CAN BAYESIAN NETWORKS BE USED TO PRIORITIZE RESTORATION OF CHINOOK SALMON SPAWNING HABITAT IN DATA POOR NORTHERN CALIFORNIA WATERSHEDS?

A Thesis

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Steven Michael Brumbaugh

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Steven Michael Brumbaugh

Approved by:

Ronald M Coleman, Committee Chair
Ronald M. Coleman, Ph.D.

__________, Second Reader
Jamie M. Kneitel, Ph.D.

Timothy Horner, Third Reader
Timothy C. Horner, Ph.D.

May 6, 2015
Date

Student: Steven Michael Brumbaugh

I certify that this student has met the requirements for format contained in the University format manual, and that this thesis is suitable for shelving in the Library and credit is to be awarded for the thesis.

__________________________, Graduate Coordinator 6 MAY 2015
Jamie M Kneitel, Ph.D. Date

Abstract

of

CAN BAYESIAN NETWORKS BE USED TO PRIORITIZE RESTORATION OF CHINOOK SALMON SPAWNING HABITAT IN DATA POOR NORTHERN CALIFORNIA WATERSHEDS?

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Steven Michael Brumbaugh

California's native salmonid populations are declining, as evident by the 2008 fishing closures on one historically abundant species, Chinook Salmon (*Oncorhynchus tshawytscha*). One major impact on the spring-run of Chinook Salmon within the Central Valley has been the damming of natal rivers, severely limiting available spawning habitat. Additionally, many of the streams used by spring-run Chinook Salmon lack extensive habitat data, such as substrate composition, velocity, depth, and woody debris availability, and specific factors limiting spawning habitat suitability are poorly understood.

Bayesian Networks are one modeling method that could help to understand these systems and direct restoration efforts toward the most limiting factors within a watershed. These networks are capable of incorporating quantitative data (e.g., derived from empirical studies, literature review, and publicly available spatial data) and qualitative

data (e.g., expert elicitation), making them a powerful tool for decision making in data-poor environments. Bayesian Networks are also easily updatable as new empirical data become available.

I constructed a Bayesian Network for a Northern California stream, Deer Creek in Tehama County, to provide a useful tool for guiding restoration of spring-run Chinook Salmon spawning habitat. I developed the network using habitat variables thought to be indicators of habitat quality, including stream slope, average width, mean minimum coniferous cover from above, soil type, water year type, and potential existence of a partial barrier downstream. I used the Norsys Netica software to establish the Bayesian Network, and applied this network to each subreach (defined in this context as a riffle-pool stream segment) to determine the suitability of each subreach for Chinook Salmon spawning. Probability of redd (spawning nest site) presence over 50% was used to indicate good habitat suitability for spawning. Redd data was split into two independent sets. I used redd data from one 6 km reach to fit the model (i.e., develop conditional probabilities by back calculating from known outcomes), and used redd data from a second 6 km reach for prediction and comparison with the empirical data for purposes of model validation.

I used two types of model validation. I conducted a sensitivity analysis on the network, to determine the influence of each independent variable and determine whether it had an unexpected or disproportionate effect on the outcome. I also conducted an ANOVA comparing redd densities from subreaches predicted to be good spawning habitat against those predicted to be poor spawning habitat by the network, to assess if there was a statistically significant difference between the two.

Of the four scenarios I modeled with the network, three exhibited significantly higher redd densities in subreaches designated as good spawning habitat according to probability of redd occurrence (National Hydrography Dataset streamline under dry conditions, traced streamline under dry conditions, and traced streamline under non-dry conditions). The National Hydrography Dataset (NHD) streamline under non-dry conditions overestimated likelihood of redd presence. This was likely due to an exaggerated effect of mean minimum coniferous cover from above within the NHD model. My results, particularly using the traced streamline network, indicate that Bayesian Networks can be used to predict habitat use and prioritize spawning habitat restoration for Chinook Salmon in a data-poor northern California watershed.

Ronald M Coleman, Committee Chair
Ronald M. Coleman, Ph.D.

May 6, 2015
Date

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INTRODUCTION

As many of California's native salmonid populations continue to decline, it is becoming increasingly important to identify restoration opportunities within their respective watersheds. The Chinook Salmon *(Oncorhynchus tshawytscha)* is a notable member of this group that draws a great deal of interest due to its commercial, cultural, and recreational value (Yoshiyama et al. 1998). In California's Central Valley, two runs of Chinook Salmon have been federally listed under the Endangered Species Act, winter-run as "endangered" and spring-run as "threatened" (NOAA 2005). Winter-run Chinook Salmon are native only to the Sacramento River mainstem and its upper tributaries (primarily above Shasta Dam) and are now confined primarily to the mainstem and Battle Creek (Moyle 2002). Spring-run Chinook Salmon, in contrast, were once abundant throughout the Central Valley, with populations in various tributaries to the Sacramento and San Joaquin Rivers (Yoshiyama et al. 1998). Though the San Joaquin River populations of spring-run went extinct between 1945 and 1950 with the construction of Friant Dam occurring in 1948 (Moyle 2002), there are still numerous populations in the Sacramento River basin.

Chinook Salmon are anadromous, meaning they hatch in freshwater and migrate to the ocean to mature before returning to spawn (Gross et al. 1988), and runs are identified by their unique life-history strategies (Moyle 2002). Chinook Salmon are also semelparous and die soon after spawning. Adult spring-run Chinook Salmon migrate in the spring (March through June) and hold over the summer in cold pools, historically within higher elevation freshwater streams, until early fall when they spawn. Spawning nests, or redds, are constructed in gravels within streams, and can be identified by clean gravel with a distinct bowl shape (or pot) in the substrate and a downstream tailspill of gravels that have been excavated by the female during construction of the redd. Size of the redd can then also be used to distinguish Chinook Salmon redds from those of other salmonids, because Chinook Salmon redds are typically larger than the redds of other salmonids in the Central Valley (Gallagher and Gallagher 2005). Additionally, salmon use chemical signatures to navigate back to their natal watersheds and spawn once they mature (Dittman and Quinn 1996). Spawning areas therefore represent a critical component of Chinook Salmon life-history, and are vital to the persistence of the species, regardless of run or stream of origin.

Modeling is increasingly being used in fisheries science as a way to guide conservation efforts. Often times these models (e.g., Salmod, Shiraz, EDT) rely on a great deal of empirical habitat data, based on extensive stream surveys (e.g., substrate composition, detailed velocity information, depths, etc.), in order to inform various parameters (Bartholow 2004, Scheuerell et al. 2006, Steel et al. 2009). Many Northern California streams lack detailed empirical habitat data, but geospatial or qualitative data may be available. One tool that allows for the incorporation of empirical, geospatial, and/or qualitative data (i.e., expert opinion) into a model is a Bayesian Belief Network, sometimes simply referred to as a Bayesian Network (Pollino et al. 2007a, Pollino et al. 2007b).

Bayesian Networks

Bayesian Networks are a tool that can be used within data poor watersheds by people or organizations needing to direct habitat restoration for fishes of various life stages. By customizing variables and conditional probability tables, application of Bayesian Networks can be used to investigate complex biological and ecological management problems (Borsuk et al. 2004, Marcot et al. 2001, Ticehurst et al. 2007). Bayesian Networks are one example of a mathematical concept known as probability theory.

Probability theory is a branch of mathematics that deals well with uncertainty, by assigning probabilities to events based on variables (DeGroot and Schervish 2010). Variables can either be empirical (e.g., observed data) or qualitative (e.g., best professional judgment) in nature. Specifically, the Bayesian Networks use Bayes' Theorem, a method of determining conditional probability. Conditional probability is the probability that an event will happen given some form of known information about a related event (DeGroot and Schervish 2010). Important to this concept are the prior probabilities, also referred to simply as priors, which represent the probability that a variable (i.e., related event) is in a particular state (Marcot et al. 2001). Determining these priors, either via empirical data or expert opinion, is critical to understanding model outputs. Data for the state of each of the informing variables in a Bayesian Network are contained in what are referred to as nodes.

Bayesian Networks are often constructed and analyzed with computer software that represents network structure with a graphic display. Nodes are linked together via arcs within the graphical interface software in order to establish a number of relationships between them. The relationships between deterministic nodes (i.e., priors) are established in the conditional probability tables (CPTs). The conditional probability tables contain the likelihood of each outcome given the state of the variable in the parent node (Pollino 2007b). For example, what is the probability of a large cobble substrate given high water velocity, medium water velocity, and low water velocity? In this case, the parent node would be water velocity and the outcome would be cobble size. Establishing the conditional probability tables is a critical point in developing the network, because these tables directly affect the outcome of a model. Fortunately, many computer software programs are capable of back-calculating CPTs based on known information of the variables states.

There is a great deal of literature that identifies values for habitat variables that correlate with spring-run Chinook Salmon spawning in well-studied watersheds (Feist et al. 2003, Isaak et al. 2007, Lunnetta et al. 1997, Toepfer et al. 2000). These traits are often not stream specific, and can be generalized for use in other watersheds (e.g., water velocity, stream slope, water temperature, cover) to determine habitat quality for Chinook Salmon. These generic values can be used in network construction, along with any available empirical data available, such as escapement estimates (i.e., estimates of fish that successfully spawned, thereby “escaping” the fishery). In the most data poor watersheds, qualitative data collected through workshops and interviews with local biologists can be incorporated to improve predictive performance of the model (Pollino et al. 2007a, Ticehurst et al. 2007)

In addition to their ability to incorporate local expertise to supplement empirical data, Bayesian Networks are also easily updatable. The conditional probability tables can be updated as empirical research within the watershed becomes available to inform our understanding of the relationships between these habitat variables (Ticehurst et al. 2007). This is of particular importance within data poor watersheds. As populations of species recognized under the Federal or California Endangered Species Acts decline, as was recently the case with spring-run Chinook Salmon, habitats used by these species will become increasingly important. It is therefore likely that knowledge and data related to these habitats will increase.

This research used a combination of empirical data, data derived from literature, and geospatial data, to determine whether networks can reliably predict good and poor spawning habitat for Chinook Salmon in a Northern California Sacramento River tributary.

Hypothesis

My hypothesis was that a Bayesian Network could be constructed to reliably predict habitat quality for Chinook Salmon spawning at a particular stream location. To test this hypothesis I developed a network that included habitat variables thought to be indicators of quality habitat (e.g., canopy cover, stream slope, existence of passage barriers) to determine the probability of suitable spawning habitat within a particular subreach, as indicated by the likelihood of redd presence. As a means of validating the network, I used a sensitivity analysis to determine the influence that each of the variables included in the network had on model predictions. Additionally, to determine whether or not the model predicted the habitat quality accurately, I compared the mean number of redds per meter found in subreaches of Deer Creek determined by the model to be good spawning habitat versus the mean number of redds per meter found in subreaches of Deer Creek determined by the model to be poor spawning habitat.

METHODS

The general process used for applying the methodology is provided in Figure 1. This process includes collection of redd location data, snapping redd data to a streamline (i.e., aligning redd locations with streamlines within ArcGIS), collection of data to inform the input variables (e.g., stream slope, average width, etc.), network training, and validation.

Location and Field Data Collection

I collected redd location data from Deer Creek in Tehama County, California (Figure 2). Deer Creek represents one of three independent spring-run Chinook Salmon populations in the Central Valley (Lindley et al. 2007). There are also no major dams or reservoirs within the watershed to prevent fish passage, the presence of which would introduce a great deal of additional complexity to the model due to altered habitat selection resulting from confinement to lower-elevation reaches.

I collected redd location data from late-September through the end of October in 2012 and 2013 in the 12 km of Deer Creek immediately downstream of the upper limit to migration, namely Upper Deer Creek Falls, on three separate visits per season. Spring-run Chinook Salmon generally spawn early in the fall from late-September through late-October, with fall-run Chinook Salmon spawning further downstream and generally peaking in mid-October through November (Moyle 2002). By sampling during this period and limited to these upper reaches, I minimized the potential for misidentification of early fall-run Chinook Salmon redds as spring-run redds. I identified redds based on

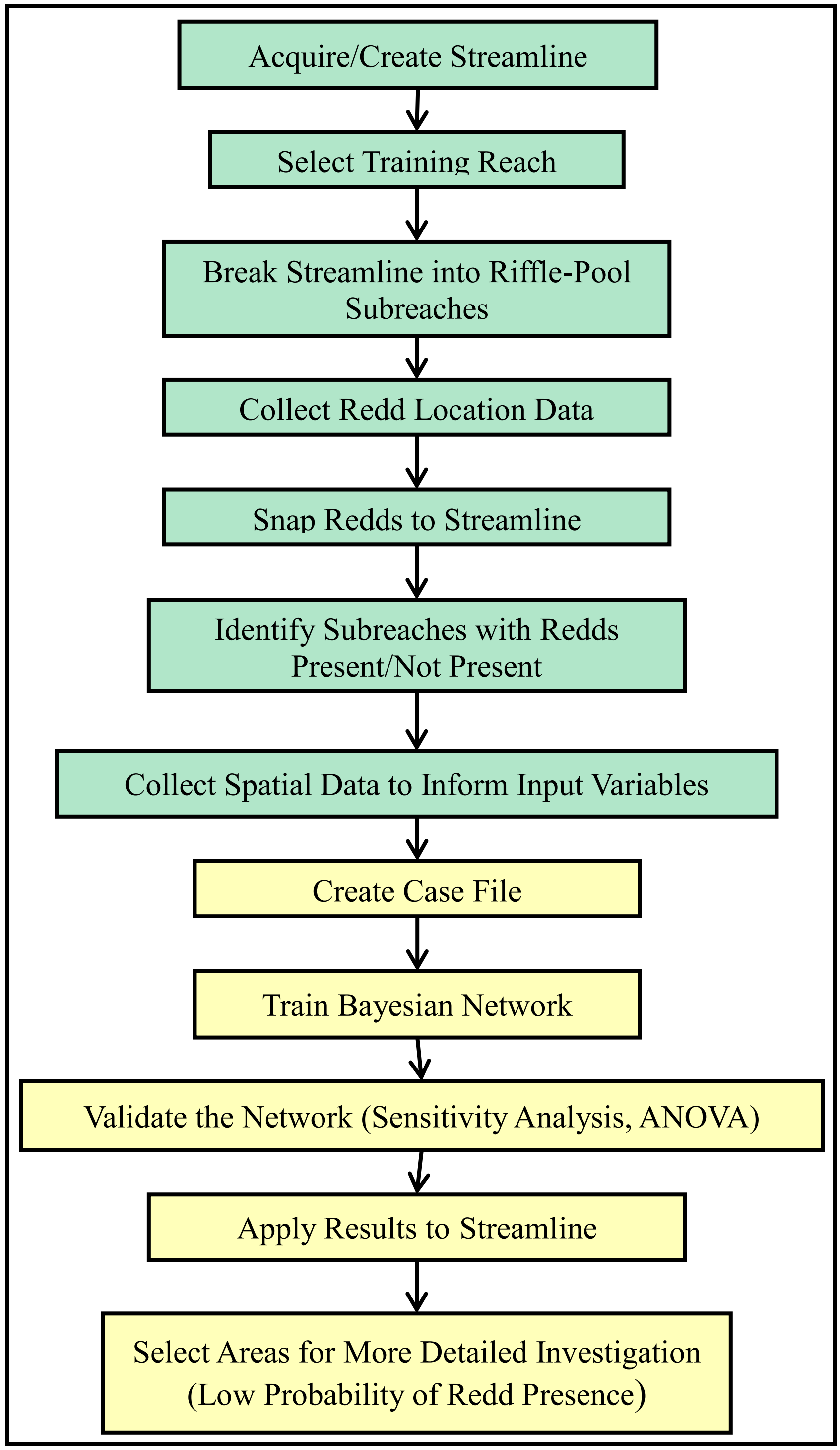

Figure 1. Overview of the methodology. Green represents data collection/GIS work. Yellow represents construction of the network.

