AN ABSTRACT OF THE RESEARCH PAPER OF

Karina Tereza Bohle for the degree of Masters in Forestry in Forest Engineering presented on May 31, 2005.

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Kevin Boston

Abstract

Operational forest planning is characterized by a lack of formal planning often using only the intuition and experience of the forest planners. There are a number of sources of variability found in operational planning. Like most businesses there is significant variability in the demand forecasts obtained from customers. Forestry differs from many other businesses with significant variability in the supply due to the high sampling errors commonly used in forestry to in the statistical prediction of the volume, the non uniform distribution of the trees in the stand and finally the variability regarding the harvesting production. The aim of this project is to develop some the tools and processes to improve the forecasting of logging production at both the unit and daily levels. Data was collected from the Oregon State University student logging crew operating on the

McDonald-Dunn forests. For the unit forecasting model, an existing production model from the literature was used, since no unit model was developed in this study due to the small data set and the limited timeframe. This statistical model was selected because it uses a prediction variable that can be estimated prior the operation is executed. For the daily production forecasting level, the following data was collected: location map, number of pieces, crew size, hours worked and weather conditions. This data was then analyzed using linear regression analysis. The statistically significant variables found in this study to predict daily production were skidding distance, average temperature and hours worked. The model was able to explain 76 % of the variation in the daily production from the sampled area. One of the significant variables found from this study was skidding distance. A decision support system was developed using GIS techniques that easily measure this variable. The GIS system found the path from the landing to the stump by applying a shortest path algorithm to minimize the total cost incurred in the operation. Both the unit and daily level forecasts were applied to two scenarios to demonstrate the system. The first scenario forecasts the production using the actual stream pattern, and the second scenario uses a high density stream pattern that in some cases affects the path distance. The decision support system was able to capture these differences on the forecasted productivity.

Keywords: operational planning, harvesting productivity, geographic information systems

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Introduction

Today's market conditions have made the standing resource-to-customer supply chain an extremely complex process just to manage and optimal planning extremely more difficult (Penfold, 2003). In forestry, there is a need to improve profit making amidst increasing financial pressures to lower operating costs and a desire to improve customer service. Thus, supply chain management has become the dominant business practice in the forestry industry with the aim of increasing the chain's profitability, by improving the overall efficiency of all the different components in forestry supply chain operations.

Supply chain management, first defined in the late 1970's and early 1980's by business practitioners, is considered a distinct business management approach or philosophy. Sjöström (2000) defines it as: "[T]*he concepts and tools of business management which seek to integrate business processes across boundaries among corporations, organizations and functions, and along any supply chain from raw materials through all sorts of operations and production to final consumption, in order to add value*".

The implementation of supply chain practices have improved the efficiency in some of the largest and most successful companies in a range of industries: e.g., Procter & Gamble, National Semiconductor, Wal-Mart, IBM, International Paper, Dell Computer (Simchi-Levi *et al.*, 2000). Jones (1999) states that depending on business efficiency, the following improvements are achievable in the forestry industry when the supply chain is well-managed: (15%-60%) inventory reduction, (20-30%) supply chain cost reduction, and (20%-30%) improved delivery performance.

In deciding which supply chain management improvement techniques to implement, a company must first answer the basic question of, which supply chain management strategy should the company adopt; pull-based or demand driven, push-based or production driven, or a combination of pull-push that includes elements of both systems. In general, a push strategy is characterized by focusing on cost and efficiency, including: (a) resource allocation, (b) cost minimization, (c) emphasis on economies of scale that can result in long lead times. Alternatively, pull strategies are distinguished by focusing on customer service, including: (a) a focus on responsiveness, (b) creation of short lead times, (c) order fulfillment process and maybe incur a higher production costs.

Differentiating the characteristics of the business industry is the first step in selecting appropriate supply chain techniques such as: e-business, cross-docking, just-in-time inventory, information technology and decision support systems, and forecasting techniques (Simchi-Levi *et al.*, 2004). In North America, forestry companies typically adopt push based strategies, in which forecasting techniques are very important to anticipate changes in the supply. In other parts of the world, companies are adopting a pull-push supply chain, where customer demand drives part of the supply chain, but the co-production of additional products is sold through a push process to assure that the entire tree is sold.

There are significant gains to be made with the full adoption of supply chain management techniques. The following examples show some of the potential of improvements when only one portion of the supply chain is improved. Weyerhaeuser showed a 40 percent increased the returns on capital investment after effectively implementing a manufacturing decision system to maximize the return of a forest product mill from the raw material flowing to it. The system was able to optimize the allocation of logs to various mills. Temple-Inland Forest Products sawmills also reported an improvement in profit margin of 3.3 percent. They implemented a simulation program to solve the problem of valuation and allocation of logs to their mills (Wagner *et al.* 1996). The gains from the supply chain are not limited to just the allocation of logs to sawmills, but can enhance the performance of the logistics portion of the supply chain. Weintraub and Epstein (2002) describe the logistic portion of the forestry supply chain beginning with logging operations, log loading and trucking logs to customers. The implementation of the Chilean truck scheduling system, (ASICAM) had remarkable impacts in the Chilean forestry industry savings of 15 to 35 percent of transportation cost were reported (Epstein *et al.*, 1999).

As described above, there are a variety of areas in the forestry industry where the supply chain can be improved. The variety of products generated in the forestry sector leads to a number of branches in supply chains, with the common goal of integrating the supply and demand to improve both customer service and economic efficiency of the total operation.

In general, the wood allocation systems can be partitioned into a three–step hierarchical planning process which involves a large spectrum of a company's activities from the strategic, tactical and operational levels (Penfold, 2003). The strategic level addresses the company's long-term competitive position. Decisions, on what silvicultural regime to use and which facilities to develop or close, are usually analyzed for multiple crop rotations. The tactical level planning involves decisions on a shorter period of time, up to half of the rotation. At the tactical level, decisions involve the selection of individual units to be harvested and associated road management projects. Often, the tactical schedule identifies the desired mix of ground and cable logging systems. The final level in the hierarchy is the operational level that usually accounts for the annual, monthly and weekly planning horizons that schedule operations to meet customer orders and assigns the cutting instructions to individual harvesting crews.

Annual decisions are centered around the scheduling of harvesting crews to logging units to best meet the overall demands. The monthly decision determines which orders will be promised to be fulfilled based on the forecasted production for the next week. While the weekly schedule assigns the cutting instructions to crews to fulfill those orders. At the operational level, there is a significant amount of variability regarding the production system that can be assigned to the characterization of the supply and the logging production. Weintraub and Epstein (2002) on a study of the Chilean forestry industry stated that one of the weaknesses of the supply chain is the coordination of harvesting decisions. They argue that improvements in the daily coordination of timber harvesting, along with the transportation to the first destination, would strengthen the overall supply chain.

Variation in harvesting production is one of the largest causes of variations found throughout the forestry supply chain. This variation is caused by diverse factors, and the system may be considered more complex than most other production systems because of the large variability imposed by site conditions (climate, soil, topography, tree density, tree size and the spatial distribution of trees on the forest.) Therefore, estimating the production in logging systems is always a difficult task. Forecasting harvesting production would help to improve the overall coordination of activities within the supply chain by improving the data used in the annual, monthly and weekly production estimates. Having the ability to accurately forecast harvesting production also allows the matching of harvesting systems capabilities with the harvesting units that best meet customer demand. It facilitates the evaluation of alternative harvesting system options and resources harvesting crews with the people and equipment to ensure that desired production is maintained. Appropriate estimations of these production rates would expedite a harmonious flow of activities within the primary forestry supply chain leading to increased efficiency and customer order fulfillment (Craig 1970, Dey 2004).

Methods for development of productivity forecasting equations

The most common methods that have been used to collect production data are detailed time studies and shift-level studies. Detailed time studies collect data on each production cycle where the conditions of each cycle are also recorded. Shift-level techniques estimate daily production by averaging the total output divided by hours for each day. These techniques differ in labor costs, accuracy of results, and type of information collected.

Detailed times studies work well for collecting delay free production; however because of their short duration, large delays are often not properly recorded and they also imprecisely estimate long-term trends and the range of logging conditions that are measured (Olsen *et al.*, 1998). Shift-level time studies are collected over longer periods of time representing a broad range of conditions and long term productivity of harvesting system(s). This type of study describes the operation's daily activities summarized by the logging crew. One disadvantage of these studies is that they don't record small delays which are confounded with productive time (Olsen *et al.*, 1998).

Reviewing these shift-level time studies provides us with insight into those variables that might be useful in a logging production forecasting system. Murphy

(1978) mentioned some likely reasons for daily variations in a cable logging operation on *Pinus radiata* in New Zealand. He found that yarding distance is highly significant, as well as shifts to new landings or where native logs were pulled in addition to exotic logs. Daily productivity was also considerably higher in the directionally felled areas. Evanson and Kimberley (1992) showed that daily variations on cable logging production in *Pinus radiata* were affected by the mean extracted piece size, number of chokers, and yarder type.

Regression analysis of ground skidding operations repeatedly showed a common set of independent variables including: load weight, number of pieces per load, skidding distance, slope, total volume per turn. Many others included horse power and machine type (Tufts *et al.* 1988, Johnson 1988, Legault and Powell 1975, Andersson and Young, 1998). However, these studies include variables with a high degree of collinearity such as total volume versus number of logs per turn that may decrease precision due to the loss in degrees of freedom.

There are numerous other production studies that describe forest operations, but very few of them focus on forecasting logging production. Most of these equations have variables that lack the characteristic needed for forecasting, in that these variables are difficult to be estimated prior to harvesting the unit. An efficient forecasting model must contain variables that are easily collectable prior to the operation's execution. These studies show that a recurrent variable with potential forecasting capabilities is the skidding or yarding distance and the machine type.

Decision support system for forecasting productivity

Halleaux and Greene (2003) state that harvesting planning will rapidly increase in the future as more environmental regulations are adopted and as the marketplace insists on the adoption of a certification system. Currently, there are few formal planning tools used in operational harvesting planning. A number of systems have been developed to support harvesting planning but few have found long term practical applications.

Simulation techniques, weighting systems and mobility models have been widely used to develop decision support systems for harvesting planning and operation management. Windsauer and Bradley (1981) developed a computer simulation model designed to provide cost and productivity estimates under different stand harvest conditions. An interactive computer program, LOGCOST, developed by Giles (1986) predicts stump to mill logging and transportation costs adapted for conditions in southwestern Idaho. The program was intended to evaluate the economic tradeoffs of different stand management strategies.

