A MULTI-OBJECTIVE ANT COLONY OPTIMIZATION ALGORITHM FOR INFRASTRUCTURE ROUTING

A Thesis

by

WALTER MILLER McDONALD

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2012

Major Subject: Civil Engineering

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Approved By:

Chair of Committee,	Kelly Brumbelow
Committee Members,	Francisco Olivera
	Sergiy Butenko
Head of Department,	John Niedwecki

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ABSTRACT

A Multi-Objective Ant Colony Optimization Algorithm for Infrastructure Routing.

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Walter Miller McDonald, B.S., Texas Tech University

Chair of Advisory Committee: Dr. Kelly Brumbelow

An algorithm is presented that is capable of producing Pareto-optimal solutions for multi-objective infrastructure routing problems: the Multi-Objective Ant Colony Optimization (MOACO). This algorithm offers a constructive search technique to develop solutions to different types of infrastructure routing problems on an open grid framework. The algorithm proposes unique functions such as graph pruning and path straightening to enhance both speed and performance. It also possesses features to solve issues unique to infrastructure routing not found in existing MOACO algorithms, such as problems with multiple end points or multiple possible start points. A literature review covering existing MOACO algorithms and the Ant Colony algorithms they are derived from is presented. Two case studies are developed to demonstrate the performance of the algorithm under different infrastructure routing scenarios. In the first case study the algorithm is implemented into the Ice Road Planning module within the North Slope Decision Support System (NSDSS). Using this ice road planning module a case study is developed of the White Hills Ice road to test the performance of the algorithm versus an as-built road. In the second case study, the algorithm is applied to a raw water transmission routing problem in the Region C planning zone of Texas. For both case studies the algorithm produces a set of results which are similar to the preliminary designs. By successfully applying the algorithm to two separate case studies the suitability of the algorithm to different types of infrastructure routing problems is demonstrated.

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1. INTRODUCTION

Often route planning for the construction of new infrastructure is solved on an open grid framework. Large open grid problems with no existing networks or junctions are combinatorially huge and challenges arise when trying to create a constructive search technique to solve them. Infrastructure planners and developers can utilize a multi-objective algorithm capable of producing desirable routes on an open grid framework. Such is the case in design of many types of roads, pipelines, and utilities. This thesis proposes a multi-objective ant colony optimization algorithm capable of producing solutions to infrastructure routing problems with more than one objective.

Ant Colony Optimization was first proposed by Marco Dorigo in his PhD work to solve the Traveling Salesman Problem (TSP) (Colorni et al. 1992). Since then ant colony optimization has been applied to many different discrete optimization problems such as the job-shop scheduling problem, the quadratic assignment problem, multiple knapsack problem, graph coloring, flow shop scheduling, and classic vehicle routing problems (Cordon et al. 2002). Current ant colony optimization algorithms have been successfully applied to a variety of real world problems, but few have been applied to infrastructure routing problems on an open grid (Mora et al. 2006).

Classical optimization methods for infrastructure routing seek to find a solution by reducing a multi-objective problem into a single objective. These classical methods have significant shortcomings as they require objective data a priori which may or may not be available and are time intensive when producing multiple solutions since multiple

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This thesis follows the style of *Journal of Water Resource Planning and Management.*

runs are needed to produce a variety of solutions. Oftentimes the objectives are not measurable by the same standard such as cost, speed, and environmental impacts, and thus cannot be reduced to a singular metric. Such infrastructure routing problems require multi-objective optimization methods to produce solutions that represent an approximation of the Pareto-tradeoff relationships.

Most path finding ant colony algorithms create solutions over predefined networks but many infrastructure planning problems do not have existing networks in place and thus must be solved on an open grid. Few multi objective ant colony algorithms have been developed to solve such path finding problems on an open grid. To my knowledge no multi-objective ant colony optimization algorithms have been developed to address issues unique to infrastructure routing such as a desirable route between multiple end points or problems with multiple possible start points.

This thesis seeks to develop a new multi-objective ant colony optimization algorithm capable of approximating Pareto-optimal solutions for multi-objective infrastructure routing problems. The algorithm contains features derived from traditional multi-objective ant colony optimization techniques and others which are unique to infrastructure routing problems. It also includes several pre-processing and post-processing techniques to improve the performance of the algorithm. This algorithm has been implemented within NSDSS.net (the North Slope Decision Support System) and a case study using this tool to develop optimal ice road routes has been completed. The algorithm has also been applied to a second case study involving raw water transmission pipeline routing within the Region C planning zone of Texas.

The remainder of the thesis is structured as follows. A literature review of current multi-objective ant colony optimization problems from which many aspects of this algorithm are derived is covered. Then the algorithm is discussed in detail, including the ant search as well as pre-processing and post-processing techniques used to improve the performance of the algorithm. Following the description of the algorithm the two case studies conducted using the algorithm are discussed. The first is the White Hills Ice Road case study which was conducted using the ice road planning module within NSDSS. The second is a raw water transmission pipeline routing case study from the Lower Bois D'Arc Reservoir to Pilot Grove Creek in the Region C planning zone in Texas.

2. LITERATURE REVIEW

Ant Colony Optimization is a growing field in engineering and there are many different ant colony algorithms that have been created in the past two decades. Because the algorithm created within this thesis is multi-objective in nature that is the type of ant colony algorithm I will focus on. Most multi-objective ant colony algorithms can be described by the single objective ant colony algorithm that they stem from. In this section I will introduce ant colony optimization and describe the different multi-objective ant colony systems that have recently been developed as well as the ant systems that they were inspired from. I will discuss the major algorithmic components that play a role in the design and performance, and those which make each algorithm unique.

Ant Colony Optimization was first proposed by Marco Dorigo in his PhD work to solve the Traveling Salesman Problem (TSP) (Colorni et al. 1992). This algorithm is based on of the foraging behavior of ants to find the shortest path between the nest and their food source. An ant will deposit pheromone after it finds a food source as it makes its way back to the nest. In the absence of any pheromone ants movements are random but in the presence of pheromone ants are more likely to follow the pheromone path. Many ant species are almost blind and through this indirect form of communication they are able to determine where food sources are. Experiments have shown that ants exhibit a bias towards following paths with a high pheromone concentration. The higher the amount of pheromone the more desirable that path will be to an ant (Goss et al. 1989).

Ant colony optimization is derived from this phenomenon in which artificial ants search for an endpoint and deposit pheromone on the path of their solutions.

Initially, three different versions of Ant System (AS) were proposed (Dorigo et al., 1991; Colorni et al., 1992; Dorigo, 1992). These were called “ant-density”, “ant-quantity”, and “ant-cycle”. In the first two versions, ant-density and ant-quantity, the ants updated the pheromone trails while they moved from node to node. In the third version, ant-cycle, the pheromone update happened after all of the ants finished constructing a tour and the amount of pheromone was a function of the quality of their solutions. Because the ant cycle version outperformed the other two variants, ant cycle is synonymous with AS and the other two variants are no longer used (Dorigo and Stützle 2004).

Since then ant colony optimization has been applied to many different discrete optimization problems such as the job-shop scheduling problem, the quadratic assignment problem, multiple knapsack problem, graph coloring, flow shop scheduling, and classic vehicle routing problems (Cordon et al. 2002). Beyond established optimization problems, ant colony optimization has been applied to successfully solve a wide array of real world problems (Dorigo and Stützle 2004). Current ant colony optimization algorithms have been successfully applied to a variety of problems but few have been applied to open graph problems where no existing network is in place (Mora et al. 2006).

Multi-objective problems can be classified as problems with multiple sometimes conflicting objectives that must be optimized. As a result there is usually no single solution to a multi-objective problem. Instead there is a group of alternatives that represent solutions that are non-dominated or Pareto dominant.

Multi-objective ant colony optimization (MOACO) algorithms can be classified by specific algorithm components that they have in common. The first is multiple colonies, where a set of ants represents a colony that seeks a solution. Each colony constructs its own solution using its own pheromone and heuristic information. The second is the pheromone and heuristic information that the colonies use to build their solution. Ant colonies either use one or multiple pheromone or heuristic matrices to build their solutions. The third is the pheromone and heuristic aggregation that the ant colonies use in their decision making process. The aggregating procedure is usually either an aggregated weighted product, an aggregated weighted sum, or random. The weights given to the pheromone and heuristic matrices represent the emphasis given to give to each matrix. These weights are either set dynamically, in which different weights are used during different times throughout the algorithm to emphasize different matrices at different stages, or fixed where the weights are set a priori. The fourth is the pheromone update process which is usually updated as an iteration-best or the best-so-far solution. The fifth is the Pareto-archive which varies depending on how it is stored and used throughout the run.

The Ant System was the first ant colony algorithm developed by Marco Dorigo (Colorni et al. 1992). It introduced a distributed problem solving environment based on the ants behavior and used it to solve the traveling salesman problem. The algorithm has a pheromone matrix τ_{ij} for each arc and the pheromone values are initially set to the value τ_0. There is a heuristic matrix as well $\eta_{ij} = 1/d_{ij}$ where d_{ij} represents the distance between city i and city j. As the ant constructs its solution it uses a probabilistic action choice rule, called random proportional rule, to decide which node to move to next given by

$$p_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l \in N_i^k}[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}, if\ j \in N_i^k, \tag{2.1}$$

where α and β are two parameters that determine the relative weights given to the pheromone and heuristic matrices, respectively, and N_i^k is the feasible neighborhood of ant k in city i. After every ant has constructed a tour the pheromone trails are updated, first by pheromone evaporation given by : $\tau_{ij} \leftarrow (1-\rho)\tau_{ij}, \forall(\mathrm{i,j}) \in \mathrm{L}$, where ρ is the evaporation rate $0 \leq \rho \leq 1$. Next, pheromone is deposited by every ant on the path it has visited given by: $\tau_{ij} \leftarrow \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}$, $\forall(\mathrm{i,j}) \in \mathrm{L}$, where $\Delta\tau_{ij}^{k}$ is the amount of pheromone deposited by ant k. The amount of pheromone is given by

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{1}{C^k}, & if\ arc\ (i,j) belongs\ to\ T^k \\ 0, & otherwise; \end{cases}, \tag{2.2}$$

where C^k, the lengths of the tour T^k built by ant *k*-th ant, is computed as the sum of the lengths of the arcs belonging to T^k. The AS algorithm is characterized by two main phases: solution construction and the pheromone update (Dorigo and Stützle 2004).

The first Ant System with multiple objectives was proposed by Paciello (Paciello et al. 2006). It was a multi-objective extension of the Ant System developed by Marco Dorigo. It was tested using three bi-objective problems, QAP, TSP, and VRPTW. It has one pheromone matrix, uses the pseudo-random proportional rule, and updates pheromone of non-dominated solutions only. The algorithm has one pheromone matrix and two heuristic matrices, one for each objective. The decision rules for the ants is as follows:

$$p_{ij}^{h} = \frac{\tau_{ij}[\eta_{ij}^{0}]^{\lambda\beta}[\eta_{ij}^{1}]^{(1-\lambda)\beta}}{\sum_{l\in N_{i}^{h}}\tau_{ij}[\eta_{ij}^{0}]^{\lambda\beta}[\eta_{ij}^{1}]^{(1-\lambda)\beta}}\ if\ j\ \in\ N_{i}^{h}, \text{ and 0 otherwise.} \tag{2.3}$$

In order to force the ants to search in different regions of the objective space, λ is calculated for each ant h as $\lambda_h = (h-1)/(m-1)$. Thus in the most extreme cases the first ant *m* with $\lambda = 0$ considers only the second objective and the ant with $\lambda = 1$ considers only the first objective. The pheromone update is performed only by the ants that have found non-dominated solutions and the pheromone update is given as follows: $\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \rho\Delta\tau$, where $\Delta\tau$ is given by

$$\Delta\tau = \frac{1}{\sum_{k=1}^{k} f(C^k)} \tag{2.4}$$

where k represents the number of objectives.

Ant Colony System was proposed by Dorigo and Gambardella and is an extension of the Ant System (Dorigo and Gambardella 1997a, 1997b). It differs from Ant System in three main aspects. First, the pseudorandom proportional rule provides a means to balance between the exploration and exploitation phases of the algorithm. When an ant is determining its next step, the step with the maximum weighted average is chosen with the probability of q_0 while a random proportional rule is used with probability 1-q_0, where $0 \le q_0 \le 1$ usually fixed to 0.9 (Onwubolu 2004).

$$P_{ij} = \begin{cases} arg\ \ max_{ij}\ \{[\tau_{ij}]\alpha + [\eta_{ij}]\beta\} & if\ q\ \le\ q_0 \\ \hat{j} & otherwise \end{cases}, \tag{2.5}$$

where $\hat{\jmath}$ represents the random proportional rule as in AS. Second, the global updating rule is applied only vertices which belong to the best-so-far ant path. The pheromone update is give by: $\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \rho\Delta\tau_{ij}^{best}$ $\forall(\mathrm{i,j}) \in \mathrm{T^{best}}$ where $\Delta\tau_{ij}^{best} = 1/C^{best}$, where C^{best} is the lengths of the iteration-best tour. Finally, each time an ant uses an edge (i,j) it uses a local pheromone updating rule which evaporates some of the pheromone from the edge to increase the exploration of other paths given by: $\tau_{ij} \leftarrow (1-\xi)\tau_{ij} + \xi\tau_0$, where $\xi, 0 < \xi < 1$, and τ_0 are two parameters and τ_0 is set as equal to the initial value of the pheromone trails.

ACS was the first ACO algorithm to use candidate lists to restrict the number of available choices to be considered at each construction step. In general, candidate lists contain a number of the best rated choices according to some heuristic criterion (Dorigo and Stützle 2004).

The multi-objective version of Ant Colony Systems was proposed by Baran and Shaerer to solve a vehicle routing problem with time windows (Baran and Shaerer 2003). They tested the algorithm using the Vehicle Routing Problem with Time Windows (VRPTW) which "is an extension of the Vehicle Routing Problem, in which the aim is to find a set of minimum-cost vehicle routes that originate and terminate at a central depot, for a fleet of vehicles that serve a given set of customers with known demand." They used two ant colonies to optimize a bi-objective problem. Both colonies have separate pheromone trails but only the global best of the two colonies is allowed to update pheromone. The algorithm uses one pheromone trail and two heuristic matrices.

It still uses as state transition rule of exploration versus exploitation considering multiple objectives as follows

$$P_{ij} = \begin{cases} arg \quad max_{ij} \ \{[\tau_{ij}][\eta_{ij}^0]^{\lambda\beta}[\eta_{ij}^1]^{(\lambda-1)\beta}\} & if \ q \ \le \ q_0 \\ \hat{j} & otherwise \end{cases}, \tag{2.6}$$

where λ is computed for each ant k as $\lambda = k/m$, where m is the total number of ants in the colony. The variable β represents the weight of the objectives with respect to the pheromone trail and $\hat{j}$ represents the decision rule, which is determined just as in AS. The local update of the pheromone is given by $\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \rho\tau_0$, and τ_0 is initialized using the following for each objective function $f^1(C_k)$ and $f^2(C_k)$

$$\tau_0 = \frac{1}{n * f^1(C_k) * f^2(C_k)}, \tag{2.7}$$

where n is the number of nodes. The global pheromone update is given by

$$\tau_{ij} = (1-\rho)\tau_{ij} + \frac{\rho}{f^1(s_p)f^2(s_p)}. \tag{2.8}$$

An Ant-Q algorithm first proposed by Gabardella and Dorigo is based on a distributed reinforcement learning technique and was first applied to the design of irrigation networks (Gambardella and Dorigo 1995). The Ant-Q algorithm differs from ACS only "in the definition of the term t_0 which in Ant-Q is set to $\tau_0 = \gamma \max_{j \in N_i^k}\{\tau_{ij}\}$ where γ is a parameter and the maximum is taken over the set of pheromone trails on the arcs connecting the city i on which ant k is positioned to all the cities the ant has not visited yet (i.e., those in the neighborhood N_i^k)" (Dorigo and Stützle 2004). Eventually Ant-Q was abandoned because it was found that if τ_0 is set to a very small value, the two algorithms perform similarly.

The multi-objective version of Ant-Q (MOAQ) was proposed by Mariano and Morales and implements a colony of agents to perform the optimization of each objective (Mariono and Morales 1999). MOAQ uses one pheromone trail and two heuristic matrices, one for each objective. One colony optimizes for the first objective while the second colony optimizes for the second objective. MOAQ returns a set of nondominated solutions and non-dominated solutions fitting all problem constraints are assigned a reward while solutions violating constraints are punished.

Another extension of the ant system developed by Stützle and Hoos is the Max-Min Ant System (MMAS) (Stützle and Hoos 2000; Stützle 1997). MMAS is characterized by a strong exploitation phase of the algorithm because it only allows the best-of-iteration solutions to deposit pheromone and imposes limits on the pheromone values in order to avoid premature convergence. MMAS introduces four major changes to the original AS. First, it has a strong exploitation phase by only allowing the best-of-iteration or best-so-far ants to deposit pheromones on their trails. Secondly, it introduces a limit on the range of pheromone values on each arc $[\tau_{min}, \tau_{max}]$, by doing this it prevents pre-convergence on non-optimal solutions. Third, the pheromone trails are initially set to τ_{max}, which, when coupled with at pheromone evaporation rate, greatly increases the exploration phase of the algorithm in the beginning of the ant search. Finally, each time the ant system reaches a stagnation point, where no new optimal paths are being produced, the pheromone trails are reinitialized to τ_{max}. The pheromone matrix is updated by the following: $\tau_{ij} = \rho\tau_{ij} + \Delta\tau_{ij}^{k}$ where ρ is the evaporation rate and $\Delta\tau_{ij}^{k}$ is the amount of pheromone that ant k deposits on its path. In MMAS $\Delta\tau_{ij}^{k}$ is defined as follows:

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{1}{L^{k}(t)} & if\ arc(i,j) is\ used\ by\ ant\ k\ in\ interation\ t \\ 0 & otherwise \end{cases}, \qquad (2.9)$$

where $L^{k}(t)$ is the tour length of the kth ant.

The MMAS version for multiple objectives (M3AS) was proposed by Pinto and Baran to solve a multicast traffic engineering problem (Pinto and Baran 2005). It uses one global pheromone matrix and a separate heuristic matrix for each objective, given by $\eta_{ij}^{k} = 1/d_{ij}^{k}$, where k is the number of objectives and d_{ij}^{k} the objective score or cost. The algorithm uses as pseudo-random rule for the ants decision rules as follows:

$$p_{ij} = \frac{\tau_{ij}^{\alpha}\sum_{k=1}^{k}[\eta_{ij}^{k}]^{\lambda^{k}}}{\sum_{l\in N_i}\tau_{ij}^{\alpha}\sum_{k=1}^{k}[\eta_{ij}^{k}]^{\lambda^{k}}} \text{ if } j \in N_i, \quad 0 \text{ otherwise} \qquad (2.10)$$

where λ^{k} represents the relative influence of each objective among heuristic information. The pheromone matrix has an upper bound τ_{max} which only the non-dominated solutions can update.

The Omicron ACO (OA) algorithm proposed by Gomez and Baran (Gomez and Baran 2005) is inspired by MMAS. OA is a population based algorithm where a population of individuals is maintained which contains the best solution so far. “It is based on the hypothesis that it is convenient to search for nearby good solutions. The main difference between MMAS and OA is the way the algorithms update the pheromone matrix. In OA, a constant pheromone matrix τ^{0} with $\tau_{ij}^{0} = 1, \forall i, j$ is defined”(Gomez and Baran 2005).

The multiobjective version of the Omicron ACO (MOA) algorithm was proposed by Gardel and colleagues (Gardel et al. 2006) under the name Electric Omicron. The MOA was first applied to the multi-objective Reactive Power Compensation Problem. The initial pheromone trails are set in the same manner as in OA and two heuristic matrices, one for each objective are combined by: $\eta_{ij} = w_1 * \eta_{ij}^1 + w_2 * \eta_{ij}^2$ where w_1 and w_2 are weighted factors (w_1+ w_2 = 1) that change dynamically with each iteration of the algorithm.

BicriterionAnt is a bi-objective algorithm developed by Iredi and co-workers (Iredi et al. 2001) which proposed two ACO methods to solve the Single Machine Total Tardiness Problem (SMTTP) with changeover costs. The BicriterionAnt algorithm uses two pheromone matrices τ and τ' and two heuristic matrices η and η', one for each objective. By doing so different ants conduct searches in different regions of the objective space along the Pareto Front. To force the ants to search in different regions of the Pareto optimal space each of the ants in the colony gives a different importance to each of the objective by weighing them differently. Ant $k, k \in [1, m]$in the colony uses $\lambda_k = \frac{k-1}{m-1}$. Every ant makes its decision using the following probabilities:

$$p_{ij} = \frac{\tau_{ij}^{\lambda\alpha} * \tau'^{(1-\lambda)\alpha}_{ij} * \eta_{ij}^{\lambda\beta} * \eta'^{(1-\lambda)\beta}_{ij}}{\sum_{h \in S} \tau_{ij}^{\lambda\alpha} * \tau'^{(1-\lambda)\alpha}_{ij} * \eta_{ij}^{\lambda\beta} * \eta'^{(1-\lambda)\beta}_{ij}} . \tag{2.11}$$

Thus in extreme cases the ant *m* with λ = 1 considers only the first objective and ant 1 with λ = 0 considers only the second criterion. Two methods are explored to update the pheromone, update by origin where an ant only updates in its own colony and update by region in the non-dominated front. A set is maintained of non-dominated solutions and only ants that found non-dominated solutions may update the pheromone matrices.

The multi-objective network ACO (MONACO) was proposed by Cardoso et al. (2003) to solve the dynamic problem of message traffic in a network. The algorithm uses a single heuristic matrix $\eta_{ij} = \sum_{k=1}^{K} d_{ij}^{k}$ and multiple pheromone matrices τ^{K} for each objective, where K is the number of objectives. At the end of each iteration, pheromone is laid on the trails given the following equation: $\tau_{ij}^{k} = (1 - \rho_k)\tau_{ij}^{k} + \Delta\tau_{ij}^{k}$ where $\tau_{ij}^{k} = \frac{Q}{f^k(s_h)}$ with $\rho_k$representing the pheromone evaporation rate for objective k. Q represents a constant related to the amount of pheromone laid by the ants, and s_h is the solution build by ant h. The non dominated solutions are then stored in a non-dominated archive representing the Pareto set.

COMPETants was developed by Doerner, Hartl and Reimann (Doerner et al. 2001) to solve a multi-objective transportation problem. A main feature of COMPETants is the uses of two ant populations with different priority rules. In COMPETants rather than a fixed population, the population size undergoes adaptation during the algorithm execution. More computational power is assigned to the ant colony which finds solutions with better objective scores. Some ants called spies not only utilize their own information but also the foreign pheromone information. The decision rules for the ants is as follows:

$$p_{ij}^{h} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{I \in N_i^h}[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}, \text{ if } j \in N_i^h, 0 \text{ otherwise} \qquad (2.12)$$

where each colony uses its own pheromone and heuristic information. For the spy ants, the decision rule is give by

$$p_{ij}^{h} = \frac{[0.5\tau_{ij}^{0} + 0.5\tau_{ij}^{1}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{I \in N_i^h}[0.5\tau_{ij}^{0} + 0.5\tau_{ij}^{1}]^{\alpha}[\eta_{ij}]^{\beta}}, \text{ if } j \in N_i^h, \text{ 0 otherwise} \tag{2.13}$$

where the spies combine the information of both pheromone trails.

SACO was proposed by T'Kindt (2002) to solve a 2-machine bicriteria flowshop scheduling problem. The algorithm uses one pheromone and one heuristic matrix. It was developed to solve a lexicographical problem, where only one best solution is returned at the end of the algorithm execution. Each ants decision rule is determine by one of two modes. The first is an intensification mode where the edge with the highest pheromone value τ_{ij} is chosen. The second is a diversification mode, where an ant uses the random-proportional rule to select the next job. They use the parameter p_o to determine the probability of being in either mode, which is given by $p_0 = \frac{\log(n)}{\log(N)}$ where n is the iteration number, with $n \in [1, N]$. Pheromone evaporation is applied to every edge and pheromone update is done only to the best of iteration solutions, as follows:

$$\tau_{ij} \leftarrow \begin{cases} \tau_{ij} + \frac{1}{f(s)}, & if\ arc(i,j) \in s_{best} \\ (1-\rho)\tau_{ij}, & otherwise; \end{cases} \tag{2.14}$$

where s_{best} is the best objective value found and ρ is the evaporation rate.

Pareto Ant Colony Optimization (P-ACO) was proposed by Doerner et al. (2001) to solve a multi-objective portfolio selection problem. The algorithm is based on ACS, but the pheromone update is performed by both the best and the second-best ant. It uses one heuristic matrix and multiple pheromone matrices τ^k, where k represents the number of objectives. Given the pheromone information and the set of all feasible projects, a feasible project *i* is selected to be added to the current portfolio *x* according to a pseudo-random-proportional rule given as follows:

$$i = \begin{cases} \arg max_{i \in \Omega(x)} \left\{\left[\sum_{k=1}^{K}(p_k * \tau_i^k)\right]^{\alpha} * [\eta_i(x)]^{\beta}\right\} & if\ q \leq q_0 \\ \hat{\imath} & otherwise \end{cases} \tag{2.15}$$

where q is a random number and q_0 is a parameter to be set by the user representing the probability that the portfolio is chosen which gives the highest aggregate value of pheromone and attractiveness. The node $\hat{\imath}$ is selected according to the decision:

$$p_{ij}^{h} = \frac{\sum_{k=1}^{K}[p_k\tau_{ij}^{k}]^{\alpha}\eta_{ij}^{\beta}}{\sum_{i \in N_i^h}(\sum_{k=1}^{K}[p_k\tau_{ij}^{k}]^{\alpha}\eta_{ij}^{\beta})}\ if\ j \in N_i^h,\ \text{and 0 otherwise} \tag{2.16}$$

where p_k is determined randomly for each ant. Pheromone update is performed after each iteration using the following equation: $\tau_{ij}^{k} = (1-\rho)\tau_{ij}^{k} + \rho\tau_0$ where ρ is the evaporation rate and τ_0 is the initial pheromone value. Since the pheromone update is done only by the best and second best ants, the update rule for each objective k is given by: $\tau_{ij}^{k} = (1-\rho)\tau_{ij}^{k} + \rho\Delta\tau_{ij}^{k}$ where $\Delta\tau_{ij}^{k}$ represents an increasing quantity related to the best and second best solutions represented by the following:

$$\Delta\tau_{ij}^{k} = \begin{cases} 10 & if\ arc(i,j) \in\ S_{best} \\ 5 & if\ arc(i,j) \in\ S_{second-best} \\ 0 & otherwise; \end{cases} \tag{2.17}$$

The non dominated solutions are then stored in a non-dominated archive representing the Pareto set.

Multi-objective ant colony system algorithm (MOACSA) was developed by Yagmahan and Yenisey to solve a flow shop scheduling problem (Yagmahan and

Yenisey 2010). The algorithm is based on ACS and uses one global pheromone matrix and one global heuristic matrix. All initial pheromone trails τ_0 are set to a small value and calculated by $\tau_0 = [n * (\left(M(S') + F(S')\right)]^{-1}$, where "n is the number of jobs, M(S') is the makespan of the solution and F(S') is the flowtime of the solution for sequence S' generated by the NEH heuristic." While constructing a solution the ants apply a local pheromone updating rule $\tau_{ij} = (1 - \rho l)\tau_{ij} + \rho l \tau_0$ where ρl ($0 < \rho l < 1$) is the local pheromone evaporating parameter and τ_0 is the initial pheromone level. The global updating rule is performed only by the iteration-best solutions and is given by: $\tau_{ij} = (1 - \rho)\tau_{ij}^k + \rho \Delta\tau_{ij}$.

