WOODJAM NORTH PROSPECTIVITY

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GEOGRAPHIC
INFORMATION
SYSTEMS

GOLD FIELDS

ABSTRACT

This document contains a project report for Gold Fields Canada Exploration focusing on applying prospectivity modeling techniques to the Woodjam North exploration dataset. The primary goal of this project was to determine if the present data collection within the study area is able to support a predictive model.

Gold Fields Mining Ltd. is one of the world's largest producers of gold and maintains an extensive exploration program of both greenfield and near mine projects at various stages of development. Gold Fields Canada Exploration is currently completing concept studies on the Woodjam copper-gold project located in south-central British Columbia.

The overall goal of this project was to deepen the knowledge and skills acquired from BCIT through the utilization of GIS for mineral exploration targeting. In addition, applying spatial data modeling, statistical analysis, and predictive analytic techniques to a working dataset with real world constraints may help determine the practical application of this type of analysis. The resulting benefits of eliminating non-prospective areas will help reduce the risks involved in expensive drilling programs and ensure the cost effectiveness of the exploration program.

Based on expert opinion and previous exploration targeting success, the final iteration of the modeling process focused of quantifying a spatial relationship between proximal distances to high chargeability responses while being within a favorable chargeability threshold. As well, the model incorporated proximal distances to a derived lineament dataset from ground magnetic surveys, gravity surveys, and digital elevation models.

The project timeline included 342 hours combined project management and technical work over the period of January 13th, 2012 to May 21st, 2012.

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1. INTRODUCTION

Prospectivity modeling is increasingly being used in mineral exploration as a way to predict the occurrence of mineralization. This type of spatial analysis using Geographic Information Systems (GIS) is an efficient and accurate way to quantify relationships between existing targets (e.g. mineral deposits) and various datasets to produce a quantitative measure of the favorability of a specific mineral deposit type.

In recent years, computer processing power and GPS accuracy has developed to the point where it is possible to perform this complex spatial analysis at the target scale of a mineral system (Partington, 2010). These new approaches in spatial data modeling are helping to find positive relationships between mineral occurrences that might warrant more detailed analysis at a later stage of exploration.

This document contains a project report for Gold Fields Canada Exploration focusing on applying prospectivity modeling techniques to the Woodjam North dataset. The report consists of sections describing the project sponsor as well as the project objectives, methodology, and results.

2. PROJECT STATEMENT

This project is being undertaken to determine if the present data collection within the Woodjam North dataset is able to support a predictive model. The project is motivated by the challenges presented to traditional methods of mineral exploration in the area and attempts to reduce the risks involved in expensive drilling programs by narrowing search areas and eliminating non-prospective areas.

3. SPONSOR BACKGROUND

Gold Fields is one of the world's largest producers of gold from eight operating mines in South Africa, Ghana, Australia and Peru. The company has an annual production of 3.5 million Au Eq. ounces and combined resources and reserves totaling over 300 million Au Eq. ounces. The company also maintains an extensive exploration program with both greenfield and near mine projects at various stages of development. Gold Fields holds a growth strategy target of 5 million Au Eq. ounces in production or in development by 2015 (Gold Fields, 2011).

Gold Fields Canada Exploration is currently completing concept studies on the Woodjam copper-gold project located in south-central British Columbia near the town of Horsefly. Exploration efforts on the project have shown that the Woodjam property is prospective for porphyry bulk-tonnage deposits similar to Northgate's Kemess Mine and Imperial Metals' Mount Polley Mine.

Woodjam is a joint venture agreement with partners Consolidated Woodjam Copper Corp. (CWC) where Gold Fields holds the option to earn up to a 70 per cent interest in the project.

4. PROJECT GOALS AND OBJECTIVES

The overall goal of this project is to deepen the knowledge and skills acquired at BCIT in the practical application of GIS for mineral exploration targeting. Specifically, this project's objectives are aimed at applying spatial analysis techniques to mineral exploration datasets in order to quantify their predictive capacity.

4.1 PROJECT OBJECTIVES

The primary objective of this project is to determine if the present data collection within the Woodjam North dataset is able to support a predictive model. This is achieved through conducting spatial analysis and applying predictive analytic techniques to quantify relationships that may exist within the study area. In order to do this, several secondary objectives were undertaken.
Including:

- Performing a lineament analysis to map structural features through remotely sensed data
- Compiling top of bedrock lithology from subsurface drill log data and field mapped outcrop units to assay values of drill core and surface samples
- Interpreting geophysical data from gravity, IP, and ground magnetics surveys

4.2 PROJECT DELIVERABLES

Deliverables for this project include elements of the Woodjam North dataset compiled for spatial analysis. As well, a series of predictive maps outlining the input layers that make up the weights of evidence model will be provided. Model validation complete with calculated weights and variances will determine suitability of the data. A final prospectivity map will be assembled showing probable areas of mineral occurrence.

5. PROJECT BACKGROUND

This project involves applying spatial data modeling, statistical analysis, and predictive analytic techniques at a scale that has not previously been attempted within the BCIT GIS program. The following section gives some background on the Woodjam property as well as a review of the major elements that make up this project

5.1 WOODJAM PROPERTY

The Woodjam claim group is located within the Quesnel Trough, a regional depositional belt that has historically shown abundant occurrences of copper-gold mineralization (Goodall, 2006). The property is largely vegetated by first and second growth fir and pine forests and is predominately covered by thick blankets of glacial overburden. The combined claim area totals approximately 27,000 hectares.

Exploration on the property is challenging due to the extensive surface cover and large search areas within the claims. Because of these challenges, a large dataset of high density geophysical surveys, subsurface drilling and remotely sensed images have been collected. As seen in Figure 1, active exploration efforts are currently broken into two broad claim groups of Woodjam North and Woodjam South

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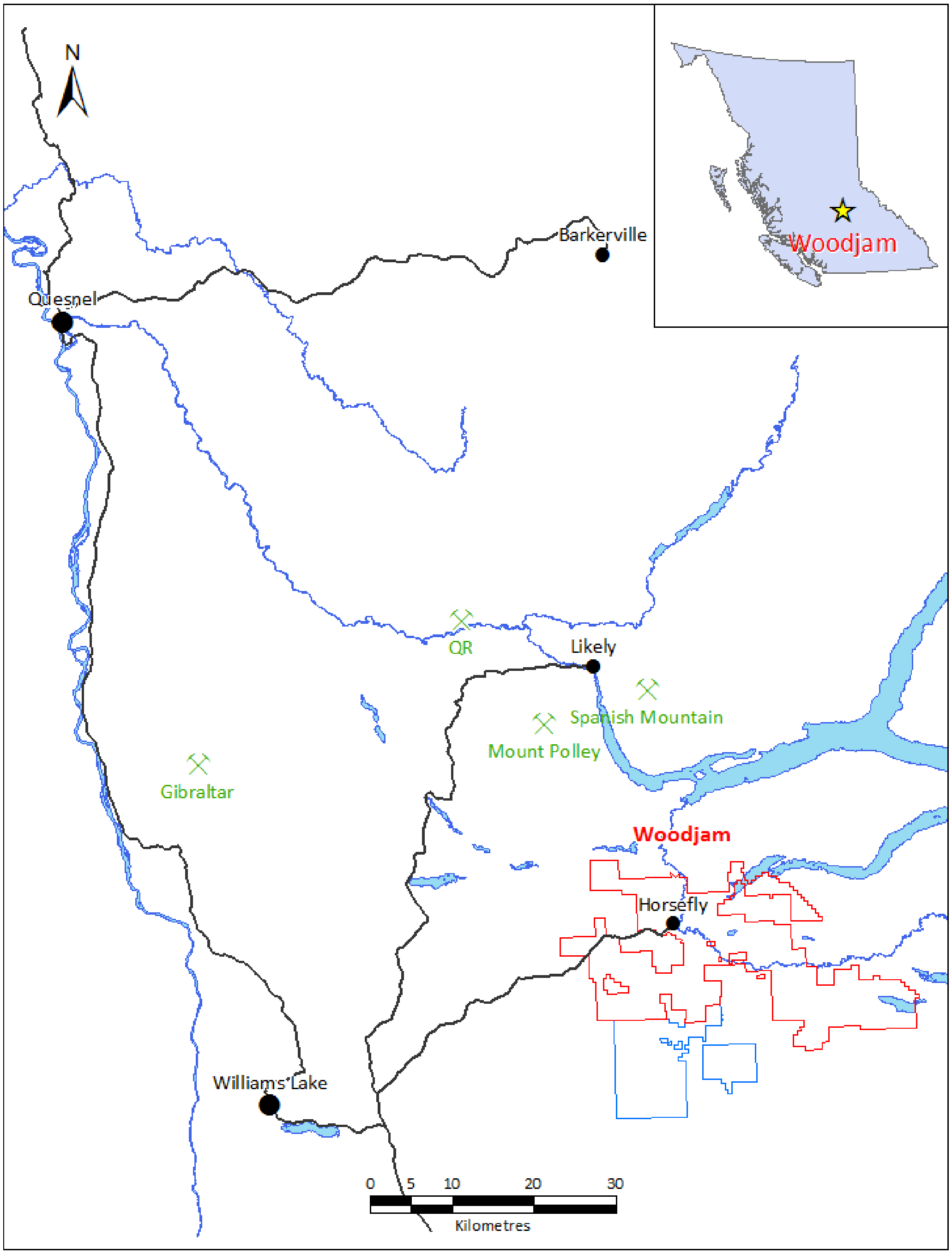

Figure 1. Woodjam property location in south-central British Columbia

5.2 SPATIAL ANALYSIS AND PROSPECTIVITY MODELING

Spatial analysis is an integral part of a GIS that permits studying a feature's geometric or geographic properties. This allows the GIS to find relationships within a dataset based on a features proximity, adjacency, or containment. Prospectivity modeling takes this a step further and applies statistical methods to these relationships to evaluate their predictive capacities. In order to generate the input layers for this type of analysis a solid understanding of the geological controls within the study area is needed.