Wang and Greene (1999) published an interactive simulation system to model the interaction among stand characteristics, harvesting methods and machinery. The program is able to evaluate the interaction when performing activities such as: forwarding, skidding or felling. A limitation of this program is that it does not consider the effect of slope in any of the analysis as it was generated for the southeastern US with its flatter terrain when compared to the western US. Machine productivity is based on previous production studies and one will need to carefully consider the appropriateness to extrapolate the results to another harvest area. A ground-based timber harvesting production model through computer simulation was developed by Wang and LeDoux (2003); the system evaluates impacts on costs, production and traffic intensity for soil compaction. Both of these applications required a stand generator program to create stand conditions necessary to perform the harvesting simulations.

SKIDPC was developed to estimate mobility of ground vehicles, and provide estimates of production per hour and unit cost per hour. It calculates the velocity of a skidder based on the mechanics of the vehicle. The variables are geometry of the skidder and horsepower mechanics, tree or log geometry and soil strength (Olsen and Gibbons (1983), Spong (2001)). It is able to generate an estimate of the total turn time, given knowledge regarding the load size.

PLANS is a system of computer programs that was developed to help harvest planners to make decisions in harvesting operations. This system supports trial and error process when designing a harvesting plan, then the best plan is selected by comparison. SIMYARD is a simulation model in PLANS for steep terrain operations. SIMYARD predicts yarding cost and production for cable logging operations; this program requires input information from time-studies and stand description (McGaughey and Twito, 1987).

Halleux and Green (2003) developed a spatial simulation tool to assist in forest planning. Their tool was an Arc-view extension to assist harvest planners by using spatial information obtained from scanned air photos or detailed data from a geographic information system. The program estimates harvesting cost components and site disturbance. The model creates travel patterns for ground based machines and compares different harvesting settings based on projected average skidding cost and site disturbance levels. It does not account for the slope of the terrain on skidding distance calculations.

STHARVEST software is a spreadsheet application designed to estimate costs for harvesting small-diameter stands; it is becoming widely used by the USDA Forest Service (per. comm. G.E. Murphy, 2005). It combines production equations from numerous studies to estimate cost and productivity using a relevance weighting system (Hartsough *et al.*, 2001). This tool is designed to support the appraisal of stand management decisions by the USDA Forest Service.

Currently, harvest schedulers make decisions based on personal experience, which can result either in overstocking of raw material that leads to additional storage costs or shortages that can significantly decrease customer service. The use of decision support tools may reduce the uncertainty of their forecasts. Decisions taken on a daily basis regarding landing location and areas to be skidded have a great deal of variation. To help facilitate the decision making process a decision support system is needed that can forecast production both at harvest unit level and on a daily basis.

Objectives

The main objectives of this study are to determine the variables that affect production at the operational level, and the amount of variability that can be explained by a prediction model using variables that can be easily measured prior to the beginning of harvesting operations. Additionally, this study seeks to develop a support system that integrates the daily and unit level forecast system on a geographic information system platform.

Methodology

The purpose of this paper is to develop the analytical methods used to support the forecasting of logging production. One application is to forecast the average production for the entire unit that would be achieved prior to logging while the second will assist in forecasting the daily production. To develop the forecasts at these two levels, a four-part methodology has been developed. They are: (1) A description of the stand and harvesting operations, (2) a description of the data collection procedures, (3) steps to develop the forecasting model and (4) the procedures for developing the GIS framework.

Stand and Operation descriptions

The study area (Figure 1) was in the MacDonald-Dunn Research Forest which is located on the hills surrounding Corvallis. It is managed by Oregon State University, College of Forestry (OSU), and is primarily used for teaching, research and outreach activities, but it is also utilized for recreation purposes.

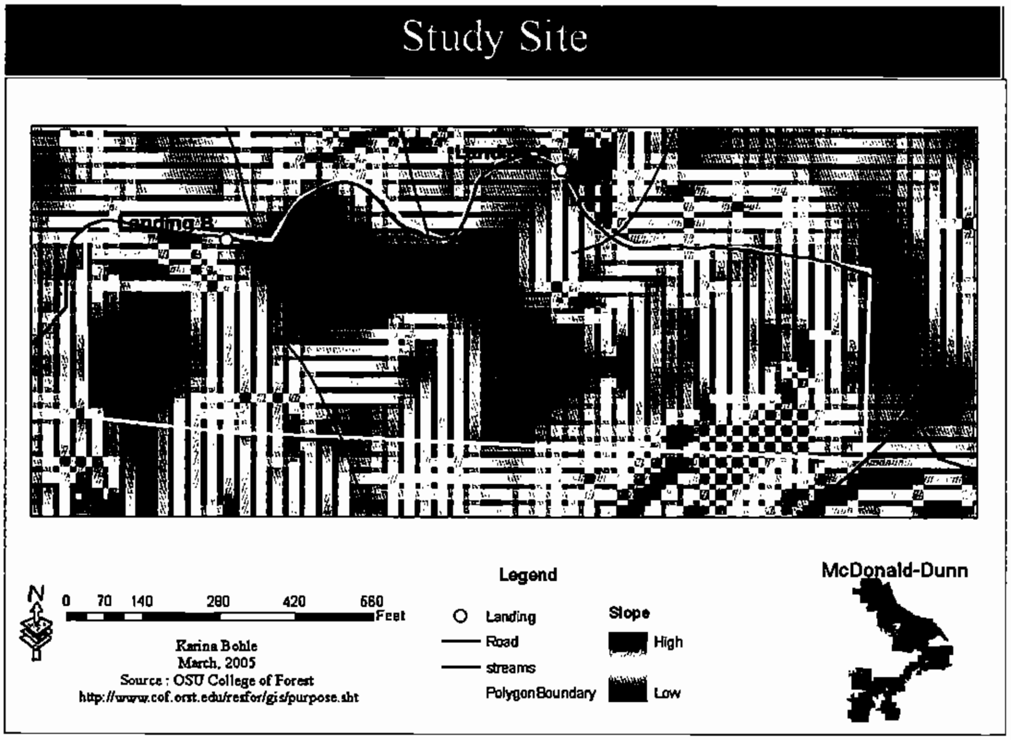

Figure 1. Study location

The area used in the study is a forty year old Douglas–fir stand with a total area of 96.49 acres, from which approximately 13-acres were harvested during this study. According to the forest inventory information obtained from the College of Forestry staff, the unit had a dominant height of 33.25 m (109.08 ft), an average diameter breast height (dbh) of 26.41 cm (10.39 in), a basal area of 13.01 m^2 per hectare (186 ft^2 per acre), volume of 467 m^3 per hectare (6674.08 ft^3 per acre).

The logging operation in the study used a John Deere 540B skidder. The trees were felled manually and bucked in the forest. The logs were then skidded along skid trails to one of the two landings. The student logging crew performed all work on the unit. The student logging crew is a training program for interested students to gain experience in practical logging skills; the students carry out all phases of logging operations. The members have little or no experience in logging, but were trained and supervised by Jeff Wimer, who has 26 years logging experience.

Data collection

Production data was collected during the beginning of August through to mid-September 2004. A total of 15 days of data were collected during this period. The student logging crew were provided with forms to record daily productivity and a set of potential independent variables that were thought to affect the productivity. The variables that were measured are:

- Daily production (number of logs extracted that day)
- Location of skidding area to be used to calculate skidding distance
- Crew size
- Shift length (hours worked)
- Weather conditions (temperature and precipitation)

To estimate skidding distance, the logging crew supervisor was provided with a map on which he drew the approximate location that the crew worked and the location of the landing used for each day. The average skidding distance (ASD) was calculated afterwards for each day from each of the maps, by drawing a straight line from the landing to the center of the approximate location the crew worked. The daily temperature was obtained from records[1] online. The weather station used was located near Corvallis at the coordinates 44 ° 35 ' 25 " N latitude and 123 ° 17 ' 28 " W longitude, at an elevation of 121 m (400 ft) . Table 1 shows the summary statistics for the different variables recorded during this study period.

Table 1. Summary statistic of the variables measured during the operation

Statistic	Number of Logs	Ave. T^0 (F^0)	Average skidding distance (ft)	Shift (hours)	Crew size	Pp (mm)
Min	23	61	114.29	6.5	3	0
Mean	89.33	70.33	353.93	8.43	5.20	0.05
Max	183	76	510.44	10.25	6	0.6
Std. Error	13.82	1.45	28.35	0.27	0.24	0.04
Std. Dev	53.53	5.60	109.81	1.05	0.94	0.16

Developing the model

A multiple linear regression model was selected to be the first attempt to forecast logging production as suggested by (Olsen *et al*, 1998). The modeling was carried out using S-PLUS 6.1 for Windows Academic Site Edition, Release 1.

[1] http://www.wunderground.com/weatherstation/WXDailyHistory.asp?ID=KORCORVA4&day=10&year=2004&month=8&graphspan=month

The steps taken during the modeling process are described in the following sections.

Testing Independence Assumption

In this study, average daily production observations are collected on a daily basis. When data is collected over time or space, there is a chance that the assumption of independence among the variables will be violated. Some of the potentially correlated variables likely to be found in production studies are piece size and volume per turn, or turn time and skidding distance. When the assumption of independence is violated, the model results tend to be further from the long- run mean than is expected. In addition, serially correlated samples tend to be closer to each other, decreasing the variability and causing misleading results. Therefore, it is important to perform the appropriate analysis to determine the independence of the dependent variable's observations.

Serial correlation analysis was based on the "First Order Auto-Regressive Error" model which simply says, the error is composed of a random error that fulfills the linear model assumption plus another component at time (t-1) which is weighed by the autocorrelation coefficient (Ramsey and Shafer, 2002) . Visual analysis using lag plots and numerical analysis using Durbin-Watson statistic were calculated for testing first-order autocorrelation in regression residuals. If the test indicates that correlation exists, then a correction or transformation to the data must be applied. If serial correlation is not present, the least squared method can be used. In this data set, there was no evidence of serial correlation and no transformations to the data were required, the least squared method was used.

Potential problem points

The least squared regression analysis can be unduly influenced by outlier points (Ramsey and Schafer, 2002). Outlier points are observations that come from populations that do not correspond to the one being analyzed, therefore they must be excluded. To omit an observation just because it is influential is not justified; therefore, a case-influence exploration was performed. The following statistics tests were used to indicate possible statistically significant problem points.

- Cook distance assesses the overall changes in the coefficient when an observation is omitted.
- High leverage measures usualness of the explanatory variables.
- Studentized residual is a measure for outlierness.

If some observations are *case-influenced*, then a further analysis must be completed to discover the nature of the problem point(s). If case influences exist, the model will be reported with all the observations, then subsequently without the potential problem points. To avoid any problem points the data collection guidelines must be clearly defined before the study starts. In this data set no problem significant problem point were found.

Variable selection and model refinement

The response variable (daily productivity) was plotted against the explanatory or independent variables to check for possible relationships. A series of correlation coefficients were calculated between each independent variable and the response. A high correlation between the response and independent variables is an indicator of a potential variable for the model.