The preceding material covered the prevalent multi-objective ant colony optimization algorithms that have been developed in the past two decades. The field of multi-objective ant colony optimization continues to grow both in its structure as well as its applications. The following section will discuss the multi-objective ant colony algorithm that is inspired by the previous work done to develop multi-objective ant colony optimization algorithms.

3. MULTIPLE-OBJECTIVE ANT COLONY OPTIMIZATION

3.1 MOTIVATION AND OBJECTIVE

Motivation for this algorithm developed from the North Slope Decision Support System (NSDSS) project. This project was tasked with developing an algorithm which would create optimal ice road routes on the North Slope of Alaska considering multiple objectives. The North Slope is characterized by vast costal marshes and foothills, where ice roads are designed over a vast expanse of tundra with no existing infrastructure network or considerable topographic variations. The algorithm created would have to utilize and open graph network with no existing networks or junctions in place to develop solutions considering multiple objectives such as length, water use, construction time, and environmental impacts. Multi-objective ant colony optimization was chosen as a constructive search technique that could develop a group of Pareto-optimal solutions on an open graph framework. Much in the same way that ants search a vast expanse of terrain for food and then develop a shortest path to that food source, our artificial ants search an open graph for the shortest path between the start and end point. What we are seeking to do is develop a MOACO infrastructure routing algorithm capable of producing a Pareto-front of desirable routes.

3.2 INTRODUCTION

Ant Colony Optimization is a path finding algorithm inspired from the foraging behavior of real ants in the natural environment. When an ant finds a food source, it deposits pheromone as it makes its way back to the nest. Ants are essentially blind creatures and through this indirect form of communication they are able to determine where food sources are. As more ants traverse along a path, the stronger the pheromone becomes and the more likely that the ants will chose to take that path. As a colony of ants goes back and forth between a food source, the ants begin to converge to the paths with the strongest pheromone scent. This collaborative behavior allows ants to develop paths in complex and dynamic environments between their nest and a food source.

Ant Colony Optimization uses artificial ants that explore a graph network in order to find an optimal path. The process of constructing solutions involves ants exploring a graph by moving along the links between vertices until a solution is found. Artificial ants share many of the same path finding characteristics as real ants. Just like in nature, artificial ants retrace their path and deposit pheromone after they find a solution. Natural forces cause pheromone which is deposited by real ants to evaporate over time. So in order to mimic this pheromone evaporation is applied to the pheromone deposited by the artificial. This leaves a preference for new and higher quality solutions as the ants continue to find better trails while the algorithm progresses. Artificial ants also have features and advantages that natural ants do not have. The ants are able to use their memory to store their own path information and then use this information to analyze and compare paths between each other. They also are able to employ heuristic information to help build their solutions.

This multi-objective ant colony optimization algorithm was developed to explore an open graph network in order to solve common infrastructure routing problems. It draws heavily from previous work including MOAQ (Mariono and Morales 1999), MMAS (Stützle 1997), and Bicriterion Ant (Iredi et al. 2001). The algorithm is designed to fit the problem of infrastructure routing on an open graph without a previous network in place. This algorithm proposes unique functions to enhance the both speed and performance. It also possesses features to solve issues unique to infrastructure routing that traditional MOACO algorithms lack in nature.

3.3 THE ALGORITHM

This Multi-Objective Ant Colony Algorithm (MOACO) is used to find desirable routes of a minimum cost path problem containing multiple objectives. There are often different objectives when designing new infrastructure such as cost, length, time of construction, etc. and a MOACO approach to developing infrastructure routes provides solutions that can be optimized for different objectives and sets of objectives. By allowing a decision maker to analyze the tradeoffs between different paths in the Pareto-optimal space, he or she can gain a better understanding of the problem.

3.3.1 Multiple Colonies

This algorithm takes a multiple colony approach to the multiple objective problem where each colony uses a different set of objective heuristic information. A multiple colony approach allows different sets of ants (colonies) to seek solutions in an open graph separately from one another, resulting in solutions found in different areas of the objective space. Each colony of ants uses a different set of objective information depending on the number of objectives and colonies. The different objective information serves as the a priori heuristic information that the ants use to build their solutions. The heuristic information, combined with the pheromone information which the ants deposit after they have found a solution, serve to guide each colony of ants to a desirable set of solutions. By taking a multiple colony approach, optimal paths for different objectives and sets of objectives can be found. Multiple colonies will search different areas of the objective space creating a diverse set of Pareto-optimal solutions. This allows a decision maker to visually see the tradeoffs between the optimal paths for different objectives.

3.3.2 Heuristic Information

For each objective O_n where n = number of objectives, C_{n+1} colonies are created. Each colony seeks solutions for a single objective except for the n+1 colony which seeks an additive solution of all of the objectives. This objective selection approach allows the ants to seek solutions across different regions of the objective space and produces a diverse set of solutions across the Pareto front. Each corresponding colony has its own heuristic information matrix η_{ij}^{C} which represents the objective information of colony C on the link connecting node i and j.

3.3.3 Pheromone Information

Each colony in the algorithm also has its own pheromone matrix τ_{ij}^{C} , which represents the pheromone information of colony C on the link connecting node node i and j. It is this matrix that the ants use to store the deposited pheromone information of the colony. Pheromone deposits allow the ants to exploit areas of the graph where better solutions are likely to be found and guide the ants toward optimal solutions. Pheromone acts as a collaborative communication tool between the ants. After an ant has deposited pheromone onto its path, other ants are then able to use that information combined with heuristic information to build their own solutions. It is pheromone deposits that trigger the transition of the ants from an exploratory phase to an exploitation phase where optimal solutions are exploited in the objective space.

3.3.4 Ant Colony Search

Each colony C_{n+1} contains a set of ants A_{Cx} (where C represents the colony of ants and x is the number of ants in the colony) that seek to find a path from the start point to the end point. Each ant uses the pheromone information and the heuristic information on each edge between vertices to build their solutions. Each colony has its own pheromone matrix τ_{ij}^{C} which it uses to store the deposited pheromone information and its own heuristic information matrix η_{ij}^{C} that represents the objective information on each vertex for that colony.

Each ant begins at the starting point and makes a decision as to which available node to move to based on the pheromone and heuristic information on the edges between the nodes. Each edge is given a weight in proportion to the strength of its aggregated pheromone and heuristic information. An ant makes a probabilistic decision of which node to move to based on an aggregation of the heuristic and pheromone information of the available nodes. After a node is chosen, the ant moves along the edge to the new node, records its step and then repeats this process. The probabilistic decision of which node to move to next, called the random proportional rule, is given by

$$P_{ij} = \frac{[\tau_{ij}]\alpha + [\eta_{ij}]\beta}{\sum_{j \in N_i^h} [\tau_{ij}]\alpha + [\eta_{ij}]\beta} \quad if\ j \in N_i^h \tag{3.1}$$

where P_{ij} represents the probability of moving from node i to node j and N_i^h represents feasible neighborhood of ant h within node i. The variables α and β represent the weights given to the pheromone and heuristic matrices respectively.

An ant's path is terminated under two conditions. The first is that it has successfully found the endpoint. The second is that it has "cornered" itself and no longer has any available nodes to move to. An ant cannot move to a node more than once, i.e. move backwards or cross its own path. In the case that an ant has cornered itself, it terminates its path and starts over from the starting point until it finds a feasible path to the endpoint.

Once an ant has found a solution, the ant's generated path is saved and the next ant in the colony begins finding a solution. If it is the first ant in the colony its objective score and path are saved as the best-route-thus-far in the current iteration of the colonies search. After the first ant has found a solution, the next ant in the colony goes out and finds a new path. This new path is then compared with the best-route-thus-far, if it has a better objective score than the current path then the new path replaces the previous solution. If it is not, then the current ant's solution is not saved. This process is repeated until every ant in the colony has found a solution. After all of the ants in the colony have found a solution, the ant with the path with the best-route-thus-far retraces its path, laying pheromone upon the trail. Pheromone evaporation is then applied to all previous pheromone within the matrix.

There exists a parent group of solutions Q which represents all non-dominated solutions found during the ant colony iterations. Once a colony has found a solution, it is compared against the solutions in the parent group Q. If it is a non-dominated solution then the path is saved in Q, otherwise it is thrown out. After the parent group has been updated, a new iteration begins where the ants then attempt to find a new solution using the heuristic information coupled with the updated pheromone matrix.

3.3.5 Exploration Versus Exploitation

There are two phases of the ant search, exploration and exploitation. Both phases are characterized by the ants searching behavior as influenced by the pheromone deposits. In the beginning of the algorithm, or the exploratory phase, there is little pheromone information in the pheromone matrix so the ants' behavior is influenced primarily by the heuristic information. Because there is little pheromone information to influence the behavior of the ants, the ants explore a wider area of the graph in an attempt to find the best route to the end point. After many iterations, stronger pheromone trails begin to build around optimal paths and the pheromone information begins to have a stronger effect upon the decision of the ants. During this phase the ants begin to exploit the optimal paths with stronger pheromone trails which is called the exploitation phase of the algorithm.

3.3.6 Aggregation

A weighted approach is used for the aggregation of the heuristic and pheromone information. An ants' decision making process from node to node is influenced by the heuristic and pheromone information on the links between each node. Each matrix is given a weight to determine the strength of influence of the matrix within the ants' node to node decision making process. The heuristic matrix η is given the weight α and the pheromone matrix τ is given the weight β**.**

$$A = \alpha\ \tau + \beta\ \eta \tag{3.2}$$

3.3.7 Pheromone Update

After every ant within the colony has found a solution, the ant with the solution with the best objective score is allowed to deposit pheromone ρ on its trail. By allowing only the ant with the best objective score to deposit pheromone, the ants begin to exploit higher quality solutions.

Pheromone evaporation is a technique used in the algorithm that is inspired by what happens in nature during an ant colonies search for food. After an ant deposits pheromone on a trail physical forces begin to dilute the strength of the pheromone deposits and evaporate the pheromone from the trail. Just like in nature, artificial pheromone trails are gradually evaporated over time. With each new iteration a pheromone evaporation rate λ (0.7) is applied to the pheromone matrix to reduce the strength of the pheromone trails over time. This gradually evaporates the pheromone deposited on old paths and favors newer, and likely better paths.

$$\tau_{ij} = (1 - \lambda)\tau_{ij} \tag{3.3}$$

3.4 UNIQUE FEATURES

3.4.1 Multiple Start Points

There are often scenarios in infrastructure routing where a single starting point is not defined. Such is the case when developing a spur road from a stretch of highway or a water transmission pipeline from a river to a new treatment facility. In these cases there is not a defined starting point and multiple feasible locations could produce optimal solutions. In such cases, the ant colony optimization approach used for a single start and single endpoint cannot be applied to solve the problem. To address this scenario we have created a new starting procedure of each ant which is able to determine the optimal location of the starting point by using a pheromone based approach similar to the ants' path construction.

In this situation the algorithm uses a probabilistic decision influenced by pheromone deposition, similar to the route finding process. The multiple starting points, whether it be a stretch of highway that is segmented into a group of nodes or multiple user defined points, are grouped together into a matrix $\mathrm{S_j}$ where j = the number of starting points. The probabilistic decision is similar to equation (1) where node i represents the virtual starting point, node j represents the possible starting point, and N_i^h represents the feasible neighborhood of ant h within node i. In this case the feasible neighborhood will be all points within matrix $\mathrm{S_j}$. From the virtual start point the ant makes a probabilistic decision of which starting node to move to, and then from that starting node the ant begins to build its path. Each ant in the colony begins its procedure from a virtual starting point which exists in an undefined point in space. From here an ants' first decision is to select which start point S_j to begin to build its solution from. Because the ants are starting from an undefined point in space, there can be no unique heuristic information given to the links between the virtual start point and the starting points S_j in the problem. In this case each link is given an equal heuristic value.

Once an ant has selected a starting point, it begins to build its solution in the same procedure as before. After every ant has found a solution, the ant with the solution with the best objective score deposits pheromone not only on its path, but also on the link between the virtual start point and the starting point S_i that it used to build its solution. In the next iteration, the ants will use both the heuristic information and the pheromone information that was deposited previously on the links between the virtual start point and the starting points S_j to build their solutions. By using this technique, the ants begin to quickly exploit the most desirable starting points and in the same way that they find an optimal path, they are able to find an optimal starting point. The same rules of pheromone deposit and evaporation that hold for path building also hold here for determining a starting point.

3.4.2 Multiple End Points

There are often more than two points that need to be connected in infrastructure routing problems. In ice road construction there is frequently more than one drill site locations that an oil company must build a road to. In water transmission systems a lake may provide water to multiple water treatment plants. When such is the case the traditional ant colony optimization technique will fail to produce a solution that represents a least cost path between the starting point and all of the endpoints. We have developed new ant colony techniques that are able to find optimal solutions to multiple end point problems.

3.4.2.1 Ant Colony Divisions

A scenario with multiple end points requires a new approach to determine an optimal path that will connect all points together. We have developed new ant colony techniques that are capable of finding solutions to these problems. One solution involves dividing each colony up into smaller divisions of ants, one for every endpoint. Each division is assigned a specific end point in which it tries to find an optimal path. When each division is isolated to communicating only to itself within its own pheromone matrix, the algorithm will create unconnected separate paths to each endpoint. However, we allow the ants to share a common pheromone matrix where each division updates the pheromone matrix with its best objective score solution. This approach allows the ants from different divisions to communicate and collaboratively build their solutions within each colony. By doing so, the ants paths from each division will eventually converge together following many iterations to create and optimal path between all of the endpoints. It is communication between the ants on a common pheromone matrix that allows them to exploit paths that connect all of the endpoints together.

In a multi-objective approach every division contains a set of colonies that are directly related to the number of objectives considered. The corresponding colonies from each division find solutions separately but aggregate their solutions into one path after each iteration. Each division's colonies communicate with their respective colonies in other divisions using a common pheromone matrix τ_{ij}^{C}. After all of the colonies within each division have found a solution, the solutions from the respective colonies within each division are combined together. This aggregated solution is then put into a group Q to be compared with the Pareto archive of non dominated solutions.

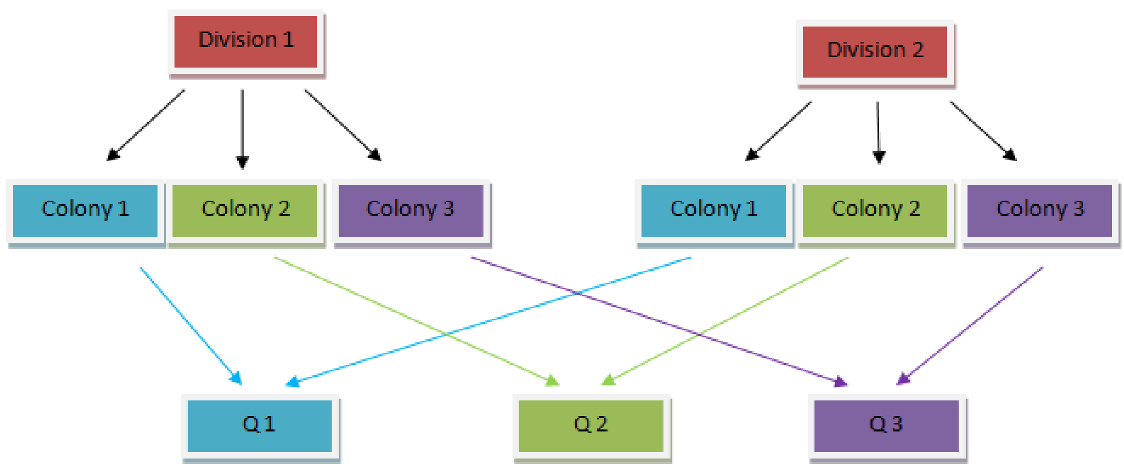

Fig. 3.1. Ant division diagram

Figure 3.1 above illustrates a bi-objective problem with two endpoints. The two divisions correspond to each endpoint, with each division containing 3 colonies. After all of the colonies within the divisions have found a best-of-iteration solution, they are paired together with their respective colonies in the other division to form a solution$Q$ to be compared against the Pareto archive of non dominated solutions.

3.4.2.2 Steiner Points

The divisional approach to multiple end point routing can be computationally intensive due to the large number of iterations that must take place before the ants paths begin to converge. Another approach to solving a multiple end point problem is to determine waypoints that act as intersections between two or more branches of the path. By determining waypoints, a single start – single endpoint approach can be taken between the waypoints and the endpoints, thus reducing the computation time of the algorithm.

The method used to determine these waypoints is the Steiner Point approach. Steiner points represent the intersection between nodes of the shortest possible path. The problem of finding the networks of the least possible length between a fixed set with a finite number of points is named after Jacob Steiner (1796-1863) (Gilbert and Pollak 1968). For example, in the case of one start point and two end points, the Steiner approach will determine the waypoint through which connecting to all other existing points will create the shortest possible network. The Steiner approach we use is possible for up to 4 total points.

For a problem with 3 total points, one Steiner point will exist that represents the intersection between the shortest possible path connecting all three points. Of the triangle connecting all three points together, if there exists an angle that is greater than 120^{o} then the shortest path linking the 3 points is simply the two shortest sides of the triangle. However, if all of the angles within the triangle are less than or equal to 120^{o} then there exists a Steiner point between all 3 points. The shortest distance path is found by linking all of the branches from each point to the Steiner point. The Steiner point makes a Y junction with each branch intersecting together to create equal 120° angles. Figure 3.2 below represents the three point Steiner Tree.

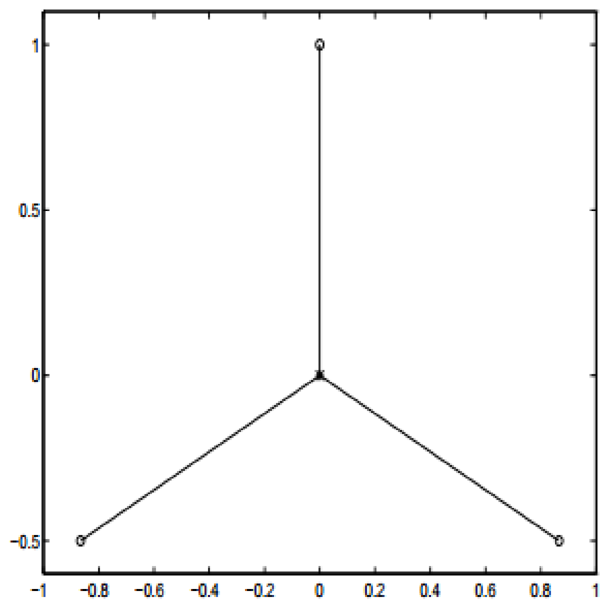

Fig. 3.2. Three point Steiner tree (Dreyer 1998). This figure represents the Steiner Point S between the 3 points A, B, and C. Every angle of the intersection AB, BC, and AC are 120 degrees.

For a problem with 4 total points, a Steiner tree can be constructed by either creating one or two Steiner points depending on the geometry between all 4 points. From the rectangle created by all four points, if there exists two angles in the rectangle that are 120° or larger, then there exists no Steiner points within the rectangle. The shortest path linking the points is then the 3 shortest sides of the rectangle. If there exists only one angle in the rectangle that is 120^o or larger, then there exists one Steiner point within the rectangle that connects 3 of the points. This Steiner point connects the opposite point of the 120^o angle with 2 of the 3 other points. Figure 3.3 below illustrates the four point Steiner Tree.

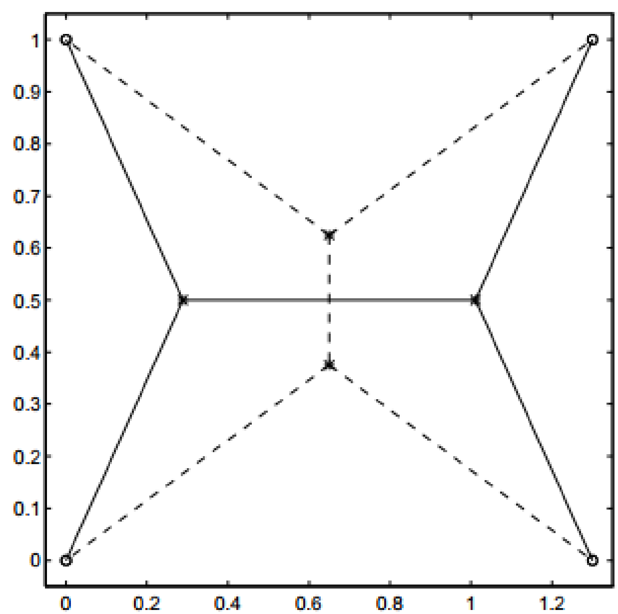

Fig. 3.3. Four point Steiner tree (Dreyer 1998)

Even though the most desirable network may not be the shortest possible route, using this approach to solving a multiple end point problem on an open graph gives a good approximation of where the optimal networks waypoints are likely to be located assuming an overriding objective is the length of the network being constructed.

3.4.3 Construction Distance Constraint

The constructability of some types of infrastructure routes are in part a function of how far from a specified supply point sections of the path are located. This algorithm addresses the problem of supply-distance availability in which constructability concerns related to in situ supply constraints are considered. In the example of ice road planning, there is a cost function associated with how far away a section of road is from a water source (lake) which provides the road material. The algorithm is capable of using this construction distance constraint as part of the path construction feasibility during the ants' path finding process.

As an ant constructs its path, it determines which supply location to draw its resources from and calculates the cost associated with using the resources for the construction of that link. Each supply location has a defined amount of resources S_{xy} (x represents the supply location and y represents the supply type) which are used by the ants in their construction process. As an ant builds a path from node i to node j, it determines the nearest supply location to use as well as the amount of resources required to build the link from node i to node j. After an ant has made the decision to move, it subtracts the amount of resources taken from S_{xy} and saves both how much resources it has used in its path thus far and from where. A path is terminated if there are no longer enough supplies from a feasible supply location to continue building the path.

3.5 PRE-PROCESSING

This ant colony algorithm is designed to be used on an open graph where no existing network or junctions are in place. An open graph framework can create a combinatorially huge problem that in turn can cause the exploratory ant search to take an extensive amount of time. Without ways to reduce the complexity of the problem, ants will get lost within the graph during this phase and seldom obtain an optimal solution. The logical step is to somehow reduce the complexity of the graph so that during the exploratory phase of the algorithm the ants can quickly explore the graph and find solutions. One way to do this is a preprocessing technique called graph pruning. Graph pruning eliminates cells within the graph in which optimal solutions are unlikely to be found, thus eliminating a large amount of unnecessary searching within the grid during the exploratory phase of the algorithm. The process creates topologically unique solutions that are dependent on the location of the start and end points as well as the locations of exclusion zones. Exclusion zones are user defined and represent areas that the user does not want the algorithm to search in. These exclusion zones could represent historical sites or environmentally sensitive areas that the infrastructure should not disturb. For each grid cell A_{xy} if there exists an adjacent cell B_{xy} which is also adjacent to every adjacent cell of cell A_{xy}, then cell A_{xy} is pruned.

The following two figures illustrate what a grid looks like before and after pruning. This process creates topologically unique paths which allow paths around both sides of exclusion zones. In this example there is one starting point within the green cell labeled S and one end point within the red cell labeled E. The grey cells labeled with an x represent excluded areas that cannot be used to find a solution. Figure 3.4 represents the search area before pruning.

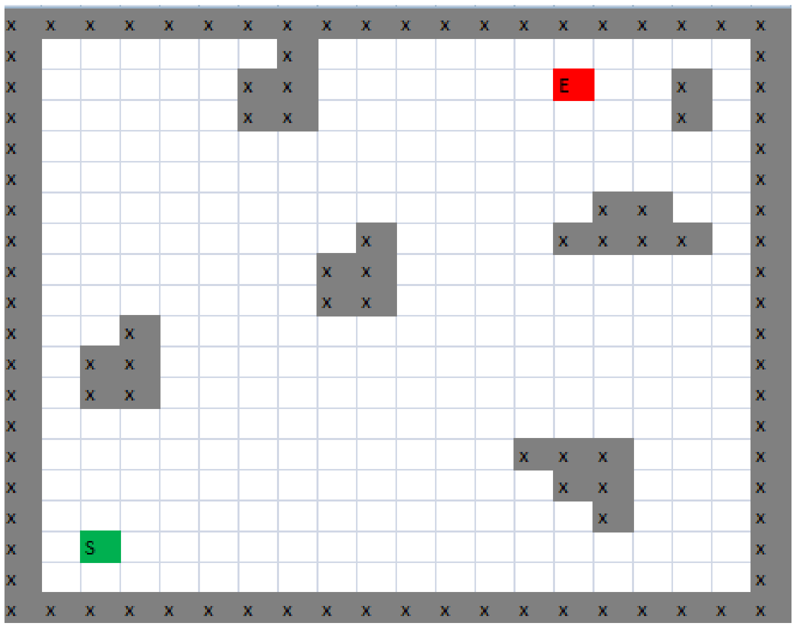

Fig. 3.4. Graph before pruning

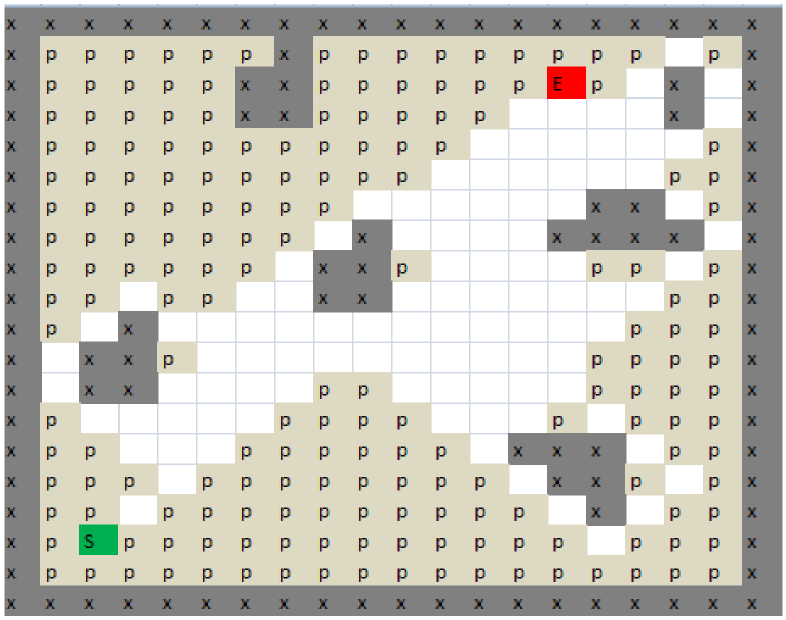

Fig. 3.5. Graph after pruning

From Figure 3.5 you can see the exclusion zones which are the dark cells marked with an x and the pruned cells which are lighter and marked with a p. The graph pruning allows paths to be taken around both sides of the exclusion zone, but eliminates unnecessary cells. Graph pruning greatly reduces the complexity in trying to find the best path.

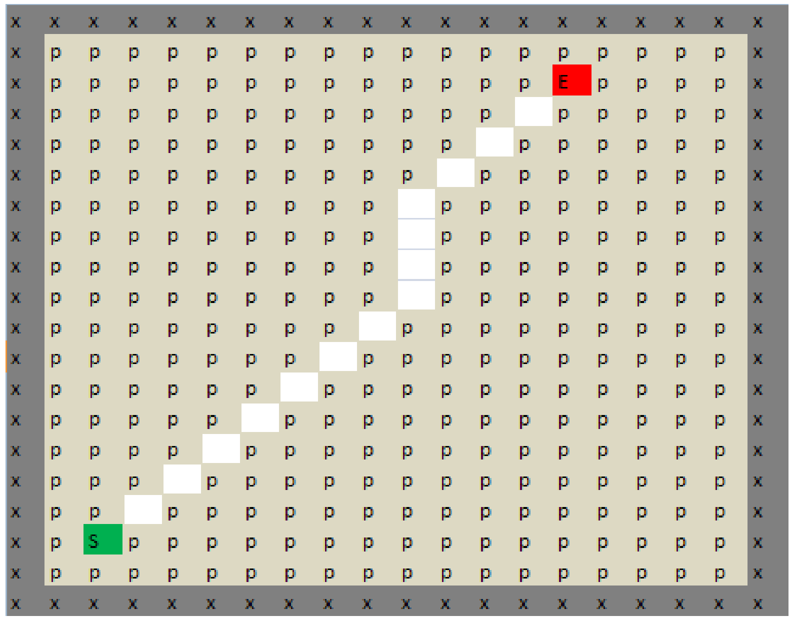

Fig. 3.6. Pruning without exclusion zones

Figure 3.6 illustrates a grid in which there are no exclusion zones present within the boundaries of the grid. Depending on which corner the pruning starts in, and which direction it moves, a different path will be projected for solutions where more than one shortest path exists, such as in the grid above.

