red) high yielding areas near drainage ways on shallow soil profiles are not significantly different from the average yielding areas.

In this study an estimate of the variance within and among the grain yield strata will be useful in calculating the number of sampling units required for a defined level of precision for future spatial variability studies (Cochran, 1977). In this study the initial variance estimate (standard error) within and among strata was underestimated for some fields, the level of precision may have been set excessively high in line with the objectives, and time constraints during harvest sampling necessitated the reduction of the initial sample number.

This study has resulted in variance estimates reflecting the within and among strata heterogeneity for the region (Table 1, S.E.M.).

Fertilizing fields by spatial variation rather than uniformily, requires the grower to set the minimum size of the strata he is willing to manage differently from other strata within the field (may be based on future fertilizer application equipment technology). Once the minimum strata size is established, the variance or heterogeneity within the strata and among strata is estimated. From the estimated variance within the strata, a sampling plan is developed for a given cost of sampling (time, labor, and money restraints). The sampling method will provide an estimate of the number of samples that can be taken at a given cost and the associated precision of the sampling method based on the variance within the strata. The sample number may be increased or decreased, with associated changes in cost and precision. The sample is then drawn and analyzed. The estimates of strata means and totals calculated with the associated variance estimates or standard errors. If a group of adjacent strata are found to have relatively high variance estimates, the confidence limits associated with the strata mean or total grain yield will be large. If the group of strata have overlapping confidence intervals, the grower may choose to combine the strata and use the mean grain yield for estimating the fertilizer required.

Alternately, if the group of adjacent strata with relatively high variances (even if the confidence intervals overlap) the grower may choose to accept a lower level of precision associated with the variance of the strata mean or total, and estimate fertilizer required for each strata. Depending on the difference among strata fertilizer requirements, the grower may then elect to manage the strata individually or collectively, depending on the cost of management and the range in fertilizer requirements among the strata.

If a group of adjacent strata have relatively low variance, fewer samples are needed to estimate the strata mean and total at the same precision as the group of strata with relatively high variances.

As the inherent variability or variance estimate of a strata increases, the precision associated with the strata mean or total estimate decreases, for a given sampling intensity.

For example one management plan may require varying the fertilizer application rate by soil type, another plan may necessitate varying the application rate by transition zones from soil type to soil type, as well as varying the fertilizer rate by soil types. Varying fertilizer application rate by transition zones would require, at a given sampling intensity and precision for both fertilizer managment plans, a lower level of inherent variation within the soil type and transition zone strata, than among the strata. If the inherent variability is moderately high, the grower could accept a lower level of precision to estimate the grain yield mean.

The inherent heterogeneity will remain unchanged, therefore, the grower must balance the cost of the survey, with the expected savings of a nonuniform management plan, and the level of precision willing to be accepted.

The inherent heterogeneity will vary from field to field. If the grower can estimate the variance associated with the heterogeneity within each field, he could estimate the cost of sampling necessary to obtain the precision desired.

Future research combining remote-sensing, spatially dependent interpolation, and soil survey methods may provide a regional and local variance estimate that can be used by growers to assess the economic value of nonuniform fertilization

Additional research may indicate associations of variance with soil characteristics. Preliminary results of this study indicate variance increases with increasing heterogeneity of soil profile depth within a general soil mapping unit. The CIR photograph of the Kaseberg 1985 study area is characterized by uniform, homogeneous color value and chroma (Figure 4 a). The soil profile is deep (Table 2) with clear transition zones. The variance (S.E.M., Table 1) is low. The CIR photograph of the Feist 1985 study area indicates greater heterogeneity within subareas or strata than the Kaseberg 1985 study area (Figure 4 b). The soil profile ranges from deep to shallow, with a large number of inclusions (Table 2). The variance of the Feist study area (S.E.M., Table 1) is higher than the Kaseberg area.

For a given level of precision for both Kaseberg and Feist study areas, the Feist study area would require more intense sampling (more total samples taken within each strata) than the Kaseberg study area. Alternatively, with a relatively larger variance estimate because of inherent heterogeneity, Feist could either accept a lower level of precision for the strata mean estimate and a shorter confidence interval, or combine adjacent strata with overlapping confidence intervals. The decision could be based on the econommic value of the management plans associated with the precision.