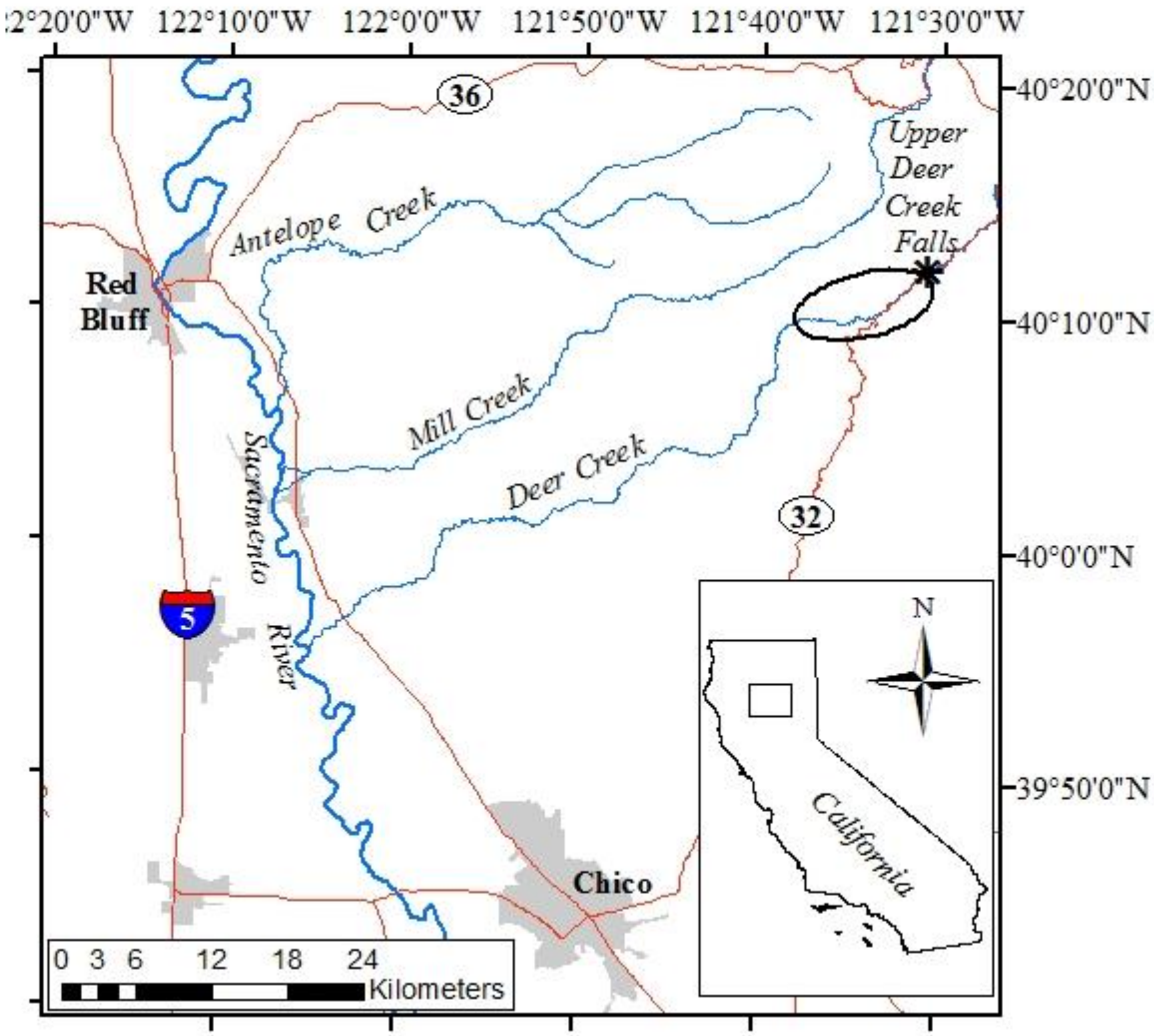

Figure 2. Location of Deer Creek, Tehama County, California. Study location is indicated by the black circle.

the standard clean gravel pot (i.e., depression within the substrate), with a tail of gravel excavated by the female during redd construction, and a redd size larger than other salmonids that may be spawning in the stream (Gallagher and Gallagher 2005). In addition, presence of females and males over suspected redd locations served as confirmation of spawning activity. I marked the location of each redd using coordinates from Trimble GeoXH handheld GPS with a Zephyr Model 2 external antenna, which yielded accuracy within 1 meter. I then entered this data into an Excel spreadsheet for the development of a GIS layer.

I split redd data into two independent datasets, each representing a 6 km reach of stream. I used one dataset during network training alone. I used the second dataset only during model validation, as suggested by Ames et al. (2005). However, due to the dispersion of redds being heavily skewed to the lower riffle-pool subreaches of the study area, splitting the data into two contiguous 6 km reaches for training and validation was impractical. Therefore, the training reach consisted of the uppermost 4 km of the study area and the lower 2 km of the study area. This allowed for the assessment of the 6 km contiguous reach between these two stream segments during model application and validation. By splitting the study area in this manner the total number of subreaches, as well as the number of subreaches containing redds, was more evenly dispersed between training and validation datasets (Table 1).

Table 1. Summary of redd presence for training and validation subreaches.

Subreach Type	*With Redds*	*Without Redds*	*Total*
Training	21	52	73
Validation	17	48	65

Creation of the Bayesian Network

The software I used for creation of the Bayesian Network was Netica, by the Norsys Software Corporation. The freeware version of this software was adequate for this project. Benefits of this software are a user-friendly interface, pre-written algorithms for conducting sensitivity analysis, and helpful graphical display of the network. This software was designed specifically for the creation of Bayesian Networks and has been used previously in published works (Marcot et al. 2001, Pollino et al. 2007a, Pollino et al. 2007b).

Development of the Bayesian Network primarily followed the methods used in Pollino et al. (2007b). In all possible cases, I utilized data derived from GIS and site visits. For certain variables, comprehensive field surveys would have been cost or time prohibitive and data was not directly attainable from GIS for certain variables. For example, instream woody debris is generally surveyed by measuring diameter and number of pieces within the channel, using a GPS to place the locations within a GIS layer. This can be very time consuming and difficult, particularly in reaches confined within steep valley walls. However, the probability of woody debris within the channel may be implied from the percent of coniferous cover present adjacent to the stream. Coniferous cover can be determined from GIS layers of vegetative cover, as was done with this network.

I selected nodes based on an extensive literature search. There are a variety of habitat suitability models that have been developed for Chinook Salmon in the

Northwestern United States (Bartholow 2004, McHugh et al. 2004, Scheuerell et al. 2006, Steel et al. 2009, Thompson and Lee 2000). Depending on scale, the most significant variables often differ. For example, on a microhabitat scale, water velocity, stream substrate, and depth are common variables, while at a macrohabitat scale (i.e., watershed scale) canopy cover is significant (Lunetta et al. 1997). However, the network also provided a means of incorporating multiple scales into the same model. Variables selected for incorporation into the Bayesian Network, along with justification for their selection, are provided in Table 2.

Most of the nodes in the network were directly related to the output node, redd presence. However, to represent passage conditions during different water-year scenarios as designated on the California Data Exchange Center managed by the Department of Water Resources (http://cdec.water.ca.gov/), I incorporated an interaction between water-year type and the existence of a partial barrier downstream into the network. This simple relationship was represented by dry water-years creating poor passage conditions when combined with a downstream partial barrier, in this case Lower Deer Creek Falls. During non-dry water-years passage conditions are good, as fish are able to pass the partial barrier with increased flows (Figure 3).

GIS Data

Baselayers. My first step in developing the model was establishing the base layers for the GIS portion of the model. The base layers include a digital elevation model (DEM), imagery from the National Agricultural Imagery Program (NAIP), and

Table 2. Variables included in the Bayesian Network with rationale for inclusion.

Variable	*Rationale*
Average Width	Knapp and Preisler (1999) found this was one of four predictors of spawning location. The three other predictors (substrate, velocity, and depth) would require extensive surveys, many of which are typically not available for data poor Northern California watersheds.
Stream Slope	Lunetta et al. (1997) and Montgomery and Buffington (1997) found that this could indicate geomorphic characteristics in a stream and thereby indicate quality of spawning habitat. Geist et al. (2000) found that slopes of less than 0.04 were suitable for salmon spawning.
Mean Min Con_CFA(Mean Minimum Percent Coniferous Cover From Above)	Lunetta et al. (1997) found that riparian vegetation within a 30m buffer of the streamline was an indicator of suitable habitat. Not only can this effect stream temperature, but LWD input that could trap smaller grain sizes appropriate for spawning in high velocity reaches. The mean of the minimum values of Coniferous Cover From Above, attained from FRAP data, were calculated for canyon walls on either side of the stream as an indicator of shading and LWD recruitment.
Soil Type	While this is likely not a good indicator of substrate itself, due to the source being general soil classification from USGS, it could be an indicator of input of fines that might affect nearby reaches or other undocumented effects of soil type.
Water Year Type	This is an indicator of whether the partial barrier is passable, partially blocking passage, or completely blocking passage.
Partial Barrier	While this is the state of upper Deer Creek, with Lower Deer Creek Falls being a partial barrier, it could be a common variable in many watersheds.

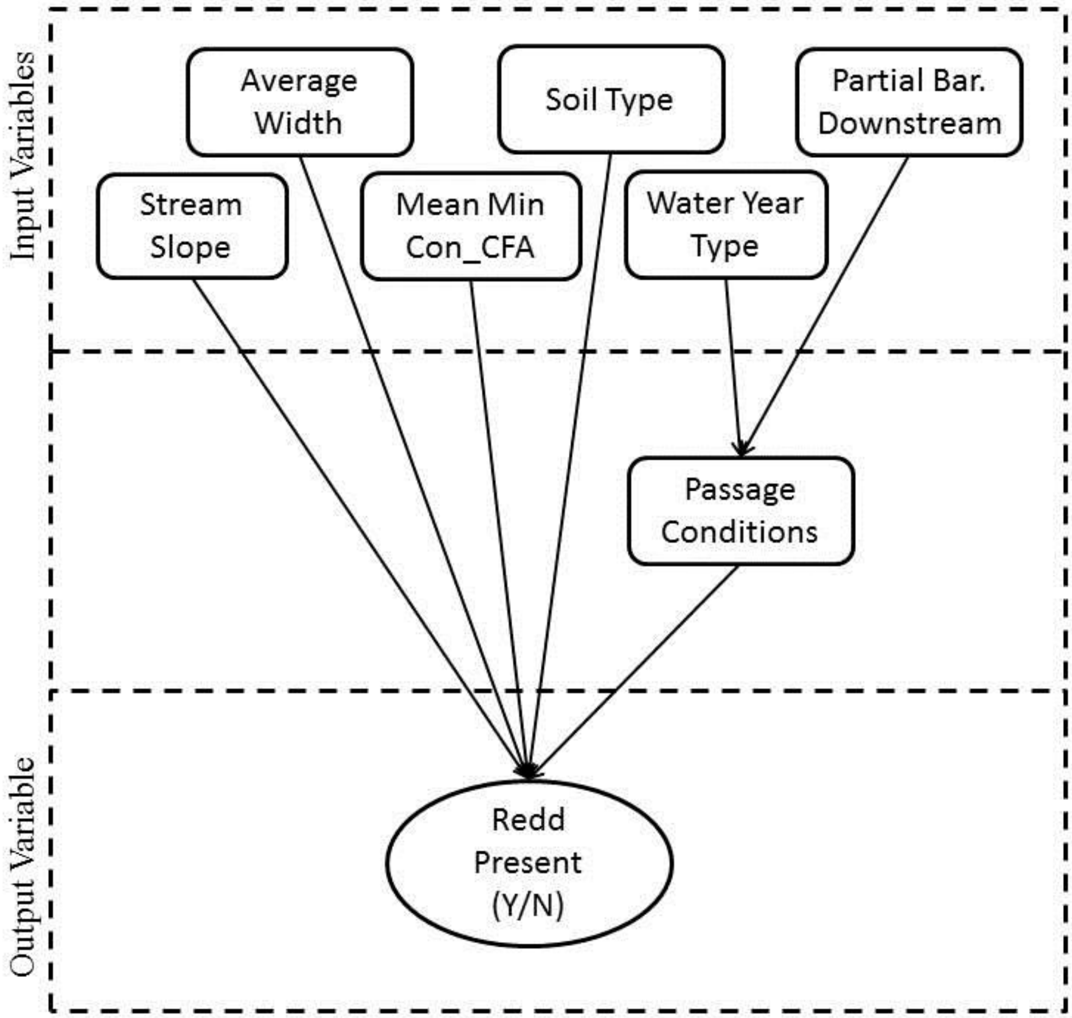

Figure 3. Structure of the Bayesian Network. Input variables are those manipulated to determine habitat quality in subreaches where the network will be applied to predict quality of habitat, as indicated by the probability of redd occurrence.

streamlines from the National Hydrology Dataset (NHD). In evaluating stream slope using GIS, stream alignment within the landscape is essential. Often times, due to the projection of a spherical earth onto a flat surface, streamlines on maps are not precisely where they occur in reality. Minimization of this distortion is necessary to increase accuracy. Neeson et al. (2008) found that, used in conjunction with calculations used to correct for outliers, a streamline that was created manually from georeferenced aerial imagery (i.e., traced) was more accurate than an NHD streamline when combined with a 10 meter DEM for GIS calculation of stream slope. However, in a modeling context, rather than an independent assessment of the accuracy of stream slope derived from GIS, it was possible that a more accurate model would result from using the NHD file. Therefore, I assessed this model using two methods of determining gradient: 1) riffle-pool subreach length using a traced streamline, and 2) riffle-pool subreach length using an NHD streamline. I defined riffle-pool subreaches as spanning from the upstream edge of a riffle or cascade to the lowest point in the adjacent pool downstream. The methods for creating these two files is further explained below.