3.6 POST-PROCESSING

In order to refine the solutions the algorithm produces, certain post-processing techniques are implemented. On occasion the ant colony solutions produce anomalies within the path such as kinks or bends that when straightened out produce a more desirable path. In this case we apply a post-processing technique called path straightening.

After an ant has found a solution, it retraces its path and where the ant encounters a kink or a bend in the path, the algorithm determines if a straight line would produce a more desirable path than the current one. If it does, then the bend is straightened out in the ants original solution and the ant continues retracing its path until the endpoint is reached.

Because of the computational complexity of an open graph, the ant colony algorithm is limited by the size of the graph it is able to solve. When solving a problem over a large area there are often topographic features that cannot be picked up at the necessary low resolution. For instance because of the large cell size it might not pick up a small pond that the road crosses or another geographic feature that would prevent an economically feasible path from traversing over or through it. In this case, a low to high resolution algorithm is run which allows the algorithm to modify the path to avoid such problem areas.

After a path is found at a low resolution in which the distance between the nodes is large, a buffer is applied around the path. The resolution of the nodes is then increased within the buffered region. The original path is retraced using the higher resolution grid and a very strong pheromone trail is laid upon the path. This pheromone trail belongs within its own matrix τ_{ij}^{*} which is exempt from pheromone evaporation. The ant colony algorithm is then run between the start and end point where the ants use both the heuristic matrix η_{ij}^{C} as well as the pheromone information from both pheromone matrices

τ_{ij}^{C} and τ_{ij}^{*} to find their solutions. By using a strong pheromone matrix on the original path, the ants are encouraged to stick to the original path, while still avoiding undesirable areas that are picked up at a high resolution.

3.7 CASE STUDY

A case study was conducted on a graph with 400 vertices to assess the performance of the algorithm under 3 separate scenarios. Each scenario used the same multi-objective information. The first objective represents the length of the path constructed, the second objective represents objective information such as slope or construction costs which will vary geographically, and the third objective was randomized for all 400 vertices. The algorithm was set to minimize all three objectives. The three scenarios tested different capabilities of the algorithm. The first scenario was a single start – single end point problem, the second was a multiple start point- single end point problem, and the third was a single start point- multiple end point problem. All three of these scenarios were tested using Visual Basic and Microsoft Excel. The parameters used are listed in Table 3.1.

Table 3.1. Algorithm Parameters

Parameter Values Considered	
Parameter	Value
Number of Ants	30
Number of Colonies	5
α	0.5
β	0.5
λ	0.7
Number of Iterations	100
Computer Specifications	Intel Core™2 Duo CPU 2.40 GHz with 4.00 GB RAM
Operating System	Windows 7 Enterprise

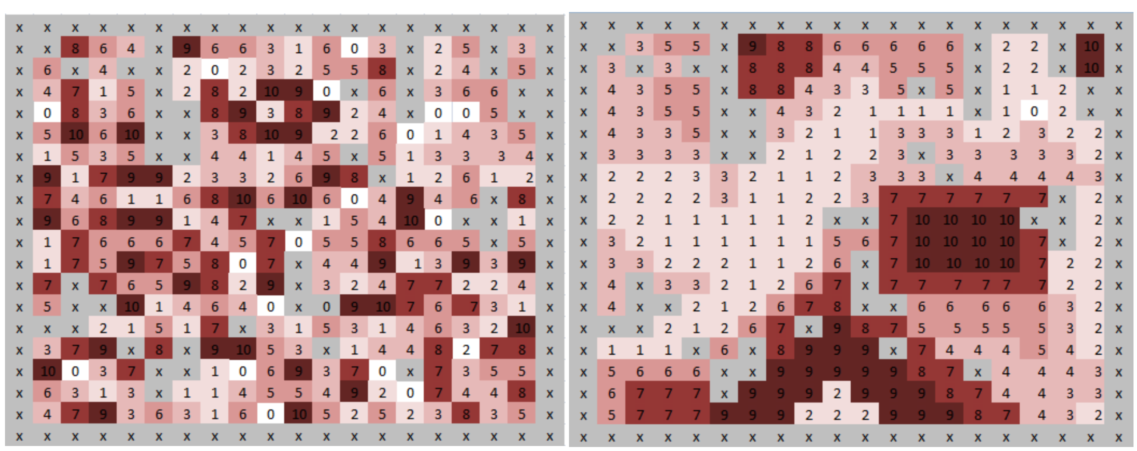

Fig. 3.7. Case study objectives

Figure 3.7 represents the heuristic objective information of objectives two and three. The figure on the right represents the heuristic information of objective two which varies geographically such as an objective of slope or construction cost would. The figure on the left represents the heuristic information for objective three and is randomized for every cell. Cells in gray represent excluded areas.

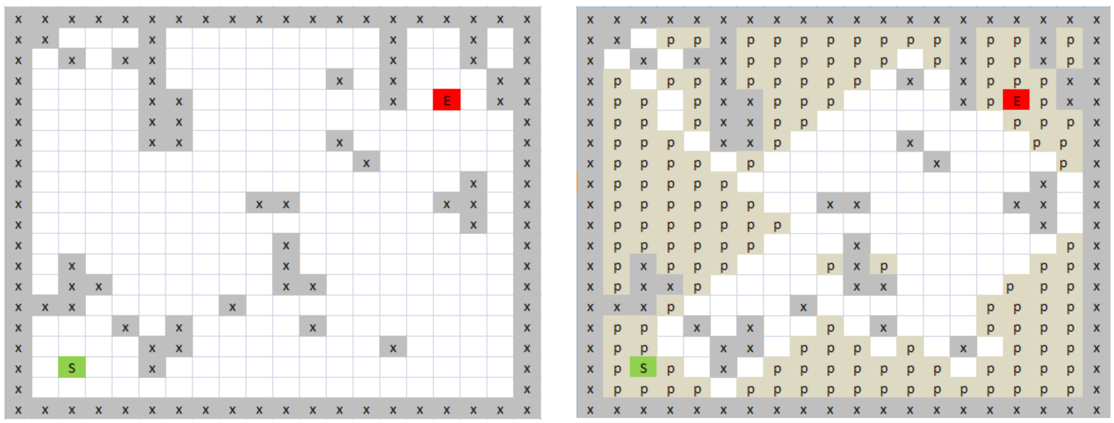

Fig. 3.8. Before and after pruning

Figure 3.8 represents the single start –single end point scenario. The figure on the left represents the problem before graph pruning. The green cell S represents the start point and the red cell E represents the end point. Grey cells marked with an x represent excluded areas and light grey cells marked with p represent the pruned area.

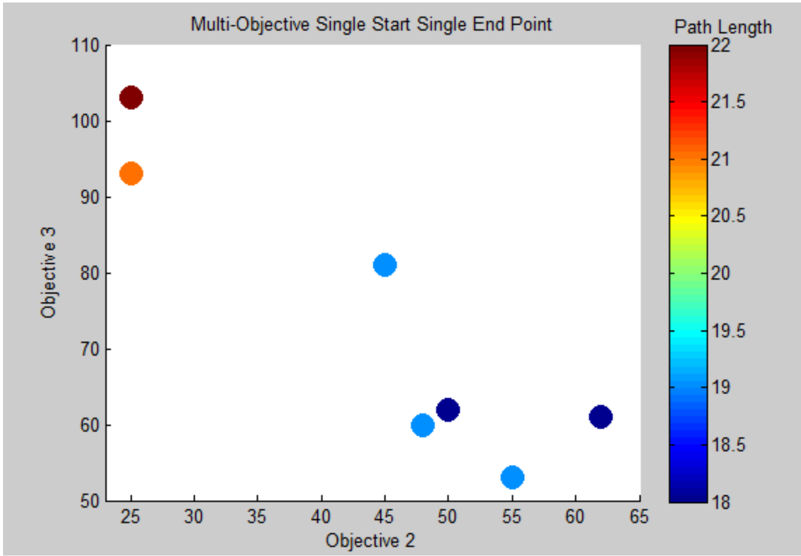

Fig. 3.9. Single start point - single end point data

The single start point – single end points scenario was run with 4 colonies of 30 ants. Figure 3.9 above illustrates the Pareto front between all 3 objectives after 100 runs. Objective 2 is on the x-axis, objective 3 on the y-axis and the length of the path is represented by the color bar. The run was completed in 200 seconds and was comprised of a total of 2,678,148 ant steps.

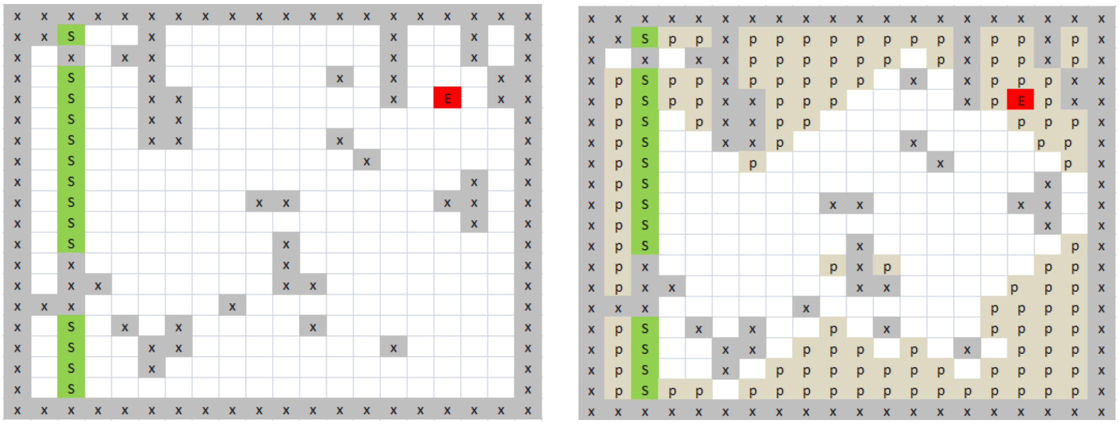

Fig. 3.10. Multiple start points before and after pruning

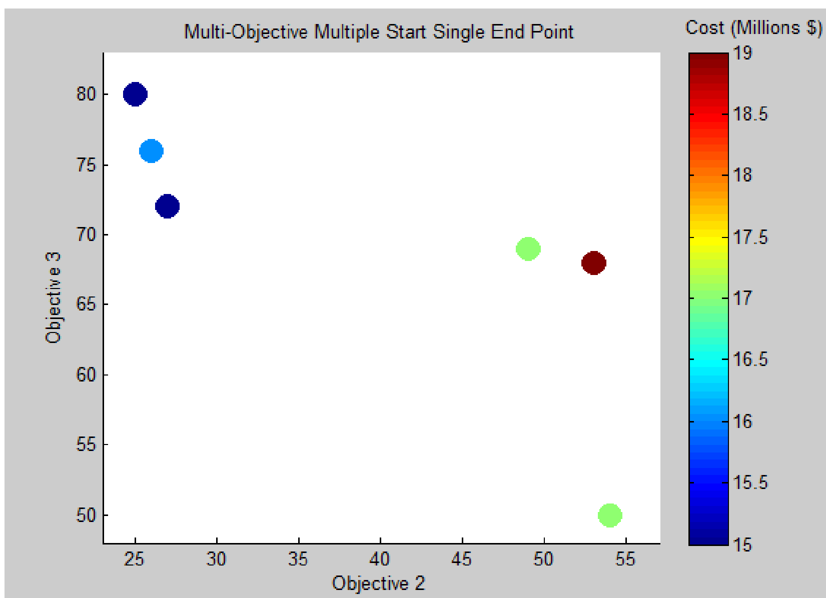

Fig. 3.11. Multiple start points - single end point data

The multiple start points – single end point scenario was run with 5 colonies of 30 ants. Figure 3.10 displays the search area for the case study and Figure 3.11 above illustrates the Pareto front between all 3 objectives after 100 runs. Objective 2 is on the x-axis, objective 3 on the y-axis and the length of the path is represented by the color bar. The run was completed in 1279 seconds and was comprised of a total of 5,310,738 ant steps.

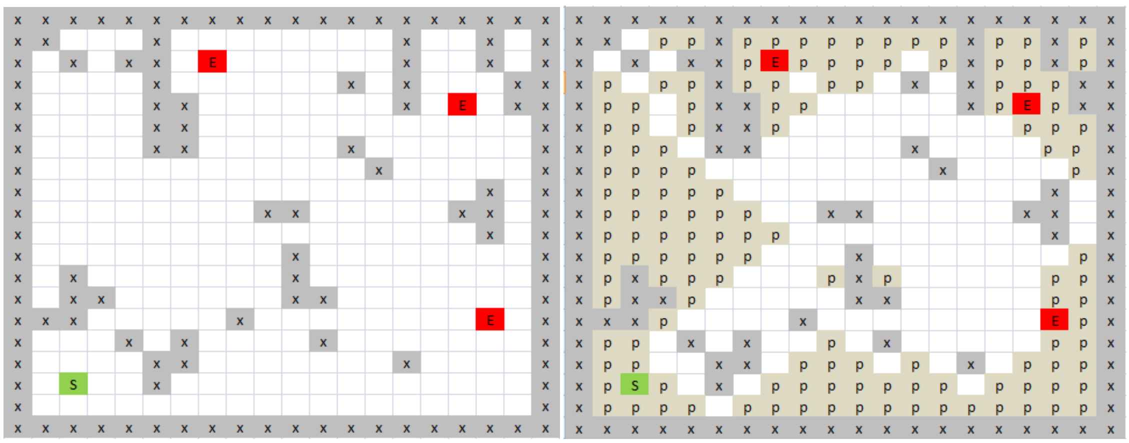

Fig. 3.12. Multiple end points before and after pruning

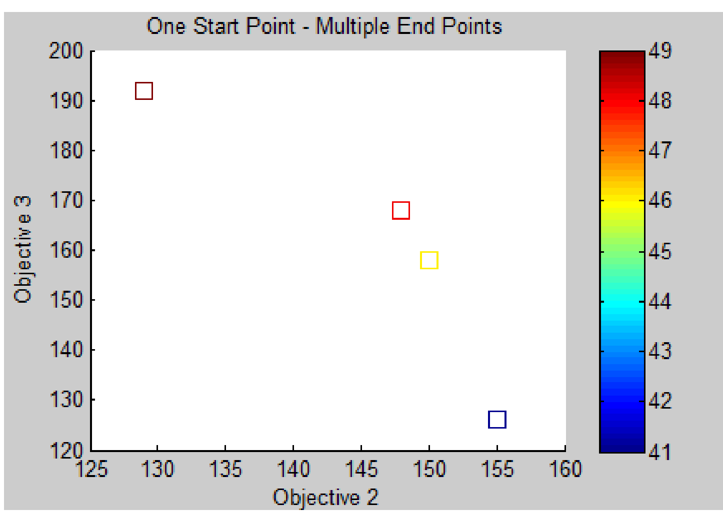

Fig. 3.13. Single start point - multiple endpoints data

The single start point – multiple end points scenario was run with 5 colonies of 30 ants. Figure 3.12 displays the search area for the case study and Figure 3.13 above illustrates the Pareto front between all 3 objectives after 100 runs. Objective 2 is on the x-axis, objective 3 on the y-axis and the length of the path is represented by the color bar. The run was completed in 732 seconds and was comprised of a total of 10,897,532 ant steps.

This case study has demonstrated the ability of the algorithm to find solutions for multiple objective routing problems on a grid network. The algorithm is able to find an approximation of Pareto optimal solutions for problems with multiple possible start points and multiple end points. It is interesting to note that the algorithm took approximately two times as many ants within 100 runs to find a set of solutions for the problem with multiple start points, as compared to the problem with one start point and one end point. This is because it takes more time to transition from the exploration phase of the algorithm to the exploitation phase because the ants are searching from multiple start points as opposed to just one. It also takes approximately four times as many ants within 100 runs to find a set of solutions for the problem with multiple end points, as compared to the problem with one start and one end point. This is because in the multiple end point problem there are divisions of ants within each colony. In this case each colony sent out 90 ants, 30 in each division, to search for a solution.

3.8 GRID DOMAIN LIMITATIONS

The algorithm's performance is restricted by the size of the search domain that it can solve in an efficient amount of time. Because the ant colony optimization algorithm is a constructive search technique that requires multiple iterations to obtain an optimal solution, there is a limit on the size of the search domain that the algorithm can feasibly explore. A case study was conducted to analyze the performance of the algorithm versus different domain sizes. The case study determined the number of ants that it takes to find a path between two corners of a uniformly weighted square domain. Because an ants' path terminates when it has cornered itself and not found a solution, it will usually take multiple ants to finally find a solution. This experiment explored the relationship between the number of ants necessary to find a path in relation to the size of the domain that the ants are exploring. Figure 3.14 illustrates the relationship. From the figure you can see that as the size of the search domain increases, the number of ants required to find a solution increases exponentially.

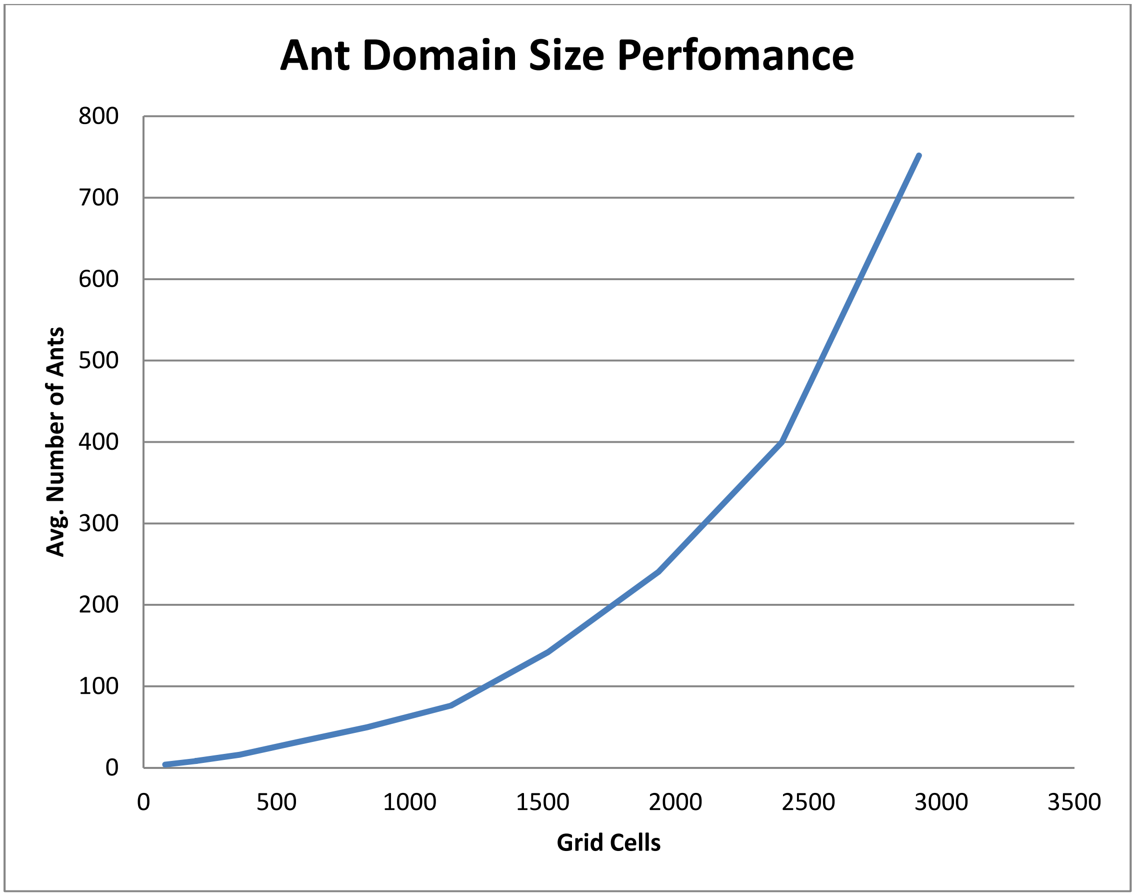

Fig. 3.14. Ant domain size performance

4. WHITE HILLS ICE ROAD CASE STUDY

4.1 INTRODUCTION

The motivation to develop this algorithm came from a project called the North Slope Decision Support System (NSDSS), comprised of a team of engineers and scientist from the University of Alaska Fairbanks, Texas A&M University, and Atkins and funded by the U.S. Department of Energy. The North Slope Decision Support System has been developed to create a water resources management solution for ice road construction in support of oil and gas exploration on Alaska's North Slope. NSDSS considers multiple objectives and values among various stakeholders including federal, state, and local agencies, non-governmental organizations, and private energy companies. Part of this solution is to develop an algorithm capable of finding optimal ice road routes.

In April of 2011 the NSDSS team held a workshop in Fairbanks, Alaska with various stakeholders in order to showcase the tool in its third stage of development. In the final day of the workshop, attendees were invited to give feedback and share ideas of possible case studies they thought the NSDDS tool could be applied to. From this exercise, the White Hills ice road was recognized as a good candidate for a case study to test the ability of the ice road planning tool. In the judgment of Alaska DNR personnel, it was both challenging and very well built. This case study would provide an opportunity to test the abilities of the tool to develop an ice road by comparing it to an existing ice road that was well designed and built in the opinion of multiple ice road experts.

The White Hills ice road was built for the drilling season of 2007-2008 by Union Oil Company of California (UOCC) a wholly-owned indirect subsidiary of Chevron Corporation. Initial operations were staged from the Franklin Bluffs gravel pad at milepost 39.6 of the Dalton Highway. Ice Roads were constructed from the Franklin Bluffs staging area to the first well location, Smilodon 9-4-9; south to the second well location, Mastodon 6-3-9; and north to the third well location, Panthera 28-6-9. Using data gathered from Chevron reports on the White Hills ice road, a case study was developed to replicate the ice road planning scenario within the NSDSS tool. Without any knowledge of the prior route of the road, the tool was used to build an ice road to the potential oil exploration sites.

4.2 BACKGROUND

The North Slope of Alaska covers roughly 230,000 km^2 on the northern portion of Alaska between the Arctic coast and the Brooks Range. The North Slope is home to a vast petroleum reserve that is currently being exploited and which provides a large amount of income for the state of Alaska and its residents. The oil fields on the North Slope near Prudhoe Bay produce 16 percent of the United States' domestic oil supply, along with 90 percent of Alaska's state revenues (Bourne 2006).

The North Slope of Alaska is home to the largest oil reserves in North America. The Prudhoe Bay oilfield was discovered in 1968 and by 1977 the Trans-Alaska pipeline was completed which kicked off oil exploration on Alaska's North Slope. Since then oil and gas activity on the North Slope has flourished.

"The state of Alaska currently receives almost 90% of its general fund revenues from petroleum revenues (royalties, production taxes, property taxes, and corporate income taxes) and will remain heavily dependent on these revenues for the foreseeable future" (Sheets 2009). The State Royalties Returned are annual payments to every resident of Alaska, including children, and has grown steadily from a few hundred dollars in the early 1980's to about $1,174 in 2011 (ADR 2011) .There has been recent interest to commercialize gas resources on the North Slope by building a pipeline to transport gas from the North Slope to major gas markets. This gas pipeline will allow the North Slope natural gas resources to be exploited alongside the crude oil that is pumped and delivered to Valdez via the Trans-Alaska pipeline. With the construction of a gas pipeline, long term exploration on the North Slope seems all but certain. In addition, There is huge support for an expansion of drilling activities into new areas on Alaska's North Slope from a majority of Alaskans, including every governor, senator, and house representative for the past 25 years (ANWR 2011).

A major component of oil and gas exploration is the infrastructure which is built and maintained to support such activities. The construction of buildings, roads, pipelines, power lines, and well pads cause alterations to the North Slope landscape. Some of the most common types of infrastructure are ice roads and ice pads which provide a cost effective means to support travel and construction activities during the winter season, while minimizing the negative impacts to sensitive tundra and North Slope species.

Prior to the adoption of ice road construction, the majority of roads on the North Slope were constructed from gravel. This type of road construction has damaging effects on the tundra as well as the wildlife on the North Slope. Roads have direct impacts over the tundra they cover and kill but also can have impacts on the tundra around them. Heavy travel on these roads can induce severe, chronic dust deposition to the surrounding ecosystems (Auerbach et al. 1997).

Ice roads are commonly used in exploration activities because they induce less damage and stress to the underlying tundra and melt away during the spring thaw. They do however have an effect on the ecosystem as they require a large amount of water for construction which could potentially have a negative impact on the water balance and water chemistry of the North Slope lakes. Prior to ice road and ice pad construction, to support exploration activities temporary roads were carved out of the tundra during the summer season. This invasive approach left lasting scars across the tundra that can still be seen today and are unlikely to recover in the near future. The tundra of the North Slope is extremely sensitive to disturbances and is slow to recover from damage (McKendrick 1987). Ice roads and ice pads provide a non-invasive way to build temporary roads and support travel for oil exploration activities. During the beginning of the winter season when the tundra underneath is frozen over, construction teams pump water from the North Slope lakes, mix the water with ice chips and snow slurry, and spray it on the road site, creating a layer of ice. This layer of ice supports travel on the North Slope during the winter season. In the spring the ice road melts turning into runoff and the underlying tundra is largely unaffected. Ice roads are thus a much better option for exploration infrastructure in terms of costs and the effects on underlying tundra.

Climate change also continues to have a large impact on exploration season of the North Slope. “Alaska’s North Slope is especially vulnerable to climatic change because higher latitudes are subject to positive snow- and sea ice-atmosphere feedbacks under warming conditions and because the dynamics of frozen seascapes and landscapes are tightly determined by thermal regime” (Kittel et al. 2011). Because of a multitude of factors including management decisions, different measurement techniques, and climate change, the winter season for oil exploration and development was reduced from 200 days in the 1970s to 100 days by the early 1990s (Campbell 2009). Today the oil exploration season has rebounded from its low levels in the 1990s and is open for around 150 days.

NSDSS has been developed to create a water resources management solution for ice road construction which considers multiple objectives including optimal water use, direct and cumulative environmental impacts, and cost reduction. The solution includes an information system, and decision support tools to develop and analyze ice road plans.

4.3 METHODOLOGY

The White Hills ice road case study has been developed within NSDSS.net, a Microsoft Silverlight-based web application which serves as the front end of the NSDSS system. It is a GIS-based map application with four modules that interact with the map:

Data Exploration, Data Publishing, Environmental Analysis, and Ice Road Planning. It is here that users can develop ice roads, upload data, and run environmental analysis.

The major difference between this case study and Bois D'Arc Reservoir pipeline routing study is that the algorithm used within this study is not multi-objective in the sense that it uses a traditional approach to multi-objective routing by reducing all the objectives into one objective. The algorithm considers objectives such as material costs, distance from permitted lakes (supply points), as well as travel time and construction duration. A monetization factor is applied to every objective so that the algorithm develops a least cost path.