5.3 MINERAL SYSTEMS CLASSIFICATION

When exploration geologists classify a mineral deposit a Mineral System approach is often used. This concept states that a particular mineral system is characterized by the geological factors that control the generation, transport, and preservation of ore components (Wyborn, et al. 1994). By answering questions that concern the history and architecture of a mineral system, diagnostic features are discovered. These features can be analyzed and used as inputs in the creation of different predictive models.

5.4 WEIGHTS OF EVIDENCE MODELS

The predictive model used for this project is a Weights of Evidence model. This method is normally applied to situations where a number of mineral occurrences are already known that act as training datasets. A series of predictive maps for a particular deposit are derived and statistically analyzed using the training data to test their predictive capacity (Partington and Sale, 2004). Weights are estimated from the association between known mineral occurrences and the layers used as predictors. Using this data, prior and posterior probabilities can be calculated.

If the prior probability is assumed to be equal to the training point density, then the posterior probability of a deposit given one or more evidential layers will either increase or decrease as compared to the prior probability (Sawatzky et al, 2009).

6. PROJECT DATA

The project datasets used in this model include data collected from geophysical surveys, field mapped lithological units and subsurface drill logs, and lab certified drill assay results.

6.1 DATASETS AND DATA DICTIONARY

Data set	Type	Use	Projection	Accuracy	Location	Format
StudyArea	Raster	Mask	UTM_NAD83_z10	50m resolution	GFE	.grd
2011 ground magnetics	Raster	Primary layer	UTM_NAD83_z10	12.5m resolution	GFE	.grd
2009-2011 gravity survey merge	Raster	Primary layer	UTM_NAD83_z10	DGPS located ~1m-5m	GFE	.grd
2008-2011 IP survey merge	Raster	Primary layer	UTM_NAD83_z10	GPS loc. ~5-10m. 100m x 100m stn. Compass/chain ln	GFE	.grd
2010 field mapping	Polygon	Primary layer	UTM_NAD83_z10	Digitally collected. GPS located ~5-10m.	GFE	.shp
ASTER DEM	Raster	Primary layer	UTM_NAD83_z10	30m resolution	QUEST	.grd
Drill assay/drill log data	point	Primary layer	UTM_NAD83_z10	DGPS located ~1m-5m. EZShot Azi/dip readings	GFE	.mdb

Layer name	Type	Attributes	Description
Study Area	Raster	Value, Count	Study area boundary
ground magnetics survey	Raster	Digital number (TMI)	Total magnetic intensity survey
gravity survey merge	Raster	Station, Line, GravData, Date	Rock density survey
IP survey merge	Raster	Digital number (Chargeability)	Inverse polarity - chargeability survey
field mapping	Polygon	GF_Unit_Code, Shape, Shape_Area	Field mapped rock units
ASTER DEM	Raster	Digital number (Elevation)	Adv. spaceborne thermal emission digital elevation
Drill assay/drill log data	point	Structure, Alteration, Assay, MinType	Drill logs and assay results

Tables 1 and 2. Data sets and Data Dictionary

6.2 STUDY AREA

The study area for this project is defined by the extents of the 2011 ground magnetics survey. The ground magnetics survey covers the core target area of the Woodjam North claims and is the highest resolution dataset provided with the smallest spatial extent. Limiting the analysis to this study area minimizes the negative effect of missing data values from overlapping grids of larger spatial extents.

7. PROJECT METHODOLOGY

The methodology behind this project follows a structured workflow, as seen in Figure 2, based around the conceptual model of the mineral system classification. Evidential maps are created from selected GIS data and each feature is given a weighted "score" based on their relative influence on the presence of known mineral occurrence.

A response is calculated to determine the posterior probability given the weighted evidence and the layers are combined via raster manipulation to create a deposit probability map. Higher scores would indicate a greater likelihood of a mineral deposit presence.

Three model iterations were attempted using combinations of derived evidential layers. The modeling process, inputs, and data manipulation are detailed here. As well, the project resources and management techniques used through the project are summarized below.

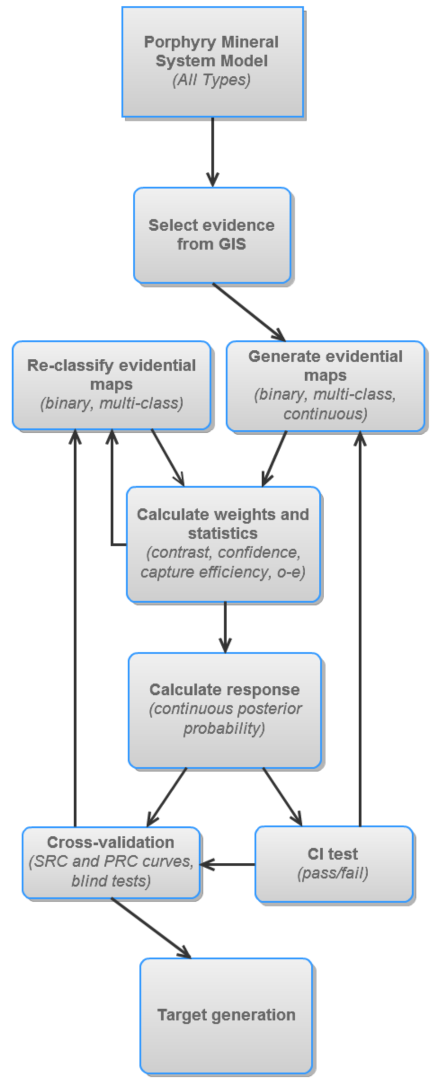

Figure 2. Project methodology flowchart

7.1 PROJECT MANAGEMENT

Management of this project was handled through a phased management approach composed of four major divisions including project planning, data compilation and editing, model building and validation, and presentation.

Monthly coordinator meetings were scheduled through the duration of the project to provide constant support and monitor progress. Major milestones were defined at intervals as a benchmark for the progress of significant areas of work completed.

7.2 RESOURCES

Software resources used for this project included ArcGIS's ArcMap and ArcCatalog with the Spatial Analyst, 3D Analyst, and Spatial Data Modeler extensions. As well, PCI Geomatica's Focus and Safe Software's FME packages were used for data manipulation. Microsoft Office was utilized for report writing and timesheet tracking. The structural geology software package GEOrient was used for plotting line rose diagrams and the freeware application Paint.NET was used for image editing.

Hardware resources used were primarily through the GIS lab at BCIT. However, work was also completed from a home office consisting of a workstation with remote desktop applications through BCIT's AppsAnywhere service.

7.3 DATA INPUT AND MANIPULATION

Data inputs, parameters, and manipulations for the modeling process are outlined below. This includes the derivation of the training point data set, lineament analysis, and evidential layers for three model iterations.

7.3.1 ENVIRONMENT SETTINGS

Environment settings specified for this project were defined globally such that they apply to all processes within the model. The output coordinate system was defined as NAD_1983_UTM_Zone_10N and the processing extent set to the extent of StudyArea raster. Raster Analysis settings were defined with a cell size of 50m and the Mask set to StudyArea raster.

These environment settings are important for Spatial Data Modeler functions and utilities to operate properly and are coincident through all iterations and modeling processes for this project.

7.3.2 TRAINING POINTS

Weights of Evidence models require a training point dataset defining areas of known mineral occurrences that are used to calculate weights for each evidential layer. The points are treated as being either present or absent in the model, and are not weighted by characteristics such as deposit size (Sawatzky et al, 2009).

Due to the advanced stage of exploration within the study area training points for the model were selected based on drill assay composite mid points and projected to surface. These composites are calculated from the gold equivalent (AuEq) value of drill assay results and represent the grams per tonne value of combined Cu and Au over a 3 meter inclusion length.

Initially, the composite table contained 567 points. A point reduction workflow was applied to these locations to determine significant points for the model. This was done by taking the 80th percentile of the assays results (~ 0.75 AuEq g/Tonne) and applying a 10m length cutoff. This resulted in 49 points that meet the cutoff criteria.

An important assumption for Weights of Evidence modeling is that there is only one training point per unit cell (Bonham-Carter, 1994). To achieve this, a 50m buffer was applied to the remaining points and overlapping areas removed based on majority area. This resulted in 19 points that meet the final criteria. The training points used in the model are summarized in Table 3 below.