Other layers I used to assess the state of input variables within the model included vegetative cover from the California Department of Forestry and Fire Protection's Fire and Resource Assessment Program (FRAP), United States Geological Survey (USGS) soil type, and road densities (Feist et al. 2003, Lunnetta et al. 1997, Toepfer et al. 2000). I excluded road densities from final analyses after determining that there were very few roads adjacent to the stream, and any effects of road networks on the stream itself would be very minor and likely not be measurable at a riffle-pool scale. After collecting and processing GIS data, I entered values for each variable on a riffle-pool subreach scale into a case file for parameterization and validation of the Bayesian Network. Where data were not available for prediction and validation, I used the “unknown” probability distribution created when training the network.

Streamlines and subreach Designation. I obtained streamlines for the entire 12 km study area using two methods. The first method was downloading a streamline from the NHD from the USGS (http://nhd.usgs.gov/data.html), and clipping the 12 km study area immediately downstream of Upper Deer Creek Falls. The second method for deriving a streamline was to trace georeferenced aerial imagery, called a digital orthographic quarter quad (DOQQ).

In order to designate riffle-pool stream subreaches, I copied satellite imagery from Google Earth and georeferenced them in ArcGIS based on NAIP imagery. The purpose of this was that the satellite imagery used by Google Earth is a higher resolution (approximately 0.6 m resolution) compared to the NAIP imagery (1 m resolution). In addition the Google imagery has far less of the stream shadowed by trees. These two factors allow for more accurate designation of riffle-pool subreaches.

Once the imagery was georeferenced and rectified, I created the streamline by tracing the imagery and creating successive segments with start and end vertices that correspond with the start and end of each riffle-pool subreach. I then extracted point features from the streamline using the Feature Vertices to Points tool. These points were then used in assigning stream subreach start and end points to the NHD file.

To assign riffle-pool subreach start and end points to the NHD file, a copy of the point file was snapped to the NHD streamline using the Near tool. The tool appends X and Y coordinates for the point on the designated line that is nearest the points in the original file to the original file's attribute table. I then exported these coordinates to a new table, added them to the map, and exported them to a shapefile. Once I did this, the NHD streamline was split into riffle-pool subreaches using the Split Line at Point tool.

For each file, stream subreaches were numbered in consecutive order from upstream to downstream.

Stream Gradient. In order to determine stream gradient, values from the DEM needed to be assigned to the start and end points of each subreach for each of the two streamlines. I did this using the Extract Values to Points tool in ArcGIS. This tool uses an input raster file and applies values from the raster to a specified point file. The output is a point file with a table that includes values from the raster, in this case elevation in meters. Once I did this, I exported the table to Microsoft Notepad, then opened it in Microsoft Excel to simplify calculation of the elevation change for each of the 138 riffle-pool stream segments.

Stream lengths for riffle-pool subreach analysis were determined by first ensuring that the streamlines were in a projected coordinate system. A projected coordinate system identifies location based on coordinates (i.e., an x,y grid) from a surface that has been projected from a 3-dimensional object to a 2-dimensional plane. I then created a field in the attribute table of both streamline files, and using the Calculate Geometry function, the length of each subreach segment in meters was automatically generated. Lengths were then transferred to the Excel file and percent gradient was determined by dividing the elevation change by the length of each segment. Gradient was a continuous variable, which I discretized within Netica as 4.0% or less (Suitable), between 4.0% and 6.5% (Marginal), and greater than 6.5% (Poor) (Lunetta et al. 1997, Montgomery and Buffington 1997, Geist et al. 2000).

Training the Model

Once the nodes of the Bayesian Network were established and relationships between the variables were developed, I parameterized the model (i.e., trained the network). Parameterization is a way of obtaining the conditional probability tables that yield the best predictive capability for the network based on known results, and begins with development of a case file. I developed two case files in Excel, one for the NHD derived streamline and one for the traced streamline, with each column heading corresponding with a node name and each row corresponding with a redd occurrence or absence. I entered values or states of each variable for each redd in the training portion of the dataset.

In order to obtain the state of the variables for redd absence, I created an equal number of records representing subreaches containing no redds. I selected subreach numbers for subreaches containing no redds at random from the 6 kilometer training portion of the study area using Excel, and entered the state of each variable into the training dataset. If the state of a variable changed within the length of a subreach, I selected the state of that variable randomly from the alternatives for inclusion in the case file. Once the two case files were established, I exported them into a .txt format for use in training the network within the Netica software (Figures 4 and 5).

Three algorithms are provided in Netica for model parameterization: the Lauritzen Spielgalhalter method, the expectation maximization algorithm, and the gradient descent algorithm. I used the expectation maximization algorithm due to its ability to deal with possible gaps in the data that may arise, which is not true of the Lauritzen Spielgalhalter method, and lower susceptibility to local maxima than the gradient descendent algorithm (Pollino et al. 2007b).

Model Validation

Validation is an important step in development of any model (Olden et al. 2002). The more accurately a model is able to represent reality, the more applicable it will be to restoration and scientific understanding of a system. I employed two methods to evaluate the networks ability to predict redd occurrence, namely sensitivity analysis and comparison with actual field data.

As a preliminary evaluation of the network I conducted a sensitivity analysis, which is commonly used with Bayesian Networks (Ames et al. 2005, Coupé and van der Gaag 2002, Pollino et al. 2007a, Pollino et al. 2007b). There were two separate training files, the NHD streamline and the traced streamline. Therefore, I ran two sensitivity analyses, one for each training file. Essentially, this analysis manipulates each

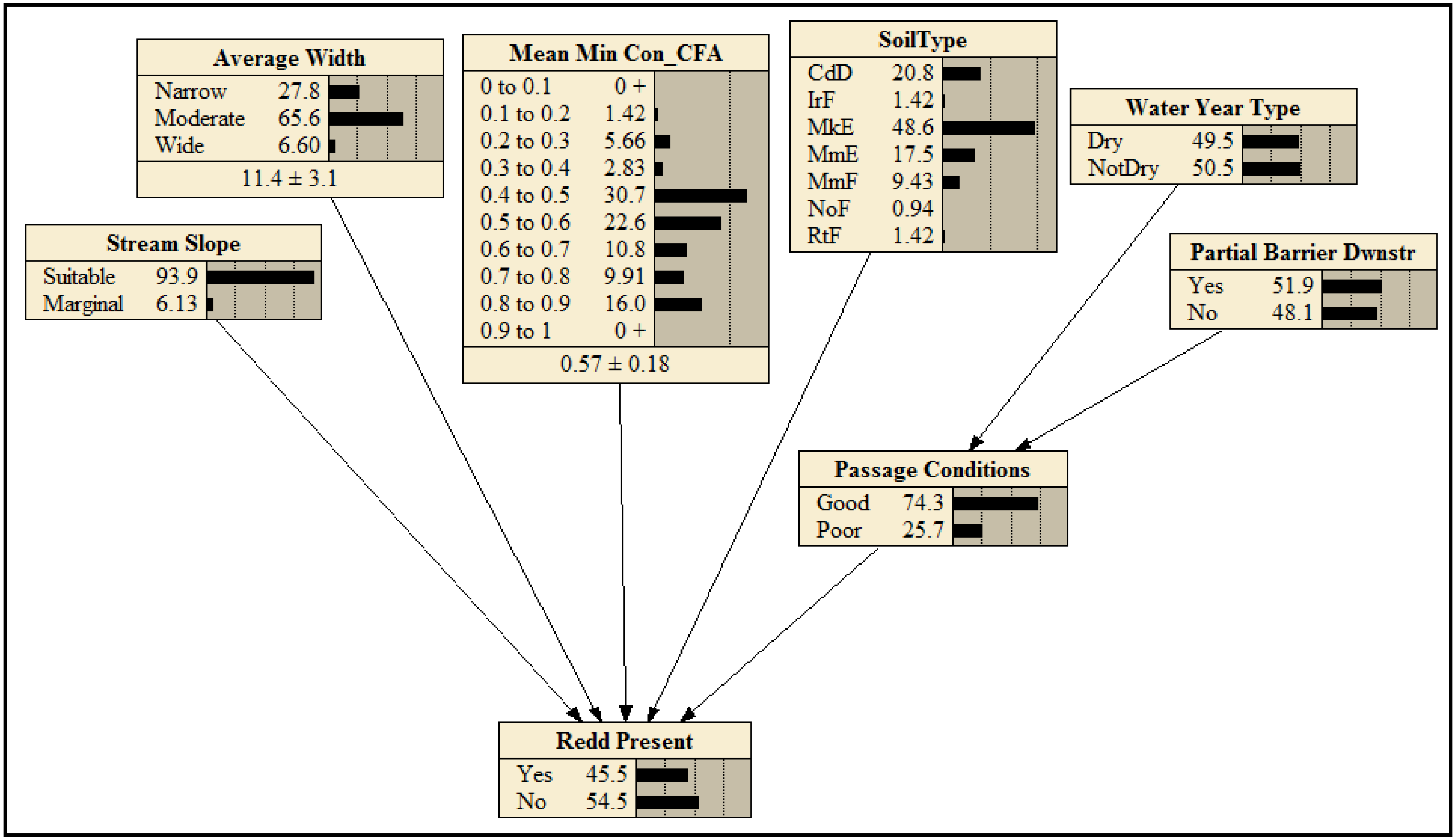

Figure 4. NHD network following training with the case file.

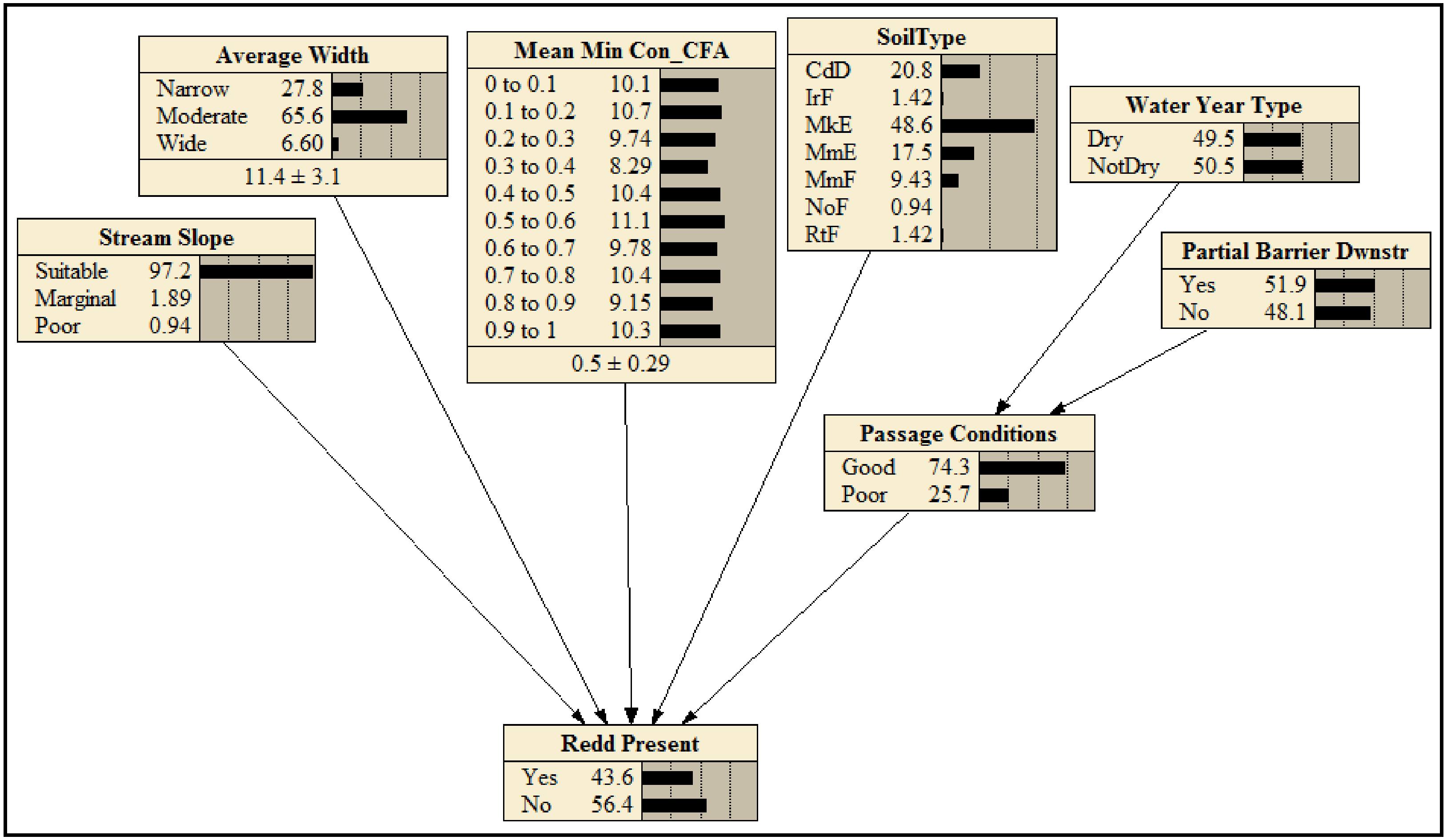

Figure 5. Traced network following training with the case file.

parameter or CPT individually either manually or via an algorithm and resulting changes in the output variable are observed (Coupé and van der Gaag 2002). In this manner, variables having an unexpected or disproportional effect on the outcome can be identified; thereby identifying potential issues in the CPTs.