The White Hills Ice Road was built in 3 sections. One section from the Franklin Bluffs staging area to the well location Smilodon has 8 river crossings and is approximately 54 km long. The second section from Smilodon north to Panthera has 5 river crossings and is approximately 16 km long. The third section from Smilodon south to Mastodon has 1 river crossing and is approximately 9 km long. A map of the preliminary route developed by Chevron is given below. Each of these three sections were modeled separately within the ice road planning module.

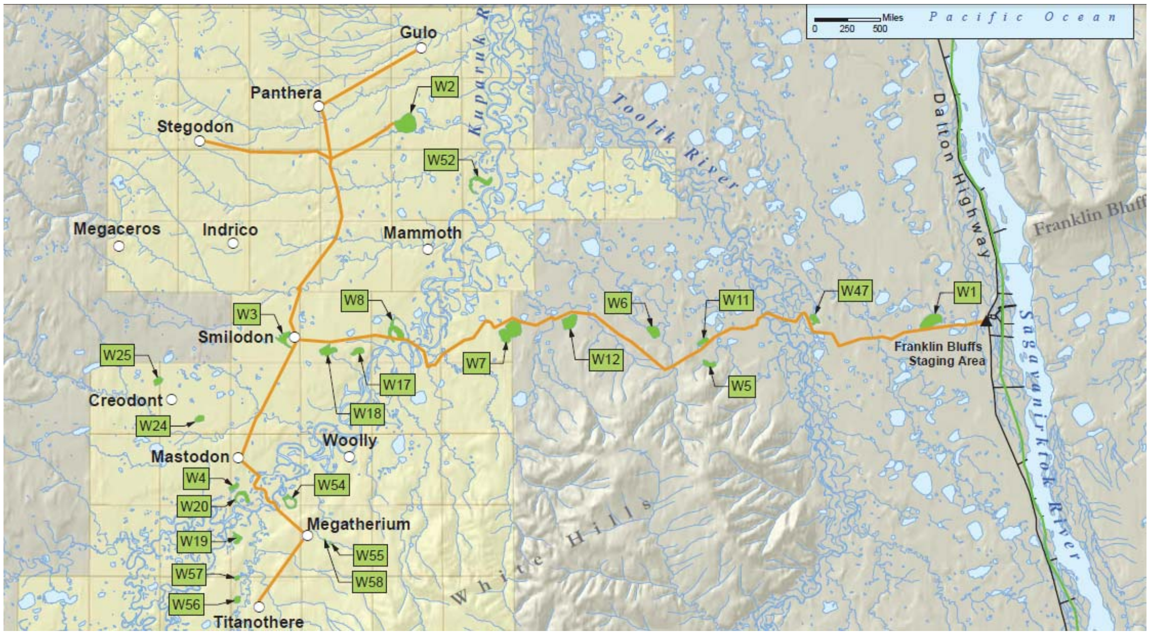

Fig. 4.1. Preliminary route (Sullivan 2007)

Figure 4.1 illustrates the preliminary route of the White Hills ice road developed by Chevron. The map also displays the lakes that were permitted for water withdrawal in the area (Sullivan 2007).

In order to model the route within NSDSS the river crossings were used as waypoints between the start and end point. This is because it is assumed that before the ice road planning process, desirable river crossings are predetermined. The river crossings used are illustrated in Figure 4.2. According to Matthew Whitman, a fisheries biologist with the U.S. Bureau of Land Management, stream locations that freeze over completely are best for river crossings because of the need to minimize impacts on winter fish habitats (Bailey 2010). During the summer, the potential route is walked and desirable stream locations are located before the route is planned. Ice bridges which are much thicker than ice roads in order to support the weight of vehicles crossing over are built at these stream crossing locations. After the season is over the bridges are broken up into chunks and removed before melting occurs to prevent flooding (Campbell 2009).

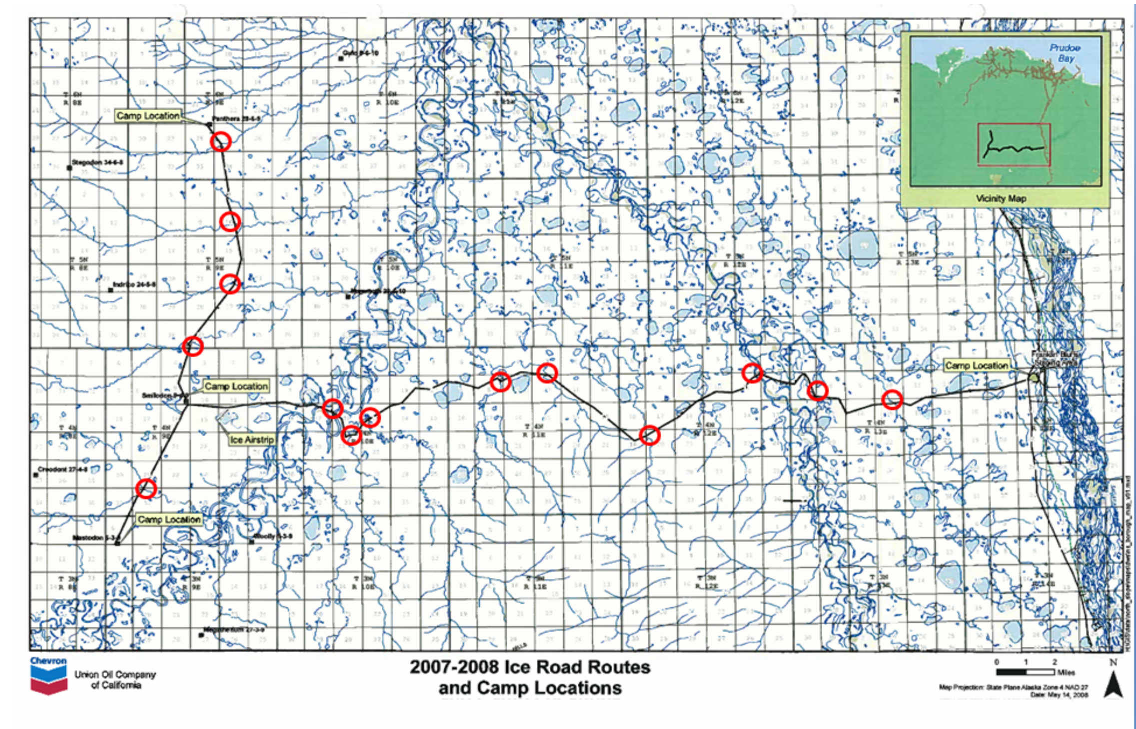

Fig. 4.2. River crossings. The figure above illustrates the preliminary White Hills ice road design (Sullivan 2008), the river crossings are marked by red circles.

In all there were 27 lakes permitted for use for the White Hills Ice road. A lake study was conducted by Arctic Slope Regional Corporation (ASRC) Energy Services, Regulatory and Technical Services (AES-RTS) (Sullivan 2007). This report provided a summary of recommended winter water withdrawals supporting onshore exploration drilling, lake bathymetry for lakes south of the proposed Mastodon drill site, and information on fish species and water quality for the 28 lakes surveyed. The amount of water permitted for withdrawal in each lake differs depending on several different factors. One is whether or not sensitive fish species are present. If sensitive fish species are present, water withdrawal is limited to 15 % of the volume under 7 feet of ice. The water withdrawal permitted for lakes with non-sensitive fish species present is 30% of the water volume under 5 feet of ice. This is due the greater tolerance of non-sensitive fish species to lower dissolved oxygen and higher concentration of dissolved solids. For all non fish bearing lakes as maximum of 20 percent of the total lake volume is available for water and ice chips. Table A.1 in the appendix contains the Lakes that were studied as well as the permitted amount of water available within each lake.

Within the NSDSS tool the Ice Road Planning module is used to conduct ice road case studies. The Ice Road Planning module allows users to develop their own ice road plans and analyze the results over multiple planning objectives. The Ice Road Planning module has four input setting categories that the user customizes to build an ice road. Within the spatial settings of the Ice Road Planning module the user can select the start point and end point using either the mouse or the latitude and longitude coordinates. The user is also able to modify the grid cell size to be used – the default is 2000m. Within the map input settings of the module the user is able to select the way points between the start and end point, select the lakes used for ice road construction material, and define exclusion zones within the search domain. Exclusion zones represent areas of the search space that the algorithm will not search in. These exclusion zones must be spatially defined within the tool by the user and can represent areas such as sensitive tundra, or polar bear zones that the user wishes to eliminate from the search space. Within the planning inputs settings the user can customize the type of road, earliest construction date, tundra opening date, and construction equipment available. The monetization factor of all three objectives can also be adjusted which include travel time ($/minute), construction cost ($/Dollar), and construction duration ($/day).

After defining all the previous settings, the first processing step Get GeoSpatial Data is run. This function loads in the geospatial input data of each grid cell from the server. Finally the Find Optimal Ice Road Routes function is run which determines the best ice road routes and gives the results in the pane of the Ice Road Planning module.

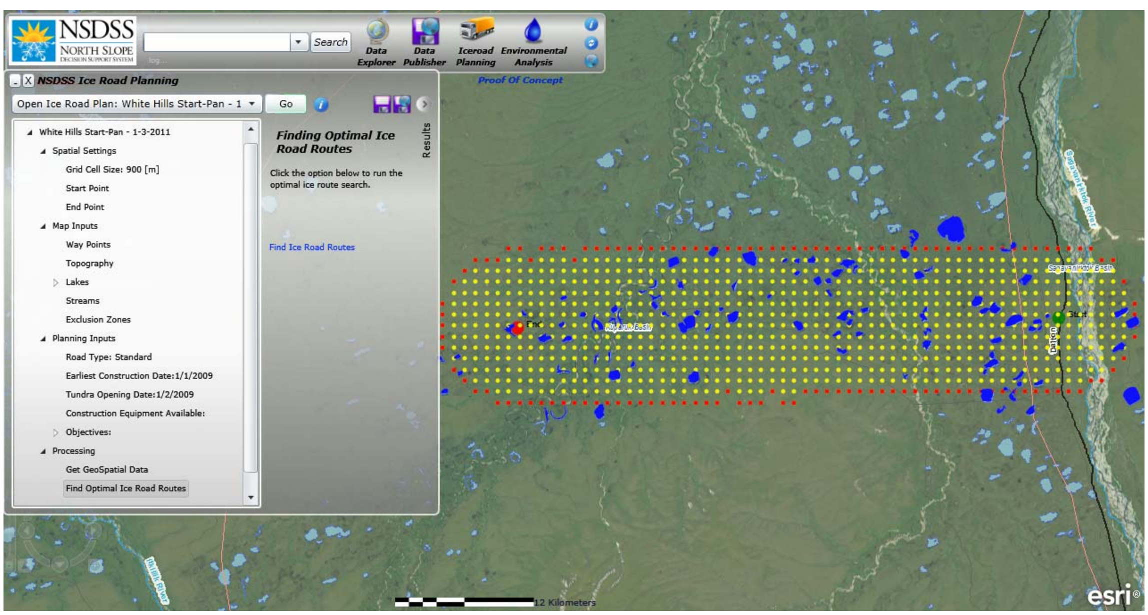

Fig. 4.3. NSDSS.net screenshot

Figure 4.3 is a screen shot of the ice road planning modules within NSDSS.net. The panel on the left shows the 4 different input settings categories and the map illustrates a search domain created within the tool.

4.4 RESULTS AND ANALYSIS

The Ice Road Planning module was run for the White Hills ice road scenario. Because the ice road had three separate sections and the river crossings were predetermined, the ice road was split at the Smilodon junction and the tool was run separately for all three sections. The first section was from the Franklin Bluffs staging area to the well location Smilodon, the second section from Smilodon north to Panthera, and the third section from Smilodon south to Mastodon. Each river crossing was used as waypoints between the start and endpoints. The model was run using 500 meter grid cells.

The four objectives tied to the cost of the road are travel time, construction cost, construction duration, and distance from supply points. The two routes were compared based on the costs associated with the routes length and spatial location. The travel time, construction cost, and construction duration are all costs associated with the length of the path. The distance from supply points is associated with the spatial location of the path in relation to the permitted lakes used for water withdrawal. The results developed from the model were compared against what was designed as a preliminary route by Chevron. The NSDSS route summary is given in Table 4.1 and a comparison of the results is given in Table 4.2. Figure 4.4 illustrates the two separate routes.

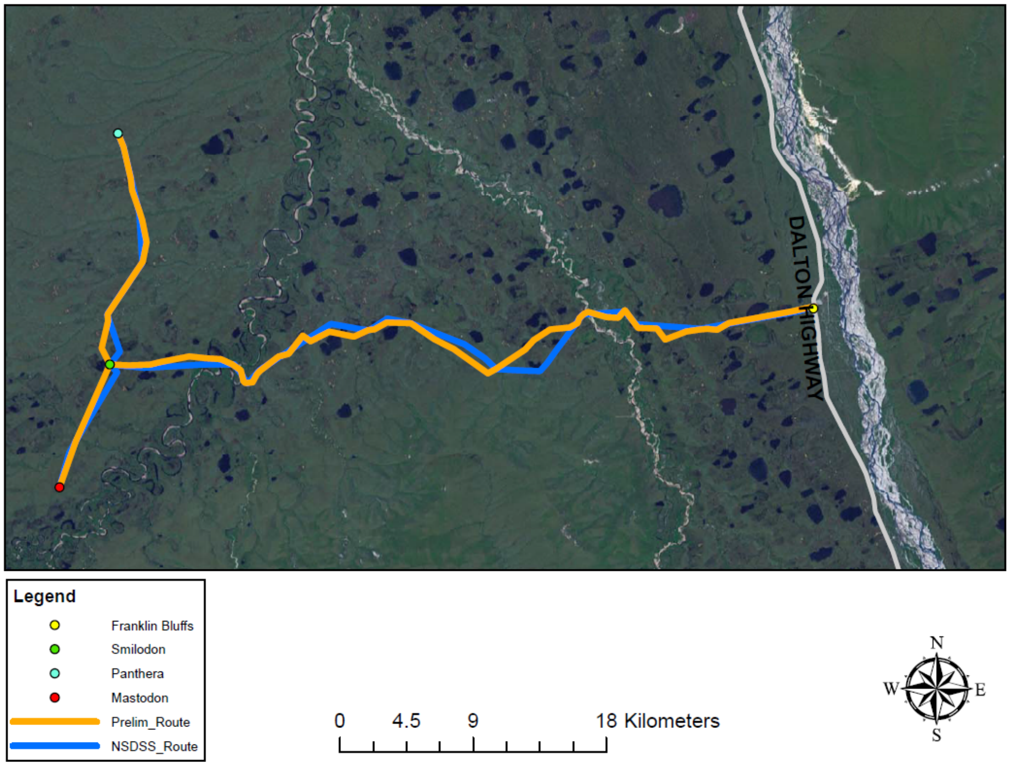

Fig. 4.4. Preliminary route vs. NSDSS route

Table 4.1. NSDSS Route Summary

WHIR Section	Length (miles)	Cost (Million $)	Water Used (M gal)	Avg. Haul Distance (miles)
Start Point to Smilodon				
1	4.53	1.15	10.359	1.63
2	3.26	0.86	7.454	0.68
3	1.62	0.35	3.704	5.6
4	4.57	1.16	10.444	5.2
5	3.8	1.01	8.698	7.99
6	1.7	0.41	3.893	0.54
7	4.88	1.2	11.158	6.67
8	0.73	0.19	1.668	4.9
9	0.91	0.2	2.087	0.95
10	5.22	1.32	11.944	6.39
∑	31.22	8	71.41	4.61
Smilodon to Pantera				
11	2.14	0.52	4.889	7.3
12	2.71	0.68	6.205	11.56
13	2.05	0.54	4.682	21.09
14	2.76	0.62	6.307	3.36
15	0.62	0.2	1.423	3.29
∑	10.28	3	23.51	9.87
Smilodon to Mastodon				
16	3.51	0.85	8.026	3.6
17	2.11	0.55	4.823	18.56
∑	5.62	1	12.85	9.22
Total	47.12	12	107.76	6.31

Within the NSDSS tool the final route had a final cost value of $12,000,000, was 47.12 miles in length, used an estimated total of 108 million gallons of water and had an average haul distance of 6.31 miles.

Table 4.2. Route Length Comparison

WHIR Section	Preliminary Design Route	NSDSS Route
	Length (miles)	
Start Point to Smilodon		
1	4.91	4.88
2	3.78	3.43
3	1.95	1.75
4	4.53	4.84
5	4.24	4.13
6	1.86	1.91
7	5.27	5.19
8	1.02	0.76
9	1.01	0.97
10	5.24	5.24
∑	33.81	33.09
Smilodon to Pantera		
11	2.22	2.34
12	2.65	2.62
13	1.78	2.11
14	0.93	2.84
15	0.61	0.61
∑	8.20	10.52
Smilodon to Mastodon		
16	3.53	3.70
17	2.04	2.19
∑	5.58	5.89
Total	47.58	49.50

In order to compare the two routes the map of the White Hills ice road preliminary design developed by Chevron, and the routes developed by NSDSS were digitized and georeferenced within ArcGIS. After this the routes were analyzed using tools within GIS. The preliminary route had a total length of 47.58 miles. The route developed by NSDSS had a total length of 49.50 miles, 2.38 miles more than the length calculated by NSDSS. This difference can be attributed to the error in digitizing and georeferencing the map within GIS.

Each run within NSDSS produced the 10 best routes according to the costs. The table of results displays the length (miles), cost (million $), water used (million gallons), and the average haul distance (miles). The results table for section 12 is shown in Figure 4.5. The results were then plotted using the length of the path, cost, and the average haul distance. The plotted results for section 12 are given in Figure 4.6.

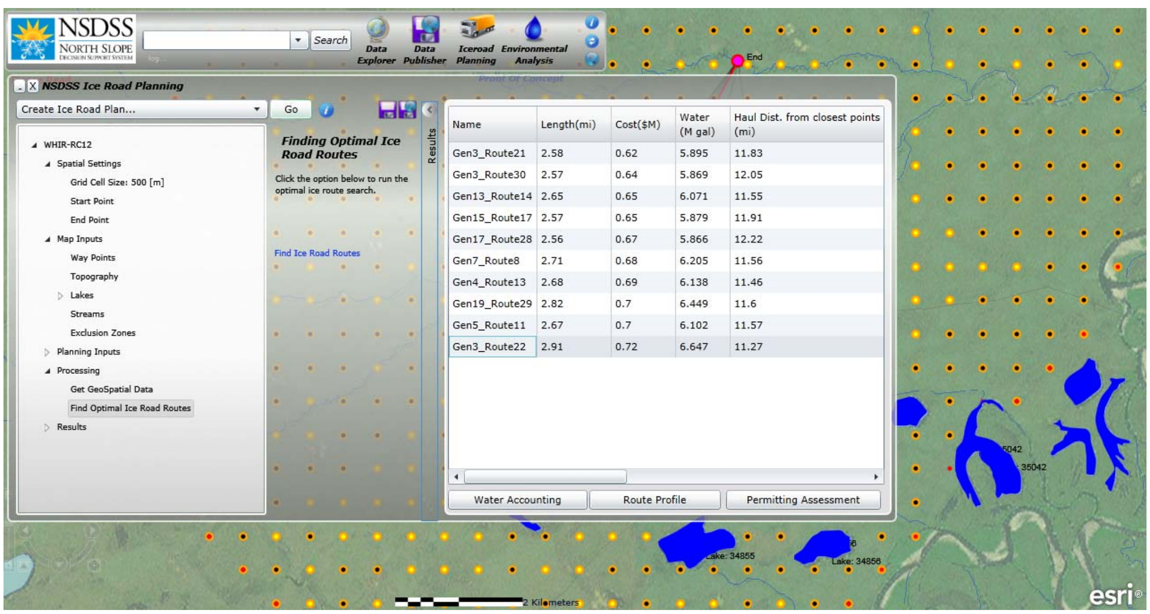

Fig. 4.5. NSDSS section 12 results

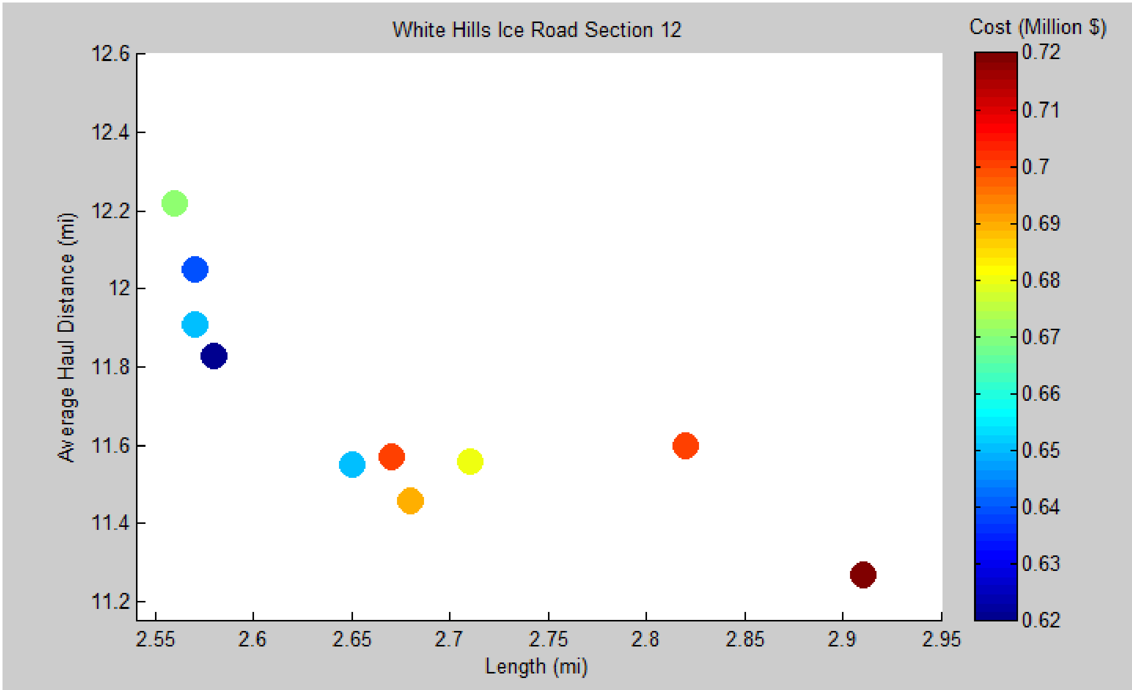

Fig. 4.6. NSDSS section 12 results – plot

Figure 4.6 illustrates the relationships between the length of the path, the average haul distance, and the cost of the path. Plots for each section can be found in the appendix. From this figure you can see that the path with the shortest length is not necessarily the path with the lowest cost. When factoring in the costs associated with the haul distance, the most desirable path is one which minimizes both the length of the path as well as the haul distance.

This case study has proven the effectiveness of using multi-objective ant colony optimization to develop least costs paths with a construction distance constraint. The case study has demonstrated the ability of the algorithm to be used as an effective means of producing approximate Pareto-optimal solutions for ice road routing problems. The ice road planning module within NSDSS can be used as a useful tool in determining desirable ice road routes at a planning level. By using a system that produces Pareto-optimal solutions for different ice road planning scenarios, a decision maker can evaluate the tradeoffs between alternatives.

5. REGION C CASE STUDY

5.1 INTRODUCTION

This multi-objective algorithm is not confined in applicability to ice road planning, there are multiple types of infrastructure planning to which this particular multiple objective ant colony optimization algorithm can be used. Many types of infrastructure routing problems are relatable in that they share common objectives such as construction costs, length, environmental impacts, etc. One type of infrastructure routing problem in particular that can be solved using this algorithm is that of raw water distribution systems. Raw water transmission routing, like ice road planning, is a multi-objective routing problem which this algorithm can be easily applied to. A case study has been developed to apply the MOACO algorithm to a raw water transmission system design.

In order to test the performance of the algorithm in a real world infrastructure planning application outside of ice road planning, a case study was conducted using the algorithm to route a raw water transmission pipeline in the Region C water planning district. The Region C planning district is comprised of 15 counties in North Texas including Dallas and Tarrant counties. Because the population of North Texas is growing and is projected to continue to grow substantially in oncoming years (Gooch et al. 2011), water managers are looking for new water supplies to meet the growing demand. One solution to create a new water supply is the construction of the Lower Bois D'Arc Creek Reservoir in Fannin County. The project is being funded by the North Texas Municipal

Water district, a government entity that provides potable water to 1.3 million customers in parts of Collin, Dallas, Denton, Fannin, Hopkins, Hunt, Kaufman, Rains, and Rockwell counties. Bois D'Arc Reservoir is expected to be a 17,000 acre lake with a storage capacity of 367,609 million gallons, and a yield of 113 million gallons per day to serve the water supply needs of the Dallas-Fort Worth area (Rich 2009). As part of this project a water transmission pipeline was designed to carry raw water south of the reservoir to a water transmission facility located near Lavon Lake in Collin County.

The preliminary design calls for a primary 90-inch pipeline running 29 miles from Bois D'Arc Reservoir to a 460-million gallon terminal storage reservoir which is located near the newly constructed water treatment plant outside of the town of Leonard. The discharge from the Leonard storage reservoir is to be comprised of 14.4 miles of 66-inch pipeline and an outfall structure at Pilot Grove Creek (Rich 2009). This pipeline was selected as a case study because it had recently been designed and would allow for a comparison between the routes the algorithm produces versus what was actually designed to be built. By comparing the results for the algorithm versus the actual preliminary design, the quality of the results can be determined using the preliminary design as a standard.

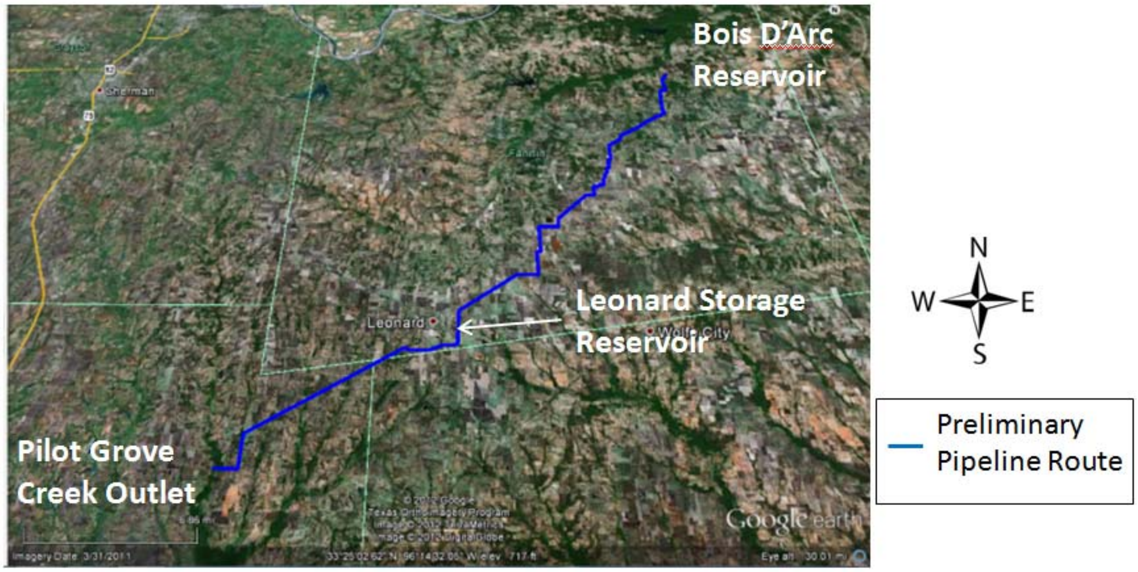

Fig. 5.1. Preliminary pipeline route

Figure 5.1 above represents the preliminary pipeline route developed by Alan Plummer & Associates. The pipeline goes from the Bois D'Arc Reservoir south to the Leonard Storage Reservoir and from there to the outlet point at Pilot Grove Creek.