A high correlation among independent variables suggests that only one of the two variables should be used; otherwise, a spurious coefficient may result (Olsen *et al.,* 1992). When too many predictors are used, degrees of freedom can be lost, leading to a large standard error.

The variable selection was completed using *stepwise analysis*. The analysis starts with a saturated model from which the most influential variables are retained in the model until a desirable model is found.

The saturated model to stepwise analysis is described as follow:

$$\mu\left(P / ASD, CS, SL, Pp, T\right) = \beta_0 + ASD \times \beta_1 + CS \times \beta_2 + SL \times \beta_3 + Pp \times \beta_4 + T \times \beta_5$$

Where,

- ASD = Average skidding distance (ft)
- CS = Crew size (workers per day)
- SL = Shift Length (hr)
- Pp = precipitation (mm)

- T = Average daily temperature (F°)
- P = Production (number of logs per day)

The criterion for the selection is to first identify the variable with the largest p-value statistics; if this is greater than 0.05, the explanatory variable is removed to form a new model. This is repeated until no more explanatory variables can be removed from the model.

The following criteria were used to assess the lack of fit of the model and included penalties for over-parameterization of the model. These criteria include penalties for having extra parameters in the model.

- The adjusted R^2 indicates how much variability is explained by a model, penalizing for any extra parameter included in the model.

- The (Cp) statistic (and plot) measures the trade-off between the bias due to excluding important explanatory variables and variance explained due to including too many variables. It corresponds to the amount by which the mean in the sampling distribution of the *ith* fitted value differs from the mean it is attempting to estimate. A model without bias should have a Cp equal to the number of parameters in the model. Thus, the smaller the Cp then the better the model.

After a suitable model is found, a residual analysis can be used to locate any remaining unwanted outliers; if the model is adequate, then the residuals must be normally distributed around a mean of zero.

Finally, if several models are found to be good alternatives, the adjusted R^2 and the Cp will lead in the model selection. The Akaike Information Criterion (AIC) statistic was also calculated to discriminate between model alternatives. This criterion includes a penalty for too many parameters. The selection among models is made by choosing the model with the smallest AIC value. A combination of these statistics addresses the selection of a model that suits this project's general objective.

Testing for other Assumptions

The robustness of each model was checked in terms of the following regression model assumptions: linearity, constant variance and normality. The assumptions are discussed for one of the models (See appendix A for details on plots). The QQ plot shows the relationship between the response values versus the fitted values. In a perfect model both values should be equal and follow a straight line. A common plot used to check for the equal variance assumption is the residual plot, which showed if the residuals are normally distributed or not.

Validation

The utility of production equations derived from time study data for forest harvesting operations is questionable when they are published without documented validation (Howard, 1992). It is necessary to statistically test the differences between the actual productivity and the productivity obtained by using the prediction equations. In this study, due to the small sample size, validation was not possible. Ramsey and Schafer (2002) recommend that the validation dataset should be about 25% of the entire set when the purpose of the regression analysis is prediction. Unfortunately this study had a small data set and validation was not completed.

Developing the GIS framework

The results from statistical analysis and the literature review show the importance of skidding distance as a key variable to forecasting logging production. To aid in the calculation of skidding distance, a GIS-decision support system was developed to help forest planners to efficiently manage the primary supply chain in the forestry industry. Besides estimating the skidding distance, the GIS system will allow a variety of production equations to be easily integrated in a single forecasting system.

Description of the model

The models were constructed in ArcGIS 9 developed by ESRI using the visual modeling functionality of ArcGIS 9 known as Model Builder[2]. Model Builder allows complex models to be built visually and performs consecutive tasks. Figure 2 shows an example of two simple consecutive tasks performed with Model Builder; *buffering* and *clipping*. A buffer is a zone of a particular distance around a feature or features (for example, finding all streams within 400 feet of a planned logging area); clipping computes the geometric intersection of the input and clip features.

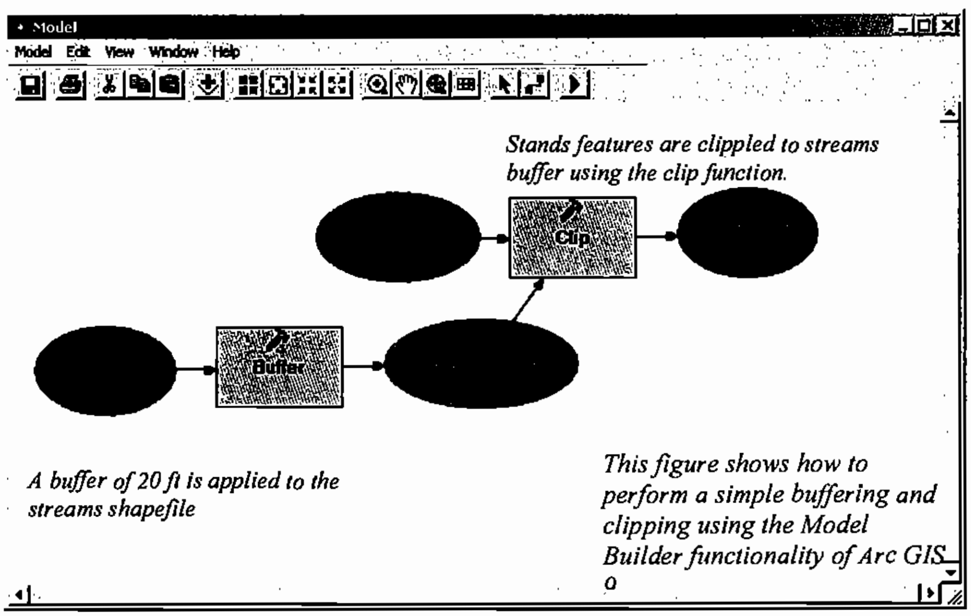

Figure 2. Model Builder diagram example of buffering and clipping

The *Spatial Analyst* and 3D analyst were used since the forecasting models required many raster-based calculations. The Spatial Analyst and 3D analyst

[2] www.esri.com

extensions for ArcGIS 9 allow the display, creation, manipulation and analysis of grid raster data.

Input data

The models, unit and daily level, require both GIS and user defined data. The GIS data includes a digital elevation model of the area, road, vegetation, stream and unit boundaries. The user must locate the following data on these map layers, landings and skidder pick-up locations. Pick-up locations, the source of the volume within the unit, for the unit analysis corresponds to a grid of points distributed in a homogeneous pattern throughout the unit. They can be fixed directly by the user or randomly located. An important aspect in the analysis is the cell size. It affects processing time and file size, as well as the degree of precision of the results. The skidder being used in the operation is approximately 3-4 meters wide, therefore a cell size of 3 meters was used in this analysis. This cell size is similar to that used in other studies such as Halleux and Greene (2003) and Wang (1997). Using a different cell size would inaccurately estimate the skid trail width. This is particularly important when modeling potential environmental impacts. A digital elevation model, using USGS 30 meter DEM, is used to generate a slope raster and a contour vector layer. The unit boundary is the outer boundary of the unit that is scheduled to be harvested. If not readily available, it may have to be digitized by the user. The landings and pick-up locations have to be created by the user before continuing the analysis.

Description of the process

A flow diagram of the analysis model is displayed in Figure 3, which is composed of: total cost model, unit level model, and daily level model. The total cost model is a common process for both forecasting models. The output of this process is the total cost raster used as input in the unit and daily level model. The analysis model uses a series of existing *Spatial Analyst* and *3D Analyst* functions that are implemented in Model Builder environment, and in Arc Map environment.

The process begins by confirming that the user has supplied all of the required input data, and setting the environment's properties (extent, mask, cell size) for the process. The *model builder* flow diagram is attached in Appendix 2.

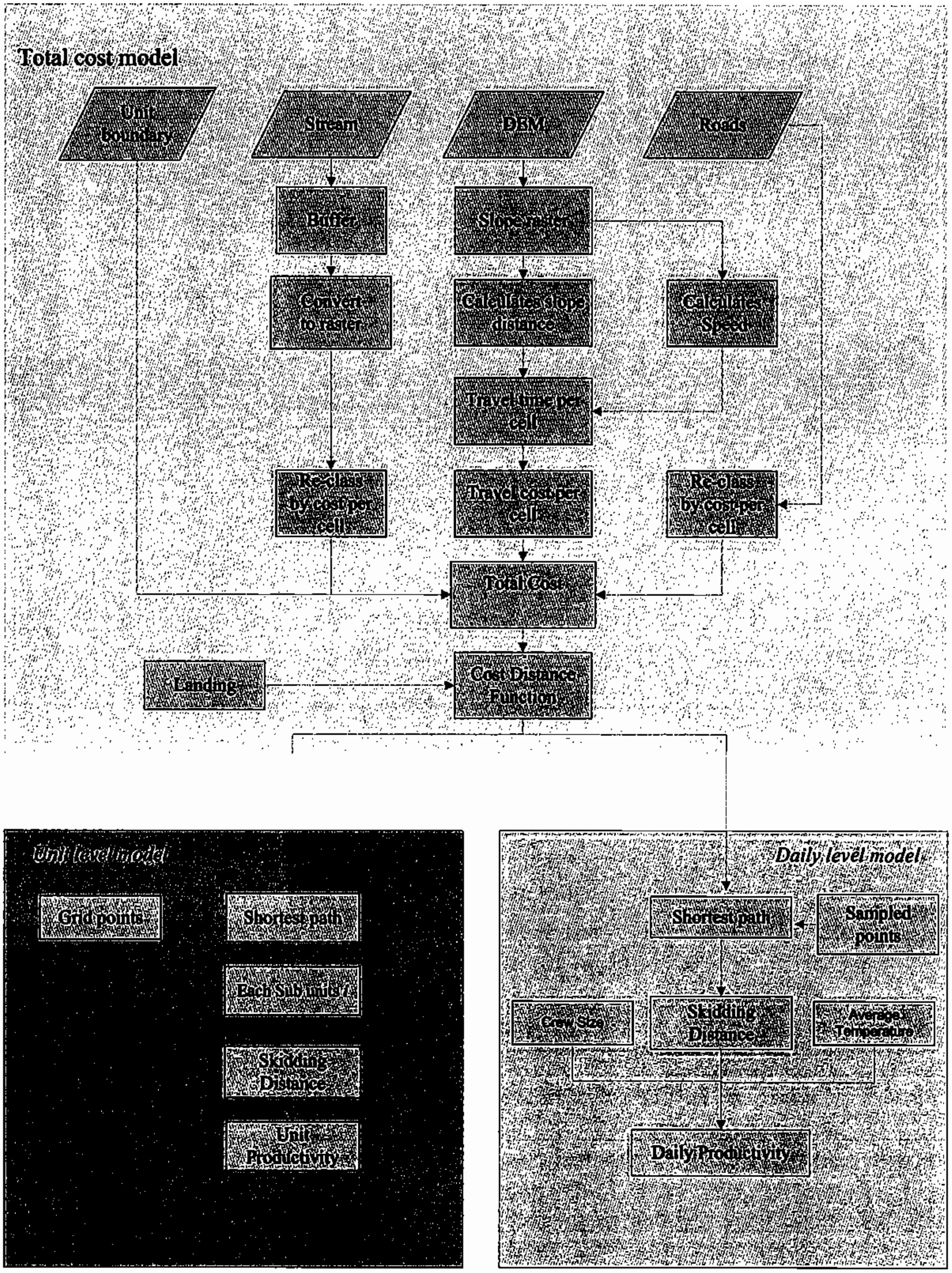

Figure 3. Flow diagram of the decision support system

Total cost model

The total cost is the summation of travel cost, an artificial stream barrier cost and road cost. The travel cost considers the operational cost of the skidder and the travel time per cell. The skidder used during the operation is a medium size skidder with an approximate cost per productive machine hour of $85/PMH or $1.42/min (pers. com. Glen Murphy). The travel cost per cell is obtained for each cell by multiplying the operational cost per minute by travel time per cell. Travel time is a variable function of the velocity and the distance. The distance is the slope distance which is obtained from the slope raster. Velocity is calculated based on machine capabilities which depend on the slope of the terrain, slip, and log load.