TP_80pct_10mCL_thin

FID	Shape	HOLE_ID	FROM_	TO	LENGTH	AU_PPM	CU_	AUEQ_G_T	LOCATIONX	LOCATIONY	LOCATIONZ	COMP_ID	Grade_Thic	TPFID
0	Point ZM	WJ06-52	308	394.2	86.2	0.53	0.12	0.75	610365	5790555	581.900024	NC	64.65	0
1	Point ZM	DH11-35	82.94	137	54.06	0.08	0.38	0.77	611672.3125	5791783	814.873779	NC	41.6262	1
2	Point ZM	WJ83-06	18.29	72	53.71	0.63	0.09	0.78	610258	5790819	910.416931	NC	41.8938	2
3	Point ZM	TK09-05	164	176	12	0.07	0.4	0.79	610382.5	5788099.5	838.711609	NC	9.48	3
4	Point ZM	WJ08-93	33.53	108.5	74.97	0.47	0.21	0.84	611160	5792078	853.984985	NC	62.9748	4
5	Point ZM	DH10-14	110.28	226.16	115.88	0.29	0.32	0.87	611367.625	5792151.5	763.644897	NC	100.8156	5
6	Point ZM	ME11-03	90.7	134	43.3	0.21	0.36	0.87	610690.75	5791038	805.101746	NC	37.671	6
7	Point ZM	WJ08-92	214.5	246	31.5	0.49	0.21	0.87	611266	5792077	683.950012	NC	27.405	7
8	Point ZM	WJ04-32	173.76	310.39	136.63	0.69	0.11	0.89	610299.1875	5790694	729.559814	NC	121.6007	8
9	Point ZM	WJ05-46	3.05	110.64	107.59	0.74	0.1	0.93	610396	5790826.5	863.770813	NC	100.0587	9
10	Point ZM	TK09-01	6.2	225	218.8	0.38	0.34	0.99	610413.6875	5788525.5	858.636536	NC	216.612	10
11	Point ZM	DH11-33	110	185.5	75.5	0.4	0.34	1.02	611198.375	5791918.5	758.094238	NC	77.01	11
12	Point ZM	TK10-12	108.1	220	111.9	0.51	0.29	1.03	610489.5625	5788470	801.495483	NC	115.257	12
13	Point ZM	WJ05-43	135.94	281.33	145.39	0.75	0.16	1.04	610416	5790672	717.36499	NC	151.2056	13
14	Point ZM	TK10-25	10	27	17	0.01	0.58	1.07	610525.9375	5788352	938.615662	NC	18.19	14
15	Point ZM	ME11-02	297	315.66	18.66	0.03	0.68	1.26	611011.9375	5791136.5	630.540527	NC	23.5116	15
16	Point ZM	DH11-30	79	225.32	146.32	1.12	0.26	1.6	611296.4375	5791832.5	755.50769	NC	234.112	16
17	Point ZM	WJ03-30	43.52	58.92	15.4	0.04	0.9	1.67	611247.0625	5791194	905.915955	NC	25.718	17
18	Point ZM	DH11-26	139.48	210	70.52	1.14	0.34	1.77	611367.3125	5791677	744.643066	NC	124.8204	18

Table 3. Training points

7.3.3 LINEAMENT ANALYSIS

A common derived dataset used in all model iterations is the merged lineament analysis. A lineament can be defined as a straight or somewhat curved feature in an image that can be the result of natural structures such as faults, fractures, lithological boundaries, or unconformities (PCI Geomatica, 2010). This process was completed on the first vertical derivative of the ground magnetics and gravity datasets as well as the ASTER DEM obtained from GeoScience BC's Quest Project. The datasets and parameters for each analysis are summarized in Table 4.

The LINE Algorithm consists of three main stages. An edge detection algorithm is applied to the input dataset to produce an edge strength image. The edge strength image is then thresholded to obtain a binary image classified as either an edge (1) or not an edge (0). In the third stage, curves are extracted from the binary edge image and linked together based on input parameters defined by the user.

Data set	Parameter	Input
2011 Ground Magnetics Survey	FILI – File In	2011_gmag_dh-takom-dcl_rtp_1vd.grd
	RADI - Filter Radius	10 (Pixels)
	GTHR - Edge Gradient Threshold	10 (Pixels)
	LTHR - Curve Length Threshold	30 (Pixels)
	FTHR - Line Fitting Error Threshold	3 (Pixels)
	ATHR - Angular Difference Threshold	30 (Degrees)
	DTHR - Linking Distance Threshold	20 (Pixels)
2009-2011 Gravity Survey	FILI – File In	2011 GRAV_1vd25M.grd
	RADI - Filter Radius	10 (Pixels)
	GTHR - Edge Gradient Threshold	10 (Pixels)
	LTHR - Curve Length Threshold	30 (Pixels)
	FTHR - Line Fitting Error Threshold	3 (Pixels)
	ATHR - Angular Difference Threshold	30 (Degrees)
	DTHR - Linking Distance Threshold	40 (Pixels)
ASTER DEM	FILI – File In	A94.dem
	RADI - Filter Radius	10 (Pixels)
	GTHR - Edge Gradient Threshold	10 (Pixels)
	LTHR - Curve Length Threshold	30 (Pixels)
	FTHR - Line Fitting Error Threshold	3 (Pixels)
	ATHR - Angular Difference Threshold	30 (Degrees)
	DTHR - Linking Distance Threshold	25 (Pixels)

Table 4. Lineament analysis datasets and parameters

The output vector lines from the three lineament analysis were merged to a compiled line shapefile. As well, interpreted line features from the 2011 field mapping dataset were appended to the compiled lines. Minor data editing was required to eliminate features mapped by the algorithm in error including the raster image boundaries. The final line feature class derived from this analysis is shown in Figure 3.

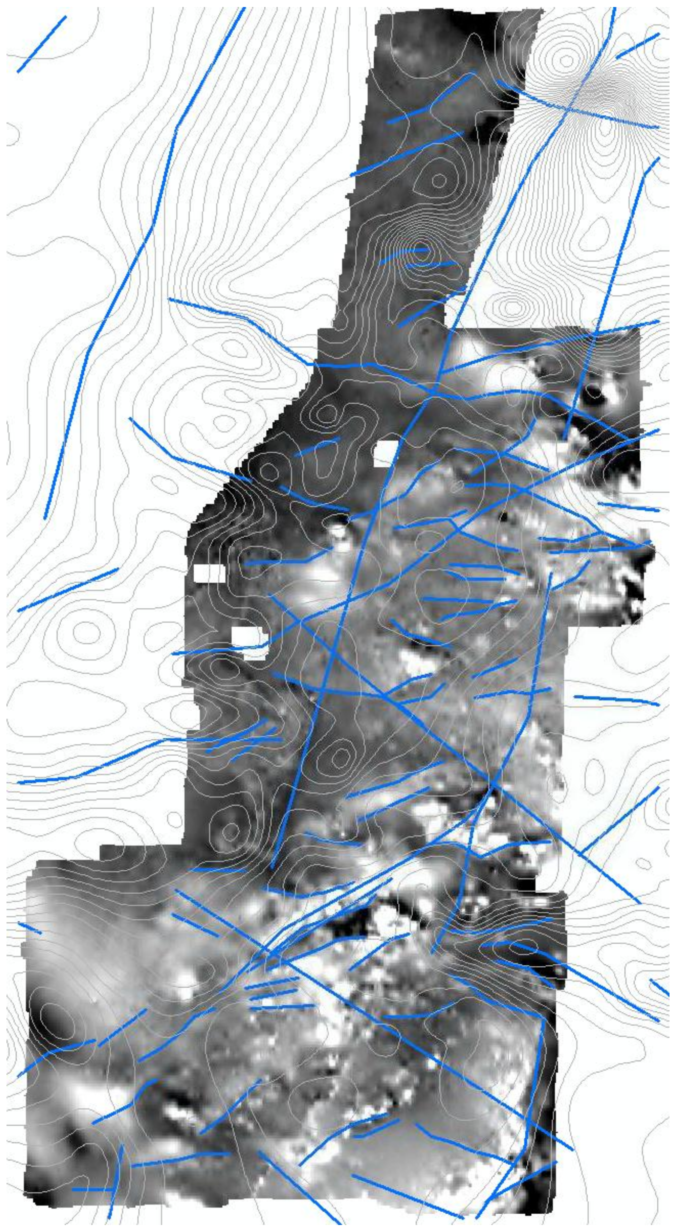

Figure 3. Compiled lineaments over 2011 gravity survey contours and 2011 ground magnetics raster.

7.3.4 MODEL #1

The first iteration of the modeling process was designed to follow the classification of a typical porphyry mineral deposit. It was primarily focused on finding a spatial relationship between favorable lithology (host rock), proximal distance to monzonite intrusions (energy source), proximal distance to ground structures (fluid transport), and favorable IP chargeability (possible hydrothermal alteration). The evidential layers derived for this model include:

- Fav_lith - location within favourable host rock unit
  - Multiclass reclassification of the 2011 field mapping where Nicola group volcanics VANTB,VANSS,IPAN are classified as “favorable”
- Prox_ipmo – proximal distance to monzonite intrusions
  - Cumulative ascending proximity raster to Takomkane porphyritic monzonite (IPMO)
- Prox_fltdir - proximal distance to NE/NW trending structure lines
  - Cumulative ascending proximity raster to selection of compiled lineament analysis
- Fav_ip – location within favorable IP chargeability threshold
  - Multiclass reclassification of the 2008-2011 900mrl IP Survey

Weights were calculated for each layer and the evidential layers were generalized for use in the model. A response was calculated and issues were noticed with the resulting posterior probability map. Primarily, the issues were a result of the dependency between prox_ipmo and drilling within the study area. Since IPMO does not frequently outcrop to surface, lithological contacts are inferred from drill log data. This introduced significant bias to the model which was discarded and a second attempt made.