Table 2. Soil profile depth to lithic contact, effective rooting depth, percent variant inclusions, available water capacity, series classification, and family or higher taxonomic class within soil survey mapping units of field study areas.

† Symbols of codes for soil survey mapping units are found in Soil Survey for respective counties (Mayers, 1959; Green, 1982; and Hosler, 1976).

‡ Definitions and abbrevations after *Soil Taxonomy*, (Soil Survey Staff, 1975).

Table 2.

Soil Survey Mapping Unit Code	Depth to Lithic Contact	Effective Rooting Depth	Percent Variant Inclusions	Available Water Capacity
Location	(cm)	(cm)	(%)	(cm)
Feist 85; Wasco County, The Dalles, Summit Ridge-Fall Canyon				
12B †	157	152	10	15-30
12D	157	152	10	15-30
12E	157	152	10	15-30
17B	68	50-68	10	8-19
17D	68	50-68	10	8-19
Kaseberg 85 & 84; Sherman County, Wasco, Locust Grove				
WaA	295	> 152	-----	38-46
WaBs	> 152	> 152	5	30-32
WaBn	295	> 152	10	38-46
WbBs	kqm 38-60 ‡	96-152	-----	18-26
WcBs	kqm 18-38	46-96	10	10-18
Smouse 85 & 84; Morrow County, Lexington-Jordan, Baseline Rd.				
45B	> 152	> 152	3	18-32
45C	> 152	152	5	18-32
75C	kqm 50-100	50-100	5	10-22

Table 2. Continued

Soil Survey Mapping Unit Code	Series Classification
Location	
Feist 85; Wasco County, The Dalles, Summit Ridge-Fall Canyon	
12B	Cantalla silt loam, 1-7% slopes
12D	Cantalla silt loam, 12-20% slopes
12E	Cantalla silt loam, 20-35% slopes
17B	Condon silt loam, 1-7% slopes
17D	Condon silt loam, 12-25% slopes
Kaseberg 85 & 84; Sherman County, Wasco, Locust Grove	
WaA	Walla Walla silt loam, very deep, 3-7% slopes
WaBs	Walla Walla silt loam, very deep, 7-20% south slopes
WaBn	Walla Walla silt loam, very deep, 7-20% north slopes
WbBs	Walla Walla silt loam, deep, 7-20% south slopes
WcBs	Walla Walla silt loam, moderately deep, 7-20% south slopes
Smouse 85 & 84; Morrow County, Lexington-Jordan, Baseline Rd.	
45B	Ritzville silt loam, 2-7% slopes
45C	Ritzville silt loam, 7-12% slopes
75C	Willis silt loam, 5-12% slopes

Table 2. Continued

Soil Survey Mapping Unit Code	Family or Higher Taxonomic Class
Location	
Feist 85; Wasco County, The Dalles, Summit Ridge-Fall Canyon	
12B	Fine-silty, mixed, mesic Typic Haploxerolls
12D	Fine-silty, mixed, mesic Typic Haploxerolls
12E	Fine-silty, mixed, mesic Typic Haploxerolls
17B	Fine-silty, mixed, mesic Typic Haploxerolls
17D	Fine-silty, mixed, mesic Typic Haploxerolls
Kaseberg 85 & 84; Sherman County, Wasco, Locust Grove	
WaA	Coarse-silty, mixed, mesic Typic Haploxerolls
WaBs	Coarse-silty, mixed, mesic Typic Haploxerolls
WaBn	Coarse-silty, mixed, mesic Typic Haploxerolls
WbBs	Coarse-silty, mixed, mesic Typic Haploxerolls
WcBs	Coarse-silty, mixed, mesic Typic Haploxerolls
Smouse 85 & 84; Morrow County, Lexington-Jordan, Baseline Rd.	
45B	Coarse-silty, mixed, mesic Calciorthidic Haploxerolls
45C	Coarse-silty, mixed, mesic Calciorthidic Haploxerolls
75C	Coarse-silty, mixed, mesic Orthidic Durixerolls

Overlay Analysis with Geographic Information Systems

Overlaying the soil survey map units onto the photo intrepreted biomass-overlay transparency-map confirmed that the outlying observations with high photo interpreted biomass and low or average yield were located near drainage ways on shallow soil profiles (Figure 4-6). The overlay analysis also associated other ground-verified outlying observations with the reasons predicted grain yield did not agree with actual yield. Perhaps of most value is correction of CIR errors because of delayed development of north-to-east slope aspect by GIS analysis.