I conducted the sensitivity analysis within the Netica software by running "Sensitivity to Findings" on the query variable. Results of this sensitivity analysis are presented as "mutual information," also known as entropy reduction value, which indicates the degree to which each variable is related to the query variable. Entropy can be defined as the uncertainty of a variable (Pollino et al. 2007b) and is calculated based on the probability distribution of that variable. The lower the calculated entropy, the more predictable, or non-random, a variable is. Mutual information builds on this by reducing the calculated entropy of one variable, $H(T)$, by the entropy of that variable given additional information from another variable, noted $H(T|X)$ below. In this example the less random T is, given information from X, the smaller $H(T|X)$ will be (i.e., lower entropy). Therefore, the mutual information value, $I(T,X)$, is larger and indicates more influence of X on the predictability of T. Conversely, the nearer $I(T,X)$ is to 0, the less influence X has on the predictability of T (Pearl 1988).

$$I(T,X) = H(T) - H(T|X)$$

As a second investigation into the legitimacy of the results, I compared the redd data collected in areas designated by the network as good (>50% likelihood of redd presence) and poor (≤50% likelihood of redd presence), using a One-Way ANOVA analysis with grouping information using the Tukey method in Minitab 16. I did this for four scenarios: using the NHD streamline under dry water-year conditions (NHDD), using the NHD streamline under non-dry water-year conditions (NHDND), using the traced streamline under dry water-year conditions (TRD), and using the traced streamline under non-dry water-year conditions (TRND). By evaluating dry and not-dry water-year conditions in both networks, I hoped to identify the effect of passage condition on the probability of redd occurrence beyond the partial barrier. If the mean redd density, expressed as redds per meter, was significantly lower in the habitats predicted by the model to be poor this could be an indicator of better predictive capabilities of the network. If there was no significant difference in the redd density between sites predicted to be good versus poor, this would indicate either a lack of suitability of the model for this application, an issue with selection of variables, or a problem with the conditional probability tables.

RESULTS

Each of the four scenarios resulted in a slightly different number of subreaches designated as good and poor (Table 3, Figures 6-9). The NHD streamline under not-dry conditions predicted more subreaches with good salmon spawning habitat than the traced streamline under not-dry conditions. Using the dry water-year scenario, both the NHD and traced streamline networks predicted a great deal fewer subreaches with good salmon spawning habitat than the non-dry water-year scenario due to inaccessibility of habitat upstream of the partial barrier.

The NHD streamline had no gradients of 6% or greater, being comprised largely of gradients of 4.0% or less and 4.0-6.5%. However, the traced streamline contained more variability in stream slope designation than the NHD streamline, with some subreaches falling into the 6% or greater category. This additional state of the stream slope variable required the inclusion of a 6% or greater condition to the node in the NHD network, in order to train the network appropriately. Corrective factors to limit the influence of outliers following methods in Neeson et al. (2008) had no effect on classification of the stream gradient.

Sensitivity Analysis

The output, Redd Presence, of the network trained with the case file for the NHD streamline was influenced most by mean minimum coniferous cover from above (Mean Min Con_CFA), followed by soil type and average stream width. However, the output for

Table 3. Subreach designations according to the Bayesian Network. Good represents greater than 50% likelihood that redds are present and poor represents a 50% or less likelihood that redds are present.

Scenario	*Good*	*Poor*
NHD Streamline-Dry Water Year	6	58
NHD Streamline-Non-Dry Water Year	23	41
Traced Streamline-Dry Water Year	14	50
Traced Streamline-Non-Dry Water Year	32	32

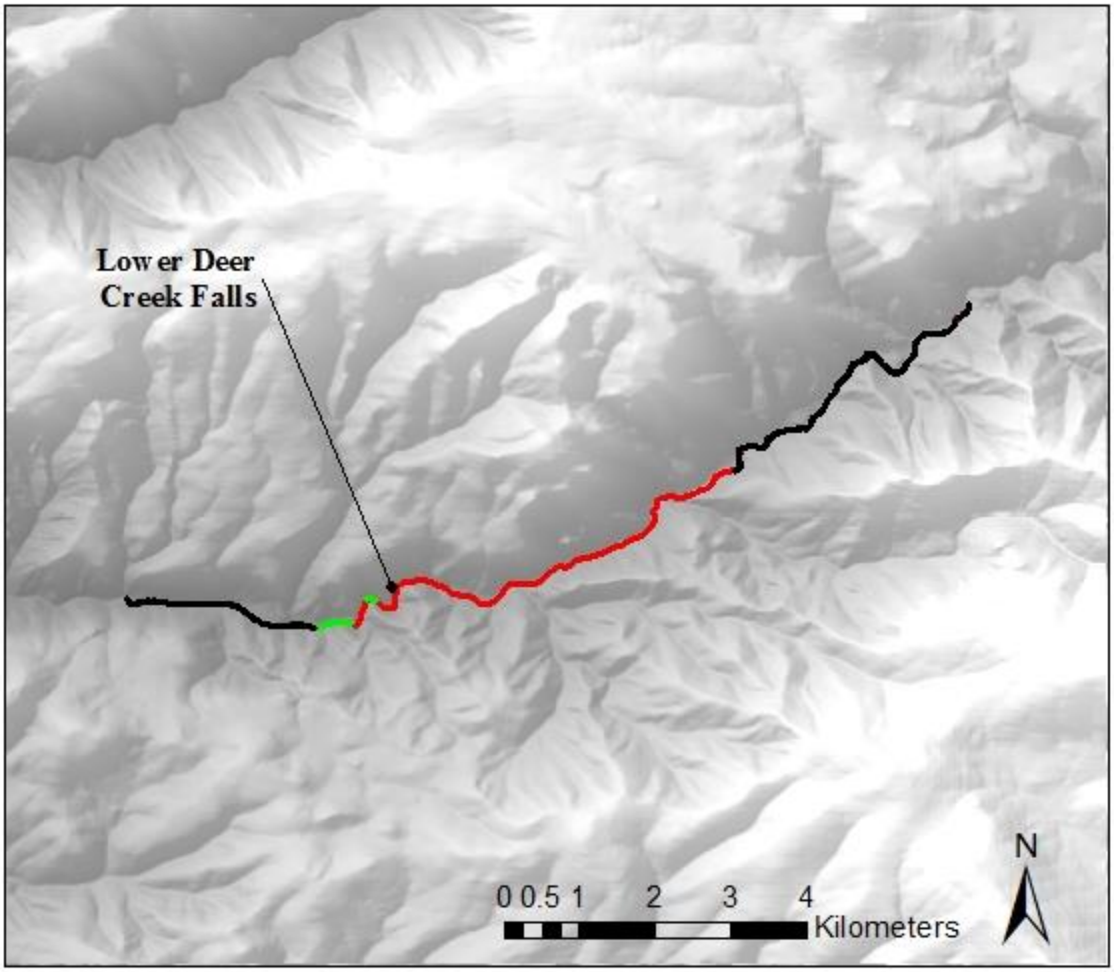

Figure 6. Results of the Bayesian Network for the NHDD scenario. Black represents training subreaches, green represents greater than 50% probability of redd occurrence, and red represents 50% or less probability of redd occurrence.

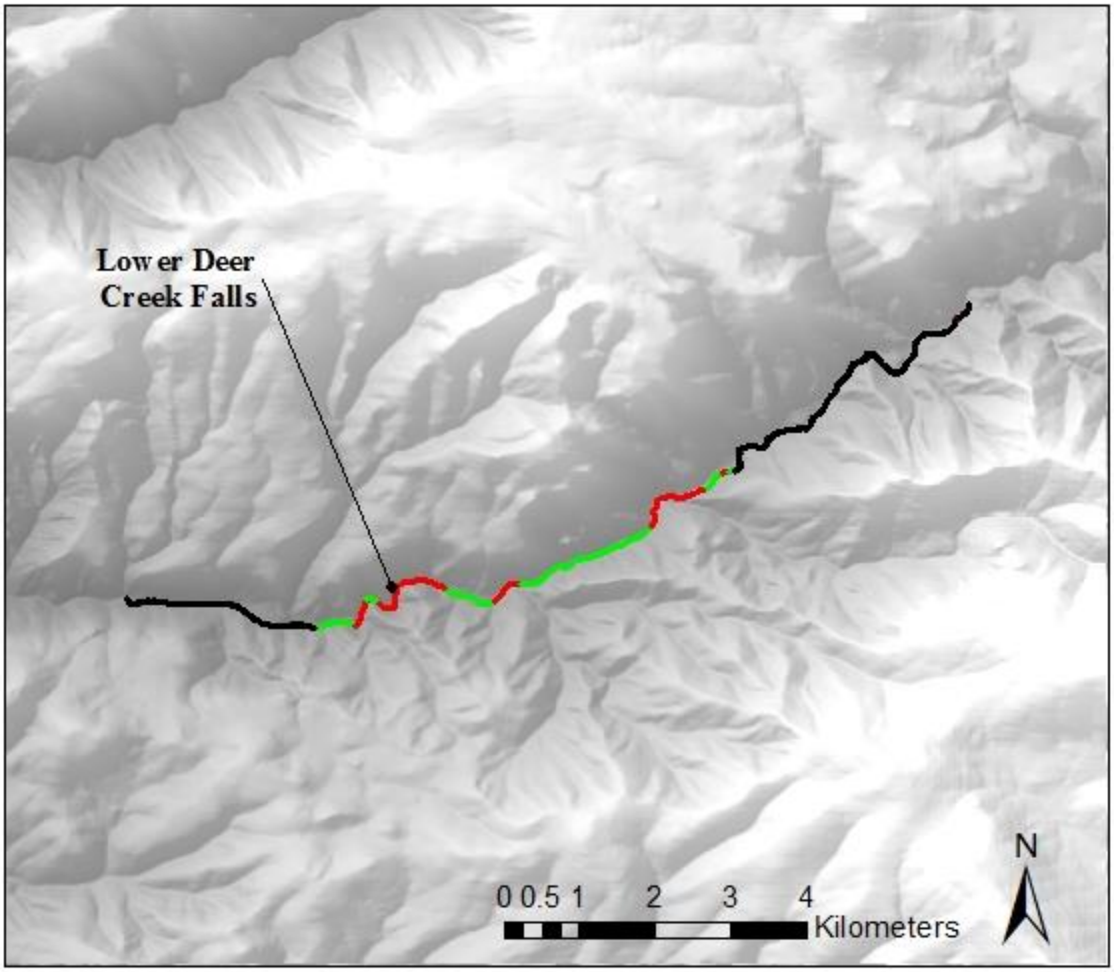

Figure 7. Results of the Bayesian Network for the NHDND scenario. Black represents training subreaches, green represents greater than 50% probability of redd occurrence, and red represents 50% or less probability of redd occurrence.

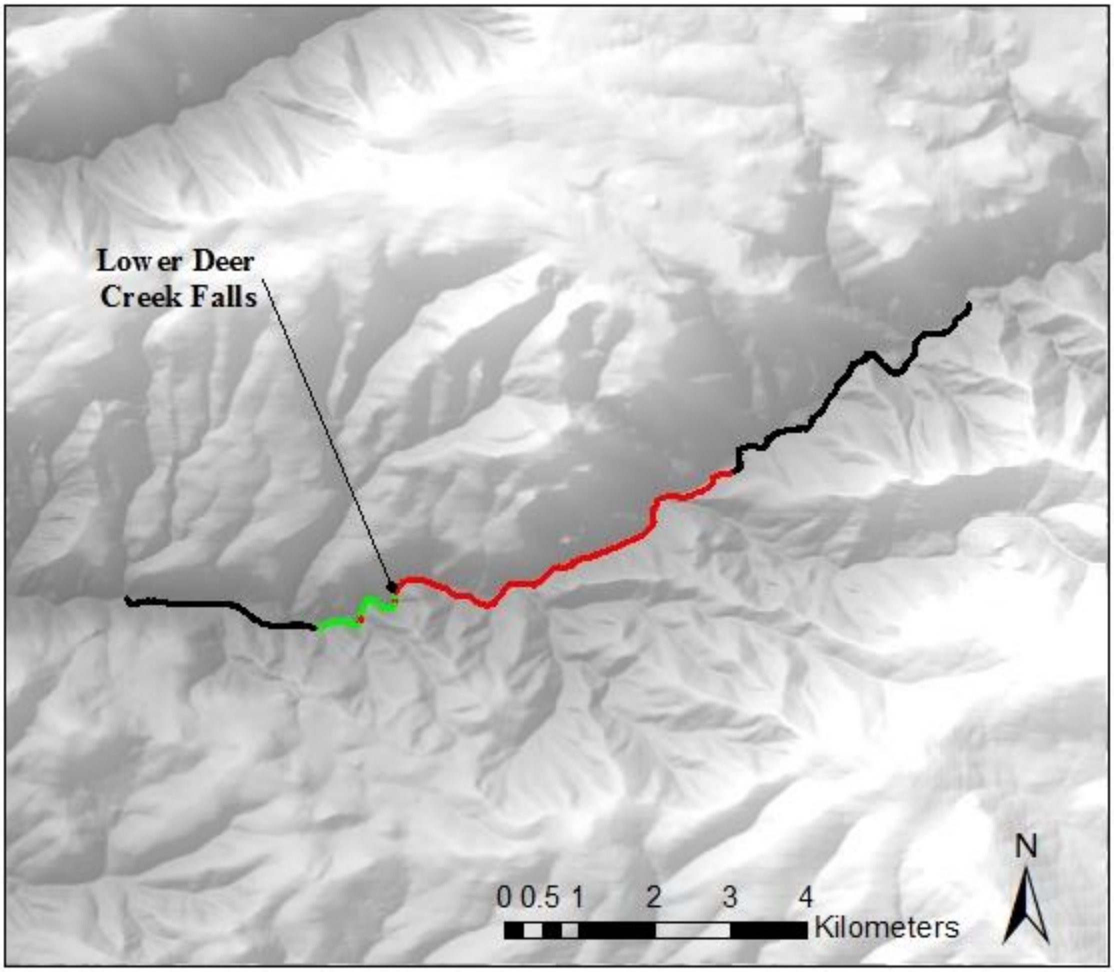

Figure 8. Results of the Bayesian Network for the TRD scenario. Black represents training subreaches, green represents greater than 50% probability of redd occurrence, and red represents 50% or less probability of redd occurrence.