A program was written in Visual Studio.Net to calculate the travel time of the skidder as it crosses each cell. Figure 4 displays this process. The program needs some parameters about the geometry of the skidder, an estimate of the load and cone index. These parameters are held constant similar to the skidder model developed by Gibbons and Olsen (1983). The program considers the following assumptions: initial velocity at each cell of zero, (100 horsepower) engine capability, constant load of 3.40 tonne (7,500 lb) and a cone index of 551.58 kilopascal (80 psi). The velocity is calculated for each individual cell where the slope from each cell is used to calculate the normal forces and resistances for the front and rear tires. The next step is to iteratively solve for the tire slip to compute available thrust. If the gross thrust is greater than the resistance then the velocity is calculated and stored. The program then goes to the next cell, otherwise it stops the process.

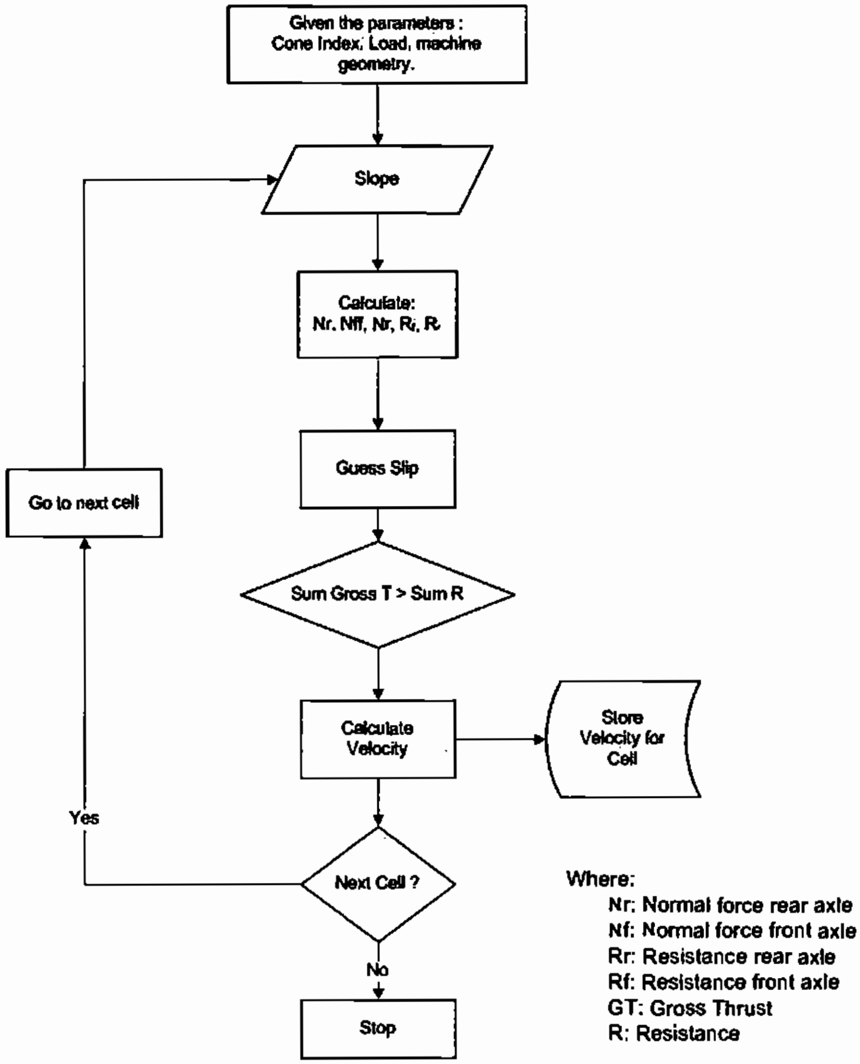

Figure 4. Flow diagram to calculate velocity per cell

<u>Stream cost</u>

Skidding over a stream must be avoided to minimize environmental impact and reduce cost. This factor was included in the analysis by associating a high cost to each cell that represents a stream. In this way, traffic over a stream would be minimized. The streams in this study are small streams, type N, according to Oregon Forest Practices Rules and a no leave-tree retention is required; however, a 20 feet buffer was required as part of the College of Forestry management plan. A range of penalty values per cell were tested from $500 to $1 to severely penalize the skidding through riparian areas; the results showed using $1 is a satisfactory penalty value as it is far more expensive than the travel cost through other grid cells.

Road cost

No road penalties were used in the model since it was assumed that maintenance would not be applied to this operation. The travel cost, stream and road cost rasters were summed to obtain a total cost raster, or skidder cost which is an input in the models.

Cost distance function

The "Cost Distance" function is used to produce an output raster in which each cell is assigned a value that is the least accumulative cost of getting back to the nearest source (landings). Cost distance functions are based on the node/link cell representation used in the graph theory (McCoy and Johnston, 2002). This function also calculates the backlink (machine path) which was used to retrace the cost path from the pick up point to the landing over the cost distance surface. The algorithm used to compute the backlink assigns a code to each cell that identifies which of its neighboring cells is on the least cost path back to the source (McCoy and Johnston, 2002). For example, in Figure 5, the backlink code zero represents each cell in the raster, each cell is assigned a value representing the direction of the cheapest cell on the way to the nearest source.

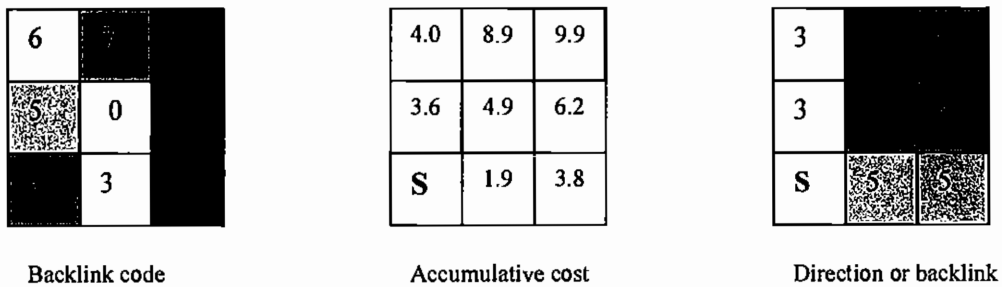

Figure 5 Diagram representing the backlink and accumulative cost

The cheapest way to get from the cell with a value of 9.9 to its source is to go diagonally to the cell of value 4.9. In the backlink or direction a value of 4 is assigned to 9.9 and to 4.9, because this is the cheapest way to go from this cell to the nearest source.

The backlink and accumulated travel cost raster generate a cost surface for the unit, which can be used to determine areas with high and low skidding costs. The machine path and accumulated travel cost raster can also be used to optimally calculate the skid trail pattern path that minimizes the skidding cost from the landing to any point in the forest.

The optimal skid trail pattern was calculated by applying the shortest path function available in *Spatial Analyst* extension to the total cost raster. This function determines the lowest cost path from a pick up point to the nearest landing. The path analysis uses the accumulated travel cost and machine path raster previously calculated using the cost distance function.

Unit Level Productivity Calculations

For the present study, no unit forecasting model was constructed because the dataset available was small for this purpose; therefore, an alternative model was selected from the literature. This model was used because estimates production based on a variable that is collected prior the operation is executed, and also expresses the variability at the unit level.

The unit productivity calculations were based on a productivity function developed by FERIC (Andersson, B and Young G. 1998) which is shown in Table 2. This equation was selected because it expresses the production as a function of the skidding distance which can be easily calculated prior to commencing the operation, Other variable required by this model is the average turn size. Any simple unit level production function that represents the geometry of the unit, characterization of the tree, and description of the harvesting unit can easily be integrated into the unit level forecasting system.

Table 2. Production equations to estimate productivity developed by FERIC

Item	Description
Travel time (min/turn):	:TTVL = 0.46+0.0166x [Distance, m)
Fixed turn time (min)	:TF = 6.55
Total Turn time (min)	:TT=TTVL +TF
Minor Delay (%)	:DEL = 5.0% of TT
Turn size (m3)	:VTURN = 3.2 m^3
Shift length	:SHIFT= 8x SMH @ 80% utilization rate
Productivity per day	:PSHIFT= (60/ (TT +DEL))x SHIFT x VTURN

The average skidding distance was based on the approximation method described by Suddarth and Herrick (1964) which divides a unit into sub-areas where the distance from the center of each sub-area to the landing is weighted by the area of each sub-area. The average skidding distance is then estimated by summing the individual weighted distances and dividing by the total area.

The average skidding distance is calculated separately for each landing, based on the optimal allocation of skidding paths, and then is weighted by the area of each landing to obtain the overall skidding distance. The harvesting unit is divided into cells of 0.1 ha; the optimal path was calculated from the nearest landing to the center of each 0.1 ha cell. This procedure gives an estimate of the harvested area that will go to each landing.

Daily Level Productivity Calculations

To demonstrate the capabilities of the system to forecast daily production, a sample of 10 harvesting points were randomly selected within the unit. The daily production for each point was calculated using the empirical equations obtained in this study for this unit and for this crew. Both production regression equations are used to assess the advantages or disadvantages of the two equations.

The rough topography conditions found in the Pacific Northwest makes it necessary to account for the slope when calculating the skidding distance. Once the shortest path was known for a point, a correction for the slope was applied using the *surface length* function included in the software which calculates the length of a line considering changes on the elevation of the terrain. This skidding distance value was then used to estimate the daily production for each of the sample points.