Color infrared photography, with limitations, provided vegetational discrimination thought to identify inclusions and map units with different moisture supply characteristics. Additional soil depth and soil moisture characteristic curves (moisture release curves) are needed to confirm that the moisture supplying capacity of inclusions and soil types is related to spatial variability of grain yield.

Figure 4. Color infrared photograph of (a) Kaseberg 1985 and (b) Feist 1985 study area. Light, pink-red, and dark-bright red areas indicate low, average, and high photo interpreted biomass, respectively. Nominal scale of aerial photographs is 1:5000. Actual scale of (a) is 1:5 500; (b) 1:6 500. Field plots in both photos (i) are approximately 30-by-120 meters.

Figure 4. (a) and (b)

Figure 5. (a) Soil survey mapping units of the Feist 1985 study area (Table 2). Scale bar in Figure 5. (a) for Figure 5. (a) = 264 meters. (b) Photo interpreted biomass polygons of the Feist 1985 study area (Figure 1). Scale bar in Figure 5. (a) for Figure 5. (b) = 129 meters. note: erosion control channels should read erosion control terraces, or erosion diversion terraces; and the 1:20 000 scale bar RF value is erroneous in Figure 5a, the scale bar distances above are correct.

Figure 5. (a) and (b)

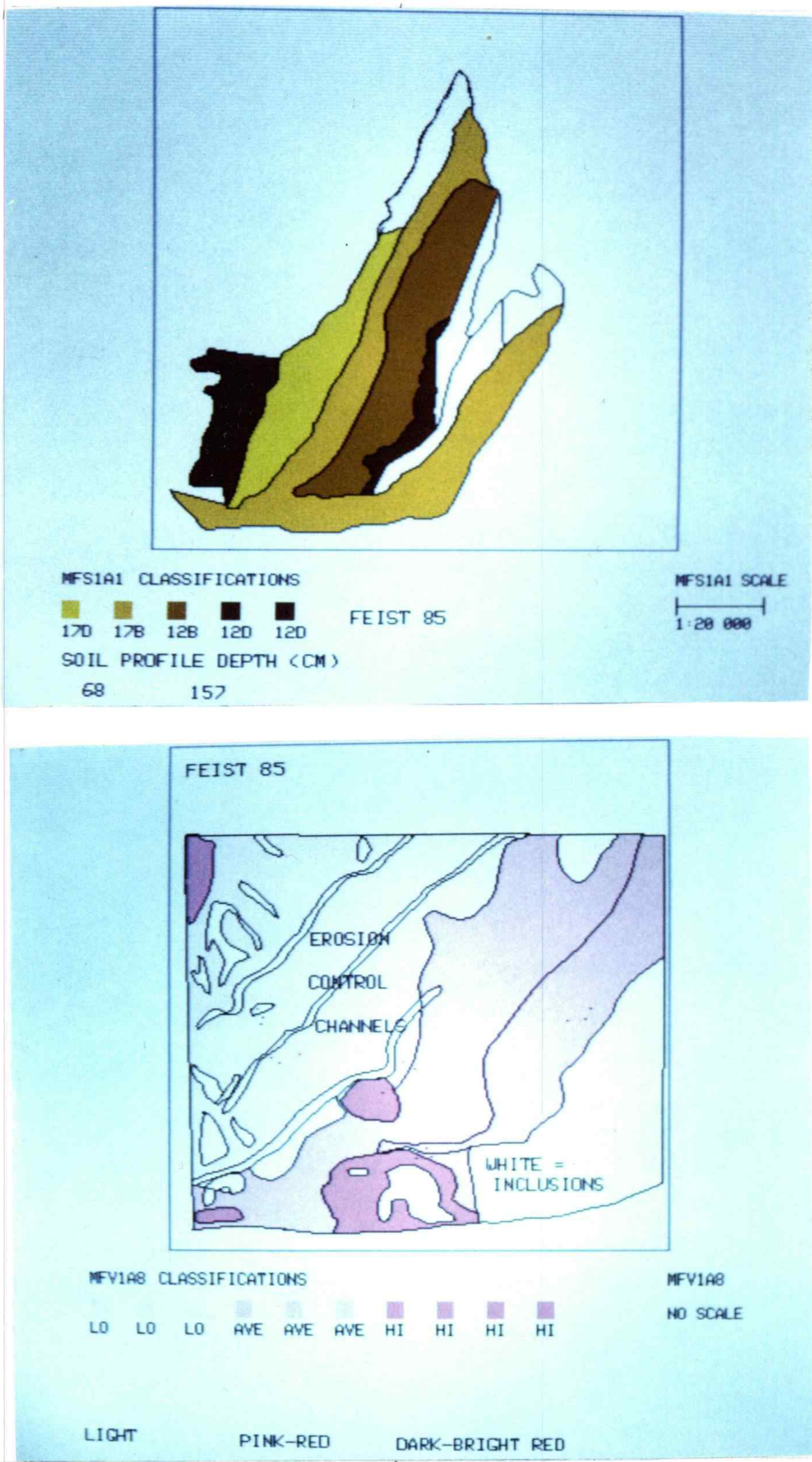
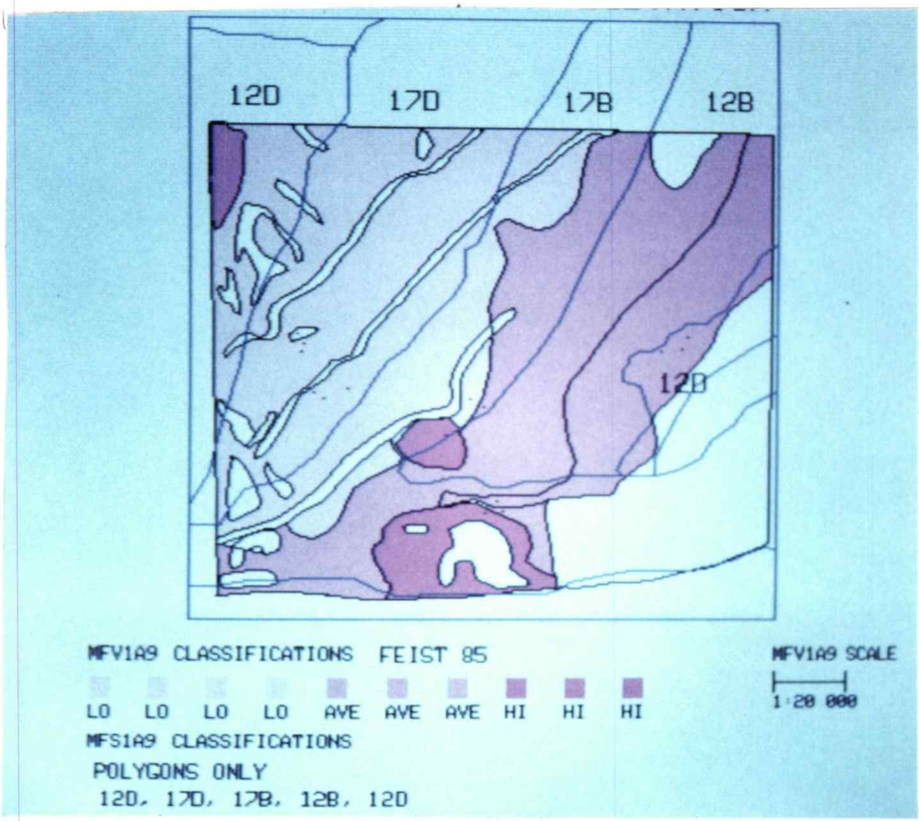
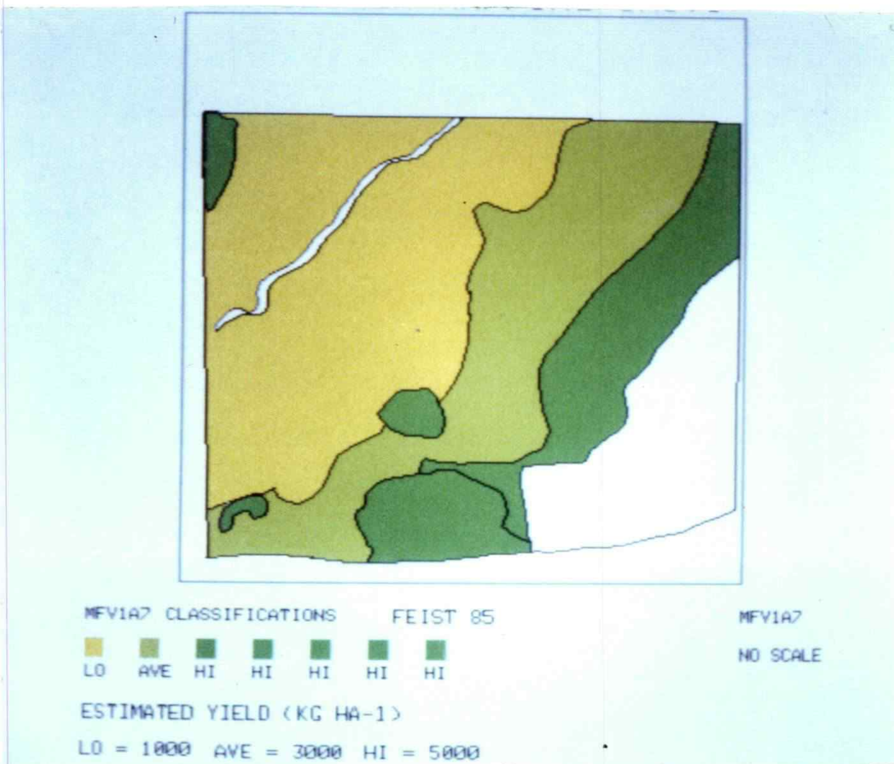