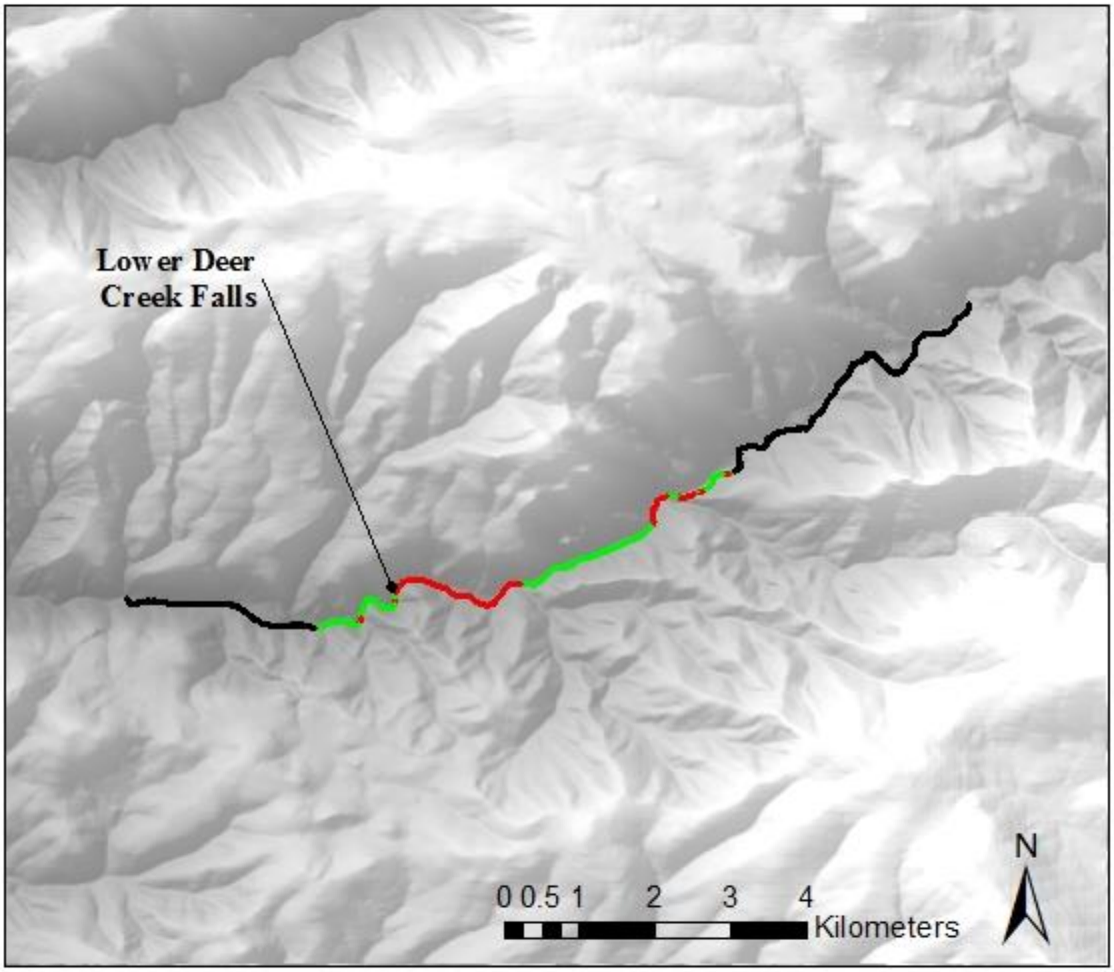

Figure 9. Results of the Bayesian Network for the TRND scenario. Black represents training subreaches, green represents greater than 50% probability of redd occurrence, and red represents 50% or less probability of redd occurrence.

the network trained with the case file for the traced streamline was influenced most by soil type, followed by average stream width and passage conditions. The primary difference between the two networks is that the NHD network showed mean coniferous cover from above as the primary influence on the output, and the traced streamline network showed mean coniferous cover as having the least influence over the output (Tables 4-5, Figure 10).

Analysis of Variance

The ANOVA analysis showed three of the four scenarios as indicating a significantly higher mean redd density for those subreaches designated as good: the NHD streamline under dry water-year conditions ($P < 0.001$), the traced streamline under drywater-year conditions ($P < 0.000$), and the traced streamline under non-dry water-year conditions ($P = 0.002$). The other scenario, NHD streamline under non-dry water-years, showed no significant difference ($P = 0.631$) between subreaches designated as good versus those designated as poor (Figure 11, Table 6). This is also reflected in the eta squared (η^2) value. According to Cohen's (1988) guidelines, the three well performing scenarios had η^2 values indicating a large effect size ($\eta^2 = 0.268$, $\eta^2 = 0.588$, and $\eta^2 = 0.143$, respectively), with small effect size being evident only in the single poorly performing NHD under not-dry water-year scenario ($\eta^2 = 0.004$).

Table 4. Mutual Information (i.e., Entropy Reduction Values) for effect of each variable on the output in the network compiled using the NHD streamline case file for training. The higher the Mutual Information value, the more influence that node has on the output node, Redd Present (yes or no).

Node	*Mutual Information*	*Variance of Beliefs*
Redd Present	0.994	0.248
Mean Min Con_CFA	0.035	0.012
SoilType	0.027	0.009
Average Width	0.025	0.008
Passage Conditions	0.016	0.005
Water Year Type	0.006	0.002
Partial Barrier Dwnstr	0.005	0.002
Stream Slope	0.000	0.000

Table 5. Mutual Information (i.e., Entropy Reduction Values) for effect of each variable on the output in the network compiled using the traced streamline case file for training. The higher the Mutual Information value, the more influence that node has on the output node, Redd Present (yes or no).

Node	*Mutual Information*	*Variance of Beliefs*
Redd Present	0.988	0.246
SoilType	0.155	0.048
Average Width	0.117	0.036
Passage Conditions	0.060	0.019
Water Year Type	0.020	0.007
Partial Barrier Dwnstr	0.018	0.006
Stream Slope	0.002	0.001
Mean Min Con_CFA	0.000	0.000

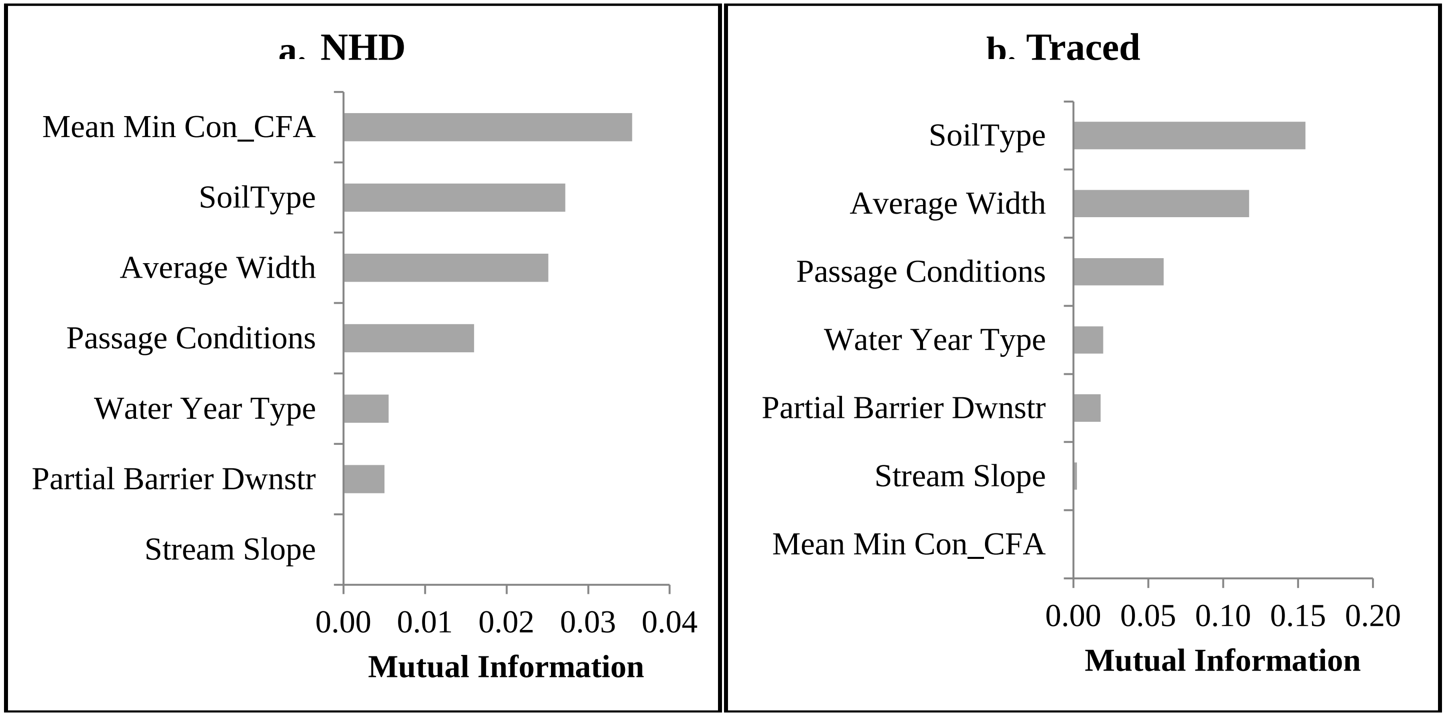

Figure 10. Graph of mutual information for the effect of each variable on the output in the network compiled with the NHD streamline (a) and the network compiled with the traced streamline (b). Larger bars represent more influence on the output variable under each network. Note the difference in scale between the two figures.

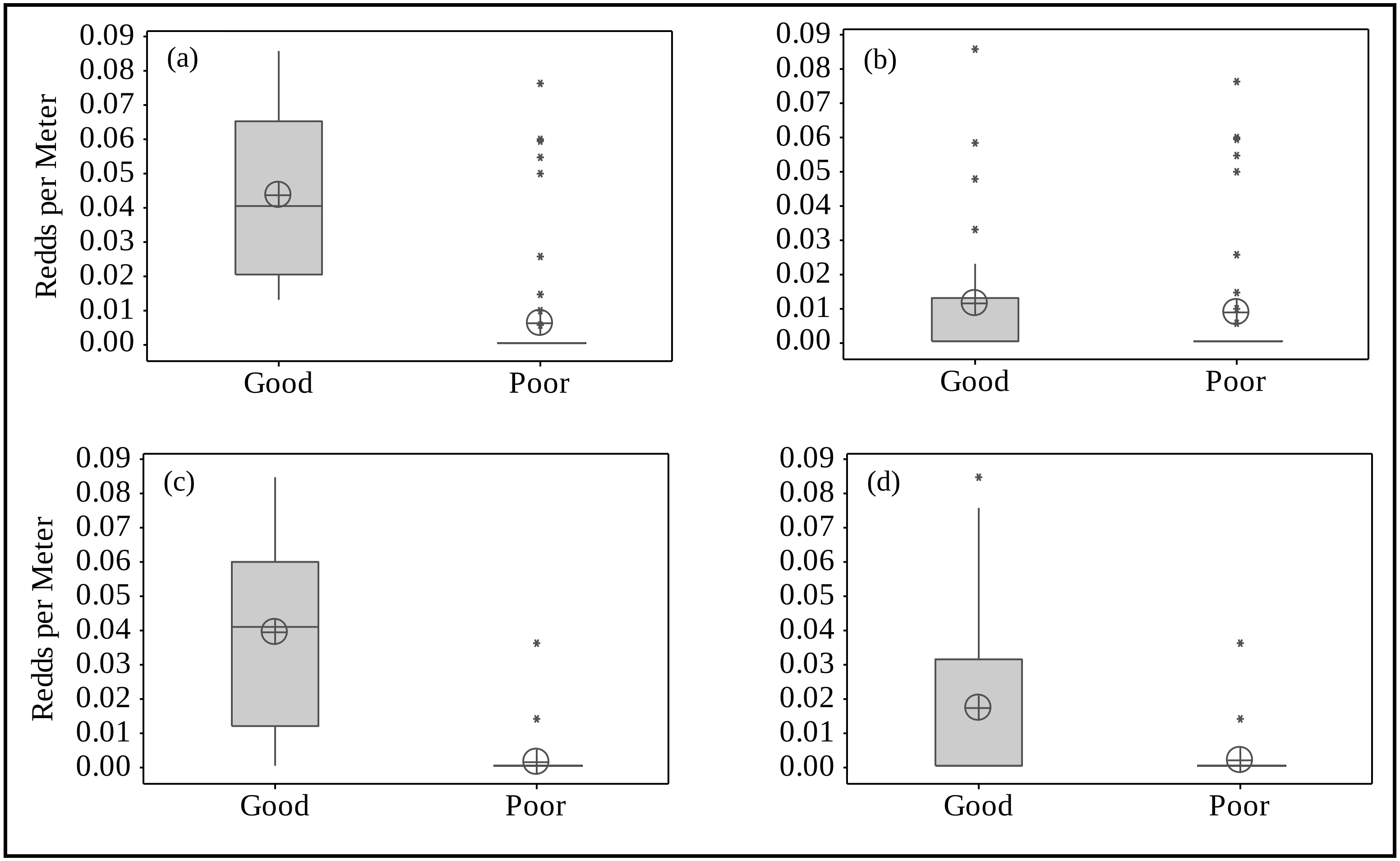

Figure 11. Comparison of redd densities between subreaches designated as good or poor by the Bayesian Network; (a) NHD under Dry Conditions, (b) NHD under not dry conditions, (c) traced streamline under dry conditions, and (d) traced streamlines under not dry conditions. Asterisks are values at least 1.5 times the interquartile range beyond the edge of the box. Crosshairs represent the mean.

Table 6. ANOVA (One-Way) summary for comparison of redd densities in subreaches designated as good and poor by the Bayesian Network for the four scenarios; NHD streamlines under dry conditions (NHDD), NHD under not-dry conditions (NHDND), traced streamlines under dry conditions (TRD), and traced streamlines under not-dry conditions. *DF* = degrees of freedom, *SS* = sum of squares, *MS* = mean sum of squares, η^2 *= eta squared).*

ANOVA

Source	*DF*	*SS*	*MS*	*F*	*P*	η^2
NHDD	1	0.008	0.008	22.71	< 0.001	0.268
Error	62	0.021	0.000			
Total	63	0.028				
NHDND	1	0.000	0.000	0.23	0.631	0.004
Error	62	0.028	0.000			
Total	63	0.028				
TRD	1	0.016	0.016	88.64	< 0.001	0.588
Error	62	0.011	0.000			
Total	63	0.028				
TRND	1	0.004	0.004	10.38	0.002	0.143
Error	62	0.024	0.000			
Total	63	0.028				

DISCUSSION

Based on the predictive ability of the traced streamline network under both dry and not-dry conditions, my results indicate that Bayesian Networks can predict habitat suitability and guide restoration for Chinook Salmon spawning habitat within data-poor watersheds. Studying spawning behavior of Chinook Salmon poses many difficult challenges. The limited duration of spawning activity and the annual nature of spawning make long-term monitoring preferable; however, time and cost can be an issue and monitoring of one stream must often be prioritized over monitoring of another (Williams 2006). Additional difficulties include feasibility of monitoring across different life-history stages and difficult access to spawning sites hindering data collection.