5.2 METHODOLOGY

The purpose of this case study is to demonstrate the applicability of the algorithm to a raw water transmission routing problem. This Region C pipeline routing problem provides a good case study of a contemporary infrastructure routing problem. A preliminary route of the pipeline was developed by Alan Plummer Associates, Inc. "The study consisted primarily of desktop analyses using information such as USGS topographic maps, aerial photography, NRCS digital soil map data, and National

Wetland Inventory (NWI) maps to identify potential wetlands, streams, and other water bodies that may be waters of the U.S. and could be affected by the pipeline construction" (Manning 2011). This preliminary pipeline route will be used as a comparison against what the algorithm develops within the model.

The design of raw water transmission facilities considers multiple objectives such as cost, time of construction, environmental impacts, easements and risk. Within this particular case there are two objectives used within the algorithm to determine the desirability of each path. The first criterion is the cost of the pipe used to deliver the raw water. The second is a level-of-impact scoring system which determines the level-of-impact from the pipeline route given the land use type. The level-of-impact scoring system developed could be used for raw water transmission routing or other pipeline infrastructure. This multi-objective approach delivers solutions that both consider the construction and material cost as well as non-material impacts and costs such as rights-of-way, permits, and mitigation. Even though the level-of-impacts can be assumed to be a measure of potential costs, there is a substantial amount of ambiguity and uncertainty due to the multitude of possible costs, permits, and time constraints that are associated with each specific impact. Thus, a level-of-impact scoring system provides a way to understand what the potential level of costs and time associated with a path might be. This impact score optimized alongside a construction and material cost, allows a planner and decision maker to understand the potential tradeoffs associated with a pipeline route. Furthermore, a decision maker can weigh specific impacts such as highway crossings or environmental impacts versus cost of pipe to gauge a tradeoff relationship between even more specific objectives.

The cost estimates were calculated using information from Appendix R of the Region C 2011 Final Plan. The Region C 2011 Plan was developed by a consultation team which includes Freese and Nichols, Alan Plummer Associates, CP&Y, and Cooksey Communications. The report is in response to Senate Bill One, passed by the 75th Texas legislature in 1997 to address Texas water issues. It gives the results of the latest round of planning for Region C which addresses the future water needs of Region C in Texas.

Appendix R contains cost estimate guidelines and specifications designed to be used for preliminary overviews and not for detailed feasibility analysis. The costs in the table for pipelines "are based on standard unit costs that include contractors' mobilization, overhead and profit. The unit costs do not include engineering, contingency, financial and legal services, costs for land and rights-of-way, permits, environmental and archeological studies, or mitigation" (Gooch et al. 2011). Table 5.1 displays the cost per length of pipe which was used to calculate the costs of the pipeline routes in the first objective.

Table 5.1. Pipe Costs

Diameter (Inches)	Base Installed Cost ($/Foot)	Cost with Appurtenances ($/Foot)	Assumed ROW Width (Feet)	Assumed Temporary Easement Width (Feet)
8	22	24	20	60
10	26	28	20	60
12	29	32	20	60
14	33	37	20	60
16	37	41	20	60
18	41	45	20	60
20	44	48	20	60
24	51	56	20	60
30	67	74	20	60
36	83	91	20	60
42	100	110	30	70
48	115	127	30	70
54	132	145	30	70
60	167	184	30	70
66	192	211	30	70
72	217	239	30	70
78	243	267	40	80
84	273	300	40	80
90	301	331	40	80
96	347	382	40	80
102	394	433	40	80
108	435	479	40	80
114	483	531	40	80
120	524	576	40	80

Notes: a. Costs based on class 150 pipe for long, rural pipelines.
b. Appurtenances assumed to be 10% of installed pipe costs.
c. For urban pipelines, add 20% to base costs and 35% to cost with appurtenances for pipes 40" or larger. Add more for smaller pipelines.
d. Adjust costs for obstacles (rock, forested areas) and easy conditions (soft soil in flat country).

The level-of-impact scoring system was used as a second objective. The scoring system determines the level-of-impact of the route based on the spatial location and land use. The impacts considered are construction impacts, right-of-way/easement requirements, business impacts, and environmental impacts. Each category has a level of impact score associated with the land use type which is rated on a scale of 1-5. Table 5.2 below represents the level of impact scoring criterion used.

Table 5.2. Level-of-Impact Scores

	Level of Impact				
Land Use	Const.	Right of Way /Easements	Business	Environ.	Total
Barren Land	1	1	0	0	2
Cultivated Crops	1	1	0	0	2
Deciduous Forest	1	1	0	0	2
Developed, High Intensity	2	5	4	0	11
Developed, Medium Intensity	2	4	4	0	10
Developed, Low Intensity	2	3	3	0	8
Developed, Open Space	2	2	2	0	6
Emergent Herbaceous Wetlands	2	1	0	3	6
Evergreen Forest	1	1	0	0	2
Hay/Pasture	1	1	0	0	2
Herbaceous	1	1	0	0	2
Mixed Forest	1	1	0	0	2
Open Water	1	1	0	3	5
Shrub/Scrub	1	1	0	0	2
Woody Wetlands	1	1	0	3	5

The scoring system of the algorithm was slightly modified to account for highway and railroad crossings. Where an ant is following a highway right-of-way, the level-of-impact score is reduced by 50% to account for the reduced right-of-way cost. When an ants' path crosses over a highway or railroad, there is a level-of-impact score of 5 to account for the impacts associated with crossing a major transportation corridor.

The first step in creating the model was to set up an ArcMap containing the necessary data to properly represent the problem. Land use information was obtained from USGS NLCD data. Aerial imagery, TxDOT roads, highways and rail lines, as well as hydrologic data were obtained through the Texas A&M University Library GIS Online Data. After collecting all of the data a rectangular area of interest was created encompassing the pipeline route from Bois D’arc Reservoir to the outlet at Pilot Grove Creek.

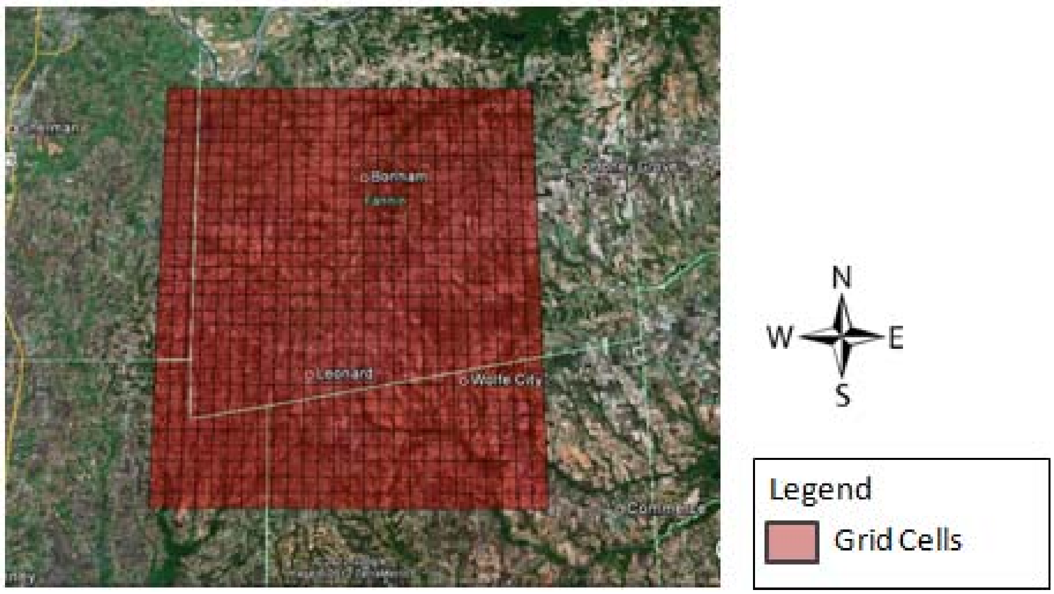

Fig. 5.2. Study area grid for pipe 1

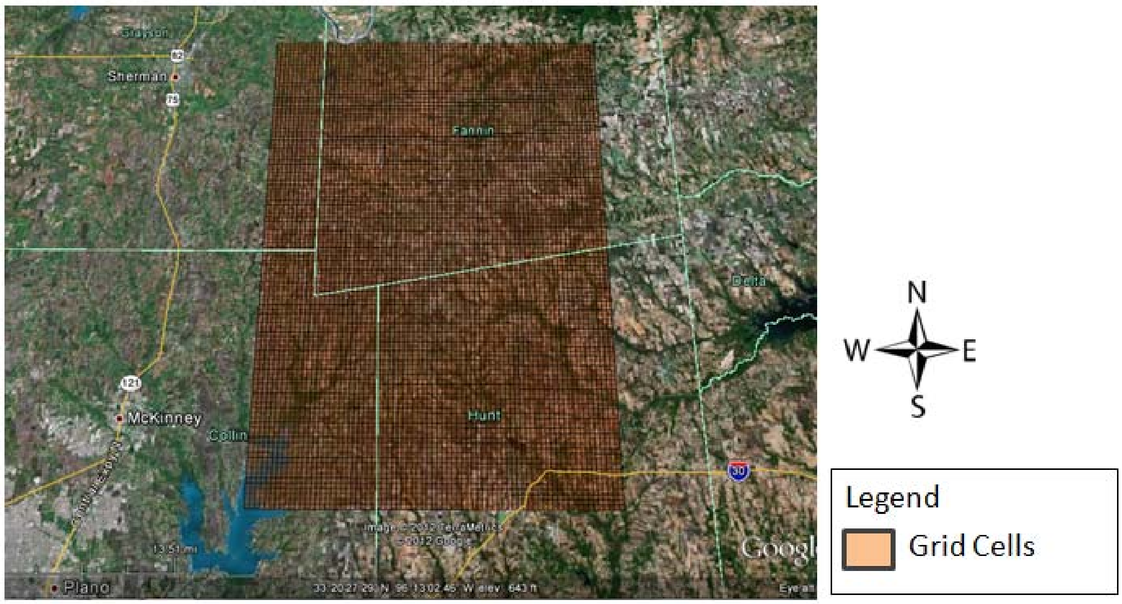

Fig. 5.3. Study area grid for pipe section 2

Because of the grid domain size limitations, the problem area was divided into different size grid cells for each of the pipelines. The study area for the first and largest pipeline from Bois D'arc reservoir to the Leonard reservoir was divided into grid cells approximately 0.5 square miles, each cell being 3370 feet wide. The study area for the second pipeline from Leonard reservoir to the outfall at pilot grove creek was divided into square grid cells 2,640 feet in length. Figures 5.2 and 5.3 illustrate the study areas for the two separate pipelines. In both cases the level of detail is sufficient to allow for a preliminary route study for this case and properly represents land uses, major infrastructure, and waterways. It is not a fine enough resolution to properly represent parallel utilities or utility crossings such as gravity sewers, water mains, power transmission lines, or oil and gas pipelines. It is also not fine enough to properly represent small public infrastructure such as parks, local and collector roads, public service facilities, schools, parks, airports, golf courses or cemeteries. This also does not take into consideration construction risk associated with tunneling, shaft construction or proximity to objects, it does not take into account specific hydraulic considerations such as bends and fittings and it does not account for cultural, archeological or historical impacts. Even though it does not represent these pertinent pipeline routing considerations, the level of detail used is sufficient for a preliminary route planning study which is not intended to take into account that level of detail.

The pipeline route was modeled in two separate sections. Because the pipe is intended enter the storage reservoir outside of the town of Levon, this location was used as a waypoint between Bois D'Arc Reservoir and the outlet structure at Pilot Grove Creek. A problem area was formulated by creating a buffer between the start point, waypoint and endpoint. The buffer distance b is a function of the distance x between the two points of interest of each section given by $b = {}^{x}/_{4}$. This method created two separate buffer areas, one between Bois D'arc Reservoir and Levon Reservoir and the other between Levon Reservoir and the outlet at Pilot Grove Creek. The distance between Bois D'arc Reservoir and Levon Reservoir is 23.7 miles, creating a buffer area of 251,253 acres. The distance between Levon Reservoir and the outlet at Pilot Grove Creek is 12.8 miles, creating a buffer area of 73,601 acres. The two buffered areas are shown in Figure 5.4.

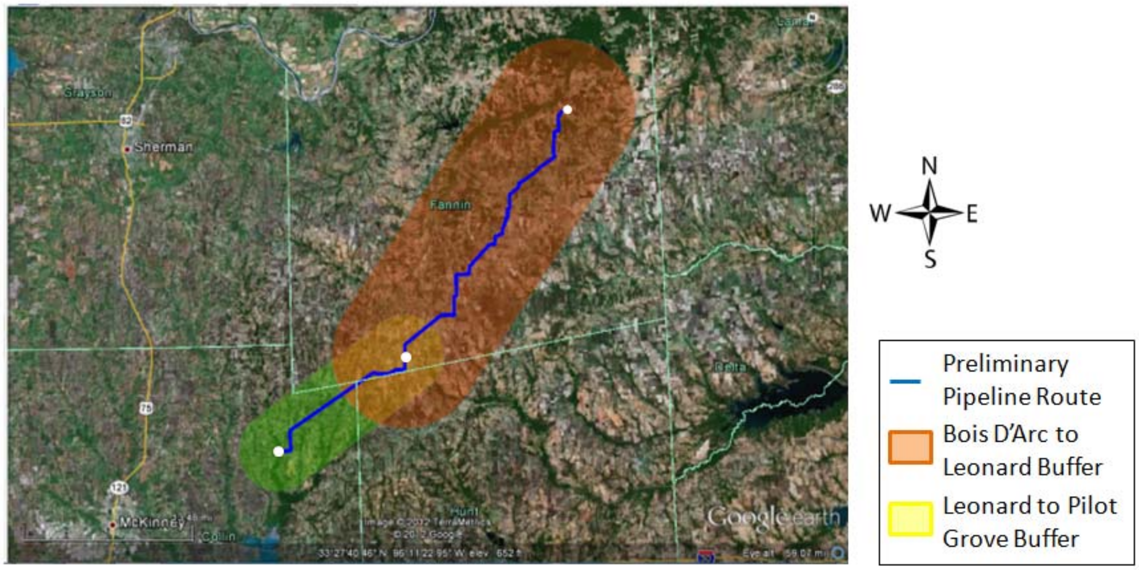

Fig. 5.4. Buffer zones

Once this map was created the pertinent information was exported into Excel and maps within Excel were formed. Landuse, highways, railroads, city boundaries and hydrologic data were imported and maps representing each were created within Excel. Figure 5.5 illustrates the land use values of the area of interest. Land use values were calculated as the land use at the center of each grid cell. This method is consistent with the method used to calculate the geospatial information using the ice road planning module within NSDSS.

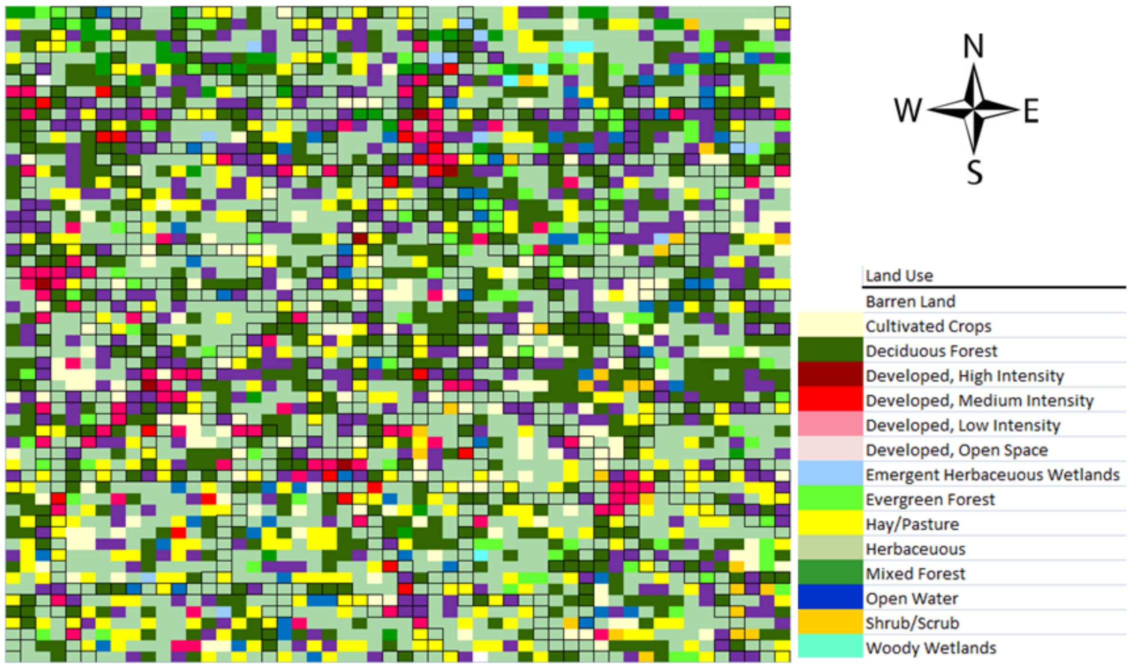

Fig. 5.5. Land use. This figure represents the different land uses within the Microsoft Excel model platform for pipe section 2. The cells with black borders represent major highways or railroads.

According to the U.S. Army Corps of Engineers there are impacts "that should be avoided and minimized to the extent practicable during final design by such means as: adjusting the pipeline alignment to avoid discrete water bodies such as wetlands and open waters, crossing streams at narrow points and at right angles to minimize crossing lengths, and reducing the construction easement clearing width to the minimum necessary at stream crossings to preserve existing riparian vegetation" (Manning 2011). Because of the low level of detail, minimizing final design objectives such as crossing lengths and stream crossings to narrow points is not possible. However, avoiding discrete water bodies such as wetlands and open waters is possible by making all wetlands and open water bodies exclusion zones. Figure 5.6 and 5.7 below illustrate the exclusion zones of both buffered areas within Microsoft Excel.

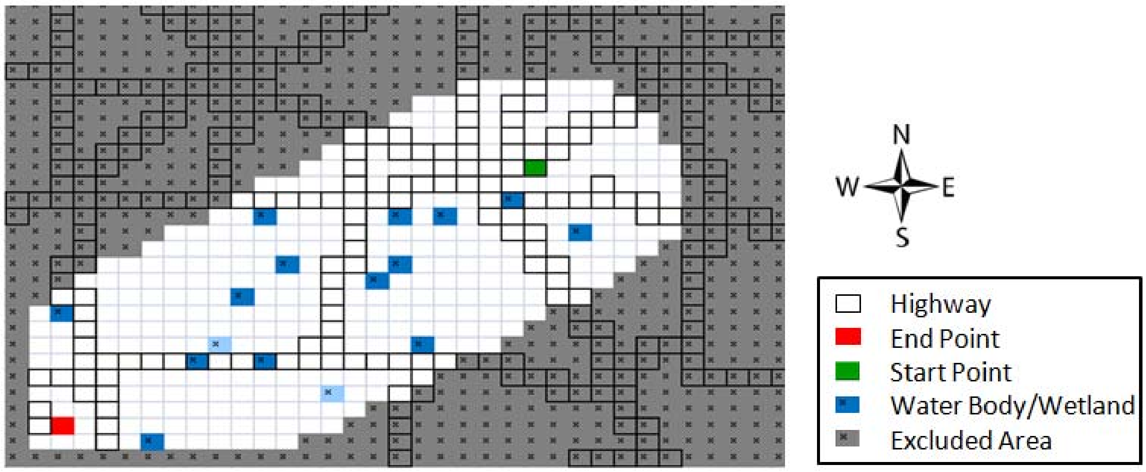

Fig. 5.6. Leonard Reservoir to Pilot Grove Creek - exclusion zones

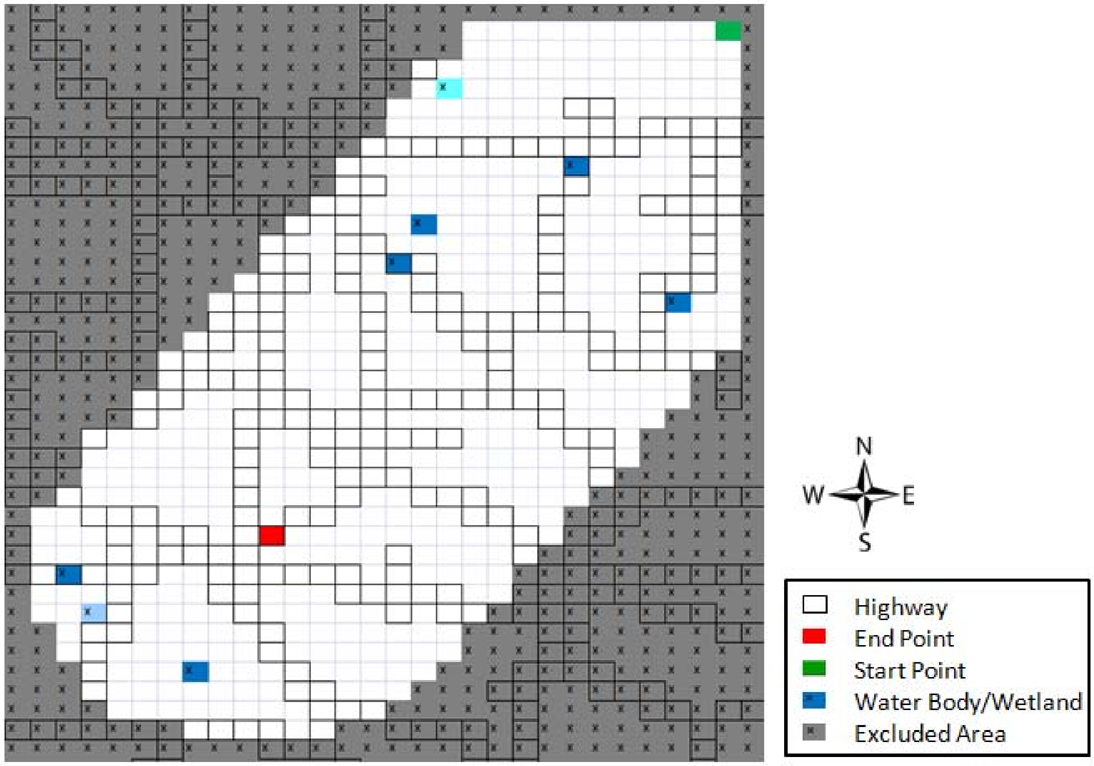

Fig. 5.7. Bois D'arc Reservoir to Leonard Reservoir - exclusion zones

The graph pruning algorithm was run for both sections using the water bodies and wetlands as exclusion zones. The pruning algorithm reduces the complexity of the problem by eliminating searching within the grid in areas that are unlikely to contain optimal solutions. Figures 5.8 and 5.9 represent the problem areas after the pruning algorithm is run.

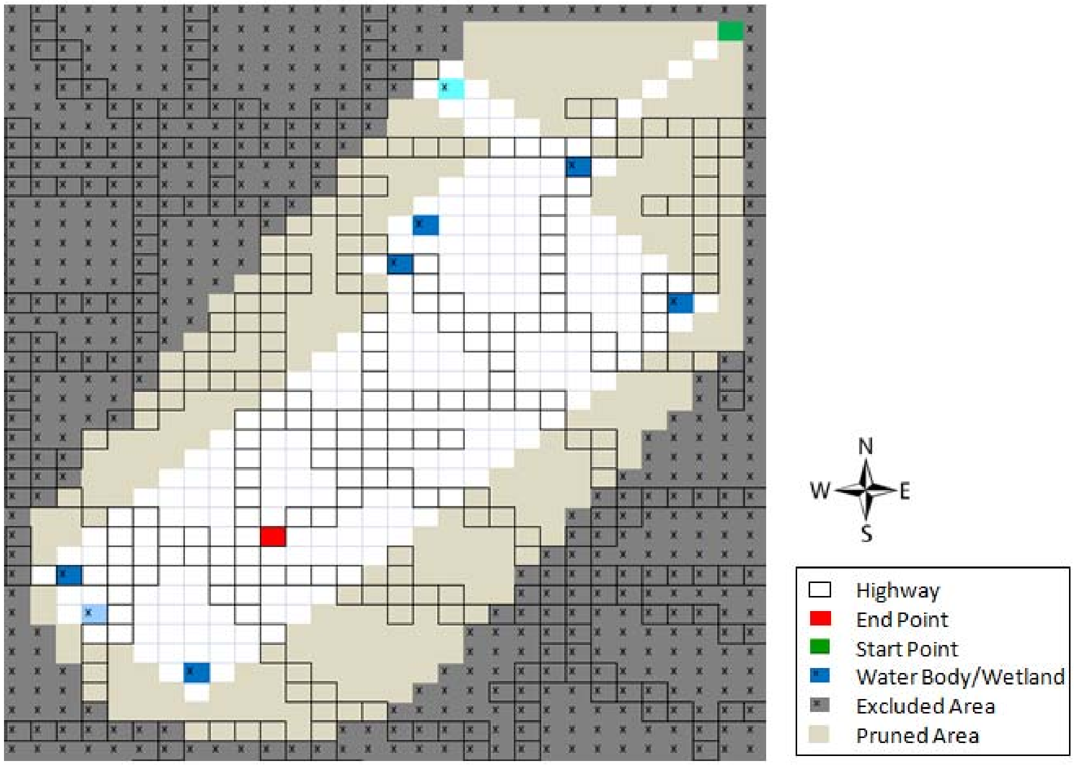

Fig. 5.8. Bois D'Arc Reservoir to Leonard Reservoir – pruned

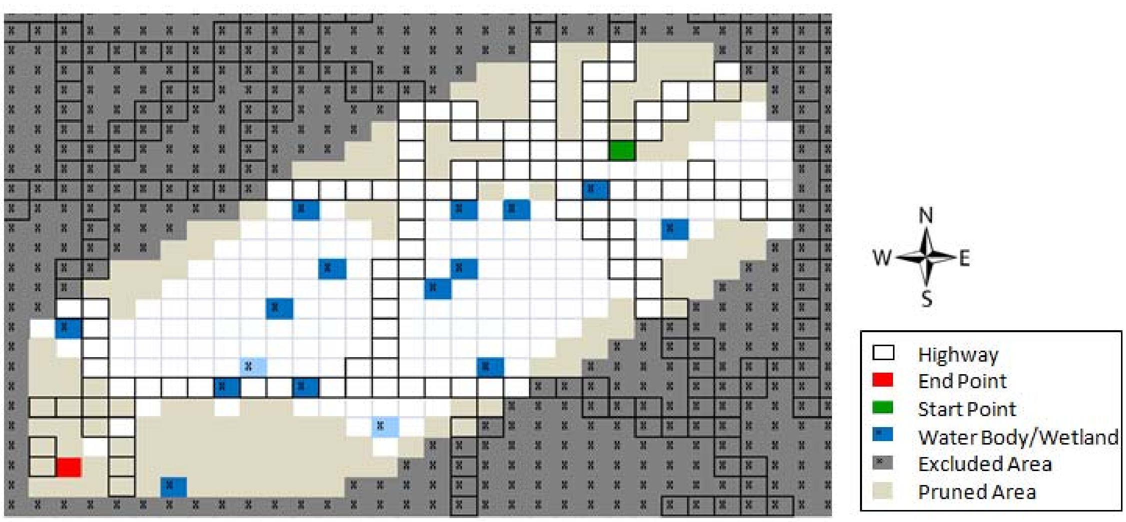

Fig. 5.9. Leonard Reservoir to Pilot Grove Creek – pruned

5.3 RESULTS AND ANALYSIS

The algorithm was run for 100 iterations using a multiple colony approach with 3 colonies representing a bi-objective problem. The first objective is the cost of the pipe, and the second objective is a minimization of the level-of-impact score. The input settings for the algorithm are represented in Table 5.3 below.