Figure 6. (a) Overlay of soil survey mapping units onto photo interpreted biomass polygons of the Feist 1985 study area. The lack of a perfect fit of the two maps results because of radial and topographic distortion of the CIR photograph. Scale bar of Figure 6. (a) for Figure 6. (a) = 146 meters. (b) A fertilizer mapping unit map of the Feist 1985 study area. Scale bar of Figure 6. (a) for Figure 6. (b) = 153 meters. note: the 1:20 000 scale bar RF value is erroneous in Figure 6a, the scale bar distances above are correct.

Figure 6. (a) and (b)





Mapping Spatial Variability

Overlay analysis with the geographic information system allowed construction of a high (first) order map identifying inclusions.

The overlay analysis suggests that the inclusions mapped in a first order soil survey may identify the spatial variability of grain yield. This depends on two questions: 1) is moisture supplying capacity of the inclusion related to soil profile depth and the basis of the photo interpreted biomass classification? and, 2) do the inclusions identified on a 1:5000 or a 1:10 000 first order soil survey represent the inherent heterogeneity of the field? A similar question to the second may be presented: with spatially dependent interpolation techniques, will the sample density for a given level of precision estimated from the semi-variogram adequately represent the inclusions mapped on a first order soil survey?

The area of the inclusions and map units can be calculated, allowing the estimated yield data from the grain yield-photo intrepreted biomass-regression analysis (Figure 1) to be incorporated into a fertilizer efficiency analysis (Table 5). The fertilizer efficiency analysis was simulated based on condition of the two hypotheses yet to be analysed: 1) CIR photography mapped inclusions based on moisture supply, and 2) moisture supply is the first limiting constraint to grain yield. Fertilizer management with a first order soil map estimates fertilizer efficiency is increased by six percent (Table 5).