A great deal of published literature is dedicated to quantifying suitability of Chinook Salmon spawning habitat variables when more extensive data collection is feasible (Feist et al. 2003, Geist and Dauble 1998, Isaak et al. 2007, Lunnetta et al. 1997, Toepfer et al. 2000). While stream-specific classifications of habitat suitability regularly outperform generalized criteria, generalized criteria derived from the literature may still provide adequate results (McHugh and Budy 2004, Mäki-Petäys et al. 2002). However, predictive modeling based on these generalized criteria, even when generalization is sufficient, is confounded in some streams because empirical data for stream characterization may be sparse. The time and cost constraints mentioned by Williams (2006) impact scientists' ability to gather extensive data to remedy this issue, and it is under these conditions that the utility of Bayesian Networks becomes apparent. By providing a nexus between qualitative and quantitative data, the ability to combine variables of different scales and classifications (e.g., physical habitat data, biological data, and behavioral data), and by explicitly accounting for uncertainty, Bayesian Networks can be used where it would be difficult to apply models requiring more extensive field data (Bartholow 2004, Lichatowich et al. 1995, Steel et al. 2009).

Predictive Capabilities of Model

Three of the model scenarios, the NHD streamline under dry conditions (NHDD), the traced streamline under dry conditions (TRD), and the traced streamline under not-dry conditions (TRND), showed a significant difference between subreaches designated as good versus poor Chinook Spawning habitat by the network. In all three of these scenarios mean number of redds per meter was higher in the subreaches designated good, which supports the hypothesis that Bayesian Networks can be designed to predict suitability of spawning habitat for Chinook Salmon.

However, one of the scenarios, the NHD streamline under not-dry conditions (NHDND), showed no significant difference between the two designations. This scenario overestimated the amount of good habitat. Based on the sensitivity analysis, “Passage Conditions” appears to have a substantial effect on both NHD and traced streamline networks. Given that even during the not-dry water year (2012) spawning upstream of Lower Deer Creek Falls was limited, the passage barrier influence made both networks appear to predict habitat suitability well under dry water-years. However, two factors may have affected the predictive abilities of the NHDND scenario. Low mutual information values for all variables in the NHDND scenario (0.035 or lower) indicate little overall improvement in prediction of redd occurrence given information about the state of the variables. Also, the difference in influence of mean minimum coniferous cover from above may account for why the NHDND scenario had a much smaller effect size (η^2 = 0.004) than traced not-dry scenario (n^2 = 0.143), indicating poorer performance. Lunetta et al. (1997) used coniferous cover as an indicator of large woody debris recruitment potential, but the relationship in the NHD network seems poorly represented and the heavy influence of coniferous cover may have negatively affected the accuracy of this network. While the NHDD showed significant difference between good and poor habitat, it appears that this difference was an artifact of the partial passage barrier rather than the overall performance of the network trained using the NHD streamlines.

Models are often assessed using iterative resampling processes to assess frequency of correct predictions (Olden 2002). However, Borsuk et al. (2004) point out how common means of testing deterministic models are not as applicable to the probabilistic Bayesian Networks. While not a common means of validation, my assessment of model results using a simple ANOVA, in combination with the standard sensitivity analysis, provided a rapid and useful indication of how well the networks predicted habitat quality. The ANOVA analyses also informed my assessment of the effect of the partial passage barrier under each network (NHD streamline and traced streamline) on model results. Of the two networks, the traced streamline predicted good and poor spawning habitat, as reflected by differences in redd density, more accurately when subreach classifications were compared using field data from the validation subreaches.

Network Structure and Parameterization

Determining the structure of the Bayesian Network is a critical step in creating a network that will yield the desired information. In a large-scale collaborative setting, network development can be a lengthy process. Often structure is dictated not only by desired network outputs, but agreement among scientists and stakeholders upon what suite of variables should be included (Borsuk et al. 2004, Bromley et al. 2005). Williams (2006) suggests that simpler models are preferable to those containing what may be “unnecessary complexity.” In this case, I intentionally kept the network simplistic, in order to determine if I could obtain a useful output with limited time and resources that may be encountered in data-poor Northern California watersheds. Even working within this limited framework, a number of considerations had to be taken into account during network construction and parameterization.

While constructing the network, it is important to consider that the state of each node within the network must be available for use in the case file, whether based on professional judgment or empirical data. Although the expectation maximization algorithm used in my network is resilient to lack of data (Pollino et al. 2007b), some data is still necessary for the software to back-calculate probabilities for the conditional probability tables. I considered other intermediate variables for inclusion in the network that would have been directly tied to microhabitat features, such as large wood recruitment and recruitment of fine sediment; however, without extensive field surveys it would be impossible to include a meaningful state of these variables in the case file. Ultimately, these variables were omitted because it was not feasible to conduct these surveys. Temperature, another important indicator of spawning habitat quality (Bell 1986, Bjornn and Reiser 1991), was also omitted because suitable temperatures for Chinook Salmon spawning were found throughout the entire study area.

Discretization of variables proved challenging as well. Continuous variables must be broken into discrete ranges in order to parameterize and run the network. However, discretization is often dependent upon professional judgment (Uusitalo 2007). While ranges for variables such as gradient can be justified based on available literature (Geist et al. 2000, Lunetta et al. 1997, Montgomery and Buffington 1997), assigning ranges for variables like average stream width and percent coniferous cover are much more qualitative in nature. This can have an effect on model performance and, if a similar network were applied in a public planning framework, this could lead to a higher degree of scrutiny.

In addition, by breaking an otherwise continuous variable into discrete classifications, subtle inaccuracies in the model may have been disguised. For example, Neeson et al. (2008) determined that accuracy of GIS derived stream gradient improved when they corrected for outliers, muting the effects of the highest and lowest values derived from the DEM. However, the corrective calculation used in their work did not work well in my network, resulting in no change in classification of stream slope.

As with stream slope, mean minimum coniferous cover was included in my network as an indicator of geomorphic characteristics. Lunnetta et al. (1997) found that the combination of stream slope and coniferous cover predicted habitat quality that was consistent with independent field surveys, at least when qualitatively compared. However, the results of the sensitivity analysis seemed to indicate that neither of these contributed much to the network trained with the traced streamline, which performed well. The low contribution of stream slope (mutual information = 0.002) could be due to inaccuracies related to the GIS derived gradient, masking of subtle differences due to discretization, or a combination of the two. The low contribution of mean minimum coniferous cover from above (mutual information < 0.001) may have been due to a lack of age of coniferous growth as a component of the variable. Seral stage data used by Lunetta et al. (1997) was a combination of age and percent coniferous cover. Therefore, seral stage rather than coniferous cover alone likely better characterized potential for the large wood recruitment that is beneficial to Chinook Salmon spawning habitat (Fausch and Northcote 1992, Merz 2001).

Soil type and average stream width had the most effect on redd presence predictions in the traced streamline trained network, with mutual information values of 0.155 and 0.177, respectively. Soil type, as classified by USGS, may be an indicator of the erosion potential of adjacent stream slopes and thereby account for potential contribution of fines. Large proportions of fine material (i.e., fines) in stream substrates has been shown to have a negative effect on redd presence and rearing juveniles (Sommer et al. 2001, Suttle et al. 2004), but is unclear whether this or other unknown correlations between soil type and habitat condition are responsible for the large influence within the network. Knapp and Preisler (1998) found stream width explained significant variation in Golden Trout spawning site selection. They were unable to account specifically for why this relationship existed. However, they note that other indicators of quality spawning habitat such as appropriate velocity, substrate, and depth were more common in wider reaches (Gallagher and Gard 1999, Geist and Dauble 1998, Shirvell 1989), which could also account for the influence on my network. Due to the extensive surveying associated with direct quantification of velocity, substrate, and depth throughout the study area, I did not explicitly account for these variables in this network.

Model Limitations

Schnute (2003) points out that modeling can serve to focus conservation efforts and monitoring, provided each model's limitations are clearly stated. The traced streamline network reliably predicted good and poor habitats, but the utility of the network to identify specific bottlenecks was questionable. This may be due to the probability distributions of individual parent nodes (i.e., input variable conditions) calculated by the network being poor representations of reality, but ultimately leading to better prediction of redd occurrence. This reinforces the notion that models, while not necessarily an accurate representation of nature (Pollino et al. 2007a, Schnute 2003, Williams 2006), are still useful. In the context of this model, it was more important to identify the presence and absence of redds than to identify exactly which variable is responsible for this result. In this way, the traced streamline model retains its utility in directing restoration efforts, with more detailed evaluation of each individual variable being reserved for more focused microhabitat studies. However, this is a limitation to model application within a restoration context.

A second limitation to Bayesian Networks is the difficulty in validating the model. As mentioned, validation cannot be conducted using traditional statistical methods (Borsuk et al. 2004). Rather, sensitivity analyses are commonly relied upon to determine reliability of the output (Coupé and van der Gaag 2002, Stewart-Koster et al. 2010). The accuracy of modeled predictions may be less clear using sensitivity analysis rather than the more commonly applied techniques (e.g., iterative methods such as bootstrapping), and results may be called into question in planning scenarios.

However, despite this limitation, Bayesian Networks do show promise for use in guiding fisheries management. Expression of outcomes in these networks as likelihood of occurrence provides a clear measure of uncertainty, and the ability to incorporate effects of variables that may not be explicitly measured (e.g., soil type as designated by USGS) provides flexibility not available in other models (Clark 2005, Ellison 2004). Therefore, future research into their applicability to fisheries management is justified.

Suggestions for Future Research

Reach Length. For my initial investigation into the predictive abilities of Bayesian Networks I elected to assess riffle-pool subreach length, designated using aerial imagery. However, Neeson et al. (2008) indicated that there was an increase in accuracy of Digital Elevation Model (DEM) derived stream gradient using longer reaches. Their results seem to indicate an increase in accuracy using 10 meter DEMs and National Hydrography Dataset (NHD) or traced streamlines up to approximately 800 meters, at which point the benefits of increasing reach length diminished. Using the 800-meter length, which was considerably longer than any of my riffle-pool subreaches, would have yielded only 15 reaches within my 12 kilometer study area. This would have posed problems, including too few reaches for comparing predicted probability of redd occurrence to actual densities, and difficulties in splitting data for training and validation. However, if the study area were long enough to provide an adequate number of 800-meter reaches, the accuracy of GIS derived gradient, and therefore modeled results, could be improved.

Microhabitat Variables. Microhabitat variables, such as substrate size, velocity, and depth, are commonly associated with Chinook Salmon spawning habitat preference (Gallagher and Gard 1999, Geist and Dauble 1998). Incorporation of these variables, while likely requiring time intensive sampling, would likely increase the accuracy of model predictions. This is somewhat counter to the idea of a rapid assessment in a data poor environment, and was therefore not included in this assessment. Inclusion in future use of networks similar to this, where this data is either available or in venues where this data is more attainable due to fewer budgetary and time constraints, is recommended.

Expansion into a life-cycle type model. The focus of this network was the spawning life stage of spring-run Chinook Salmon. However, Lindley et al. (2007) mention that Central Valley Chinook Salmon historic rearing habitat is also largely inaccessible. While a Bayesian Network is likely not the best tool for predicting population size, expansion into a framework similar to a full life-cycle model should be done to understand how habitat quality is affecting Chinook Salmon throughout their life-history. One method for doing so would be to essentially develop a number of different habitat sub-models, corresponding with life-stage, which are then related to overall productivity. The structure would be similar to the network created by Pollino et al. (2007b), though the specific nodes would differ. In this way, the habitats encountered by Chinook Salmon originating from a particular watershed could be assessed throughout the life-history and particularly influential points of habitat degradation could be addressed.

Conclusion

Based on my research, Bayesian Networks show promise as a potential tool for guiding restoration efforts in Northern California watersheds. They are able to incorporate various types of data, provide a means of dealing with uncertainty, and networks can be updated relatively quickly and efficiently. In addition to these traits, open source software for creation of these networks is readily available, broadening its applicability to agencies or organizations that may not have the resources to pay for development of proprietary models in watersheds of interest. Due to drastic reductions in historic cold water spawning and holding habitat for spring-run Chinook Salmon (Yoshiyama et al. 2001) it is essential that the quality of the habitat available to these fish is maximized. It is also important that in our efforts to conserve native populations in rapid decline, such as Chinook Salmon, we assess as many tools at our disposal as possible. Bayesian Networks are one additional tool that warrants further consideration in the conservation of California's native fishes.