Table 5.3. Algorithm Parameters

Parameter Values Considered	
Parameter	Value
Number of Ants	30
Number of Colonies	3
α	0.5
β	0.5
λ	0.7
Number of Iterations	100
Computer Specifications	Intel Core™2 Duo CPU 2.40 GHz with 4.00 GB RAM
Operating System	Windows 7 Enterprise

The pipeline was implemented into the grid cell format by using a spatial join in ArcGIS. Because the resolution is much higher for a line than a grid cell 2,640 ft in length, the path is longer than it was actually designed to be when it is represented by the grid cells. Using this method the score and costs of the preexisting pipe line were very high. Section one of the preliminary route had a level of impact score of 509,520 and a pipe cost of $79 million. Section two of the preliminary route had a level of impact score of 306,240 and a pipe cost of $31 million. Because of this, redundant cells within the preexisting pipeline route were removed to produce a better representation of the actual pipeline route and distance. It also improved the consistency between the algorithms routes and the preexisting route. With the redundant cells removed the first section of the preliminary route had a level of impact score of 353,369 and a cost of $58.9 million. The second section of the preliminary route had a level of impact score of 232,520, and a cost of $23.4 million. Figure 5.10 represents the preliminary route and illustrates how the redundant cells were removed.

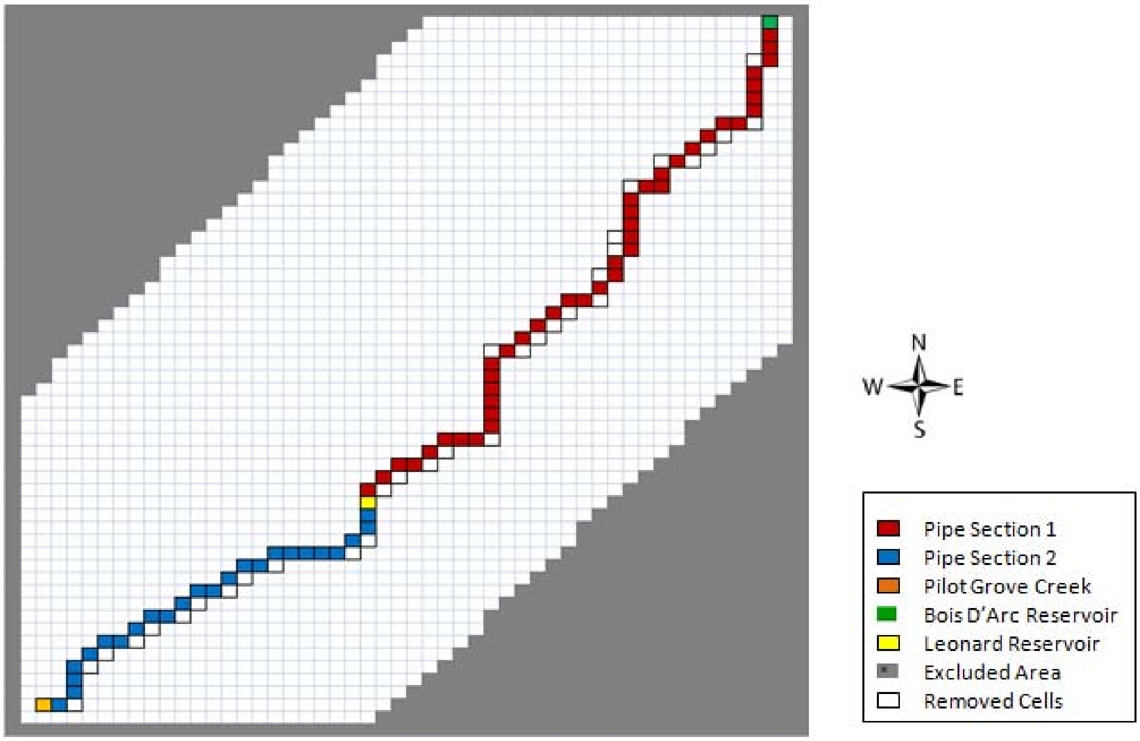

Fig. 5.10. Preliminary pipe design

Figure 5.11 represents the non-dominated solutions for section 1. The individual paths are represented by Figures 5.12 - 5.13 and the preliminary route by Figure 5.14. This section took 3,442 seconds to run and 183,383 ant steps. Figure 5.15 represents the non-dominated solutions for section 2 from Leonard reservoir to the outlet at Pilot Grove creek which are also represented in Figures 5.16 - 5.17. The preliminary route is represented by Figure 5.18. This section took 7,211 seconds to run and 815,932 ant steps. The vertical axis represents the pipe cost in millions and the horizontal axis represents the level of impact score in thousands. The algorithm produced two Pareto-optimal solutions for section one and two solutions for section two. The preliminary pipeline design route was put into the grid cell network and the length and score of the route were determined.

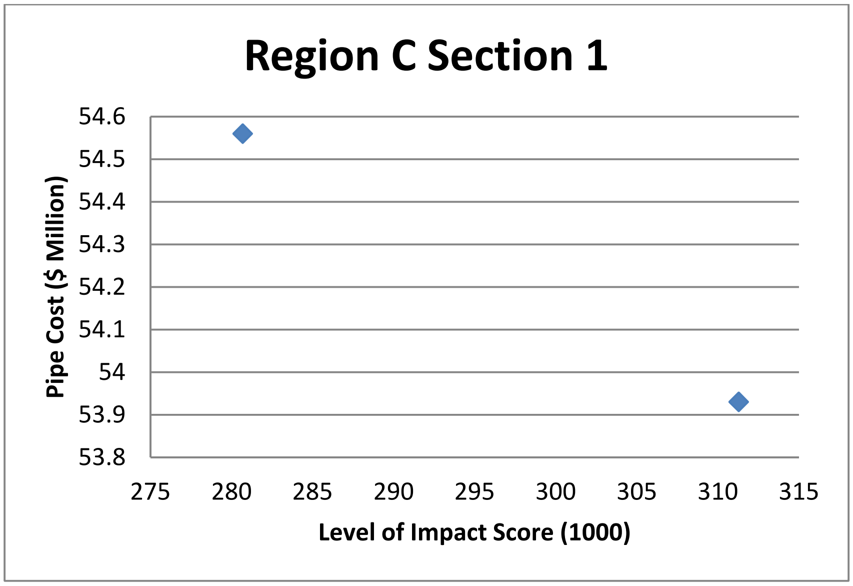

Fig. 5.11. Region C section 1

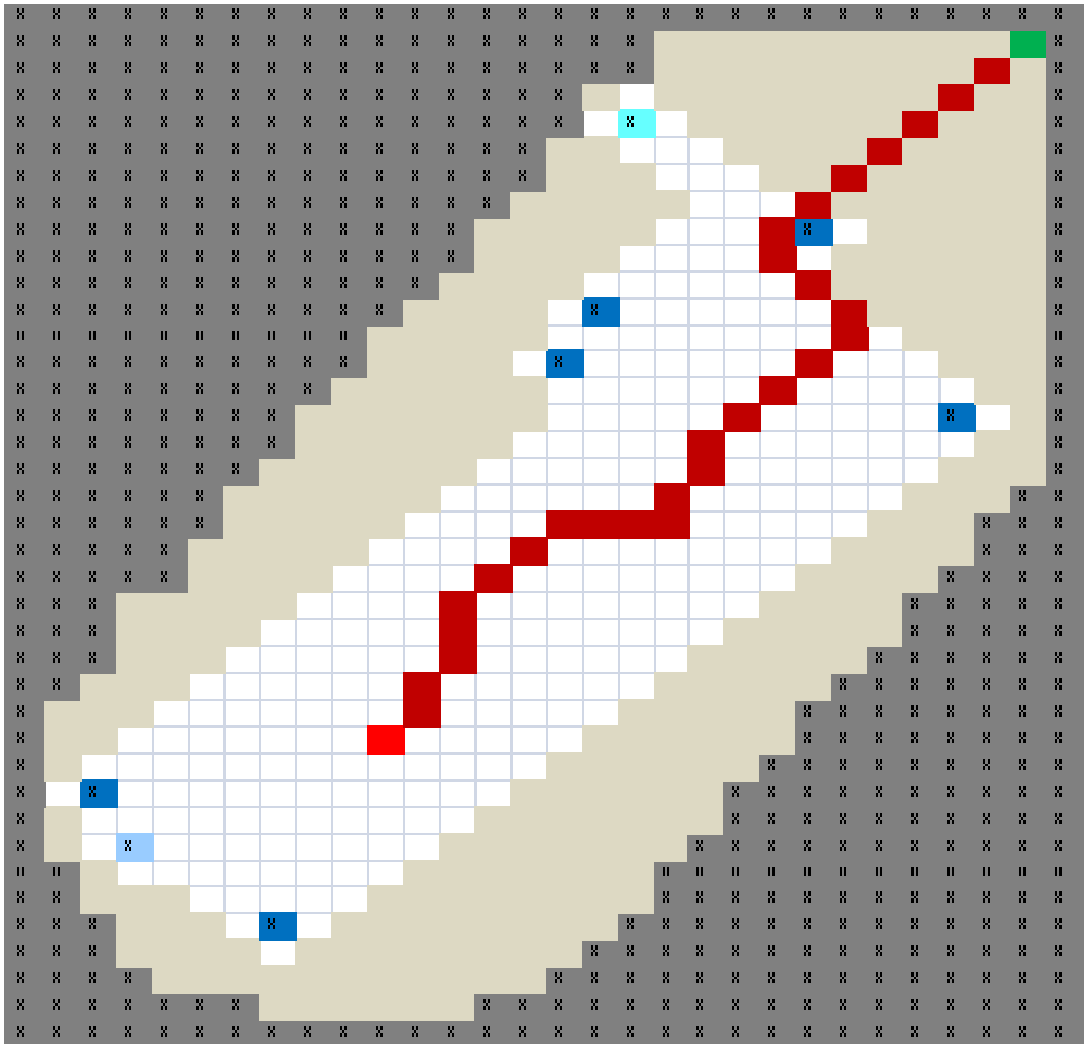

Fig. 5.12. Region C section 1 non-dominated solution 1. This figure represents a non-dominated solution for Region C section 1, with a level of impact score of 280,687 and a pipe cost of $54.5 million.

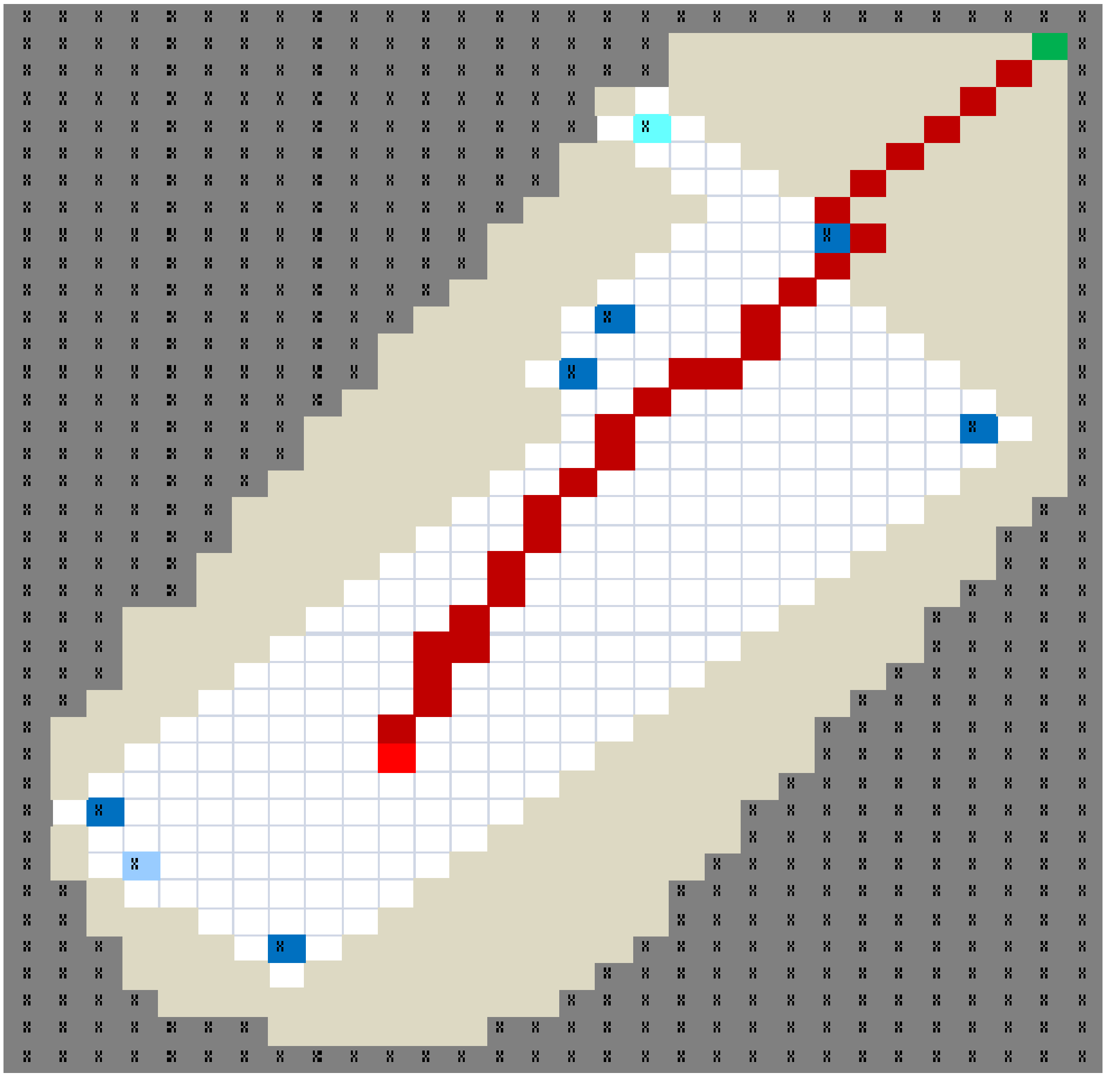

Fig. 5.13. Region C section 1 non-dominated solution 2. This figure represents a non-dominated solution for Region C section 1, with a level of impact score of 311,280, and a pipe cost of $53.9 million.

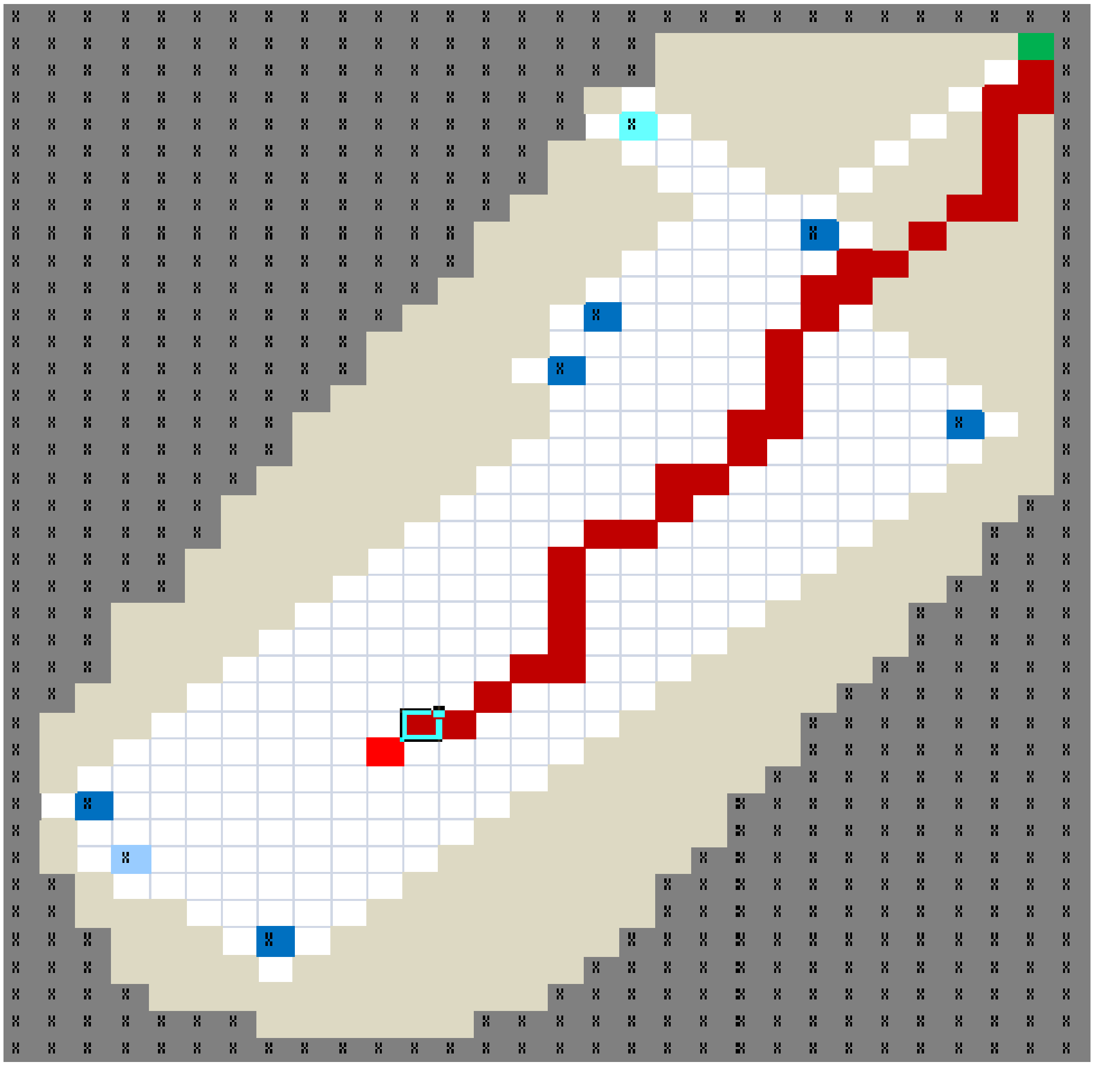

Fig. 5.14. Region C section 1 preliminary route. This figure represents the preliminary route for Region C section 1, with a level of impact score of 353,369 and a cost of $58.9 million.

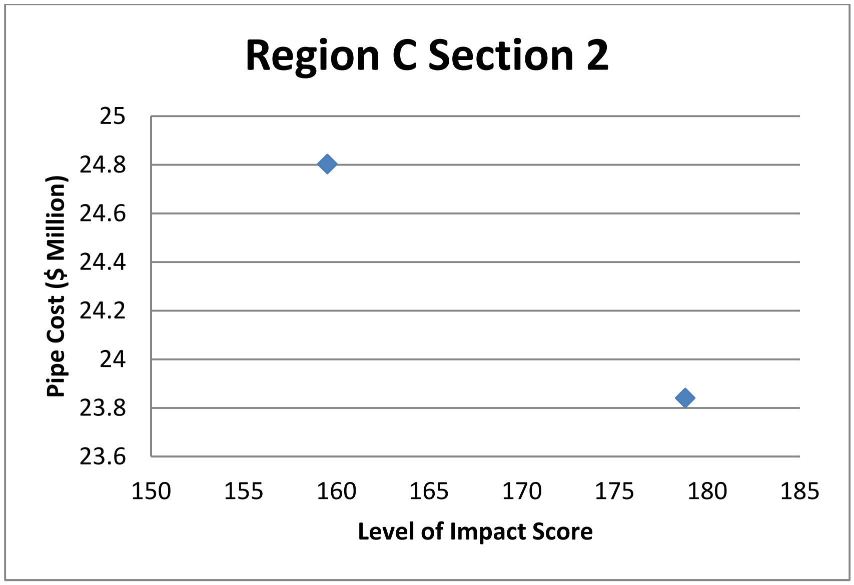

Fig. 5.15. Region C section 2

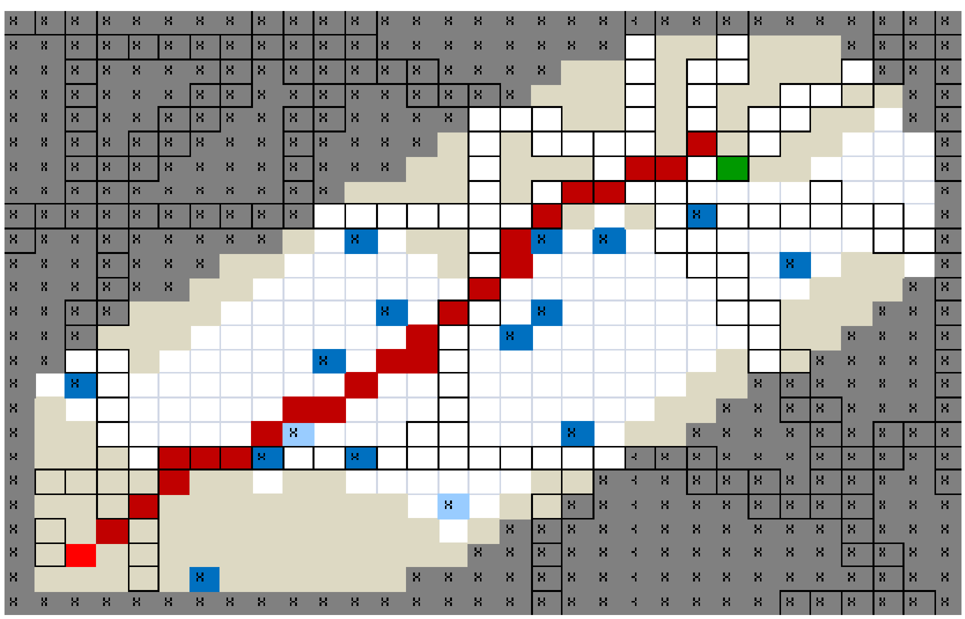

Fig. 5.16. Region C section 2 non-dominated solution 1. This figure represents a non-dominated solution for Region C section 2, with a level of impact score of 159,508 and a pipe cost of $24.8 million.

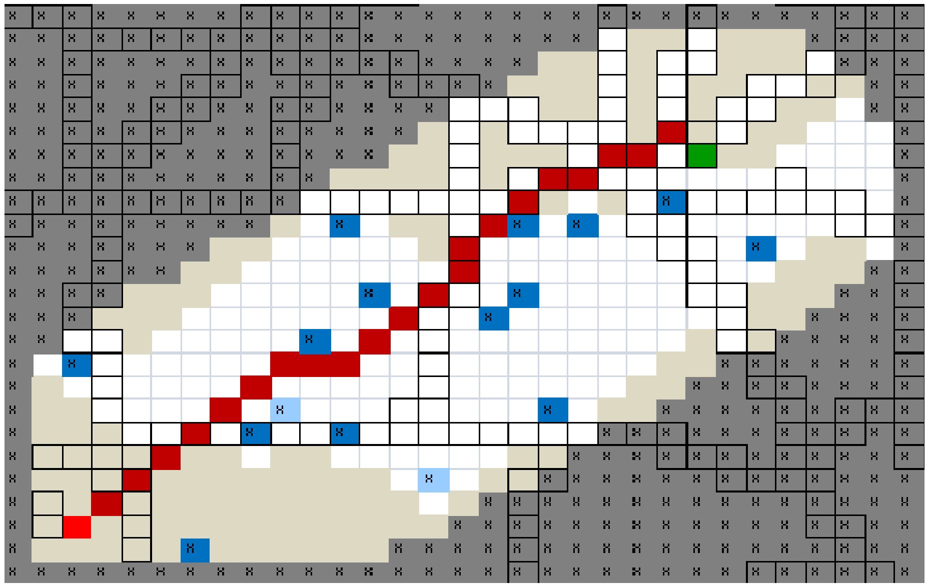

Fig. 5.17. Region C section 2 non-dominated solution 2. This figure represents a non-dominated solution for Region C section 2, with a level of impact score of 178,8125 and a pipe cost of $23.8 million.

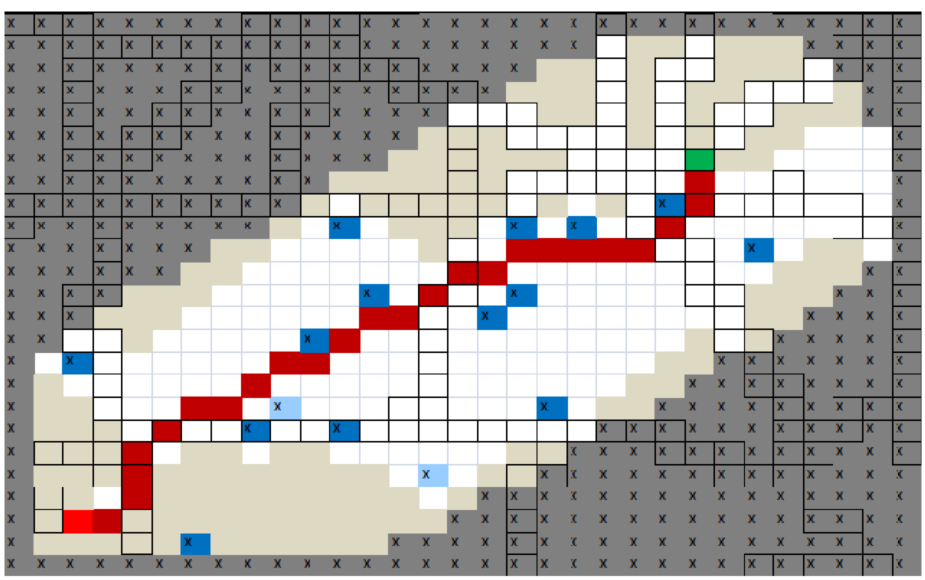

Fig. 5.18. Region C section 2 preliminary route. This figure represents the preliminary route, with a level of impact score of 232,520 and a cost of $23.4 million.

The results obtained from the algorithm are similar to the preliminary routes. The algorithm delivers solutions with similar costs but much better level of impact scores. There could be multiple reasons for this. Almost certainly the preliminary route planners did not use the same scoring system that was used in this case study, and they did not use it with this coarse level of detail. More than likely they had their own scoring system when designing the route, if a scoring system at all. Because the preliminary route developed did not take into account this level of impact score as an objective, the algorithms routes produced better results for that objective. The costs are similar because it can be inferred that cost was a major objective when designing the route. The cost functions used in this case study provided by Appendix R in the Region C final report (Gooch et al. 2011) were probably the same ones that were used in the preliminary route.

What is case study has demonstrated is the ability of the algorithm to produce approximate Pareto-optimal solutions for infrastructure routing problems apart from ice road planning. This algorithm produced multiple pipeline routes which represent an approximation of the Pareto optimal solutions. By looking at the results you can see where a path may be shorter, and thus have a lower pipeline cost, but also has a higher level of impact score. This information can be used by a decision maker to determine the tradeoff relationship between alternative non-dominated solutions.

6. CONCLUSIONS

Infrastructure routing in many cases depends on the optimization of multiple sometimes conflicting objectives. Objectives such as cost, length, construction time, and environmental impacts are all considered when developing new infrastructure routes. Traditional route finding algorithms lack the ability to quickly produce multiple Pareto-optimal solutions representing the tradeoff relationships between different objectives. Using a multi-objective search technique such as ant colony optimization provides a decision maker with a variety of alternatives from which to choose.

This thesis has proposed a multi-objective ant colony optimization algorithm capable of approximating Pareto-optimal solutions for multi-objective infrastructure routing problems. The algorithm is able to develop desirable routes on an open grid framework given spatially defined objectives. The algorithm contains features derived from existing multi-objective ant colony optimization techniques and others which are unique to infrastructure routing problems. It also includes several pre-processing and post-processing techniques which improve the performance of the algorithm. This paper has demonstrated the capabilities and applicability of the algorithm to two separate infrastructure routing problems. The algorithm has been implemented within NSDSS and a successful case study of the White Hills Ice Road using the algorithm within the ice road planning module has been conducted. The algorithm has also been applied to a second case study involving raw water transmission routing in the Region C water planning zone of Texas from the Lower Bois D'arc Reservoir to an outlet at Pilot Grove Creek.