Initial soil fertility obtained from a soil sample taken in one location of the field was extrapolated to the entire field.

A fertilizer efficiency analysis could be performed on individual fields with areal data generated from the GIS overlay analysis. Until the development of guidance systems and computer controlled application equipment, growers such as Feist and Kaseberg could apply fertilizer at different rates using a GIS created map with unit boundaries located at slope aspect and gradient reference points.

Table 3. Comparison of three levels of spatial variable nonuniform fertilizer management techniques for the Feist 1985 field study area.

† Photo intrepreted biomass (PBI) class (from Figure 1) of polygon (Figure 6) CIR color intensity (Figure 4).

‡ Estimated yield of polygons (Figure 6) obtained from photo interpreted biomass from Figure 1.

§ Polygon area calculated by a GIS function from Figure 5 & 6.

¶ Applied nitrogen calculated from estimated yield (column 2) using the Fertilizer Guide for Winter Wheat (non-irrigated--Columbia Plateau), (Gardner and Goetze, 1980). The initial nitrogen fertilizer level (32 kg ha^{-1}) of the field obtained from soil samples, taken in one area of the field and extrapolated to the entire field, was subtracted from the total nitrogen needed to produce a given yield by method outlined in the fertilizer guide.

Nitrogen fertilizer use efficiency (NFUE) was calculated by multiplying estimated yield (column 2) by polygon area (column 3), summing, and dividing by the sum of applied nitrogen (column 4) multiplied by polygon area (column 3).

Table 3.

Yield Spatial Variability

Management Level	Polygon PBI Class †	Estimated Yield ‡	Polygon Area §	Applied Nitrogen ¶	Nitrogen FUE #
		(kg ha^{-1})	(ha)	(kg ha^{-1})	(kg kg^{-1})
Inclusions					
	2.5	1000	32.6	0	
	10	1500	3	0	
	21	2200	23.6	13	
	35	3000	1.4	44	
	Deep soil	5000	17.5	128	69
Topographic					
	2.5-10	1000	35.6	0	
	35	3000	22.4	44	
	Deep soil	5000	20.2	128	57
Present Grower Fertilizer Practice					
	2.5 - 10	1000	37.8	22	
	35	3000	40.4	40	65

Table 3.

SUMMARY AND CONCLUSIONS

Aerial color infrared photography and geographic information systems have been evaluated for usefulness in mapping spatial variability of grain yield. First, color infrared photography, although useful to distinguish vegetational differences for mapping inclusions, requires complex timing, ground verification, and correction to estimate yields. A simple, precise method to identify inclusions with different moisture-supplying characters is needed. Second, geographic information systems can provide valuable overlay analysis for evaluating multiple areal data, managing year-to-year map unit fluctuation associated with rainfall, and map constuction.

Future research may examine aerial color photography of soil during the fallow period (an indication of inclusions), color photography of the wheat canopy immediately prior to harvesting (a measure of head density), or color aerial photography mapping flag leaf browning (correlated to length of grain fill) as alternate areal data layers that may increase the precision of mapping spatial variability of grain yield.

Grain yield sampled on a grid during harvest could be converted manually to raster (grid like x-y coordinate) format and incorporated into the GIS and mapped. The actual grain yield could then be analyzed by interpolation and soil survey methods for optimum precision of mapping spatial variability.

Overlaying SPOT satellite sensed digital data (20 meter resolution) onto USGS 7.5 minute quadrangle (digitized format) data with an image based GIS (a GIS utilizing an aerial photograph as a base map, other GIS polygon are superimposed onto the photograph) could enable construction of a first order soil survey of the Columbia Plateau as well as the Palouse regions of Oregon and Washington.

The next step is to integrate a global positioning system (GPS) to determine x-y field position of fertilizer equipment with a computer-aided guidance system. The positioning-guidance system using digitized maps indicating spatial variability of grain yield could control the nonuniform application of fertilizer based on spatial variability.