7.3.5 MODEL #2

The second iteration of the modeling process was designed to make use of expert opinion and previous exploration activity on the property. Previous drill targeting has successfully found a strong correlation between the margins of high IP chargeability responses and mineral occurrence. The model was focused on quantifying a spatial relationship between proximal distances to high chargeability responses while being within a favorable chargeability threshold. The model also incorporated proximal distance to ground structures and favorable lithology. Evidential layers include:

- Prox_ip – proximal distance to high IP chargeability response
  - Cumulative ascending proximity raster to reclassification of 2008-2011 900mrl IP survey
- Fav_ip – location within favorable IP chargeability threshold
  - Multiclass reclassification of the 2008-2011 900mrl IP survey
- Prox_fltdir - proximal distance to NE/NW trending structure lines
  - Cumulative ascending proximity raster to selection of compiled lineament analysis
- Fav_lith - location within favourable host rock unit
  - Multiclass reclassification of the 2011 field mapping where Nicola group volcanics VANTB,VANSS,IPAN are classified as “favorable”

Weights were calculated for each layer, the evidential layers were generalized for use in the model, and a response was calculated. This model performed significantly better but issues were also noticed with the resulting posterior probability map. In this instance, the weighted fav_lith evidential layer was causing a clipping effect through portions of the calculated response. On further inspection, the accuracy of an area field mapped as Quaternary Deposit was determined to be below the acceptable resolution of the model evidential layers. This evidential layer was discarded and a third modeling attempt was made.

7.3.6 MODEL #3

The third iteration of the modeling process was identical to Model #2 with the exception of the discarded fav_lith evidential layer. This model was accepted as the final model iteration and the workflows for calculating weights and capture efficiency are detailed below.

Prox_ip – proximal distance to high IP chargeability response

This evidential layer is based on the reclassification of 2008-2011 900mrl IP survey where a chargeability response greater than or equal to 12 is classified as 'high'. A cumulative ascending proximity raster was then created from the reclassification with the origin defined as the high IP values.

Using Spatial Data Modeler's Calculate Weights utility the proximity raster was tested against the training dataset to determine its predictive capacity. It was determined that 18 of the training points fall within 353m of the specified origin with a 98% capture confidence rating. This proximity raster was generalized into a binary raster where values less than 353m are classified as prospective. This binary raster was then weighted for use in the model.

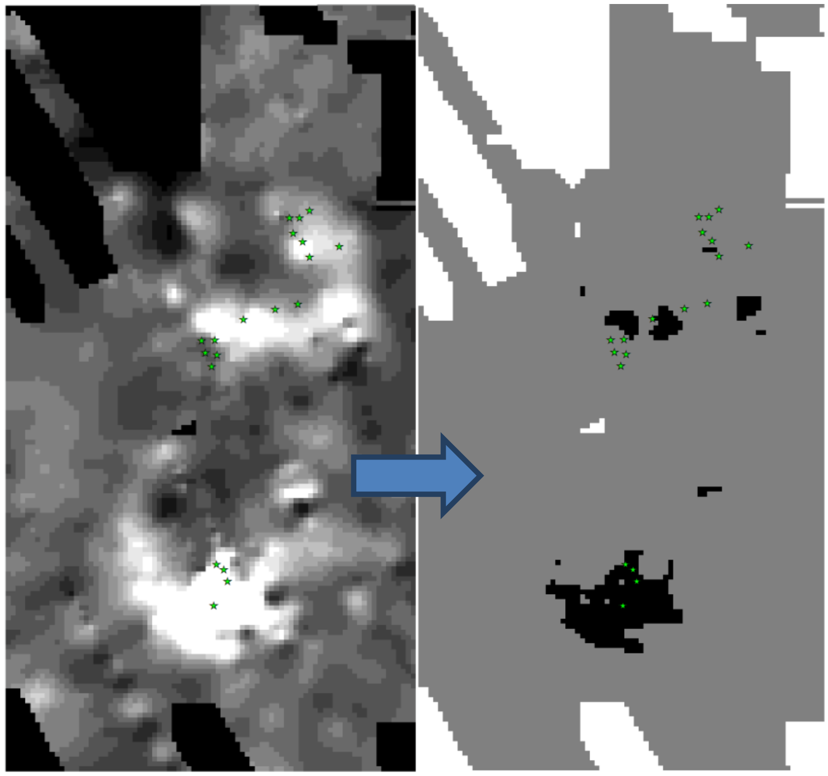

Figure 4. 2008-2011 900mrl IP survey merge

Figure 5. Reclassification showing "high" IP response

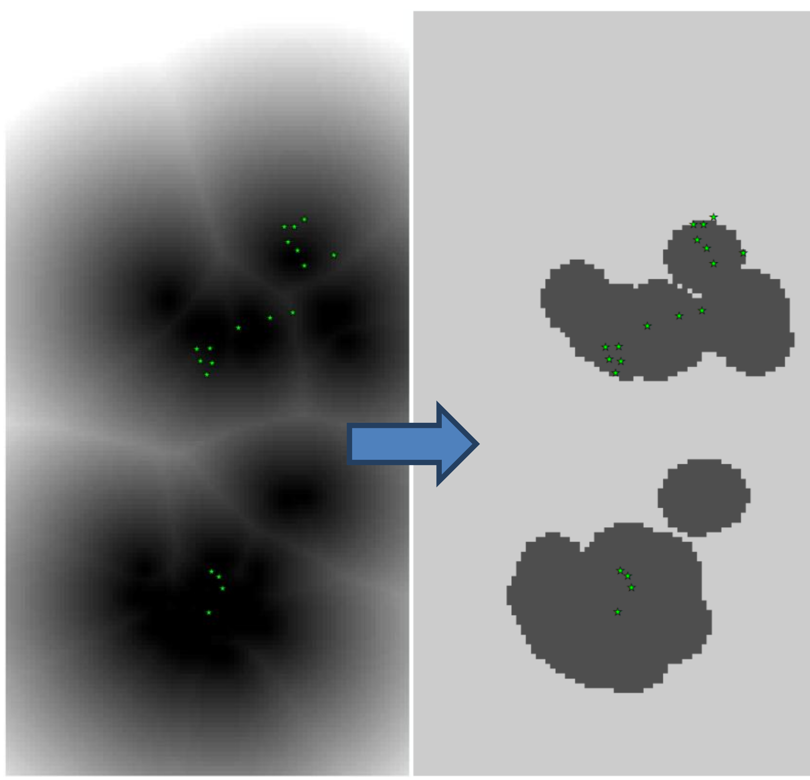

Figure 6. Ascending proximity to IP response

Figure 7. Prox_ip – Favorable proximity to IP response

Fav_ip – Location within favorable IP chargeability threshold

This evidential layer is also based on a reclassification of the 2008-2011 900mrl IP survey. This multiclass evidential layer is designated by low, moderate, and high classification thresholds. Response values 1-6 classify as low, 6-12 classify as moderate, and greater than or equal to 12 classify as high.

Spatial Data Modeler's Calculate Weights utility was used to determine the layers predictive capacity. It was determined that 14 of the training points fall within the 'moderate' to 'high' classification with a 98% capture confidence rating. Classifications defined as low failed to satisfy the predictive criteria and were weighted accordingly. This pattern reflects observations made through previous drill targeting with a 'moderate' response being most favorable.

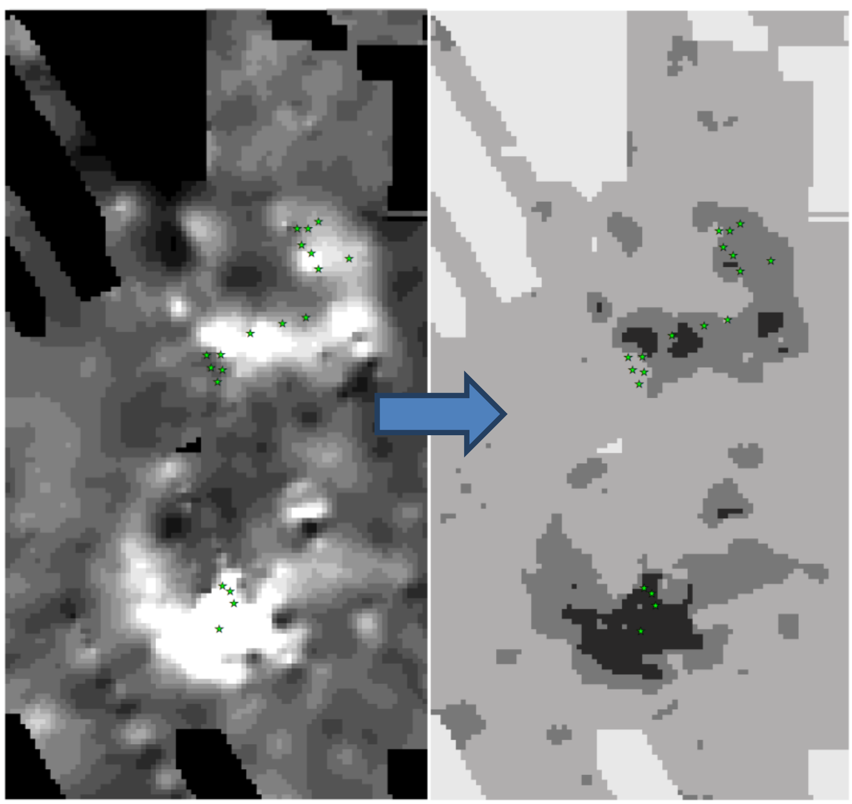

Figure 8. 2008-2011 900mrl IP survey merge **Figure 9. Fav_ip - Favorable chargeability threshold**

Prox_fltdir - Proximal distance to NE/NW trending structure lines

This evidential layer is based on the merged lineament analysis derived from ground magnetics surveys, gravity surveys, and topography. The lineament analysis was evaluated using GEOrient 's line rose diagram tool to determine a dominant orientation of the derived lines. It was found that the dominant orientation falls in a Northeast to Northwest direction. This orientation is coincident with observations made in the field concerning the structural geology within the study area.