Scenarios

Stream density is considered an important variable in logging operations because it affects the operation costs by limiting the skidding direction that can be used. Two types of stream density, current and high, were selected to demonstrate the ability of the model to forecast productivity at the daily and unit levels. For high density streams, more streams were added to the current density using the current pattern of stream.

The production for the unit forecasting level was calculated under two scenarios using one and two landings to compare the impact of skidding distance on production.. The landing allocation, for the two landing scenarios, remained the same as those landings used by the actual logging operation.. The single landing scenario was allocated in an intermediate location.

Results

Production forecasting model

The data was collected during the summer harvesting season, with a total of fifteen days worked. There were numerous mechanical problems with the skidder that reduced the productivity of this operation; therefore, the crew did not work during the entire season. The limited data is used to demonstrate the forecasting methods; in practice, however, one would acquire significantly more data points.

Statistical analysis of the data was performed. The first test was for temporal correlation due to concerns regarding the lack of independence. The results showed no evidence of serial effects. Using the Durbin-Watson test there was no significant correlation. Therefore no transformations were necessary to the data.

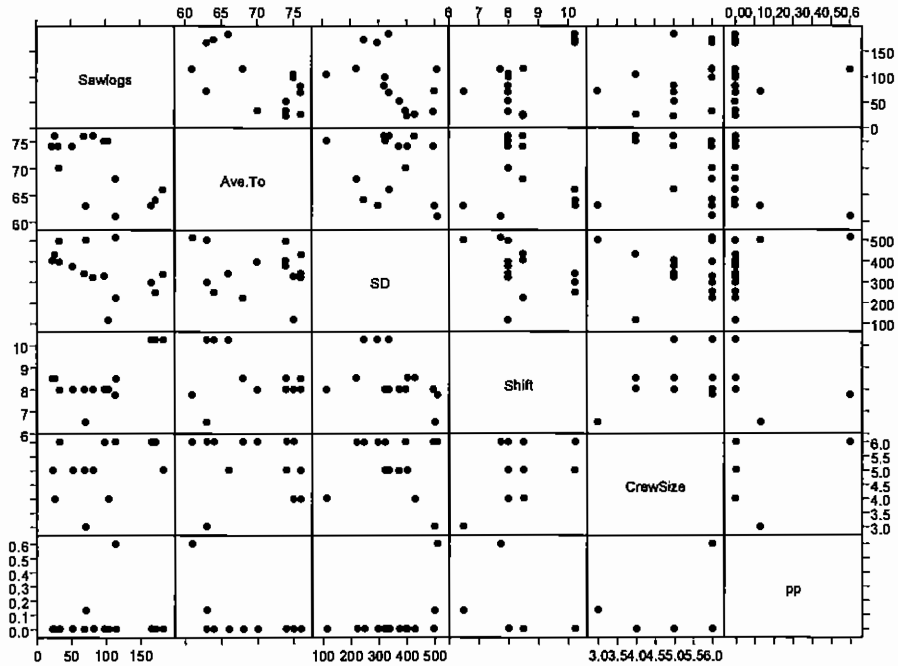

Figure 6. Matrix of relationships of the variables measured in the operation

Where,

Ave.T^0	: Average temperature
SD	: Skidding distance
Pp	: Precipitation

The first approach to analyze the data was completed by plotting the response variable against the explanatory variables to check for possible relationships. Figure 6 is a matrix of scatter plots for the potential explanatory variables and their responses. It can be seen that there is a strong inverse relationship between the independent variable, average temperature (Ave.To), and the response variable (N° of Sawlogs). As the temperature decreases the number of logs produced in a day increases. The relationship of the skidding distance (SD) is also inversely proportional. As the skidding distance increases the daily productivity decreases. Alternatively, hours worked (Shift) has a direct relationship with the response variable. Crew size (Crew Size) and precipitation (pp) did not show a clear graphical relationship. These results are quantified by the correlation coefficients shown in Table 3.

Table 3. Correlation coefficients for independent and the response variables number of sawlogs.

Variable	Correlation Coefficient
Ave. T^0	-0.625
ASD	-0.481
Shift	0.685
Precipitation	0.106
Crew Size	0.269

A good model must not include independent variables that are highly correlated; otherwise, a spurious coefficient may result. For example, when correlation coefficients are high between two variables, only one of them should be used. Table 4 shows the matrix of the correlation coefficients among potential independent variables. Precipitation has high correlations with average temperature and skidding distance, and crew size has a high correlation with number of hours worked.

Table 4. Matrix of correlation coefficients among explanatory variables

	Ave T^0	SD	Shift length	Crew Size	pp
Ave T^0	1	-0.162	-0.287	-0.176	-0.535
SD		1	-0.405	-0.079	0.470
Shift length			1	0.430	-0.288
Crew Size				1	0.094
Pp					1

Therefore, the independent variables were selected using their correlation values. Precipitation for instance, was not used in the modeling process because of the high correlation with average temperature, because the days that registered precipitation were too small.

Three statistics were calculated to investigate for potential problem points. This analysis showed three high leverage points that could adversely influence the model, therefore further tests on the model were needed. The (standardized) residuals and the Cook's distance statistics showed that the points do not significantly affect the coefficients and therefore no alterations to the data were performed.

The stepwise analysis showed that the independent variables for this daily productivity model were average temperature, hours worked (shift) and skidding distance. The adjusted R^2 for this model is 0.764; this means that 76.4% of the variability in the data is explained by the model. The standard error of the model is 26.02 pieces with a 95% confidence interval for the mean production of (32.82, 146.03) daily production. Table 5 shows the coefficients and p-values for each of the regression models. Average temperature is a highly significant variable with a p-value of 0.001. For each degree increase in temperature the production estimated is decreased by 5.7 pieces. Skidding distance is also significant with a p-value of 0.0136. The effect of this variable is a reduction of 0.21 in the number of pieces per day for each foot increased in distance. Hours worked is significant with a p-value of 0.0594. For each additional hour there is an increase in production of 16.6 pieces.

Table 5. Coefficients and p-values for forecasting production model (pieces/day)

Variables	Coefficients	p-values	Adjusted R^2
Intercept	430.84	0.0159	0.764
Ave. T^0	-5.767	0.0015	
SD	-0.216	0.0136	
Shift length	16.669	0.0594	

Where:

Ave. T^0 = Daily average temperature (F^0)

SD = Average Skidding Distance, (ft)

Shift length = Number of hours worked per day

For those cases when temperature can not be accurately forecast, another model was developed using hours worked and skidding distance. This model allows assessing the benefits of adding an extra variable in the model, and therefore the potential improvements on the production forecasting model. The results of this model are depicted in Table 6. The adjusted R^2 for this model is 0.564 with a standard error of 36.48 giving a 95% confidence interval for the mean of (9.84, 168.82).

Table 6. Coefficients and p-values for the comparative model without average temperature

	Coefficients	p-values	Adjusted R^2
Intercept	-189.448	0.117	0.564
SD	-0.154	0.150	
Shift length	38.856	0.005	

The loss of temperature as an independent variable resulted in a decrease in the variability that can be expressed by the model, as the value of adjusted R^2 decreased from 0.764 to a 0.564. This resulted in an increased estimate of standard error from 26.02 to 36.48.

Unlike the full model, the shift-skidding model was affected by influential points. Statistics applied showed that one of the data points had a high influence in the coefficients of the model, varying their values and decreasing the variation explained by the model. Therefore, this point was not included in the analysis.

Table 7. shows the values for the confidence interval in both models and their associated standard errors.

Table 7. Confidence intervals for the coefficient of the models with and without temperature as an independent variable.

	With Ave.T^0			Without Ave.T^0		
Coefficient	SE	CI. lower	CI.upper	SE	CI.lower	CI.upper
Intercept	151.382	97.65	764.03	111.607	-435.09	56.198
Ave. T^0	1.370	-8.78	-2.75	-	-	-
SD	0.074	-0.38	-0.05	0.100	-0.374	0.065
Shift length	7.930	-0.79	34.12	11.256	14.081	63.631

Figure 7 displays the effects of average temperature and skidding distance on forecasting productivity for a constant 8 hours worked. The surface shows that the productivity decreases as the average temperature and skidding distance increase, resulting in a minimum forecasted productivity of 17 pieces, at 76 degrees F and 500 ft, for these two combined factors. The maximum production could be reached at minimum values of temperature (62 degrees F) and the smallest skidding distance of 140 ft. It can be seen that for constant skidding distance, as the temperature declines the production increases.

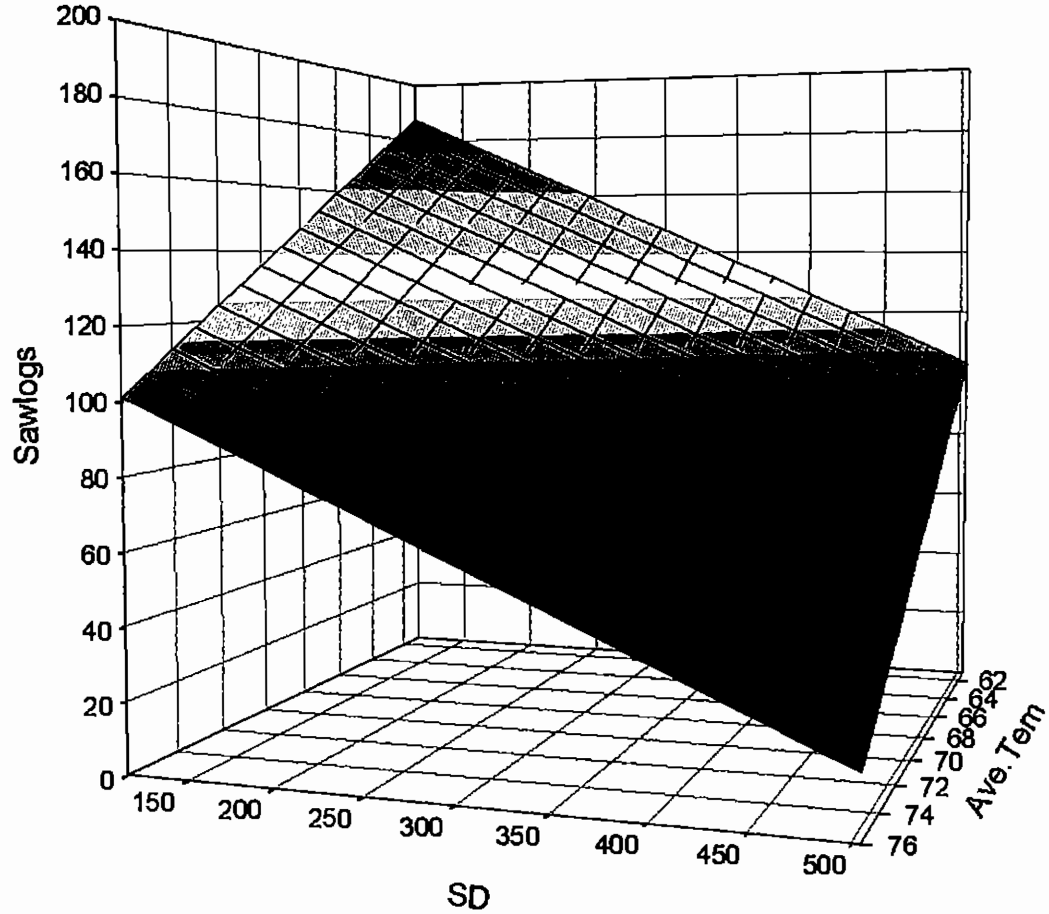

Figure 7. Effect of temperature and skidding distance on productivity, for constant 8 hours worked.