There are limitations to kinds of problems that this algorithm can solve. The algorithm is restricted by the size of the problem that it can solve in a reasonable amount of time. It is also intended to be used at a planning level of design and not in the detailed design phase. Because in many applications the algorithm it is not able to pick up detailed information about the route, it is intended to be used at a planning level phase where certain route details are not considered. The algorithm is also not guaranteed to find the exact set of optimal solutions, but a set of solutions that is close to Pareto-optimality.

There are multiple advantages to using this algorithm to solve infrastructure routing problems. The algorithm is capable of producing multiple Pareto-optimal solutions in one run as opposed to classical route finding algorithms that take multiple runs to produce multiple solutions. By providing a decision maker with a group of Pareto-optimal solutions, a decision maker is able to weigh the alternatives and determine the best solution based on his or her weight of the different objectives. This algorithm is also able to handle construction distance constraints where supply-distance availability may alter route feasibility. This algorithm can also be applied to other types of multi-objective infrastructure routing problems. From power line to highway routing, this algorithm can be used to determine Pareto-optimal routes given more than one objective.

Future work involving this algorithm could examine its performance versus other algorithms for classical optimization problems that many existing ant colony optimization algorithms have been applied to such as the Traveling Salesman Problem

(TSP) or the Knapsack problem. Other future work could involve examining the applicability of the algorithm to other engineering applications. There are many different applications for which multiple objective ant colony optimization algorithms have been applied and the performance of this algorithm to problems outside of infrastructure routing could be studied.

REFERENCES

ADR (2011),"Alaska permanent fund", *Permanent Fund Dividend Division* <http://www.pfd.state.ak.us/> (Nov. 1, 2011).

ANWR (2011), "2011 arctic power - top ten reasons to support ANWR development", <http://www.anwr.org/ANWR-Basics/Top-ten-reasons-to-support-ANWR-development.php> (Nov. 1, 2011).

Auerbach, N., Walker, M., and Walker, D. (1997), "Effects of roadside disturbance on substrate and vegetation properties in arctic tundra", *Ecological Applications,* 7 (1), 218-35.

Bailey, A. (2010), "Ribbons of tundra ice", *Petroleum News,* May 02, 2010.

Baran, B., and Shaerer, M. (2003), "A multiobjective ant colony system for vehicle routing problem with time windows", *Proc. of the 21st IASTED International Conference*, 97-102.

Bourne, J. (2006), "The interest of big oil, wild creatures, and native populations collide on the largest remaining piece of U.S. wilderness, Alaska's North Slope", *NationalGeographic*. <http://ngm.nationalgeographic.com/ngm/0605/feature1/index.html>, (Oct. 11, 2011).

Campbell, B. (2009), "Roads to resources paved with ice: construction, maintenance, travel times standardized.", *Alaksa Business Monthly*. <www.allbusiness.com mining-extraction oil-gas-exploration-extraction-oil-oil 14574389-1.html>, (Oct. 11, 2011).

Cardoso, P., Jesus, M., and Marquez, A. (2003), “MONACO - multi-objective network optimisation based on an ACO”, *Encuentros de Geometria Computational*.

Colorni, A., Dorigo, M., and Maniezzo, V. (1992), “Distributed optimization by ant colonies”, *Toward a Practice of Autonomous Systems*, 134-42.

Cordon, O., Herrera, F., and Stützle, T. (2002), “A review on the ant colony optimization metaheuristic: basis, models and new trends”, *Mathware & Soft Computing,* 9, 141-75.

Doerner, K. , Hartl, R., and Reimann, M. (2001), “Are COMPETants more competent for problem solving? - the case of a routing and scheduling problem”, *Genectic and Evolutionary Computation Conference (GECCO-2001),* San Francisco, California, 802.

Dorigo, M., (1992), “Learning and natural algorithms”, *PhD thesis*, Departimento di Elettronica, Politecnico di Milano, Milan, Italy.

Dorigo, M., and Gambardella, L. (1997a), “Ant colonies for the travelling salesman problem”, *Biosystems,* 43 (2), 73-81.

Dorigo, M., and Gambardella, L. (1997b), “Ant colony system: a cooperative learning approach to the traveling salesman problem”, *Evolutionary Computation, IEEE Transactions on,* 1 (1), 53-66.

Dorigo, M., Maniezzo, V., and Colorni, A. (1991), “The ant system: an autocatalytic optimizing process”, *Technical Report 91-016,* Milano, Italy.

Dorigo, M., and Stützle, T. (2004), “Ant colony optimization*”,* MIT Press, Cambridge, Massachusetts, xi, 305 p.

Dreyer, D. (1998), "Two heuristics for the Euclidean Steiner tree problem", *Journal of Global Optimization,* 13 (1), 95.

Gambardella, L., and Dorigo, M. (1995), "Ant Q: a reinforcement learning approach to the traveling salesman problem", *Twelfth International Conference on Machine Learning,* Tahoe City, California, 252-60.

Gardel, P., Baran, B., Estigarribia, H., Fernandez, U., and Duarte, S. (2006), "Multiobjective reactive power compensation with an ant colony optimization algorithm", *AC and DC Power Transmission, 2006. ACDC 2006. The 8th IEE International Conference on*, 276-80.

Gilbert, E., and Pollak, H. (1968), "Steiner minimal trees", *Siam Journal on Applied Mathematics,* 16 (1).

Gomez, O., and Baran, B. (2005), "Omicron ACO. A new ant colony optimizaiton algorithm", *CLEI Electronic Journal,* 8 (1).

Gooch, T., Dillard, P., and Shaffer, R. (2011), "2011 Region C water plan", *Region C Water Planning Group*.

Goss, S., Aron, S., Deneubourg, J., and Pasteels, J. (1989), "Self-organized shortcuts in the Argentine ant", *Naturwissenschaften,* 76 (12), 579-81.

Iredi, S., Merkle, D., and Middendorf, M. (2001), "Bi-criterion optimization with multi colony ant algorithms evolutionary multi-criterion optimization", *Lecture Notes in Computer Science*, Eckart Zitzler, et al. (eds.), Springer Berlin / Heidelberg, 359-72.

Kittel, T., Baker, B., Higgins, J., and Haney, J. (2011), “Climate vulnerability of ecosystems and landscapes on Alaska’s North Slope”, *Regional Environmental Change,* 11 (0), 249-64.

Manning, D. (2011), “Regulatory permit SWT-0-14659”, *Tulsa District Department of the Army Corps of Engineers*, Tulsa, Oklahoma, <http://www.swt.usace.army.mil/permits/permitdetail.cfm?PublicNoticeApplicationNumber=SWT-0-14659> , (Nov 2, 2011).

Mariono, C., and Morales, E. (1999), “MOAQ an ant-Q algorithm for multiple objective opimization problems”, *Genetic and Evolutionary Computation Conference*, Orlando, Florida.

McKendrick, J. (1987), “Plant succession on disturbed sites, North Slope, Alaska, U.S.A”, *Arctic and Alpine Research,* 19 (4), 554-65.

Mora, A., Merelo, J., Millan, J., Torrecillas, J., and Laredo, J. (2006), “CHAC. A MOACO algorithm for computation of bi-criteria military unit path in the battlefield”, *Proc. of the Workshop on Nature Inspired Cooperative Strategies for Optimization,* NICSO'2006, 85-98.

Onwubolu, G. (2004), “New optimization techniques in engineering”, *Studies in fuzziness and soft computing*, Springer-Verlag Berlin Heidenberg, Germany, 101-123.

Paciello, J., Martinez, H., Lezcano, C., and Baran, B. (2006), “Algoritmos de optimización multi-objetivos basados en colonias de hormigas”, *XXXII Latin-American Conference on Informatics,* Santiago, Chile.

Pinto, D., and Baran, B. (2005), "Solving multiobjective multicast routing problem with a new ant colony optimization approach", *Proc. of the 3rd international IFIP/ACM Latin American conference on Networking* Cali, Columbia, 11-19.

Rich, A. (2009), "Information on Lower Bois d'Arc Reservoir now available at Bonham Public Library", *NTXE-News,* April 5, 2009.

Sheets, B. (2009), "Alaska North Slope oil and gas a promising future or an area in decline?", *National Energy Technology Laboratory,* Fairbanks, Alaska.

Stützle, T., and Hoos, H. (2000), "MAX–MIN ant system", *Future Generation Computer Systems,* 16 (8), 889-914.

Stützle, T. (1997), "MAX-MIN ant system for quadratic assignment problems", *Technical Report AIDA-97-04*, Darmstadt, Germany.

Sullivan, F. (2007), "White Hills lake studies", *Chevron North American Exploration and Production Company*, Anchorage, Alaska.

Sullivan, F. (2008), "Chevron White Hills 2008 completion report", *Chevron North American Exploration and Production Company,* Anchorage, Alaska.

T'Kindt, V. (2002), "An ant colony optimization algorithm to solve a 2-machine bicriteria flowshop scheduling problem", *European Journal of Operational Research,* 142 (2), 250.

Yagmahan, B., and Yenisey, M., (2010), "A multi-objective ant colony system algorithm for flow shop scheduling problem", *Expert systems with applications,* 37 (2), 1361.