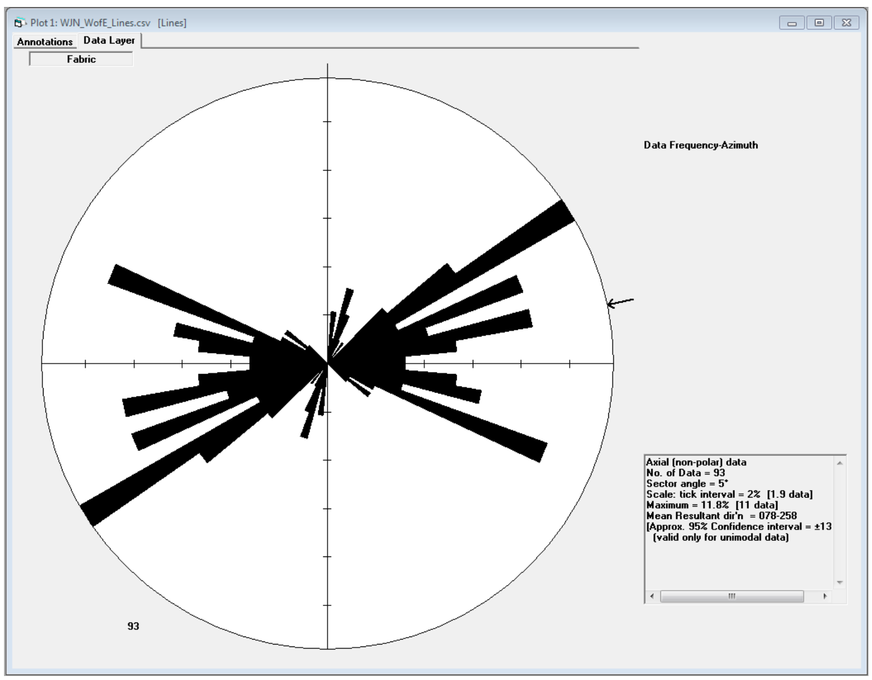

Figure 10. Dominant orientations of merged lineament analysis

A selection was made from the compiled lineament analysis where lines with a direction greater than 45° and less than 120° being considered favorable. A cumulative ascending proximity raster was created with the origin defined by the line selection.

Spatial Data Modeler's Calculate Weights utility was used to determine the layers predictive capacity. It was determined that 16 of the training points fall within 111m of the defined origin with a 98% capture confidence rating. This proximity raster was generalized into a binary raster where values less than 111m are classified as prospective. The binary raster was then weighted for use in the model.

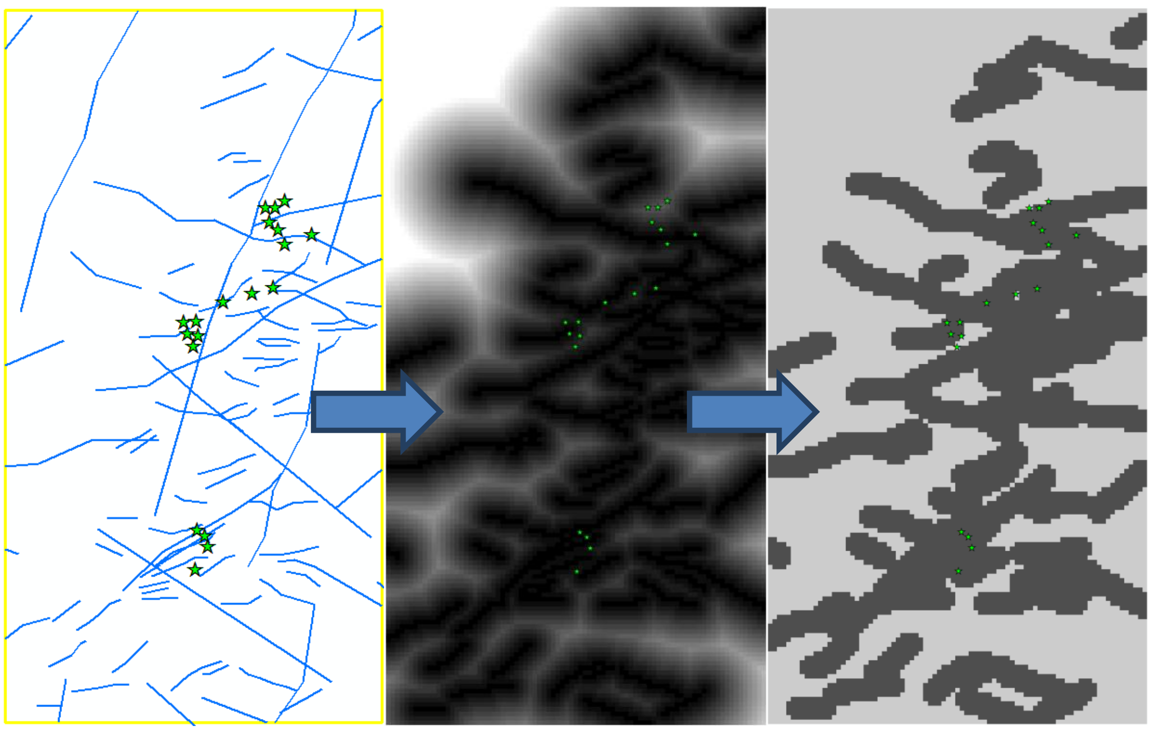

Figure 11. Derived lineament analysis   Figure12. Ascending proximity to NE/NW lines   Figure 13. Prox_fltdir – Favorable proximity to selected lineaments