The results from the second model fitted, without considering the temperature, are shown in Figure 8, for 8 hours worked. The figure shows that the production forecasting is homogeneous for the range of temperature values. This model is less powerful and underestimates forecasting when the temperature conditions are favorable (low) and overestimates when temperatures are adverse (high). From figure 8 it can be seen that these differences are significant.

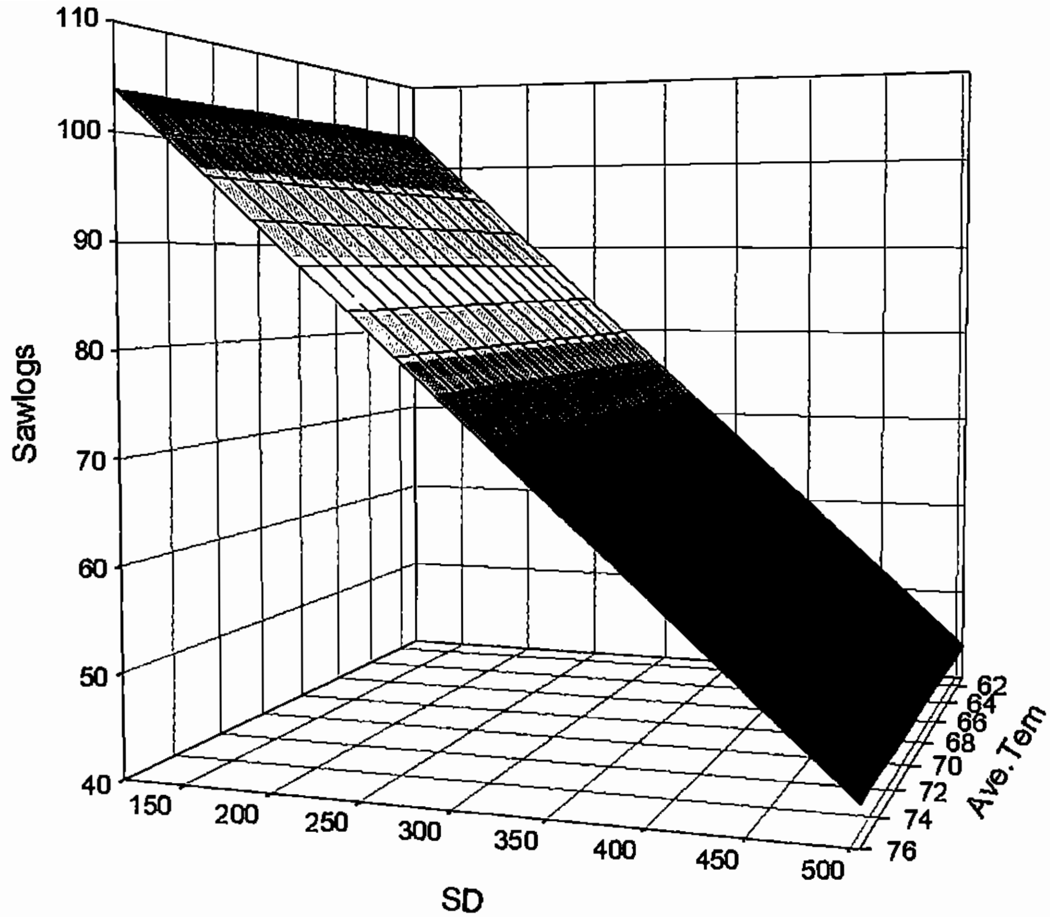

Figure 8. Effect on productivity when temperature is not included as explanatory variable, for constant 8 hours worked.

One of the advantages of implementing the system on a GIS platform is that it allows for the integration of a number of production functions and forecasting functions. Therefore, the two forecasting models developed here were implemented in the GIS support system.

Decision support system

The results given in this section are for the stream pattern and landing scenarios described in an earlier section. The purpose is to demonstrate the use of the geographic information system to determine the skidding distance that is important predictor in forecasting logging production at the operational level by forecasting the unit and daily skidding production. The results have been placed into three sections: (1) the total cost results, (2) the unit production model, and (3) the daily production model. The processes to build the decision support system are shown as a sequence of rasters graphics in Figure 9. The figure shows the flow of results for the total cost model, unit and daily level, individually.

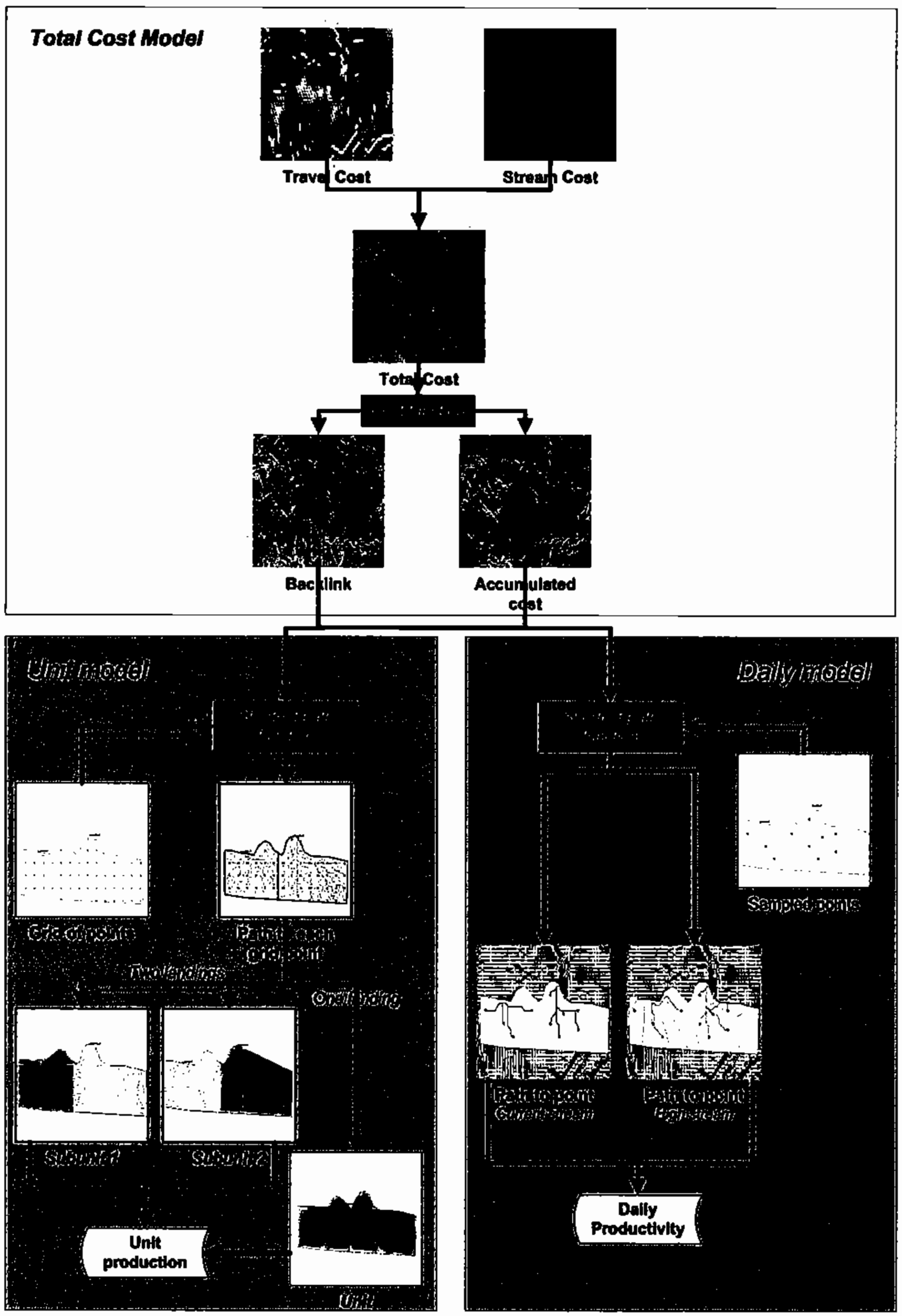

Figure 9. Flow diagram of the main raster graphics results

Total cost model

The main components of the total cost model include the travel cost and stream cost. They are the first results created in the total cost model. The summation of travel cost and stream cost is the resultant total cost raster, which represents the cost to cross each cell in the unit.

The resultant total cost and landings were used to generate the backlink (which represent the path from each cell to the landing) and accumulated cost raster, by applying *the cost function*. These two outputs were used in the unit model and daily model as input for the shortest path function. Figure 10 shows an example of the resultant shortest path for a set of sampled points. The figure shows the slope raster in the background, the unit boundary, the stream raster and the path to each point. A stream crossing has a high cost associated with it and the optimal route changes when stream density changes. The changes in path mean that the distance traveled will change and consequently affect the forecasted productivity.