APPENDICES

APPENDIX A

Case File for Network Using NHD Streamline

NewID	*AveWidth*	*StrSlope*	*MMCCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
1	15.66	Marginal	0.45	MkE	Yes	NotDry	Good	Yes
2	15.66	Marginal	0.45	MkE	Yes	NotDry	Good	Yes
3	15.66	Marginal	0.45	MkE	Yes	NotDry	Good	Yes
4	15.66	Marginal	0.45	MkE	Yes	NotDry	Good	Yes
5	15.66	Marginal	0.45	MkE	Yes	NotDry	Good	Yes
6	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
7	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
8	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
9	8.24	Suitable	0.35	MkE	Yes	NotDry	Good	Yes
10	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
11	11.85	Suitable	0.1	RtF	No	NotDry	Good	Yes
12	14.74	Suitable	0.5	NoF	No	NotDry	Good	Yes
13	10.71	Suitable	0.55	MkE	No	NotDry	Good	Yes
14	14.74	Suitable	0.5	NoF	No	NotDry	Good	Yes
15	12.15	Suitable	0.55	MkE	No	NotDry	Good	Yes
16	14.95	Suitable	0.75	CdD	No	NotDry	Good	Yes
17	14.95	Suitable	0.75	CdD	No	NotDry	Good	Yes
18	11.3	Suitable	0.8	CdD	No	NotDry	Good	Yes
19	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
20	11.3	Suitable	0.8	CdD	No	NotDry	Good	Yes

Appendix A. Continued

NewID	*AveWidth*	*StrSlope*	*MMCCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
21	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
22	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
23	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
24	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
25	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
26	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
27	11.93	Suitable	0.8	MkE	No	NotDry	Good	Yes
28	11.93	Suitable	0.8	MkE	No	NotDry	Good	Yes
29	12.45	Suitable	0.4	MkE	No	NotDry	Good	Yes
30	12.45	Suitable	0.4	MkE	No	NotDry	Good	Yes
31	12.19	Suitable	0.75	MmF	No	NotDry	Good	Yes
32	12.19	Suitable	0.75	MmF	No	NotDry	Good	Yes
33	10.63	Suitable	0.75	MmF	No	NotDry	Good	Yes
34	10.63	Suitable	0.75	MmF	No	NotDry	Good	Yes
35	13.87	Suitable	0.75	MmF	No	NotDry	Good	Yes
36	15.66	Marginal	0.45	MkE	Yes	NotDry	Good	Yes
37	15.66	Marginal	0.45	MkE	Yes	NotDry	Good	Yes
38	15.66	Marginal	0.45	MkE	Yes	NotDry	Good	Yes
39	15.66	Marginal	0.45	MkE	Yes	NotDry	Good	Yes
40	15.66	Marginal	0.45	MkE	Yes	NotDry	Good	Yes
41	15.66	Marginal	0.45	MkE	Yes	NotDry	Good	Yes
42	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes

Appendix A. Continued

NewID	*AveWidth*	*StrSlope*	*MMCCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
43	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
44	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
45	11.43	Suitable	0.35	MmE	Yes	NotDry	Good	Yes
46	11.85	Suitable	0.1	RtF	No	NotDry	Good	Yes
47	14.95	Suitable	0.75	CdD	No	NotDry	Good	Yes
48	14.95	Suitable	0.75	CdD	No	NotDry	Good	Yes
49	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
50	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
51	11.93	Suitable	0.8	MkE	No	NotDry	Good	Yes
52	11.93	Suitable	0.8	MkE	No	NotDry	Good	Yes
53	11.85	Suitable	0.1	RtF	No	Dry	Good	Yes
54	12.4	Suitable	0.4	MkE	No	Dry	Good	Yes
55	12.4	Suitable	0.4	MkE	No	Dry	Good	Yes
56	12.4	Suitable	0.4	MkE	No	Dry	Good	Yes
57	12.4	Suitable	0.4	MkE	No	Dry	Good	Yes
58	12.45	Suitable	0.4	MkE	No	Dry	Good	Yes
59	12.4	Suitable	0.25	MkE	No	Dry	Good	Yes
60	12.45	Suitable	0.4	MkE	No	Dry	Good	Yes
61	12.45	Suitable	0.4	MkE	No	Dry	Good	Yes
62	12.45	Suitable	0.4	MkE	No	Dry	Good	Yes
63	12.45	Suitable	0.8	MkE	No	Dry	Good	Yes
64	11.93	Suitable	0.8	CdD	No	Dry	Good	Yes

Appendix A. Continued

NewID	*AveWidth*	*StrSlope*	*MMCCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
65	11.93	Suitable	0.8	CdD	No	Dry	Good	Yes
66	11.93	Suitable	0.8	CdD	No	Dry	Good	Yes
67	11.93	Suitable	0.8	CdD	No	Dry	Good	Yes
68	15.32	Suitable	0.8	CdD	No	Dry	Good	Yes
69	15.32	Suitable	0.8	CdD	No	Dry	Good	Yes
70	15.32	Suitable	0.8	CdD	No	Dry	Good	Yes
71	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
72	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
73	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
74	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
75	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
76	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
77	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
78	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
79	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
80	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
81	11.3	Suitable	0.8	CdD	No	Dry	Good	Yes
82	10.13	Suitable	0.75	CdD	No	Dry	Good	Yes
83	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
84	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
85	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
86	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes

Appendix A. Continued

NewID	*AveWidth*	*StrSlope*	*MMCCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
87	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
88	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
89	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
90	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
91	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
92	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
93	13.55	Suitable	0.75	MmF	No	Dry	Good	Yes
94	12.4	Suitable	0.55	IrF	No	Dry	Good	Yes
95	10.45	Suitable	0.55	MkE	No	Dry	Good	Yes
96	11.06	Suitable	0.55	MkE	No	Dry	Good	Yes
97	10.71	Suitable	0.55	MkE	No	Dry	Good	Yes
98	10.71	Suitable	0.55	MkE	No	Dry	Good	Yes
99	10.71	Suitable	0.55	MkE	No	Dry	Good	Yes
100	10.71	Suitable	0.55	MkE	No	Dry	Good	Yes
101	13.16	Suitable	0.55	MkE	No	Dry	Good	Yes
102	13.16	Suitable	0.55	MkE	No	Dry	Good	Yes
103	13.16	Suitable	0.55	MkE	No	Dry	Good	Yes
104	13.16	Suitable	0.55	MkE	No	Dry	Good	Yes
105	13.16	Suitable	0.55	MkE	No	Dry	Good	Yes
106	13.16	Suitable	0.55	MkE	No	Dry	Good	Yes
107	12.31	Suitable	0.25	MkE	No	Dry	Good	No
108	12.31	Suitable	0.25	MkE	No	NotDry	Good	No

Appendix A. Continued

NewID	*AveWidth*	*StrSlope*	*MMCCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
109	9.69	Suitable	0.65	MmF	No	NotDry	Good	No
110	9.94	Suitable	0.65	MmF	No	NotDry	Good	No
111	9.94	Suitable	0.65	MmF	No	Dry	Good	No
112	10.66	Suitable	0.65	MmF	No	Dry	Good	No
113	10.66	Suitable	0.65	MmF	No	NotDry	Good	No
114	10.66	Suitable	0.65	MmF	No	NotDry	Good	No
115	10.66	Suitable	0.65	MmF	No	NotDry	Good	No
116	10.66	Suitable	0.65	MmF	No	NotDry	Good	No
117	11.31	Suitable	0.65	MmF	No	NotDry	Good	No
118	11.31	Suitable	0.65	MmF	No	NotDry	Good	No
119	11.31	Suitable	0.65	MmF	No	NotDry	Good	No
120	12.31	Suitable	0.65	MmF	No	Dry	Good	No
121	12.31	Suitable	0.65	MmF	No	Dry	Good	No
122	12.31	Suitable	0.65	MmF	No	Dry	Good	No
123	9.13	Suitable	0.55	MkE	Yes	NotDry	Good	No
124	9.13	Suitable	0.55	MkE	Yes	NotDry	Good	No
125	9.13	Suitable	0.55	MkE	Yes	Dry	Poor	No
126	10.05	Suitable	0.55	MkE	Yes	NotDry	Good	No
127	10.05	Suitable	0.55	MkE	Yes	NotDry	Good	No
128	10.05	Suitable	0.55	MkE	Yes	NotDry	Good	No
129	10.11	Suitable	0.55	MkE	Yes	NotDry	Good	No
130	9.05	Suitable	0.55	IrF	Yes	NotDry	Good	No

Appendix A. Continued

NewID	*AveWidth*	*StrSlope*	*MMCCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
131	9.05	Suitable	0.55	MkE	Yes	Dry	Poor	No
132	9.05	Suitable	0.55	IrF	Yes	NotDry	Good	No
133	9.05	Suitable	0.55	MkE	Yes	Dry	Poor	No
134	7.56	Suitable	0.55	MkE	Yes	Dry	Poor	No
135	10	Suitable	0.55	MkE	Yes	Dry	Poor	No
136	10	Suitable	0.55	MkE	Yes	NotDry	Good	No
137	7.79	Suitable	0.55	MkE	Yes	NotDry	Good	No
138	7.79	Suitable	0.55	MkE	Yes	Dry	Poor	No
139	11.61	Suitable	0.40	MkE	Yes	Dry	Poor	No
140	9.04	Suitable	0.45	MkE	Yes	Dry	Poor	No
141	9.04	Suitable	0.45	MkE	Yes	NotDry	Good	No
142	9.04	Suitable	0.45	MkE	Yes	Dry	Poor	No
143	8.61	Suitable	0.45	MkE	Yes	Dry	Poor	No
144	9.42	Suitable	0.45	MkE	Yes	Dry	Poor	No
145	9.42	Suitable	0.45	MkE	Yes	NotDry	Good	No
146	8.7	Suitable	0.65	MkE	Yes	NotDry	Good	No
147	8.7	Suitable	0.65	MkE	Yes	NotDry	Good	No
148	9.56	Suitable	0.65	MkE	Yes	Dry	Poor	No
149	9.56	Suitable	0.65	MkE	Yes	NotDry	Good	No
150	9.56	Suitable	0.65	MkE	Yes	NotDry	Good	No
151	9.56	Suitable	0.65	MkE	Yes	NotDry	Good	No
152	9.56	Suitable	0.65	MkE	Yes	NotDry	Good	No

Appendix A. Continued

NewID	*AveWidth*	*StrSlope*	*MMCCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
153	12.41	Suitable	0.55	MkE	Yes	Dry	Poor	No
154	12.41	Suitable	0.65	MkE	Yes	Dry	Poor	No
155	12.41	Suitable	0.55	MkE	Yes	NotDry	Good	No
156	12.41	Suitable	0.65	MkE	Yes	Dry	Poor	No
157	10.27	Suitable	0.55	MkE	Yes	NotDry	Good	No
158	10.27	Suitable	0.55	MkE	Yes	NotDry	Good	No
159	10.27	Suitable	0.55	MkE	Yes	Dry	Poor	No
160	8.29	Suitable	0.55	MkE	Yes	Dry	Poor	No
161	8.29	Suitable	0.55	MkE	Yes	Dry	Poor	No
162	13.83	Suitable	0.45	MkE	Yes	NotDry	Good	No
163	13.83	Suitable	0.45	MkE	Yes	NotDry	Good	No
164	14.11	Suitable	0.4	MmE	Yes	NotDry	Good	No
165	14.11	Suitable	0.40	MmE	Yes	NotDry	Good	No
166	14.62	Suitable	0.55	MmE	Yes	Dry	Poor	No
167	14.62	Suitable	0.55	MmE	Yes	NotDry	Good	No
168	10.99	Suitable	0.35	MmE	Yes	Dry	Poor	No
169	10.99	Suitable	0.35	MmE	Yes	NotDry	Good	No
170	10.36	Suitable	0.25	MmE	Yes	Dry	Poor	No
171	10.36	Suitable	0.25	MmE	Yes	NotDry	Good	No
172	10.42	Suitable	0.25	MmE	Yes	Dry	Poor	No
173	10.42	Suitable	0.25	MmE	Yes	Dry	Poor	No
174	10.42	Suitable	0.25	MmE	Yes	NotDry	Good	No

Appendix A. Continued

NewID	*AveWidth*	*StrSlope*	*MMCCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
175	10.42	Suitable	0.25	MmE	Yes	NotDry	Good	No
176	10.42	Suitable	0.25	MmE	Yes	Dry	Poor	No
177	10.42	Suitable	0.25	MmE	Yes	NotDry	Good	No
178	6.85	Suitable	0.45	MmE	Yes	Dry	Poor	No
179	6.85	Suitable	0.45	MmE	Yes	NotDry	Good	No
180	7.55	Suitable	0.25	MmE	Yes	Dry	Poor	No
181	9.99	Suitable	0.45	MmE	Yes	NotDry	Good	No
182	8	Suitable	0.45	MmE	Yes	Dry	Poor	No
183	9.3	Suitable	0.45	MmE	Yes	Dry	Poor	No
184	9.3	Suitable	0.45	MmE	Yes	NotDry	Good	No
185	8.57	Suitable	0.55	MkE	Yes	Dry	Poor	No
186	8.57	Suitable	0.55	MmE	Yes	NotDry	Good	No
187	8.57	Suitable	0.55	MmE	Yes	Dry	Poor	No
188	8.57	Suitable	0.55	MkE	Yes	Dry	Poor	No
189	8.57	Suitable	0.55	MkE	Yes	Dry	Poor	No
190	8.11	Suitable	0.45	MmE	Yes	Dry	Poor	No
191	8.89	Suitable	0.45	MmE	Yes	NotDry	Good	No
192	9.76	Suitable	0.45	MmE	Yes	Dry	Poor	No
193	9.76	Suitable	0.45	MmE	Yes	Dry	Poor	No
194	8.87	Suitable	0.45	MmE	Yes	Dry	Poor	No
195	8.87	Suitable	0.45	MmE	Yes	Dry	Poor	No
196	14.42	Suitable	0.55	MmE	Yes	NotDry	Good	No

Appendix A. Continued

NewID	*AveWidth*	*StrSlope*	*MMCCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
197	9.71	Suitable	0.45	MmE	Yes	Dry	Poor	No
198	9.71	Suitable	0.35	MmE	Yes	Dry	Poor	No
199	9.71	Suitable	0.35	MmE	Yes	NotDry	Good	No
200	14.74	Suitable	0.40	MmE	Yes	NotDry	Good	No
201	14.74	Suitable	0.40	MmE	Yes	NotDry	Good	No
202	8.1	Suitable	0.40	MmE	Yes	NotDry	Good	No
203	9.17	Suitable	0.40	MkE	Yes	NotDry	Good	No
204	9.17	Suitable	0.40	MkE	Yes	NotDry	Good	No
205	9.51	Suitable	0.40	MkE	Yes	Dry	Poor	No
206	9.51	Suitable	0.40	MkE	Yes	NotDry	Good	No
207	9.51	Suitable	0.40	MkE	Yes	Dry	Poor	No
208	7.12	Suitable	0.40	MkE	Yes	Dry	Poor	No
209	7.41	Suitable	0.40	MkE	Yes	Dry	Poor	No
210	7.41	Suitable	0.40	MkE	Yes	Dry	Poor	No
211	14.13	Marginal	0.40	MkE	Yes	Dry	Poor	No
212	14.13	Marginal	0.40	MkE	Yes	NotDry	Good	No