7.4 MODEL DIAGRAMS

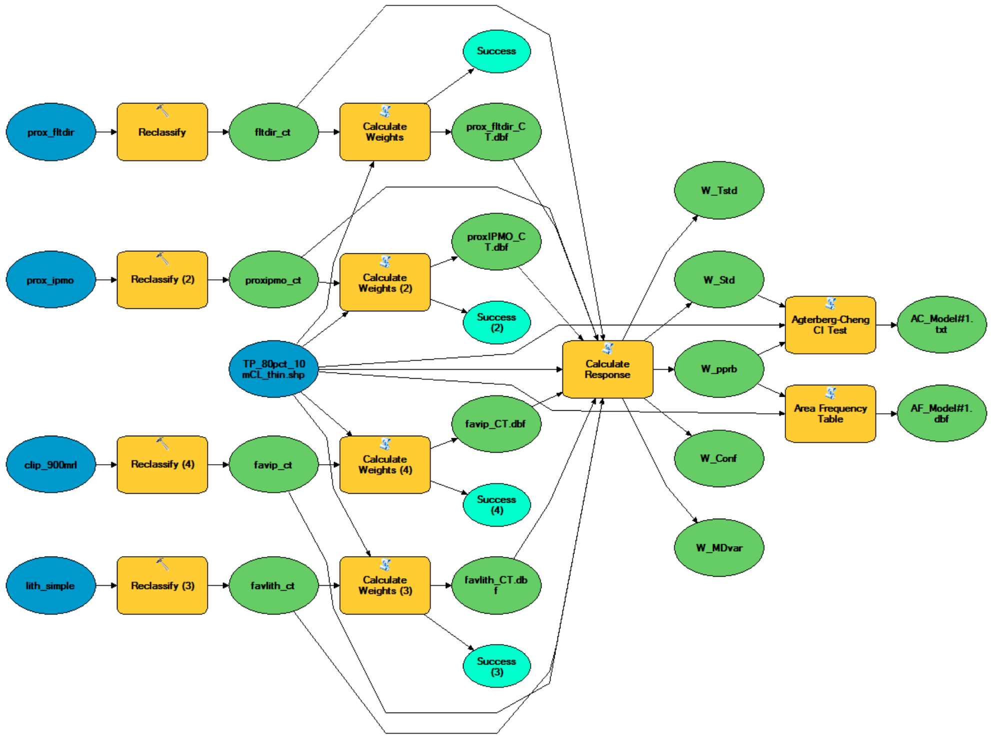

Figure 14. Model#1 geoprocessing workflow

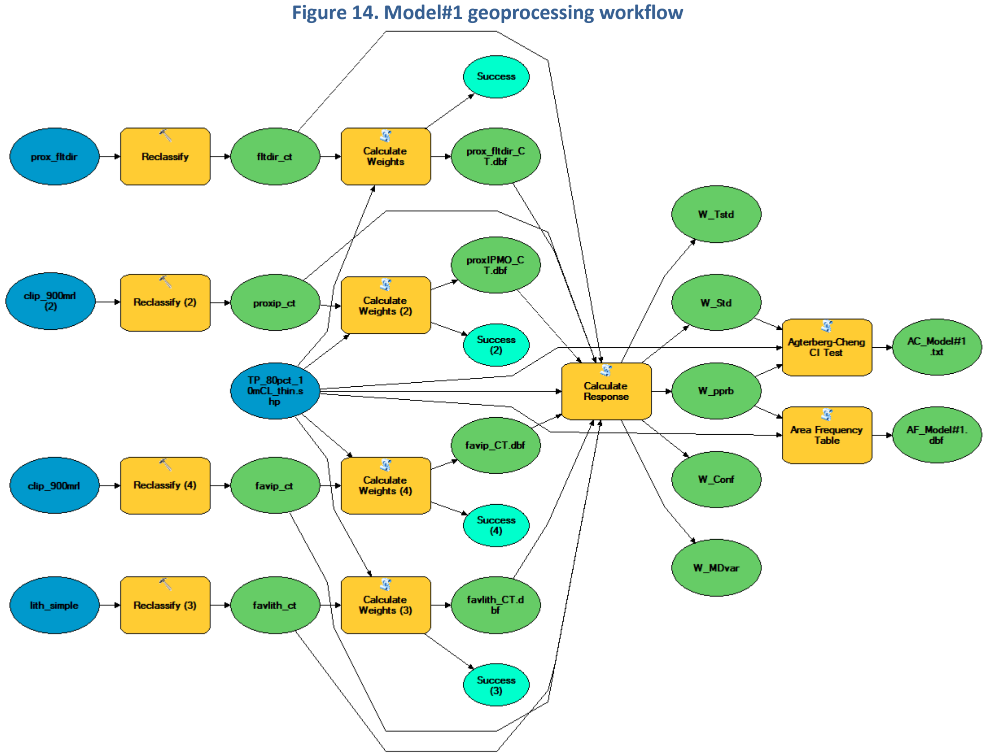

Figure 15. Model#2 geoprocessing workflow

Figure 16. Model#3 geoprocessing workflow

8. DATA MANAGEMENT

Data for this project is stored on a 1TB external hard drive with a dedicated file structure containing all project related data. The file structure is divided into the main folders of Proposal, Research, Software, Reports, and Data.

8.1 BACKUP STRATEGY

Backups of the file structure are made weekly on Friday afternoon with the data being compressed to an archive and date stamped. A copy of the archive is then transferred to a secure location where it supersedes the previous archive version.

8.2 NAMING CONVENTIONS AND VERSION MANAGEMENT

Specific naming conventions were required through the modeling process to facilitate limitations of the Spatial Data Modeler utilities. Evidential layers are limited to thirteen characters and path locations are limited to one hundred and fifty characters. As well, spaces and numeric characters within path names cause significant issues and were avoided throughout.

Version management was handled through the application of a date stamp for superseding files. For example, the date stamp _120101 would signify January 1st, 2012.

9. PROJECT RESULTS AND RECOMMENDATIONS

The accepted model as described in Section 7 – Methodology focused on quantifying a spatial relationship between the margins of high IP chargeability responses while being within a favorable IP chargeability threshold. The model also incorporated proximal distances to lineaments derived from ground magnetics, gravity, and topography. The evidential layers are now combined with Spatial Data Modeler's "Calculate Response" utility to produce a continuous posterior probability map.

9.1 ASSESSING CONDITIONAL INDEPENDENCE

An important assumption for Weights of Evidence modeling is the concept of conditional independence (CI) between map layers. Conditional independence states that each layer provides "independent" evidence of favorable or unfavorable setting. If all evidence layers are conditionally independent, then the predicted number of deposits will equal the observed number of deposits (Agterberg and Cheng, 2002).

In practice, there is always some degree of conditional dependence among predictor maps (Bonham-Carter, 1994) which results in artificial inflation or deflation of the posterior probability. The question the modeler must assess is how serious this violation is.

Spatial Data Modeler provides the "Agterberg-Cheng CI Test" tool for calculating conditional independence. Using this tool, as seen in Figure 17, Model#3 is shown to greatly violate the assumption of CI.

```
Overall CI: 4.6%
Conditional Independence Test: W
Observed No. training pts, n = 19
Expected No. of training points, T = 73.7
Difference, T-n = 54.7
Standard Deviation of T = 27.461

-----------------------------------------------
Conditional Independence Ratio: 0.26 <simply the ratio n/T>
Values below 1.00 may indicate conditional dependence
among two or more of your data sets.  <Bonham-Carter(1994,ch.9)
suggest that values <0.85 may indicate a problem>

-----------------------------------------------
Agterberg & Cheng Conditional Independence Test
<See Agterberg and Cheng, Natural Resources Research 11(4), 249-255, 2002>
This is a one-tailed test of the null hypothesis that T-n=0.  The test
statistic is (T-n)/standard deviation of T. Probability values greater
than 95% or 99% indicate that the hypothesis of CI should be rejected,
but any value greater than 50% indicates that some conditional
dependence occurs>

Probability that this model is not conditionally independent with
(T-n)/Tstd = 1.990879 is 97.7%
-----------------------------------------------

Input Data:
Post Probability: W_pprb
Post Probability Std Deviation: W_Std
Training Sites: TP_80pct_10mCL_thin
```

Figure 17. Agterberg-Cheng CI Test results

The expected (T) number of deposits is 55 more than the observed (n). This is a result of a violation of CI inflating posterior probability. This is likely due to prox_ip and fav_ip evidential layers being too dependent. Future modeling attempts may benefit from combining these layers into a single evidential layer.

Due to this violation of CI, the output posterior probability should be viewed as a relative ranking of mineral prospectivity. Conditional independence is essential if the posterior probability is used as a valid probability. However, if ranking of areas is all that is essential, then conditional independence is not important (Sawatzky et al, 2009).

9.2 CROSS-VALIDATION

Two methods were used to check the performance of this model. The success-rate curve (SRC) was created from output tables from Spatial Data Modeler's "Area Frequency" tool. As well, a comparison was made between prior probability and posterior probability for known mineral occurrence.

The SRC is a test of how well the posterior probability fits the training points used to generate the prediction map (Fabbri and Chung, 2003). A plot was made comparing the cumulative deposits and the cumulative area. The area under the curve is summed to get the "efficiency" score (Sawatzky et al. 2009). As seen in Figure 18, it was found that Model #3 holds 91.8% efficiency of classification (SRC). This curve shows how the model classifies the distribution of known deposits.

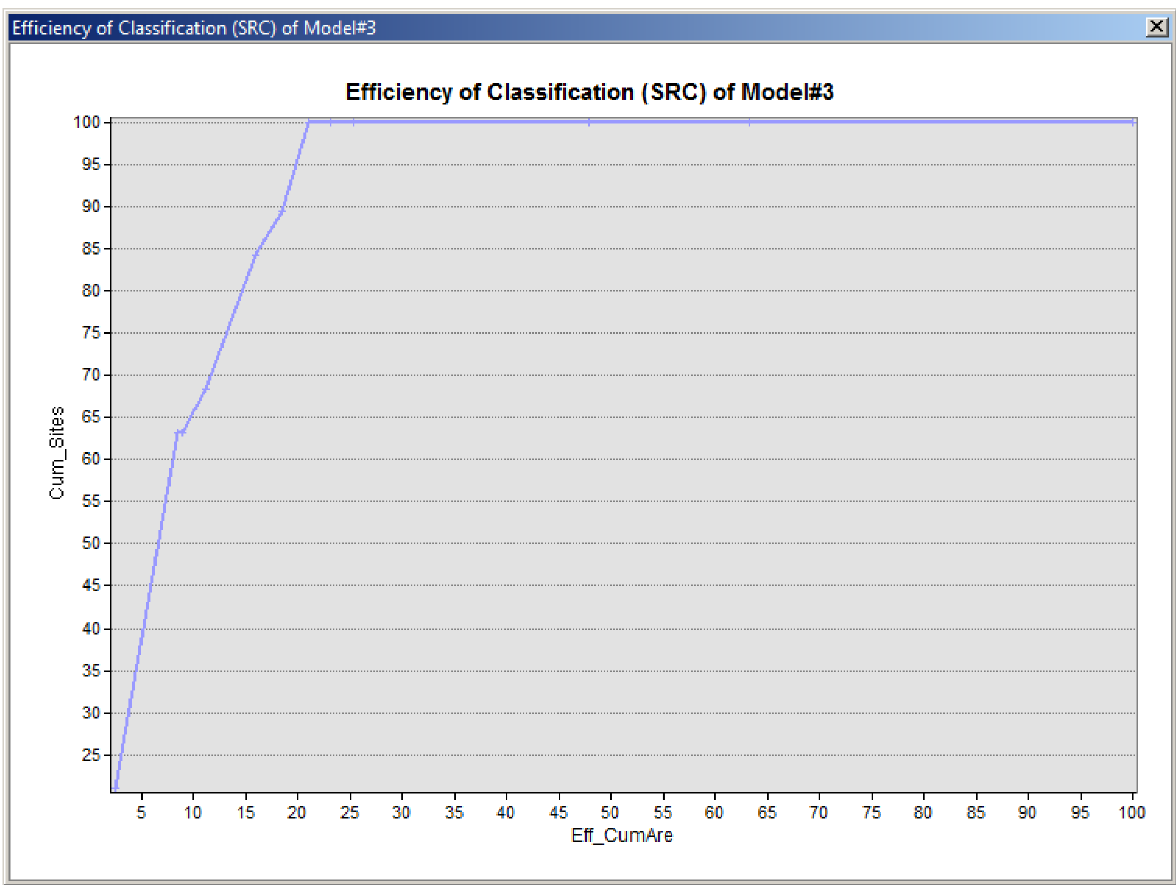

Figure 18. Model #3 Efficiency of Classification (SRC)

The second method of cross validation involved overlaying the training points on the posterior probability map. A table was created comparing the posterior probability of known mineral occurrence to the prior probability. Deposits occurring where the posterior probability is lower than the prior probability would indicate occurrence in “unfavorable” areas (Raines and Bonham-Carter, 2006). As seen in Table 5, it was found that 16 of the 19 (84%) training points fall in favorable areas of higher posterior probability than prior probability. In this comparison, I consider Model #3 to have performed adequately for the nature of this project.