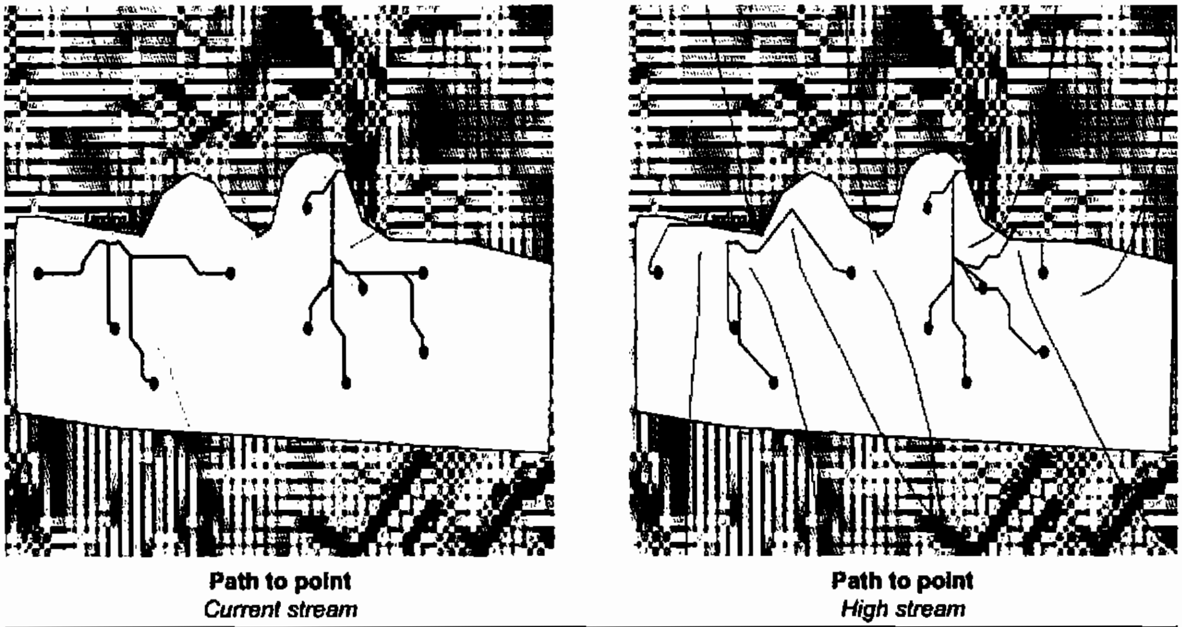

Figure 10. Shortest path to sample point for current stream and high stream scenario

Unit production model

The unit model was developed to estimate the productivity at the unit level by calculating the slope corrected AYD. In this example, a model developed by Andersson and Young (1998) was used to forecast productivity. The model requires the average skidding distance as a main input, tonne per turn, and hours worked. Two scenarios were analyzed to demonstrate how the model can be used to forecast the productivity for the unit; the first placed two landings in the unit while the second had only one landing available. For the first scenario, the results from the shortest path showed the area that goes to each of the two landings according to the number of paths. The area for subunit 1(left) was 2.35 ha (5.8 acres) and for subunit 2 (right) was 3.12 ha (7.7 acres). The average skidding distance for subunit 1 was 78.7 m (258.4 ft), for subunit 2 was 122.7 m

(402.7 ft), and the resultant weighted average skidding distance for the unit was 103.95 m (341.1 ft). For the one landing scenario, the average skidding distance for the unit was 126.3 m (414.4 ft). The forecasted production calculations for the unit under the two scenarios are shown in Table 8. A production of 100.48 m^3 per schedule day was estimated for two landings and 96.38 per schedule day for one landing. The equations used, which were developed by FERIC, are described in Table 2.

Table 8. Productivity at the unit level for one and two landings

	Scenario 1	Scenario 2
Landings	2	1
TTVL (min/turn)	2.19	2.56
TF (min/turn)	6.55	6.55
TTT (min/turn)	8.74	9.11
DEL (min/turn)	0.44	0.46
VTURN m^3	2.4	2.4
Effective day (80%) (hr)	6.4	6.4
Days to harvest the unit	25	26
Productivity per day	100.48	96.38

Given the unit has 467 m^3 / ha (from inventory data), under scenario 1 it will take about 25 days to harvest the unit and under scenario 2 it will take about 26 days.

Daily production model

The daily production model used the empirical production equations developed in the previous sections of this paper to predict the production for one day, given an area that is to be skidded that day. The idea is to forecast the skidder production given that the crew is working in a specific area. The two scenarios analyzed were current and high stream density as was used in the unit scheduling model. The results of productivity when applying both models are shown in Figure 11. Model 1 is function of average temperature, hours worked, skidding distance; and model 2 is function of hours worked and skidding distance.

Forecasted production for the current stream density scenario was higher for the majority of the sample points than when using high stream density scenario, for both statistical models. This reflects the effect of increasing the density of the streams causing an increase in the skidding distance. The production for several of the selected points was similar for both scenarios, high and actual stream density, because the increase of stream density did not affect these skid paths for these areas.

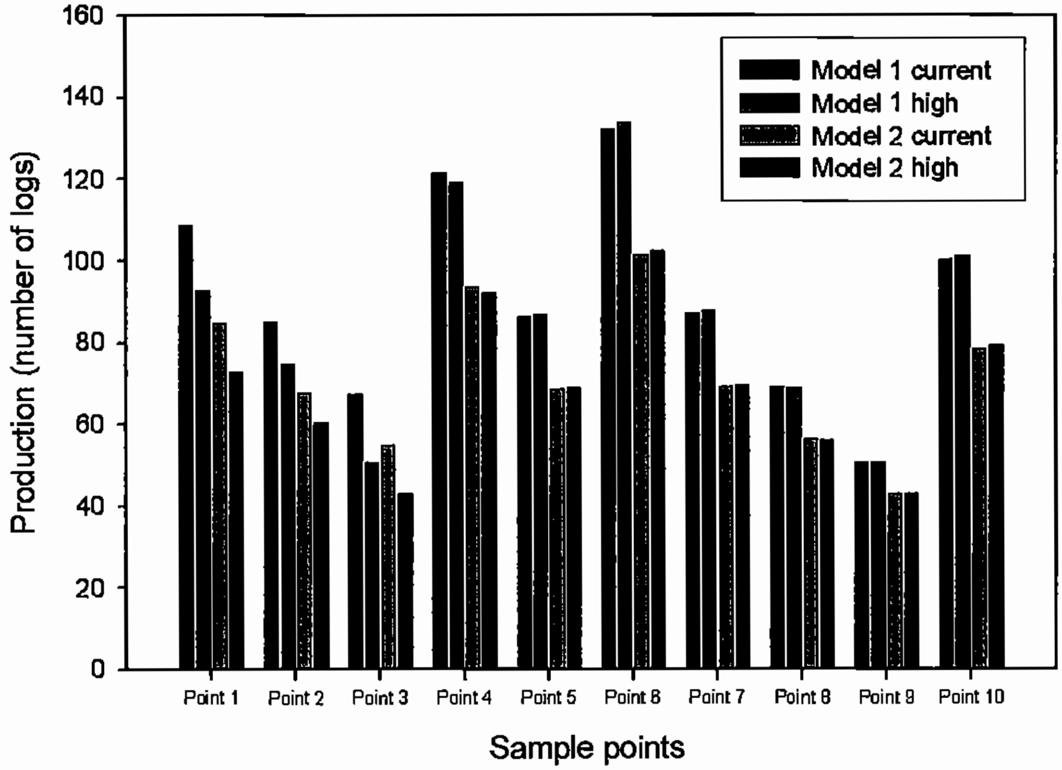

Figure 11. Production results for two stream densities and for two daily production functions, model 1 as a function of SD, Ave.Tem and Shift length and model 2 as a function of Shift and SD.

The overall production was higher, for all sample points, when model 1 was used because the significance of the predictors used by the two models is different. For model 1 the most significant variable is average temperature followed by skidding distance, and in the second model the most significant variable is shift length which was kept constant for this surface for comparisons. The graph shows the expected average daily variation that is possible to encounter on a given unit when a harvesting operation is performed.

Discussion

Estimating the productivity in a harvesting operation is always a difficult task due to the high variability caused by site conditions, the changing weather and changing volume characteristics. There is little information in the literature about the ability to forecast productivity rates on a daily or weekly basis, or for the entire harvest unit. The majority of the studies on productivity have focused on determining production based on cycle time prediction equations. In most cases production is predicted for specific machines, comparing productivity or estimating the time required for harvesting a unit under specific conditions. This study presents a valid methodology to forecast productivity on a unit level and on a daily basis.

The statistical forecasting model

The least squared analysis showed that the most significant variables to estimate productivity on a daily basis were skidding distance, hours worked and average temperature during the day. Skidding distance is an important variable affecting productivity. All other variables being equal, the farther the machine travels the lower the production will be (Conway, 1982). It was found in this study, that as skidding distance increases production decreases, and for a shorter skidding path the production was higher. Skidding distance has the advantage of being easy to calculate prior to the operation being performed.

The number of hours worked, also an important variable in the model, can vary among loggers due to maintenance schedules and training policies. When the hours worked are reduced the daily production will be affected (Pers. Com. Kevin Boston, 2005). Conversely, some loggers may decide to extend number of hours they work if there is insufficient volume to fulfill customer's orders. Productivity rates for these extended hours can decrease if they are implemented without addressing operational needs, safety, environmental conditions (Nicholls *et al.*, 2004).

The statistical analysis showed that changes in average temperature affect productivity. As the temperature increases the productivity decreases. At high temperatures loggers are working at sub-optimal hydration levels, if they don't consume appropriate fluids to replace sweat losses (Bates *et al.*, 2001). It has been demonstrated that body hydration damages performance, physical strength and aerobic power, and moreover the combination of heat stress and dehydration has a more significant effect on performance than hydration alone (Paterson, 1997). Data for this study was collected over the summer, meaning that most of the days had temperatures above the average annual temperature. Therefore, there is a need to study a broad range of weather conditions and their effect on production, such as including situations with precipitation and a broader range of temperature values. Nicholls *et al.* (2004) highlighted that a poor understanding of human factors may jeopardize profitable harvesting and contribute to low productivity. It is anticipated that productivity will be a nonlinear curve with low productivity at both high and low temperatures, or when it is raining.

Support system

The unit prediction model is intended to assist annual planning on scheduling crew capacity to meet the demands. This study uses a prediction production equation previously developed; however, other appropriate models could be used in its place that may improve the forecasts. The daily decision support model is not intended to be a validation of the statistical model, but to demonstrate the benefits of implementing the prediction model using a geographic information system platform. The model can quickly compute the average skidding distance for a variety of shaped harvesting units and stream densities. The model has the ability to find the lowest-cost skidding path from any stump to a landing location in a unit, given slope, stream and road layers. This provides the model with the ability of capturing site conditions that may be difficult to be considered in a statistical prediction model and that may affect the skidding pattern. For instance, stream density, archeological sites or any other environmental aspects easy to be managed by means of GIS. The GIS support system facilitates the displaying of the results and future incorporation of prediction models. This system is similar to the one developed by Halleux and Greene (2003) which estimates harvesting cost and environmental disturbance, but differs in the incorporation of slope of the terrain and the empirical production models.

Limitations of the models and future developments

The current statistical model was developed for a specific range of site conditions which limits its application to different stands. The conditions in a forest operation may vary by average piece size, slope of the terrain, direction of the slope, and machinery among others. Many of these conditions were not included in the data set used in this statistical model. Therefore, a broader range of site conditions need to be included in future modeling efforts. Average temperature was found to be an important variable in this model; therefore, it is necessary to extend the variables for weather conditions. Additional functionality needs to be added to the model to allow it to accommodate multiple crews as well as being able to predict productivity at a weekly level.