This study has developed three questions for further research. First, are inclusions with differing moisture supplying characteristics related to the spatial variability of grain yield? The data seem to indicate moisture supply is the first limiting constraint to grain yield. In dryland conditions, this seems logical, but may be tested in future research. Second, will a first order soil survey identifying inclusions provide a map with adequate precision of the spatial variability of grain yield? Third, will combining spatially dependent interpolation methods with remote-sensing subsidiary variables and soil survey reconnaissance estimates of regional and local variance provide an economic method for assessing the spatial variabiity of grain yield?

REFERENCES

Aase, J.K., and F.H. Siddoway. 1891. Assessing winter wheat dry matter production via spectral reflectance measurements. Remote Sensing of Environment 11:267-277.

Ahlrichs, J.S., and M.E. Bauer. 1983. Relation of agronommic and multispectral reflectance characteristics of spring wheat canopies. Agron. J. 75:987-993.

Asrar, G., E.T. Kanemasu, R.D. Jackson, and P.J. Pinter, jr. 1985. Estimation of total above-ground phytomass production using remotely sensed data. Remote Sensing of Environment 17:211-220.

________________________, and M. Yoshida. 1985. Estimates of leaf area index from spectral reflectance of wheat under different cultural practices and solar angle. Remote Sensing of Environment 17:1-11.

Avery, T.E., and G.L. Berlin. 1985. Interpretation of Aerial Photographs, Fourth ed. Burgess Publishing Co. Minneapolis, Mn. 554 p.

Beckett, P.H.T., and R. Webster. 1971. Soil variability: a review. Soils and Fertilizers 34(1):1-15.

Bouma, J. 1985. Soil variability and soil survey. pp 130-149 *in* D.R. Neilsen, and J. Bouma (Eds). 1985. Soil Spatial Variability. Proceedings of a workshop of the ISSS and the SSSA, Las Vegas, Nevada.

Bresler, E., S. Dasberg, D. Russo, and G. Dagan. 1981. Spatial variability of crop yield as a stochastic soil process. Soil Sci. Soc. Am. J. 45:600-605.

Burgess, T.M., and R. Webster. 1980. Optimal intrpolation and isarithmic mapping of soil properties: I. The semi-variogram and punctual kriging. J. of Soil Sci. 31:315-331.

______________________________, 1980. Optimal intrpolation and isarithmic mapping of soil properties: II. Block kriging. J. of Soil Sci. 31:333-341.

______________________________, and A.B. McBratney. 1981. Optimal intrpolation and isarithmic mapping of soil properties: IV. Sampling strategy. J. of Soil Sci. 32:643-659.

Cochran, W.G. 1977. Sampling Techniques. John Wiley and Sons, New York. 428 p.

Daughtry, C.S.T., M.E. Bauer, D.W. Crecelius, and M.M. Hixon. 1980. Effects of management practices on reflectance of spring wheat canopies. pp. 1-20. AgRISTARS no. SR-PO-00458, NAS9-15466; Technical Report May 1980, Laboratory for Applications of Remote Sensing, Purdue University, West Lafayette, Indiana. 47907.

Dozier, J., and A.H. Strahler. 1983. Ground investigations in support of remote sensing. pp. 959-986. *in* R.N. Colwell (ed.), and D.S. Simonett, F.T. Ulaby. (Vol. 1, eds.) Manual of Remote Sensing. V (1). Amer. Soc. of Photogrammetry. Falls Church, Va.

Gardner, H., and N.R. Goetze. 1980. O.S.U. Cooperative Extension Service. Fertilizer guide for winter wheat (non-irrigated--Columbia Plateau) FG 54. Oregon State University.

Gates, D.M., H.J. Keegan, J.C. Schleter, and V.C. Weidner. 1965. Spectral properties of plants. Applied Optics 4(1):11-20.

Green, G.L. 1982. Soil Survey of Wasco County, Oregon, Northern Part. USDA-SCS. Government Printing Office, Washington D.C. pp. 1-125, sheet no. 26.

Hosler, R.E. 1976. Soil Survey of Morrow County Area, Oregon. USDA-SCS. Government Printing Office, Washington D.C. pp. 1-225, sheet no. 44-45.