Training Point ID	Posterior Probability (pprb)
WJ08-93	0.000648
DH10-14	0.000665
WJ08-92	0.050508
DH11-33	0.050508
DH11-30	0.050508
DH11-35	0.050508
DH11-26	0.050508
WJ03-30	0.005064
ME11-02	0.006733
ME11-03	0.050508
WJ83-06	0.005064
WJ05-46	0.050508
WJ04-32	0.005064
WJ05-43	0.005064
WJ06-52	0.000648
TK09-01	0.085279
TK10-12	0.085279
TK10-25	0.085279
TK09-05	0.085279

Prior Probability	**= 0.001458**
TP in "favorable" pprb	**= 84%**

Table 5. Training points located in "favorable" posterior probability

9.3 RECLASSIFICATION OF POSTERIOR PROBABILITY

The output of Spatial Data Modeler's "Calculate Response" utility is a continuous scale posterior probability raster. As noted previously, posterior probability values should be regarded as a relative ranking of mineral potential and require a reclassification to aggregated rankings.

A technique recommended for defining thresholds is the use of the Cumulative Area- Posterior Probability (CAPP) curve, which can be created from the output of Spatial Data Modeler's "Area Frequency" tool. The CAPP curve, as seen in Figure 19, is created by plotting posterior probability and cumulative area. The raises in the CAPP curve can be used to define class breaks, and the flat sections define the class intervals supported by the data (Sawatzky et al, 2009) Using this method resulted in the creation of 7 classes. Complete thresholds below the prior probability of 0.001458 were classed together as "unfavorable", with the remaining classes increasing in relative prospectivity. Table 6 shows the class breaks chosen using the CAPP method.

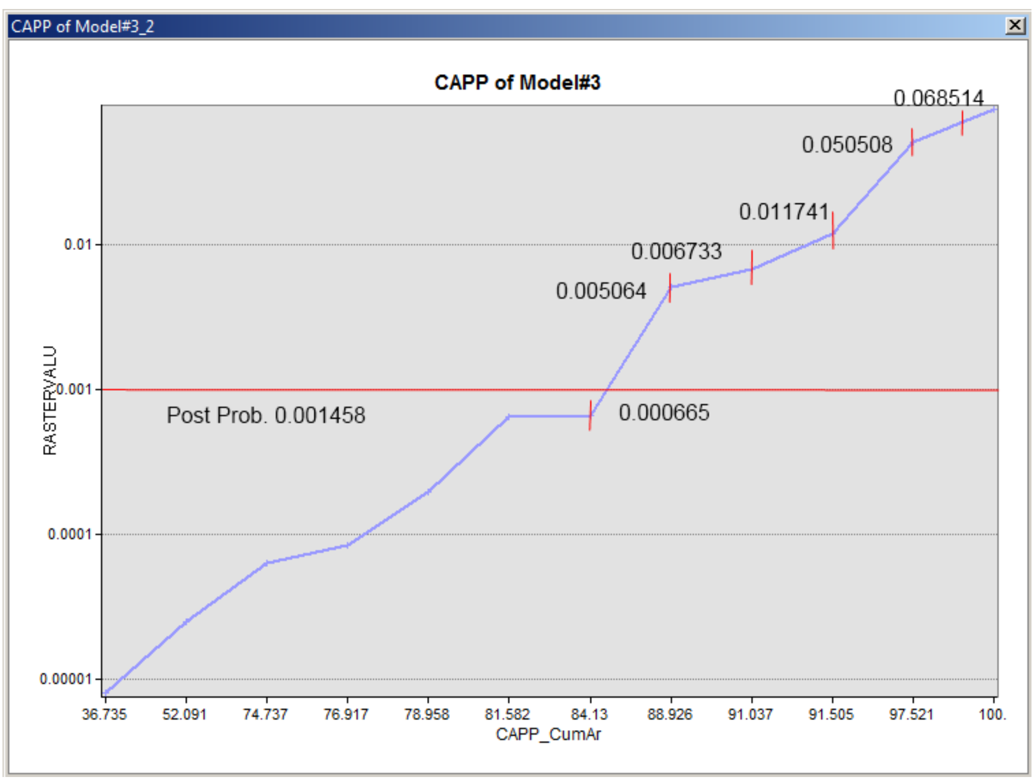

Figure 19. Model #3 Cumulative Area - Posterior Probability Curve (CAPP)

Class	Posterior probability range	Cumulative deposits	Effective cumulative area
7	>0.068514	21.0%	2.5%
6	0.050508 – 0.068514	63.2%	8.5%
5	0.011741 – 0.050508	63.2%	9.0%
4	0.006733 – 0.011741	68.4%	11.1%
3	0.005064 – 0.006733	84.2%	15.9%
2	0.000665 – 0.005064	89.5%	18.4%
1	<0.000665	100%	100%

Table 6. Class breaks chosen using the CAPP method

9.4 FINAL PROSPECTIVITY MAP AND TARGET GENERATION

The reclassification of the posterior probability map resulted in the final prospectivity map shown in Figure 20. Some broad target generation was attempted on this reclassification to highlight potential areas for further assessment.

For the target generation stage, prospective areas were compared against drilling databases to define only the areas that have not been previously explored. Figure 21 shows the resulting targets broken into two groupings. Primary targets, shown in red, occur in prospective areas with a posterior probability greater than 0.006733. Secondary targets, shown in blue, occur in less prospective areas.

It is important to note, due to the classification thresholds chosen using the above CAPP method, some secondary targets occur in areas close to or below the prior probability. While these would not be classified as valid targets I feel these areas may still warrant further investigation. Future refinements of the modeling process may validate these secondary targets.