Skidding distance used to develop the model was obtained from maps that indicated the position the crew worked each day. This is just an estimation of the real location where the harvesting crew worked, therefore it would be important in future to include a GPS unit in the skidder to record the true skidding distance, and then use this average value in the statistical model.

The statistical model predicts production on a daily level with the objective of assisting the daily operational planning, but the production at the unit level is also important in annual operational planning. The model used in this study considers only skidding distance as the main variable that predicts production, therefore it is important to analyze which other variables influence the variation on unit level production.

A bigger data set is necessary to validate the results of the prediction model. The actual sample size's variability indicates that a sample of 44 days is needed to develop prediction equations with a margin of error of 10%, for an operation that will take 60 days. This will produce future equations that estimate production within a 10% marginal error. A 10% margin of error is a compromise between samples needed and production variability allowed.

Applying the model to a commercial setting

The next step in the research is to apply the model to a commercial setting where multiple crews will need to be forecasted. The process requires developing individual production equations for the harvesting crews. The equations will include variables used in this work which are: hours worked, skidding distance and temperature, and perhaps variables that describe the variability of the stand that were not included in this application since only one stand was used. These potential stand variables might be volume per ha, stems per ha or average volume per tree. Site variables such as average or maximum slope might be included, again emphasizing variables that can be obtained from the GIS analysis. These would then be applied to conditions in the existing stand and would be used to forecast either the average production forecasts for the entire unit, or would be part of a daily forecasting system that could predict the volume from a single day or week.

Conclusions

This project developed a forecasting production model using a GIS framework that facilitates the coordination of activities to support improved performance of the primary forestry supply chain. The following main conclusions were obtained from this study:

- The main variables found in this study that estimate production on a daily basis are skidding distance, average temperature and hours worked; the model is able to explain 76 % of the variation in the daily production. A limited number of variables that can be measured prior to harvesting can be used to forecast production.
- A decision support system was developed that facilitates the forecasting of production at the unit and daily level. The unit level model uses a production equation from the literature that was scaled at the unit level production. We recommend that additional unit level forecasting be developed that considers average skidding distance, stand characteristics such as volume per ha, maximum piece size, and crew type
- A larger sample size is needed to validate the statistical model that was developed in this study. The variability in the current study shows that a

sample of 44 days will be needed for an operation that may take 60 days, with a margin of error of 10%.

By integrating statistical models, machine mechanics and GIS techniques, such as least-cost path, a forecasting model was developed for calculating unit and daily productivity for a ground-based harvesting system.

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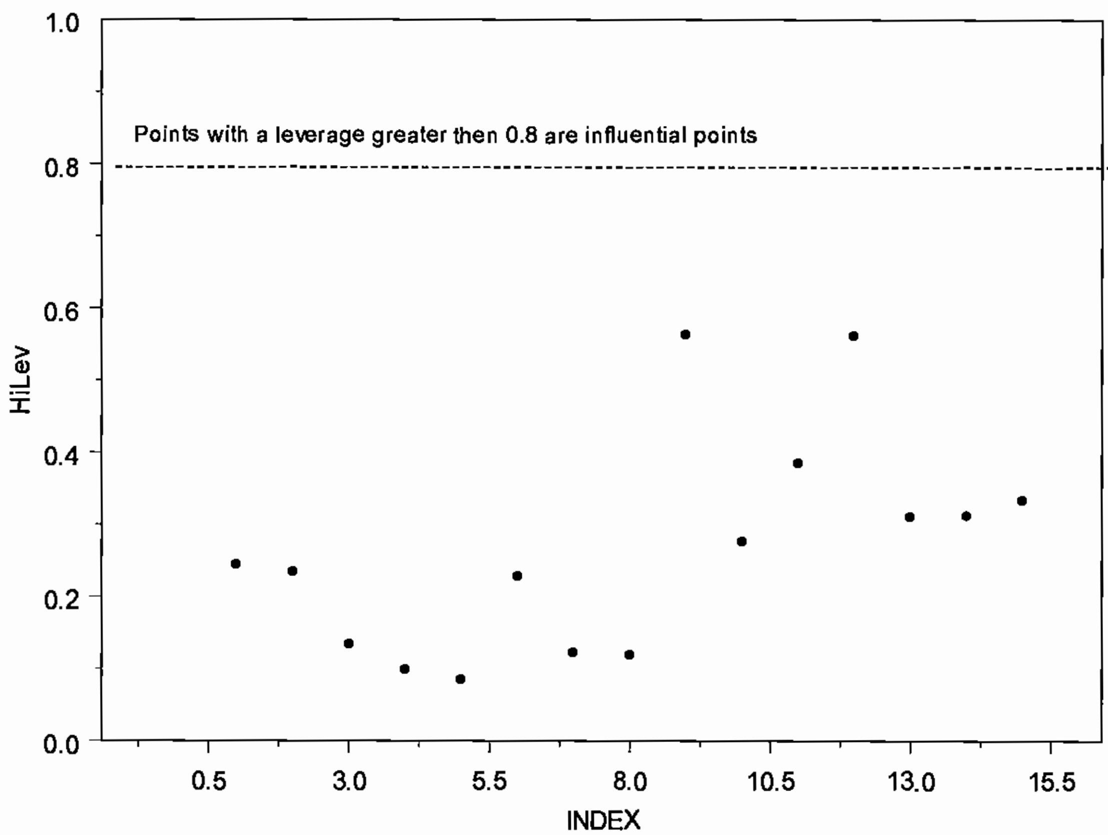
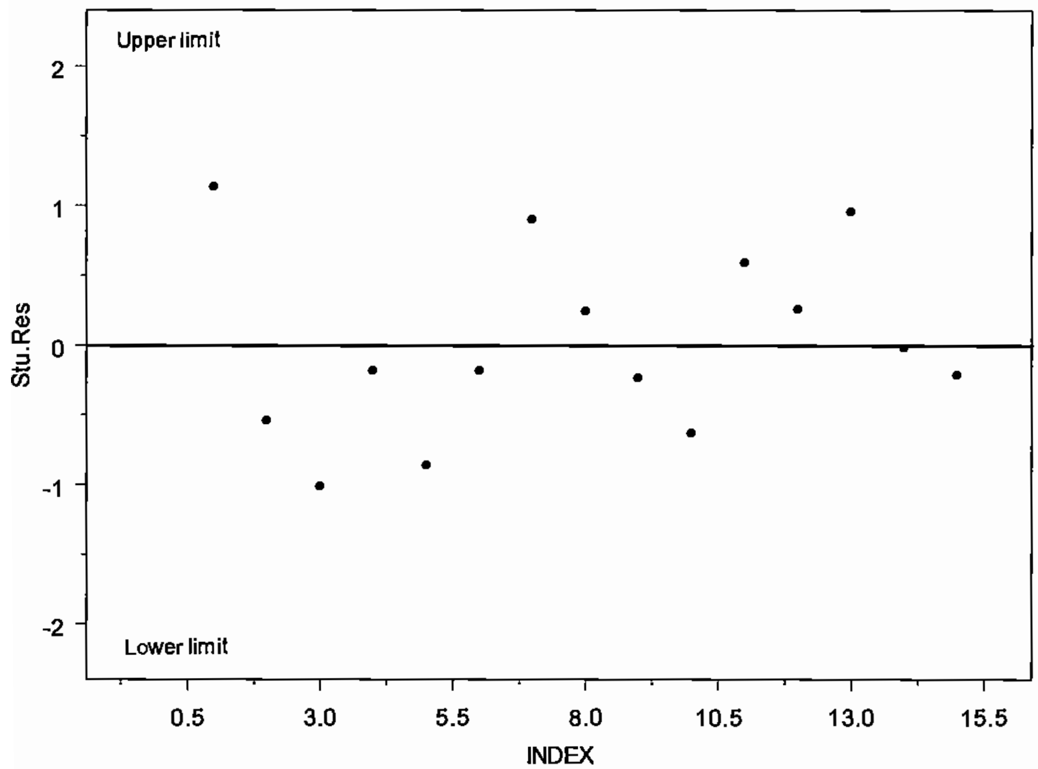
Appendix section

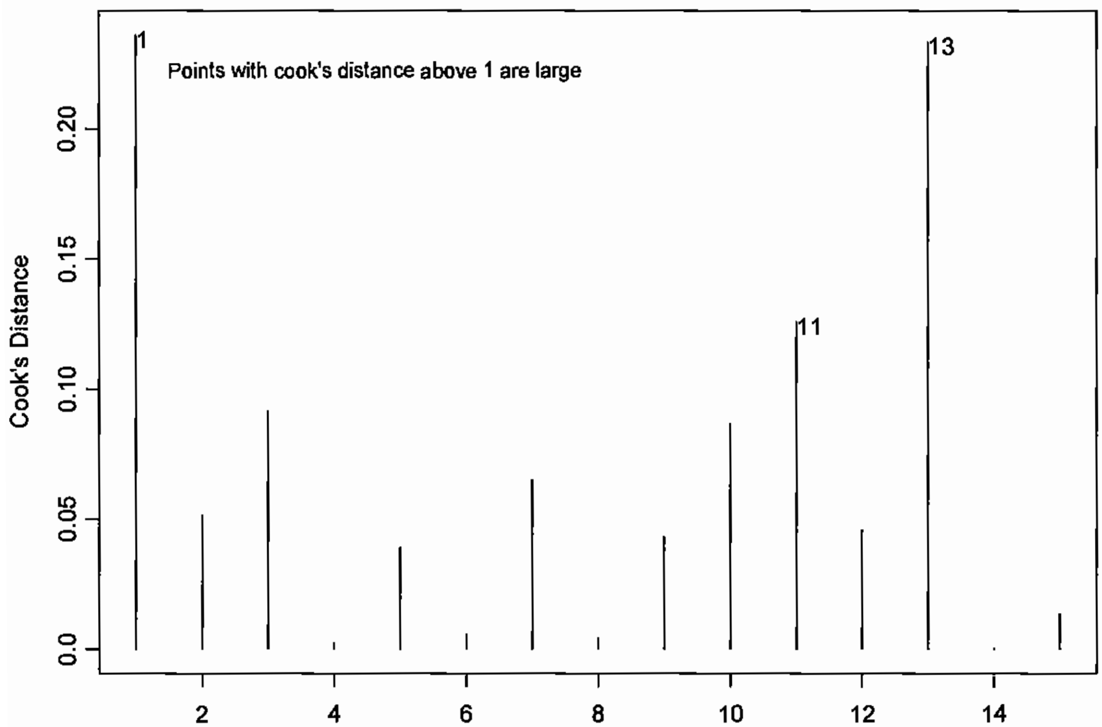
Appendix 1.
Potential problems points' graphical analysis



Leverage calculation for check for potential problems points



Studentized residual for each point in unit of standard deviations



Cook's distance for each point indicating the overall change in the coefficient when an observation is omitted.

Appendix 2. Model builder model