Knipling, E.B. 1970. Physical and physiological basis for the reflectance of visible and near-infrared radiation from vegetation. Remote Sensing of Environment. 1:155-159.

Kodak Publication No. N-17. 1981. Kodak Infrared Films. Eastman Kodak Company. Rochester, New York. pp. 18-19.

Lillisand, T.M., and R.W. Kiefer. 1979. Remote sensing and image interpretation. John Wiley & Sons, New York. 612 p.

Little, T.M., and F.J. Hills. 1978. Agricultural Experimentation, Design and Analysis. John Wiley and Sons. New York. 350 p.

Marble, D.F., H.W. Calkins, and D.J Peuquet. 1984. Basic readings in geographic information systems. Spad Sys. LTD. Williamsville, N.Y. 1 V. (loose leaf).

______, and D.J. Peuquet. 1983. Geographic information systems and remote sensing. pp. 923-958. *in* R.N. Colwell (ed.), and D.S. Simonett, F.T. Ulaby. (Vol. 1, eds.) Manual of Remote Sensing. V (1). Amer. Soc. of Photogrammetry. Falls Church, Va.

Mayers, L.R. 1959. Soil survey of Sherman County, Oregon. USDA-SCS. Government Printing Office, Washington D.C. pp. 1-104, sheet no. 14-15.

McBratney, A.B., and R. Webster. 1983. Optimal intrpolation and isarithmic mapping of soil properties: V. Co-regionalization and multiple sampling strategy. J. of Soil Sci. 34:137-162.

Myers, V.I. 1983. Remote sensing applications in agriculture. pp. 2111-2228. *in* R.N. Colwell (ed.), and J.E. Estes, G.A. Thorley (Vol. 2, eds.) Manual of Remote Sensing. V (2). Amer. Soc. of Photogrammetry. Falls Church, Va.

_____, and W.A. Allen. 1968. Electrooptical remote sensing methods as nondestructive testing and measuring techniques in agriculture. Applied Optics 7(9):1819-1838.

Neilsen, D.R., and J. Bouma (Eds). 1985. Soil Spatial Variability. Proceedings of a workshop of the ISSS and the SSSA, Las Vegas, Nv. 243 p.

Nelson, D.W., and L.E. Sommers. 1973. Determinations of total nitrogen in plant material. Agron. J. 65:109-112.

Petersen, R.G., and L.D. Calvin. 1965. Sampling. pp. 54-72. *in* C.A. Black (ed.) Methods of Soil Analysis, Part 1. Agronomy Monograph No. 9, American Society of Agronomy, Madison, Wi.

Russo, D. 1984. A geostatistical approach to the trickle irrigation design in a heterogeneous soil: 2. A field test. Water Resour. Res. 20(5):543-552.

Soil Survey Staff. 1975. Soil Taxonomy. U.S. Dept. Agr. Handbook No. 436. USDA-SCS. U.S. Goverment Printing Office, Washington D.C. 754 p.

Sokal, R.R., and F.J. Rolf. 1981. Biometry. W. H. Freeman and Co. New York. 859 p.

Steel, R.D.G., and J.H. Torrie. (1980) Principles and procedures of statistics, 2nd ed. McGraw-Hill, Inc. New York. 633 p.

Vieria, S.R., J.L. Hatfield, D.R. Nielsen, and J.W. Biggar. 1982. Geostatistical theory and application of variability of some agronomical properties. Hilgardia 51(3):1-75.

Warrick, A.W., and W.R. Gardner. 1983. Crop yield as affected by spatial variations of soil and irrigation. Water Resour. Res. 19(1):181-186.

Webster, R., and T.M. Burgess. 1980. Optimal intrpolation and isarithmic mapping of soil properties: III. Changing drift and universal kriging. J. of Soil Sci. 31:505-524.

Wiegand, C.L., A.J. Richardson, and E.T. Kanemasu. 1979. Leaf area index estimates for wheat from LANDSAT and their implications for evapotranspiration and crop modeling. Agron. J. 71:336-342.