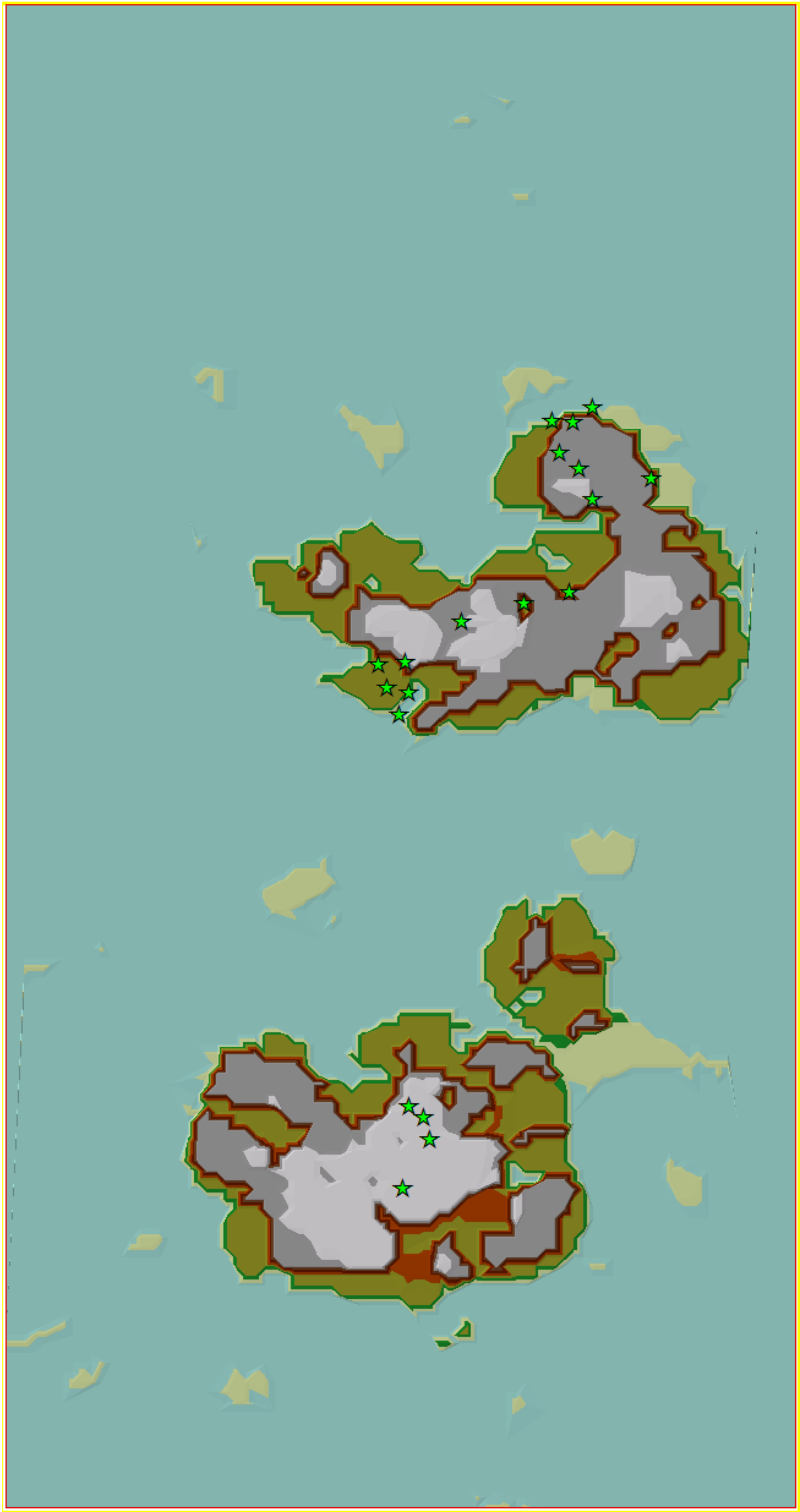

Figure 20. Final prospectivity map

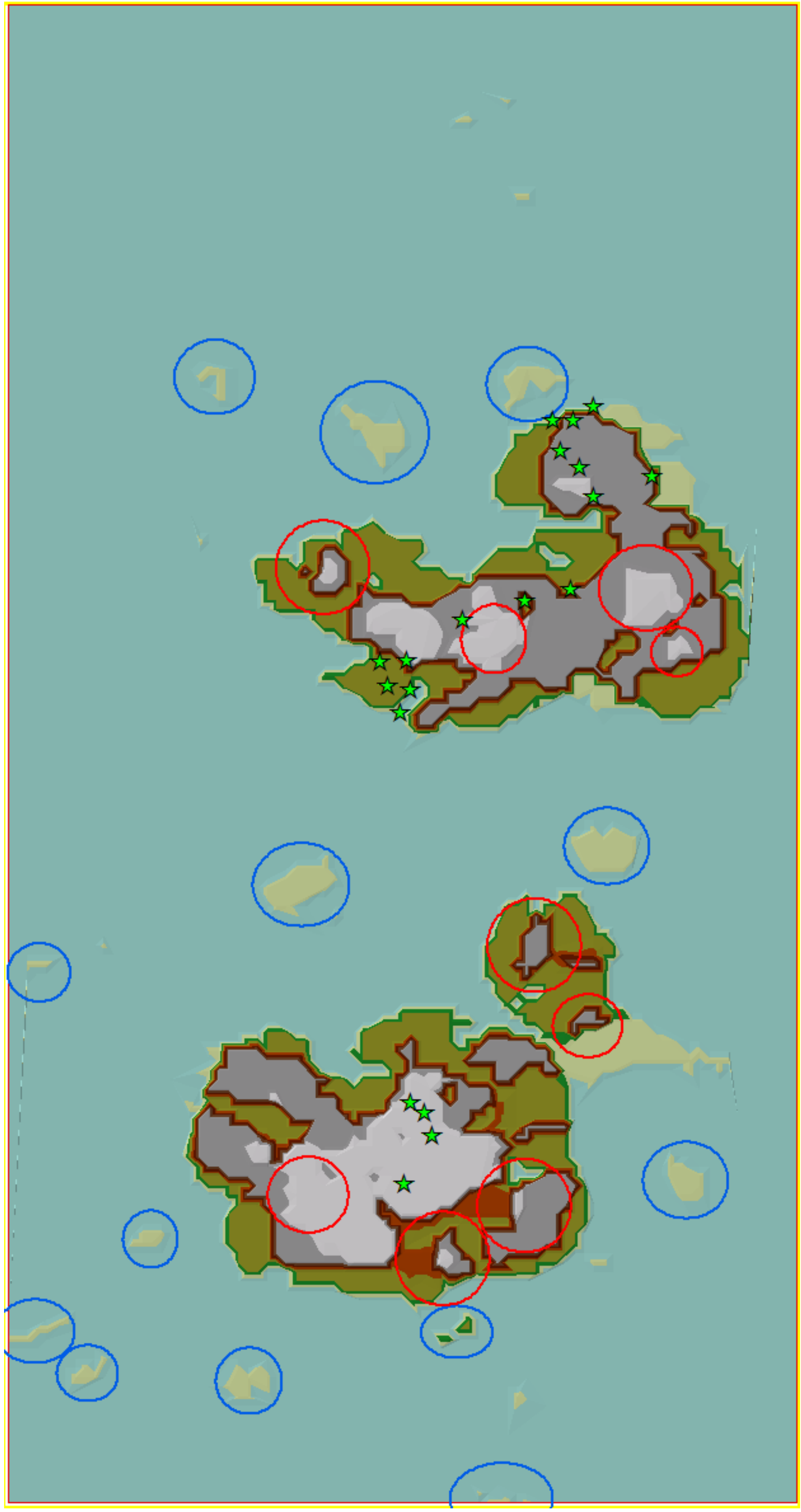

Figure 21. Primary targets (red) and secondary targets (blue)

9.5 RECOMMENDATIONS

By assessing the performance of this model recommendations should be made for future modeling attempts. Improving performance of this model can be achieved in several areas.

Weights of Evidence models are heavily reliant on their training datasets. During the generation of evidential layers significant bias can be introduced to the modeling process through the selection and distribution of the training points. In this model, the only dataset that was not derived empirically was the training points. Spatial Data Modeler utilities include a method for deriving training points empirically but this workflow was avoided due to the availability and distribution of known mineral occurrence.

As well, performance may be improved through a more comprehensive conceptual model. The final model iteration only uses three evidential layers, which could be considered as too few. More reliable maps are produced from datasets with several evidential layers.

More rigorous assessment and cross validation of the model can be achieved through the application of Prediction Rate Curves (PRC) and Receiver Operator Curves (ROC). These validation techniques require the derivation of a second training dataset of “Non-Deposits” that defines the locations where mineral occurrences are known not to occur. This technique was avoided due to time constraints and this dataset not being readily available.

As noted during validation, the final model was shown to greatly violate the assumption of conditional independence. Future modeling attempts may benefit from combining dependent layers into a single evidential layer. As well, Logistic Regression is often used to calculate posterior probability when there are conditional dependence problems.

10. CONCLUSION

A structured workflow based around the conceptual model of the mineral system was undertaken to perform a simple Weights of Evidence model for the Woodjam North dataset.

The overall goal of this project was to deepen the knowledge and skills acquired from the BCIT GIS program through the utilization of GIS for mineral exploration targeting. In this aspect, this project was successful. In order to complete this project, complex spatial analysis and raster manipulation techniques introduced through the GIS program were expanded upon and applied to a working dataset with “real world” constraints.

The primary objective of this project was to determine if the present data collection within the Woodjam North dataset is able to support a predictive model. The process outlined in this document required broad simplifications and generalizations to satisfy the modeling parameters. This has led to a dilution of resolution in the model and an inherent uncertainty in the training dataset.

Further refinement of the training points and evidential layers is needed to justify the defined targets outlined in this document.

However, given the above conclusions I feel that the process outlined is a valid proof of concept for the application of data driven predictive models. Approaching this project from a research and development point of view will facilitate future modeling attempts and refinements can be made.

11. REFERENCES

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APPENDIX A. SPONSOR DETAILS

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APPENDIX B. TIME ACCOUNTING TABLE

Task	Description	Report # 1 Hours	Report # 2 Hours	Report # 3 Hours	Report # 4 Hours	Final Report Hours	Total Hours to date	Original Est. Hours	Current Est. Hours	Difference Est. Hours	Percent Complete
1	**Project Planning**										
1.1	Meet with project sponsor	4	4				8	4	8	-4	100%
1.2	Research	5.5	4	15.5	6	10.25	41.25	50	41.25	8.75	100%
1.3	Choose input layers for model				8		8	10	8	2	100%
2	**Data Compilation & Editing**										
2.1	GDB creation						0	8	0	8	--
2.2	Data cleaning	1.5	1	1.25			3.75	20	3.75	16.25	100%
2.3	Data editing		10				10	20	10	10	100%
2.4	Derive model input layers		3.25	20.25	52.5	31.5	107.5	60	107.5	-47.5	100%
3	**Model Building and Validation**										
3.1	Build model				6.5	26	32.5	30	32.5	-2.5	100%
3.2	Model validation					11.25	11.25	10	11.25	-1.25	100%
4	**Presentation**										
4.2	Final presentation					15	15	20	15	5	100%
4.3	Final report					52	52	60	52	8	100%
4.4	BCIT open house			10	5.5		15.5	4	15.5	-11.5	100%
5	**Project Management**										
5.1	Sponsor Meeting						0	18	0	18	--
5.2	Coordinator Meeting	1	1	0.75	0.75	5	8.5	18	8.5	9.5	100%
5.3	Report writing	7.75	8.25	7	5.5		28.5	30	28.5	1.5	100%
	TOTAL	19.75	31.5	54.75	84.75	151	341.75	362	341.75	20.25	100%
	FINAL Approx. Total	20	20	60	90	170	360	360	360	0	100%