APPENDIX B

Case File for Network Using Traced Streamline

NewID	*AveWidth*	*StrSlope*	*MMCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
1	15.66	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
2	15.66	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
3	15.66	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
4	15.66	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
5	15.66	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
6	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
7	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
8	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
9	8.24	Marginal	0.35	MkE	Yes	NotDry	Good	Yes
10	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
11	11.85	Suitable	0.1	RtF	No	NotDry	Good	Yes
12	14.74	Suitable	0.5	NoF	No	NotDry	Good	Yes
13	10.71	Suitable	0.55	MkE	No	NotDry	Good	Yes
14	14.74	Suitable	0.5	NoF	No	NotDry	Good	Yes
15	12.15	Suitable	0.55	MkE	No	NotDry	Good	Yes
16	14.95	Suitable	0.75	CdD	No	NotDry	Good	Yes
17	14.95	Suitable	0.75	CdD	No	NotDry	Good	Yes
18	11.3	Suitable	0.8	CdD	No	NotDry	Good	Yes
19	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
20	11.3	Suitable	0.8	CdD	No	NotDry	Good	Yes
21	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
22	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
23	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes

Appendix B. Continued

NewID	*AveWidth*	*StrSlope*	*MMCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
24	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
25	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
26	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
27	11.93	Suitable	0.8	MkE	No	NotDry	Good	Yes
28	11.93	Suitable	0.8	MkE	No	NotDry	Good	Yes
29	12.45	Suitable	0.4	MkE	No	NotDry	Good	Yes
30	12.45	Suitable	0.4	MkE	No	NotDry	Good	Yes
31	12.19	Suitable	0.75	MmF	No	NotDry	Good	Yes
32	12.19	Suitable	0.75	MmF	No	NotDry	Good	Yes
33	10.63	Suitable	0.75	MmF	No	NotDry	Good	Yes
34	10.63	Suitable	0.75	MmF	No	NotDry	Good	Yes
35	13.87	Suitable	0.75	MmF	No	NotDry	Good	Yes
36	15.66	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
37	15.66	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
38	15.66	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
39	15.66	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
40	15.66	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
41	15.66	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
42	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
43	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
44	12.24	Suitable	0.45	MkE	Yes	NotDry	Good	Yes
45	11.43	Suitable	0.35	MmE	Yes	NotDry	Good	Yes
46	11.85	Suitable	0.1	RtF	No	NotDry	Good	Yes
47	14.95	Suitable	0.75	CdD	No	NotDry	Good	Yes
48	14.95	Suitable	0.75	CdD	No	NotDry	Good	Yes

Appendix B. Continued

NewID	*AveWidth*	*StrSlope*	*MMCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
49	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
50	13.7	Suitable	0.8	CdD	No	NotDry	Good	Yes
51	11.93	Suitable	0.8	MkE	No	NotDry	Good	Yes
52	11.93	Suitable	0.8	MkE	No	NotDry	Good	Yes
53	11.85	Suitable	0.1	RtF	No	Dry	Good	Yes
54	12.4	Suitable	0.4	MkE	No	Dry	Good	Yes
55	12.4	Suitable	0.4	MkE	No	Dry	Good	Yes
56	12.4	Suitable	0.4	MkE	No	Dry	Good	Yes
57	12.4	Suitable	0.4	MkE	No	Dry	Good	Yes
58	12.45	Suitable	0.4	MkE	No	Dry	Good	Yes
59	12.4	Suitable	0.25	MkE	No	Dry	Good	Yes
60	12.45	Suitable	0.4	MkE	No	Dry	Good	Yes
61	12.45	Suitable	0.4	MkE	No	Dry	Good	Yes
62	12.45	Suitable	0.4	MkE	No	Dry	Good	Yes
63	12.45	Suitable	0.8	MkE	No	Dry	Good	Yes
64	11.93	Suitable	0.8	CdD	No	Dry	Good	Yes
65	11.93	Suitable	0.8	CdD	No	Dry	Good	Yes
66	11.93	Suitable	0.8	CdD	No	Dry	Good	Yes
67	11.93	Suitable	0.8	CdD	No	Dry	Good	Yes
68	15.32	Suitable	0.8	CdD	No	Dry	Good	Yes
69	15.32	Suitable	0.8	CdD	No	Dry	Good	Yes
70	15.32	Suitable	0.8	CdD	No	Dry	Good	Yes
71	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
72	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
73	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes

Appendix B. Continued

NewID	*AveWidth*	*StrSlope*	*MMCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
74	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
75	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
76	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
77	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
78	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
79	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
80	13.7	Suitable	0.8	CdD	No	Dry	Good	Yes
81	11.3	Suitable	0.8	CdD	No	Dry	Good	Yes
82	10.13	Suitable	0.75	CdD	No	Dry	Good	Yes
83	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
84	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
85	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
86	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
87	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
88	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
89	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
90	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
91	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
92	14.95	Suitable	0.75	CdD	No	Dry	Good	Yes
93	13.55	Suitable	0.75	MmF	No	Dry	Good	Yes
94	12.4	Suitable	0.55	IrF	No	Dry	Good	Yes
95	10.45	Suitable	0.55	MkE	No	Dry	Good	Yes
96	11.06	Marginal	0.55	MkE	No	Dry	Good	Yes
97	10.71	Suitable	0.55	MkE	No	Dry	Good	Yes
98	10.71	Suitable	0.55	MkE	No	Dry	Good	Yes

Appendix B. Continued

NewID	*AveWidth*	*StrSlope*	*MMCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
99	10.71	Suitable	0.55	MkE	No	Dry	Good	Yes
100	10.71	Suitable	0.55	MkE	No	Dry	Good	Yes
101	13.16	Suitable	0.55	MkE	No	Dry	Good	Yes
102	13.16	Suitable	0.55	MkE	No	Dry	Good	Yes
103	13.16	Suitable	0.55	MkE	No	Dry	Good	Yes
104	13.16	Suitable	0.55	MkE	No	Dry	Good	Yes
105	13.16	Suitable	0.55	MkE	No	Dry	Good	Yes
106	13.16	Suitable	0.55	MkE	No	Dry	Good	Yes
107	12.31	Suitable	0.25	MkE	No	Dry	Good	No
108	12.31	Suitable	0.25	MkE	No	NotDry	Good	No
109	9.69	Suitable	0.65	MmF	No	NotDry	Good	No
110	9.94	Suitable	0.65	MmF	No	NotDry	Good	No
111	9.94	Suitable	0.65	MmF	No	Dry	Good	No
112	10.66	Suitable	0.65	MmF	No	Dry	Good	No
113	10.66	Suitable	0.65	MmF	No	NotDry	Good	No
114	10.66	Suitable	0.65	MmF	No	NotDry	Good	No
115	10.66	Suitable	0.65	MmF	No	NotDry	Good	No
116	10.66	Suitable	0.65	MmF	No	NotDry	Good	No
117	11.31	Suitable	0.65	MmF	No	NotDry	Good	No
118	11.31	Suitable	0.65	MmF	No	NotDry	Good	No
119	11.31	Suitable	0.65	MmF	No	NotDry	Good	No
120	12.31	Suitable	0.65	MmF	No	Dry	Good	No
121	12.31	Suitable	0.65	MmF	No	Dry	Good	No
122	12.31	Suitable	0.65	MmF	No	Dry	Good	No
123	9.13	Suitable	0.55	MkE	Yes	NotDry	Good	No

Appendix B. Continued

NewID	*AveWidth*	*StrSlope*	*MMCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
124	9.13	Suitable	0.55	MkE	Yes	NotDry	Good	No
125	9.13	Suitable	0.55	MkE	Yes	Dry	Poor	No
126	10.05	Suitable	0.55	MkE	Yes	NotDry	Good	No
127	10.05	Suitable	0.55	MkE	Yes	NotDry	Good	No
128	10.05	Suitable	0.55	MkE	Yes	NotDry	Good	No
129	10.11	Suitable	0.55	MkE	Yes	NotDry	Good	No
130	9.05	Suitable	0.55	IrF	Yes	NotDry	Good	No
131	9.05	Suitable	0.55	MkE	Yes	Dry	Poor	No
132	9.05	Suitable	0.55	IrF	Yes	NotDry	Good	No
133	9.05	Suitable	0.55	MkE	Yes	Dry	Poor	No
134	7.56	Suitable	0.55	MkE	Yes	Dry	Poor	No
135	10	Suitable	0.55	MkE	Yes	Dry	Poor	No
136	10	Suitable	0.55	MkE	Yes	NotDry	Good	No
137	7.79	Suitable	0.55	MkE	Yes	NotDry	Good	No
138	7.79	Suitable	0.55	MkE	Yes	Dry	Poor	No
139	11.61	Suitable	0.40	MkE	Yes	Dry	Poor	No
140	9.04	Suitable	0.45	MkE	Yes	Dry	Poor	No
141	9.04	Suitable	0.45	MkE	Yes	NotDry	Good	No
142	9.04	Suitable	0.45	MkE	Yes	Dry	Poor	No
143	8.61	Suitable	0.45	MkE	Yes	Dry	Poor	No
144	9.42	Suitable	0.45	MkE	Yes	Dry	Poor	No
145	9.42	Suitable	0.45	MkE	Yes	NotDry	Good	No
146	8.7	Suitable	0.65	MkE	Yes	NotDry	Good	No
147	8.7	Suitable	0.65	MkE	Yes	NotDry	Good	No
148	9.56	Suitable	0.65	MkE	Yes	Dry	Poor	No

Appendix B. Continued

NewID	*AveWidth*	*StrSlope*	*MMCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
149	9.56	Suitable	0.65	MkE	Yes	NotDry	Good	No
150	9.56	Suitable	0.65	MkE	Yes	NotDry	Good	No
151	9.56	Suitable	0.65	MkE	Yes	NotDry	Good	No
152	9.56	Suitable	0.65	MkE	Yes	NotDry	Good	No
153	12.41	Suitable	0.55	MkE	Yes	Dry	Poor	No
154	12.41	Suitable	0.65	MkE	Yes	Dry	Poor	No
155	12.41	Suitable	0.55	MkE	Yes	NotDry	Good	No
156	12.41	Suitable	0.65	MkE	Yes	Dry	Poor	No
157	10.27	Suitable	0.55	MkE	Yes	NotDry	Good	No
158	10.27	Suitable	0.55	MkE	Yes	NotDry	Good	No
159	10.27	Suitable	0.55	MkE	Yes	Dry	Poor	No
160	8.29	Suitable	0.55	MkE	Yes	Dry	Poor	No
161	8.29	Suitable	0.55	MkE	Yes	Dry	Poor	No
162	13.83	Suitable	0.45	MkE	Yes	NotDry	Good	No
163	13.83	Suitable	0.45	MkE	Yes	NotDry	Good	No
164	14.11	Suitable	0.4	MmE	Yes	NotDry	Good	No
165	14.11	Suitable	0.40	MmE	Yes	NotDry	Good	No
166	14.62	Suitable	0.55	MmE	Yes	Dry	Poor	No
167	14.62	Suitable	0.55	MmE	Yes	NotDry	Good	No
168	10.99	Suitable	0.35	MmE	Yes	Dry	Poor	No
169	10.99	Suitable	0.35	MmE	Yes	NotDry	Good	No
170	10.36	Suitable	0.25	MmE	Yes	Dry	Poor	No
171	10.36	Suitable	0.25	MmE	Yes	NotDry	Good	No
172	10.42	Suitable	0.25	MmE	Yes	Dry	Poor	No
173	10.42	Suitable	0.25	MmE	Yes	Dry	Poor	No

Appendix B. Continued

NewID	*AveWidth*	*StrSlope*	*MMCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
174	10.42	Suitable	0.25	MmE	Yes	NotDry	Good	No
175	10.42	Suitable	0.25	MmE	Yes	NotDry	Good	No
176	10.42	Suitable	0.25	MmE	Yes	Dry	Poor	No
177	10.42	Suitable	0.25	MmE	Yes	NotDry	Good	No
178	6.85	Poor	0.45	MmE	Yes	Dry	Poor	No
179	6.85	Poor	0.45	MmE	Yes	NotDry	Good	No
180	7.55	Suitable	0.25	MmE	Yes	Dry	Poor	No
181	9.99	Suitable	0.45	MmE	Yes	NotDry	Good	No
182	8	Suitable	0.45	MmE	Yes	Dry	Poor	No
183	9.3	Marginal	0.45	MmE	Yes	Dry	Poor	No
184	9.3	Marginal	0.45	MmE	Yes	NotDry	Good	No
185	8.57	Suitable	0.55	MkE	Yes	Dry	Poor	No
186	8.57	Suitable	0.55	MmE	Yes	NotDry	Good	No
187	8.57	Suitable	0.55	MmE	Yes	Dry	Poor	No
188	8.57	Suitable	0.55	MkE	Yes	Dry	Poor	No
189	8.57	Suitable	0.55	MkE	Yes	Dry	Poor	No
190	8.11	Suitable	0.45	MmE	Yes	Dry	Poor	No
191	8.89	Suitable	0.45	MmE	Yes	NotDry	Good	No
192	9.76	Suitable	0.45	MmE	Yes	Dry	Poor	No
193	9.76	Suitable	0.45	MmE	Yes	Dry	Poor	No
194	8.87	Suitable	0.45	MmE	Yes	Dry	Poor	No
195	8.87	Suitable	0.45	MmE	Yes	Dry	Poor	No
196	14.42	Suitable	0.55	MmE	Yes	NotDry	Good	No
197	9.71	Suitable	0.45	MmE	Yes	Dry	Poor	No
198	9.71	Suitable	0.35	MmE	Yes	Dry	Poor	No

Appendix B. Continued

NewID	*AveWidth*	*StrSlope*	*MMCFA*	*SoilType*	*PartialBar*	*WaterYr*	*PassCond*	*ReddsPresent*
199	9.71	Suitable	0.35	MmE	Yes	NotDry	Good	No
200	14.74	Suitable	0.4	MmE	Yes	NotDry	Good	No
201	14.74	Suitable	0.4	MmE	Yes	NotDry	Good	No
202	8.1	Suitable	0.4	MmE	Yes	NotDry	Good	No
203	9.17	Suitable	0.4	MkE	Yes	NotDry	Good	No
204	9.17	Suitable	0.4	MkE	Yes	NotDry	Good	No
205	9.51	Suitable	0.4	MkE	Yes	Dry	Poor	No
206	9.51	Suitable	0.4	MkE	Yes	NotDry	Good	No
207	9.51	Suitable	0.4	MkE	Yes	Dry	Poor	No
208	7.12	Suitable	0.4	MkE	Yes	Dry	Poor	No
209	7.41	Suitable	0.4	MkE	Yes	Dry	Poor	No
210	7.41	Suitable	0.4	MkE	Yes	Dry	Poor	No
211	14.13	Suitable	0.4	MkE	Yes	Dry	Poor	No
212	14.13	Suitable	0.4	MkE	Yes	NotDry	Good	No

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