APPENDIX

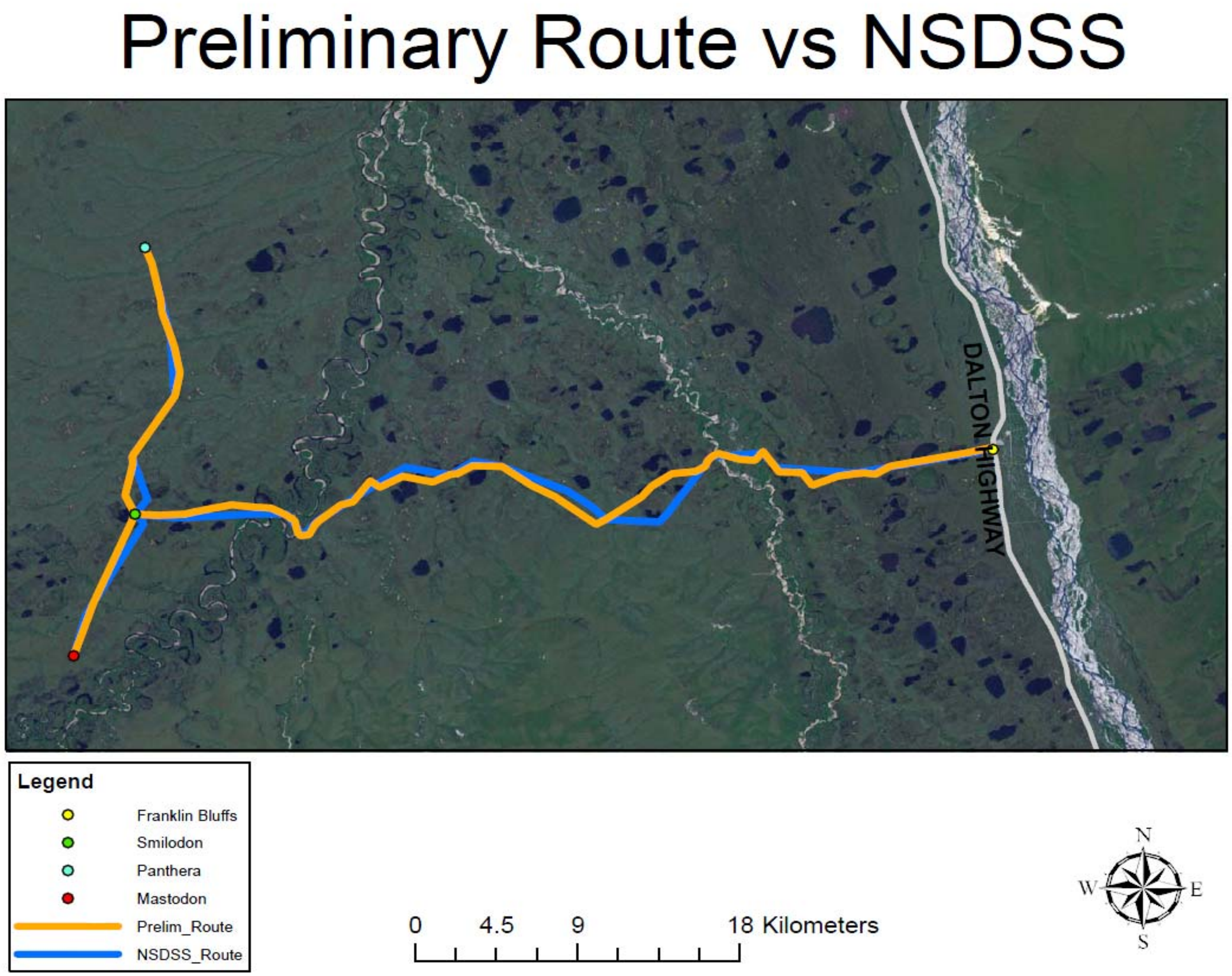

Fig. A.1. Preliminary route vs. NSDSS

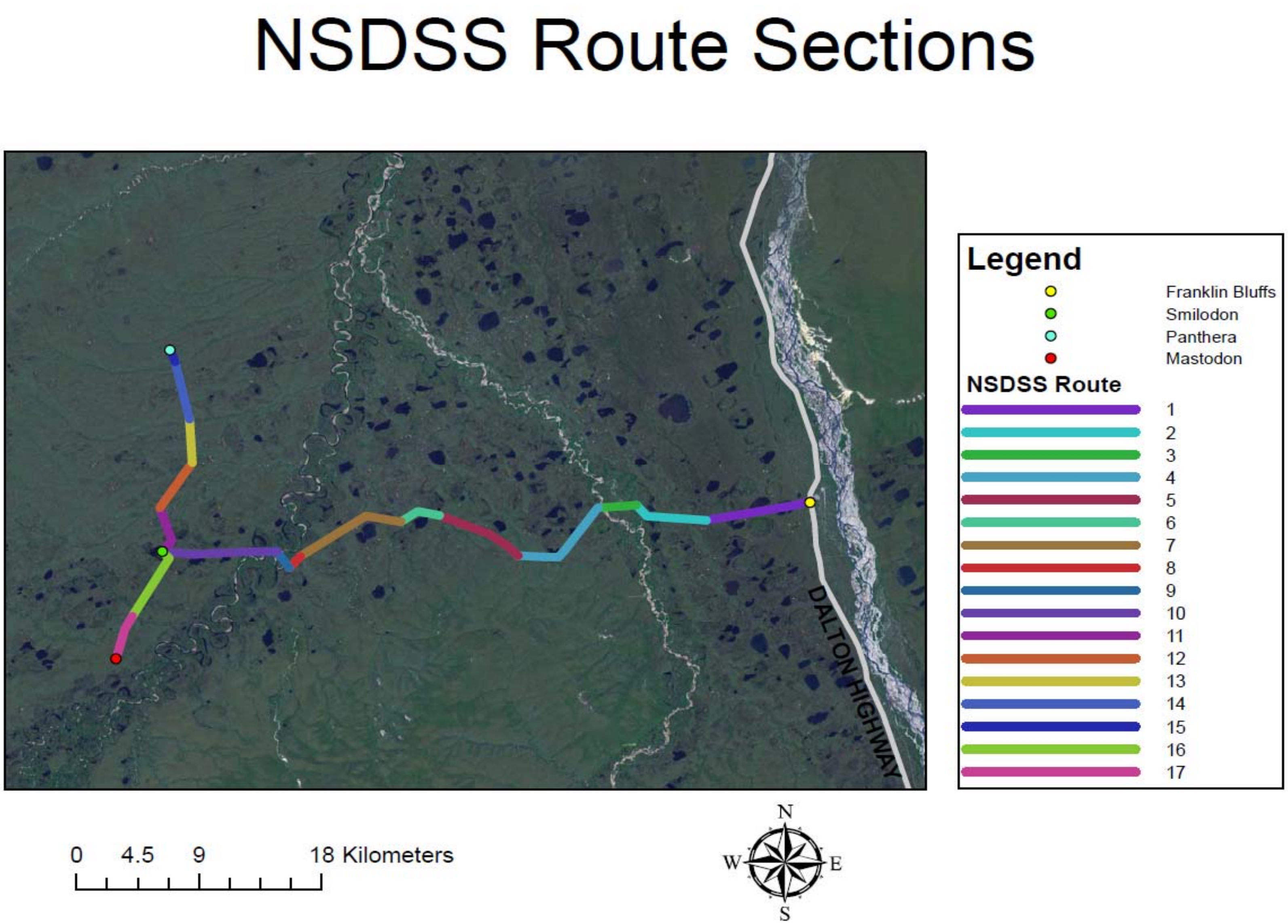

Fig. A.2. NSDSS route section

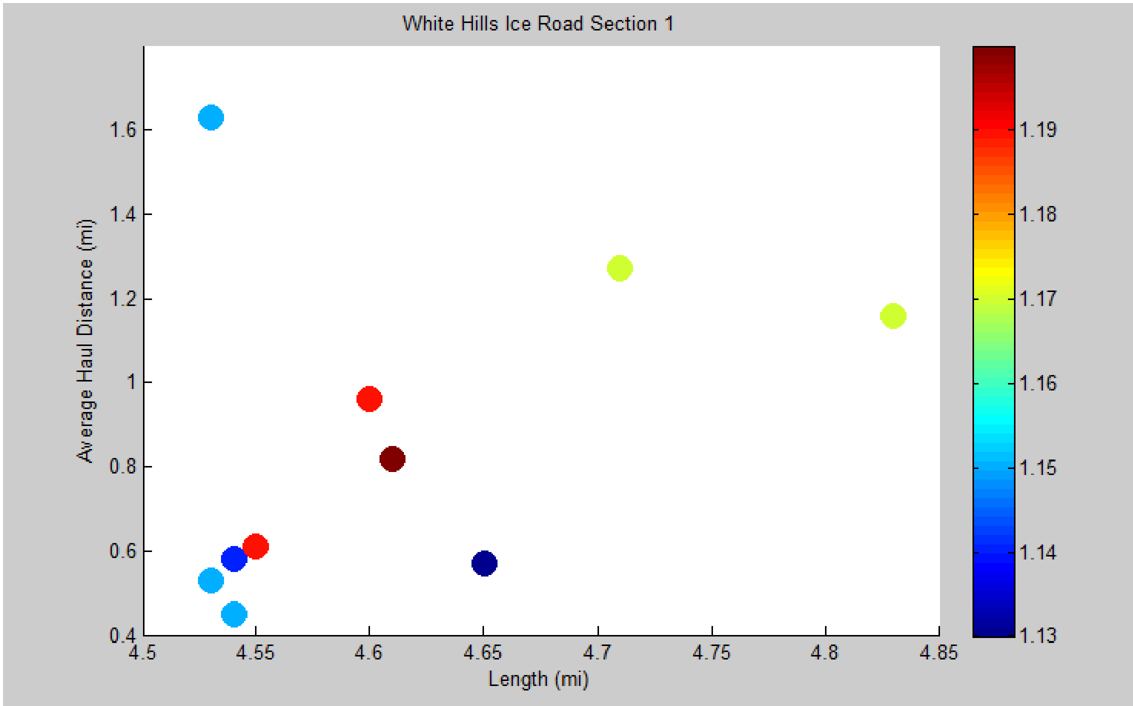

Fig. A.3. White Hills Ice Road plot section 1

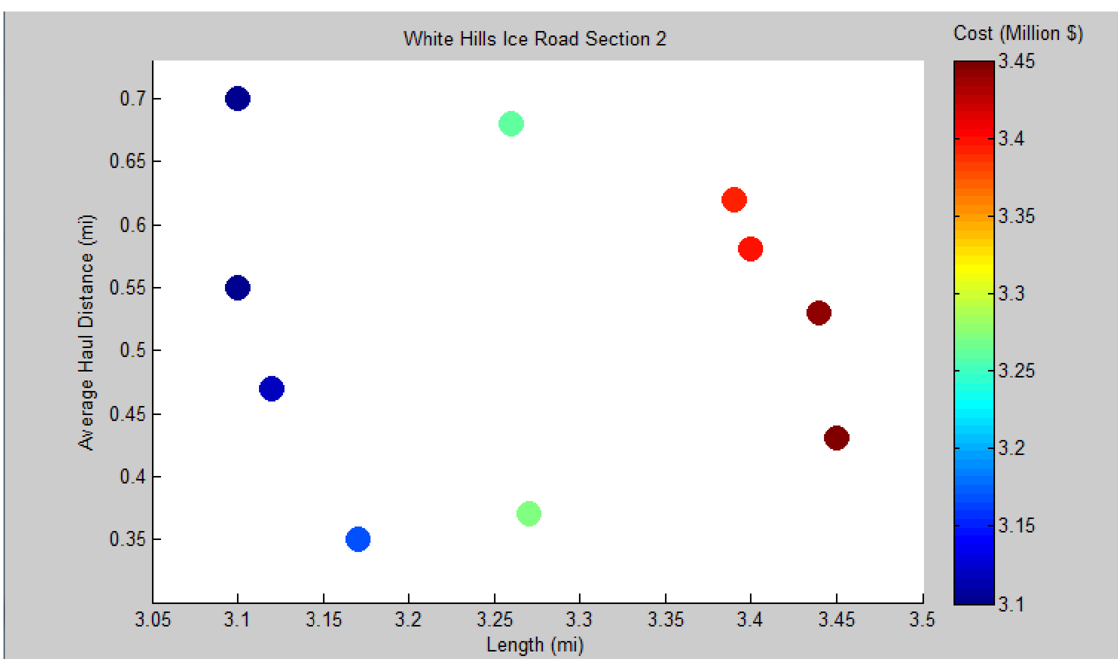

Fig. A.4. White Hills Ice Road plot section 2

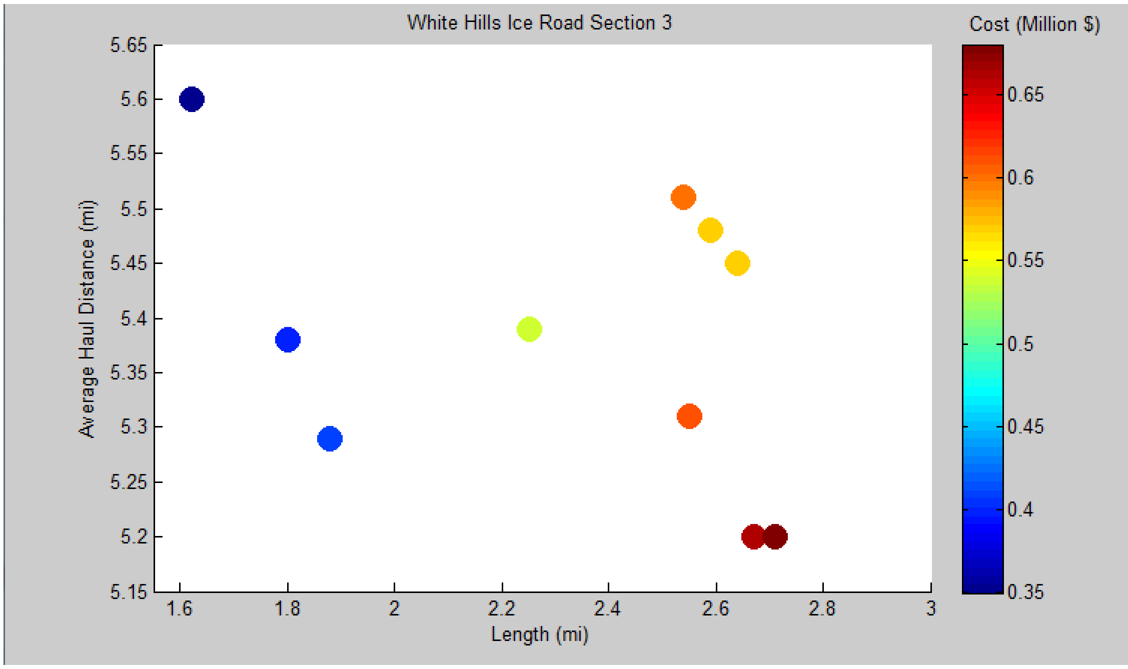

Fig. A.5. White Hills Ice Road plot section 3

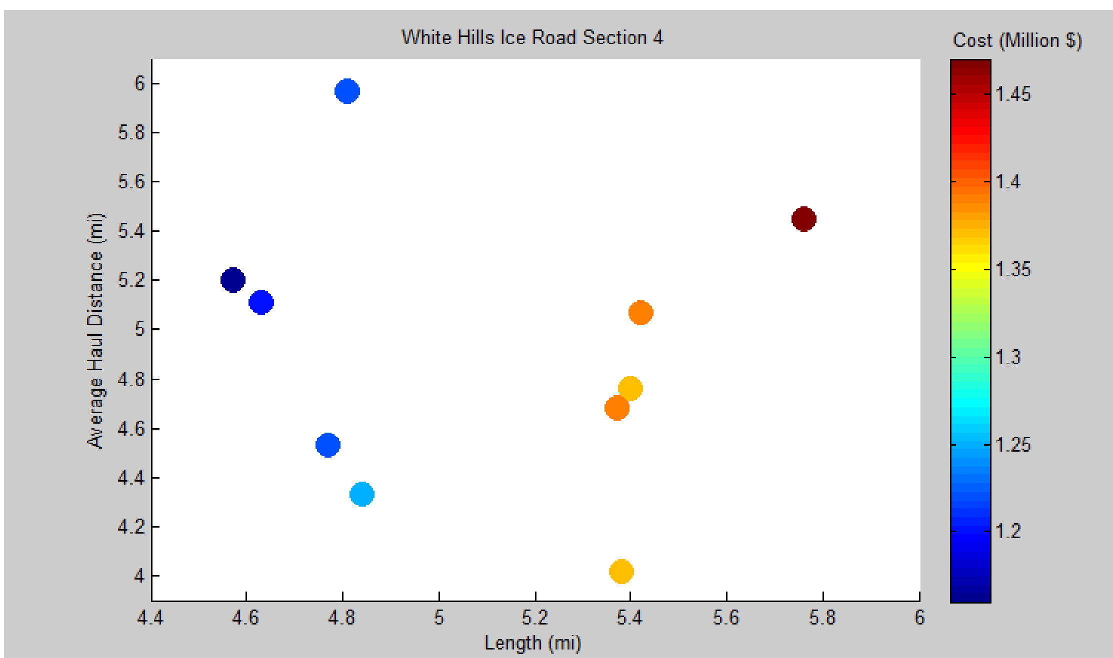

Fig. A.6. White Hills Ice Road plot section 4

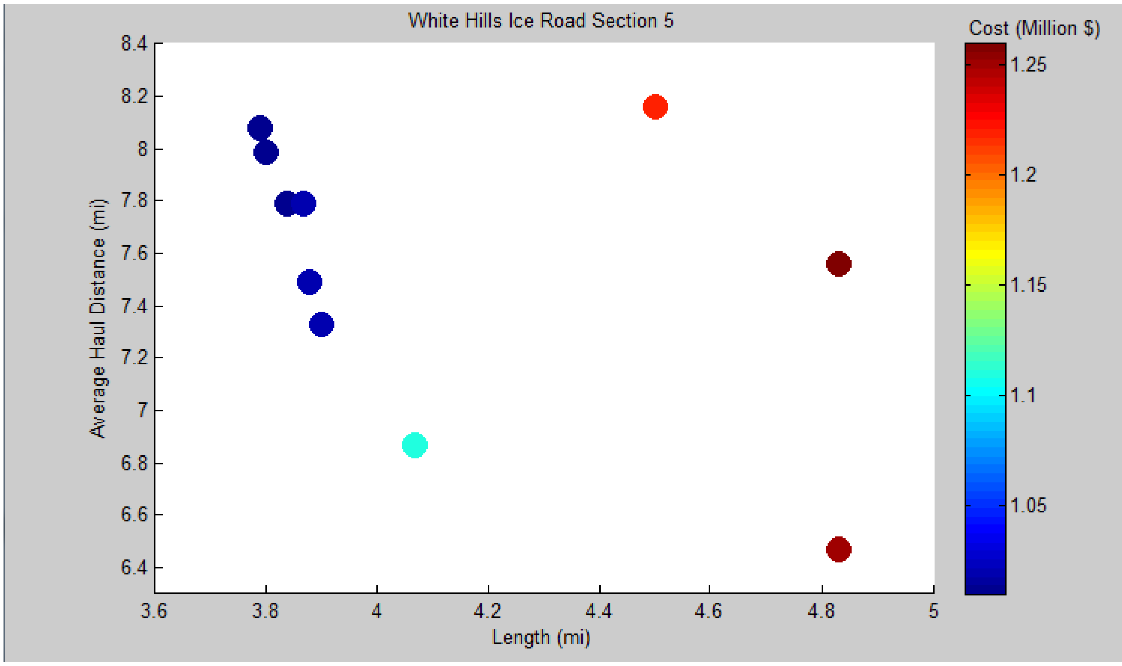

Fig. A.7. White Hills Ice Road plot section 5

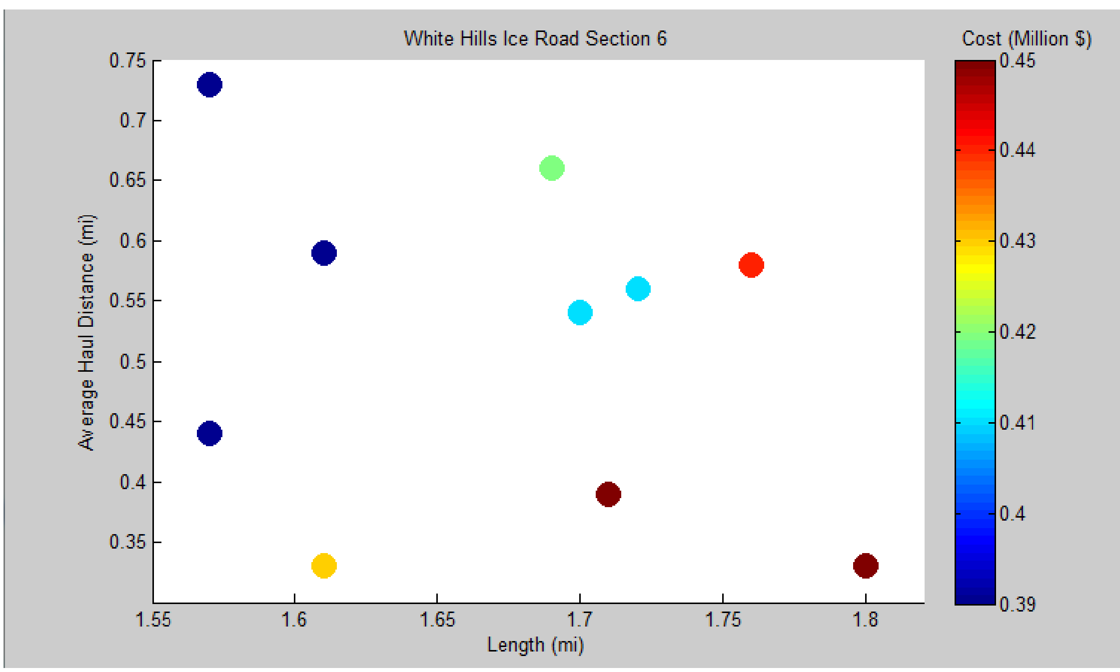

Fig. A.8. White Hills Ice Road plot section 6

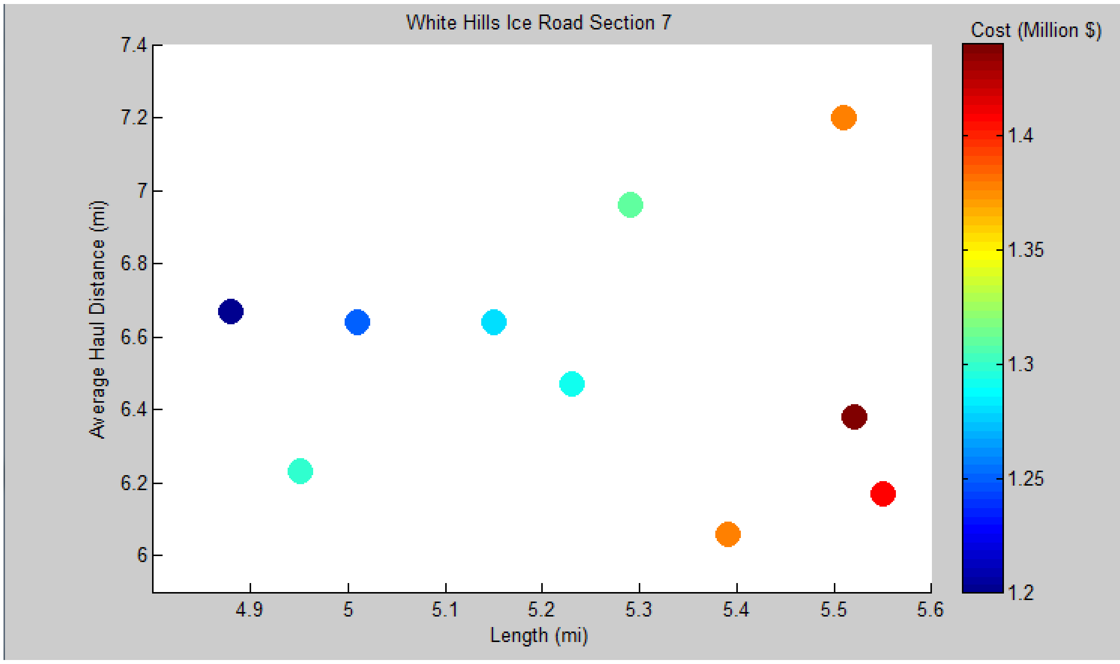

Fig. A.9. White Hills Ice Road plot section 7

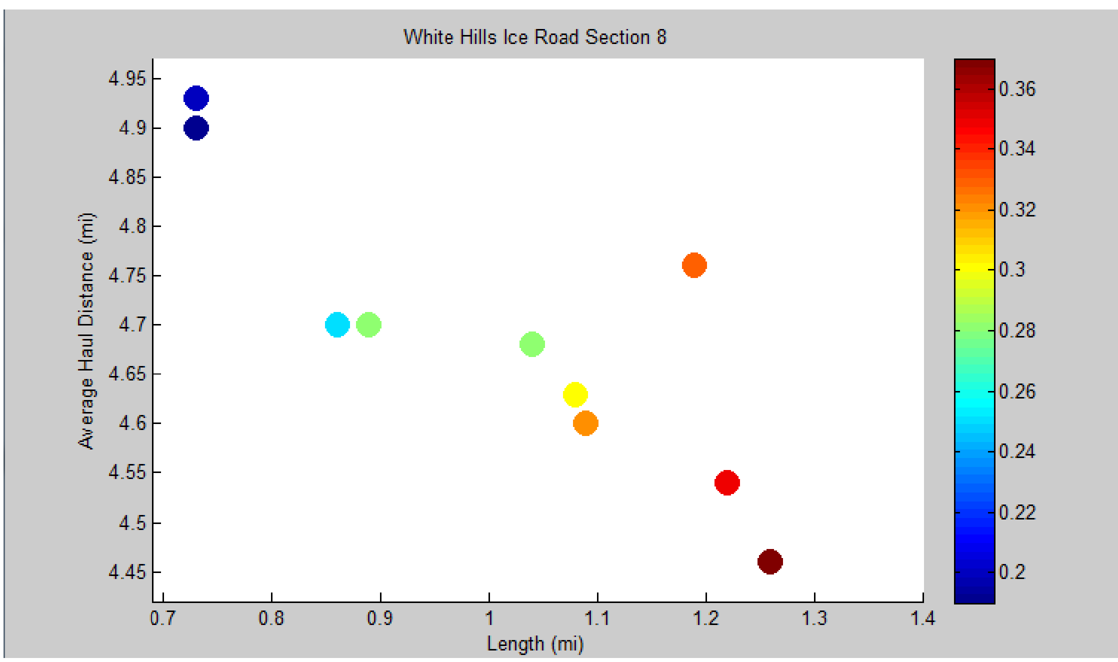

Fig. A.10. White Hills Ice Road plot section 8

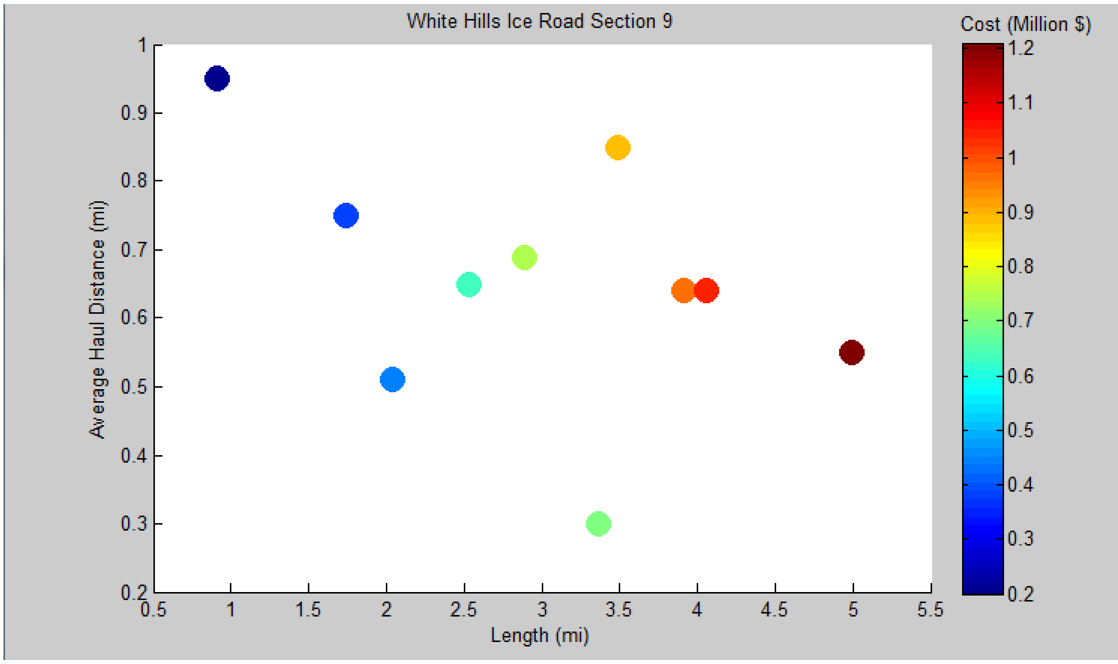

Fig. A.11. White Hills Ice Road plot section 9

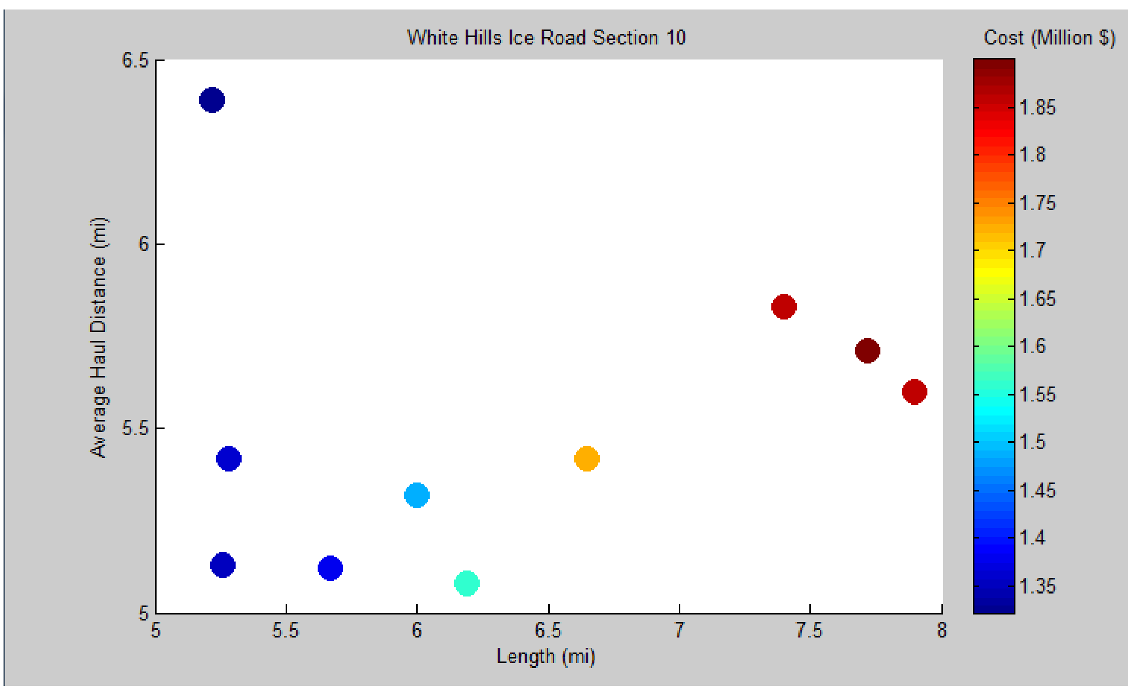

Fig. A.12. White Hills Ice Road plot section 10

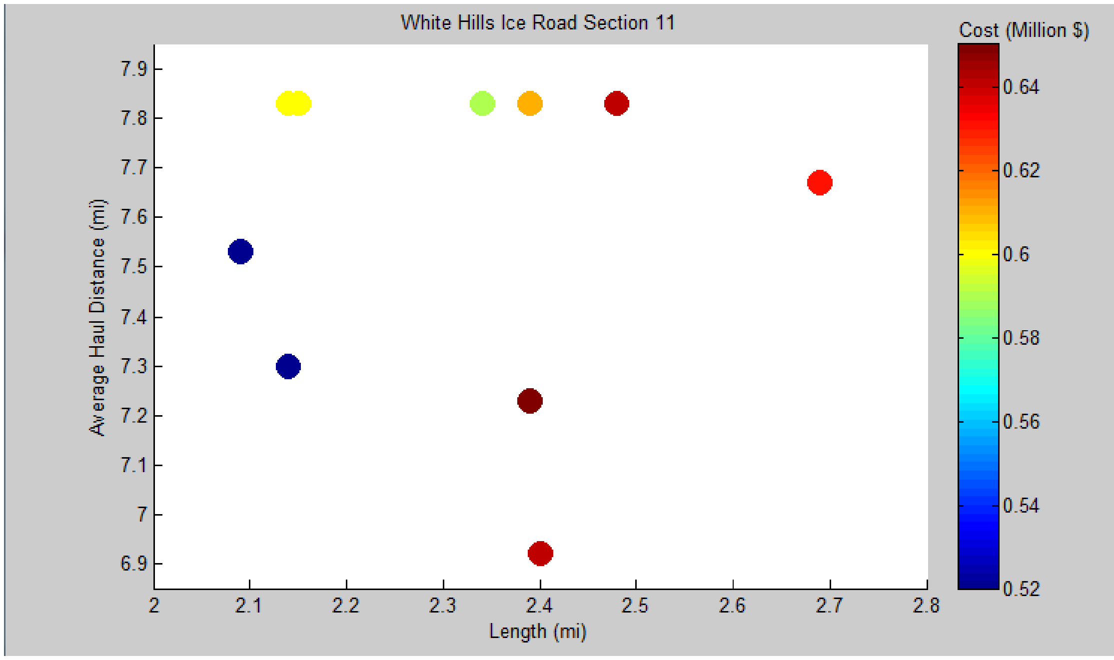

Fig. A.13. White Hills Ice Road plot section 11

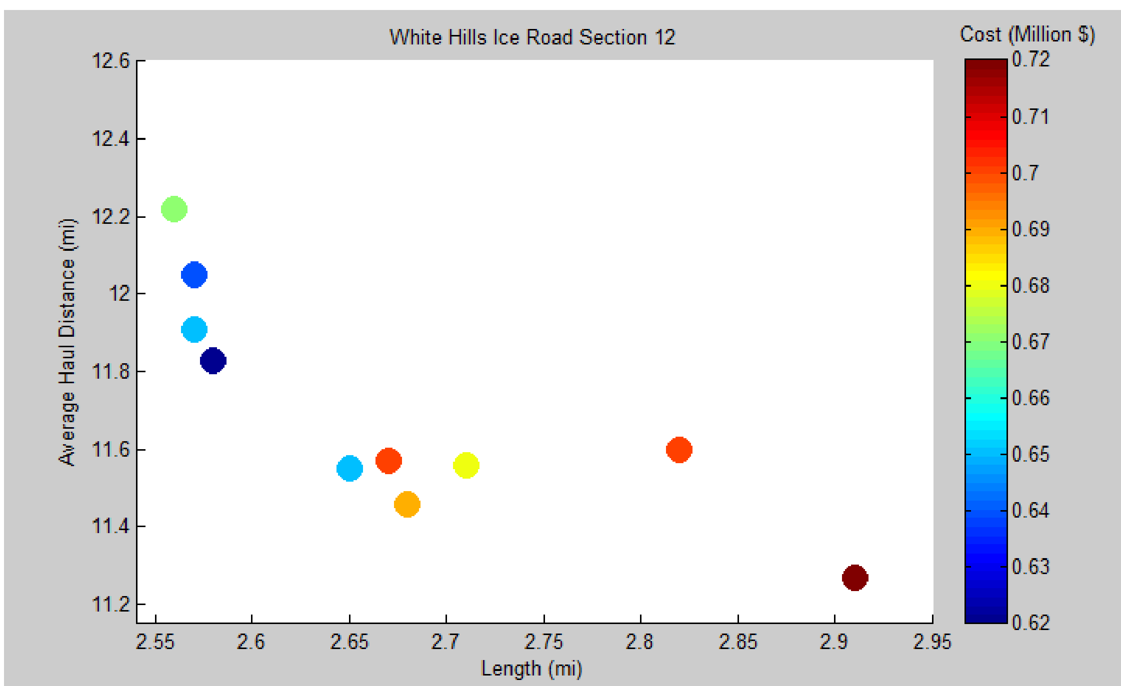

Fig. A.14. White Hills Ice Road plot section 12

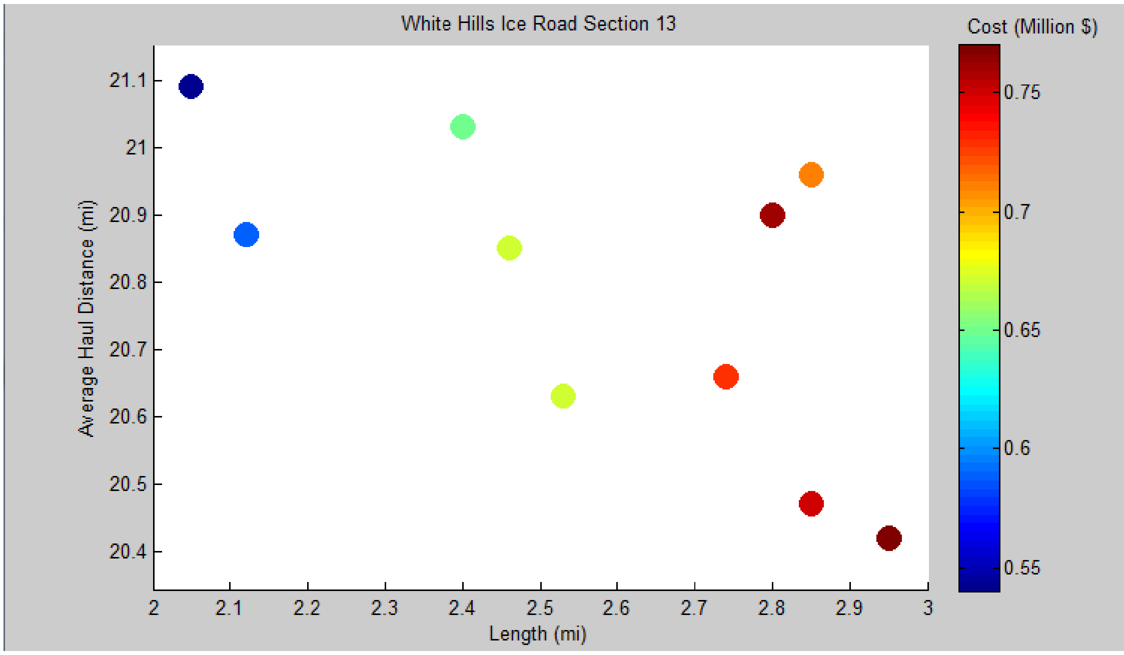

Fig. A.15. White Hill Ice Road plot section 13

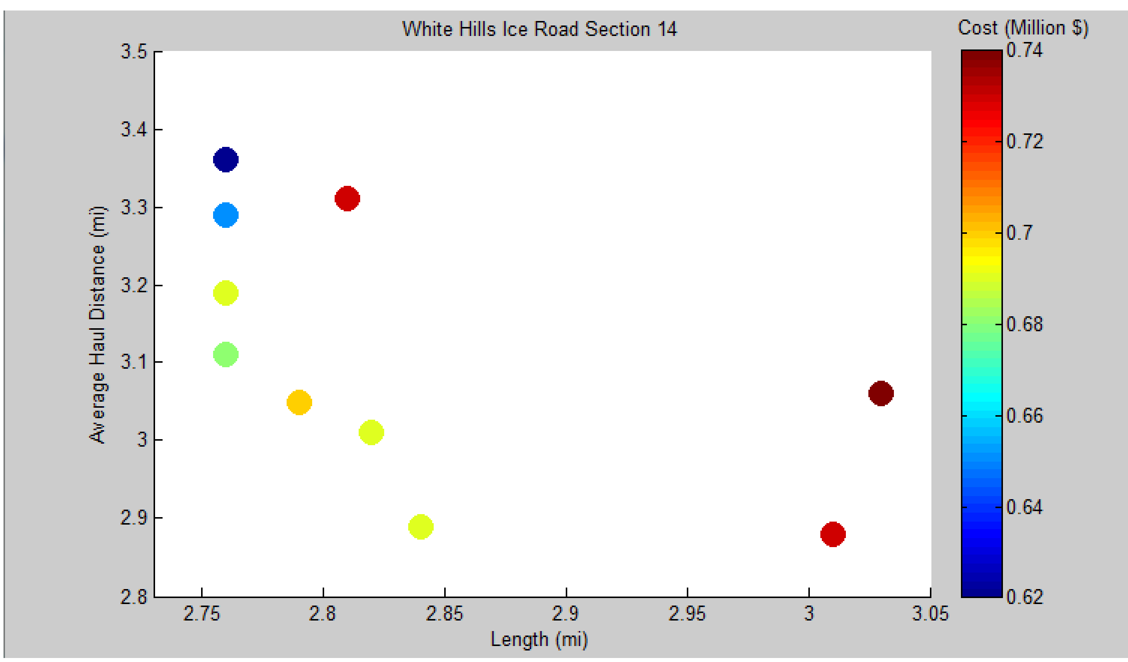

Fig. A.16. White Hills Ice Road plot section 14

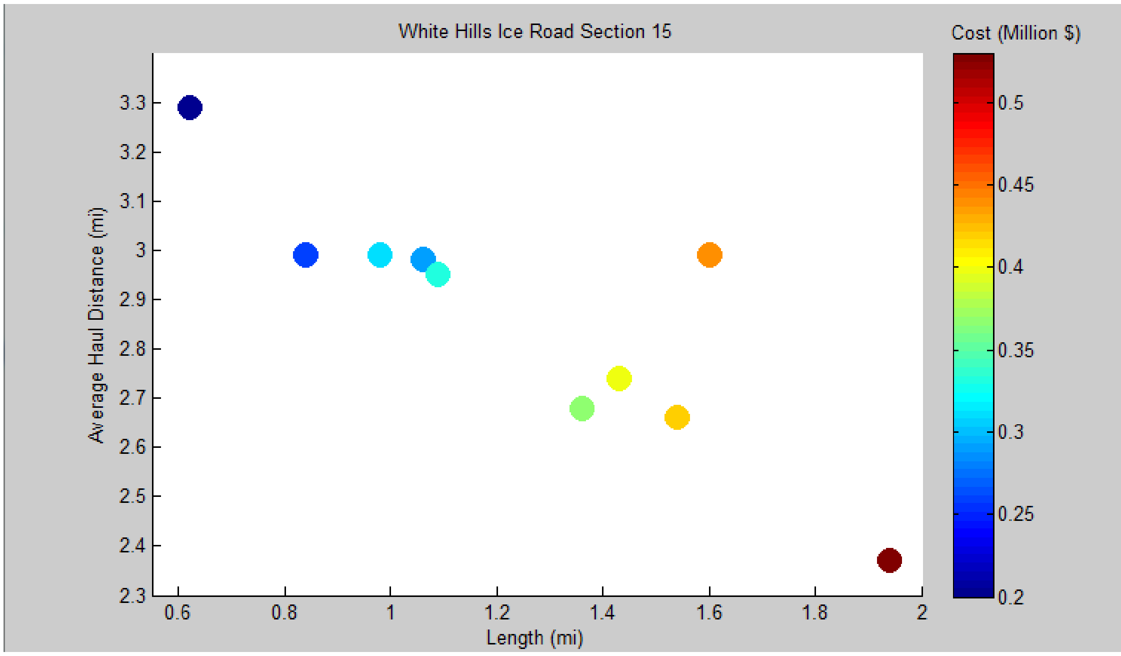

Fig. A.17. White Hills Ice Road plot section 15

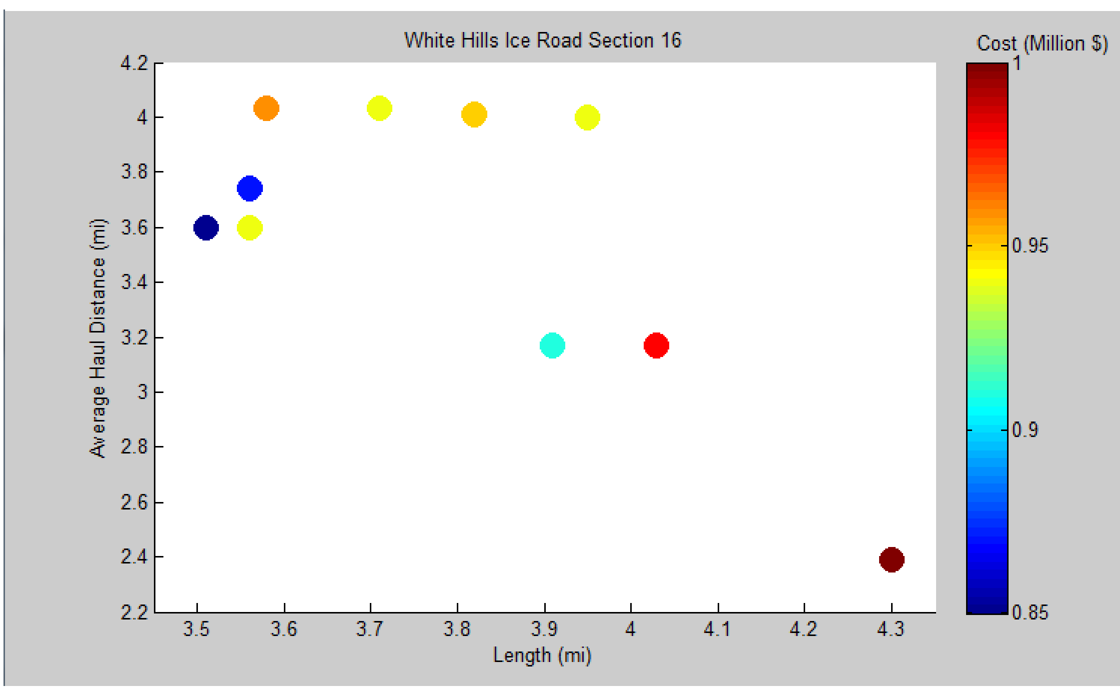

Fig. A.18. White Hills Ice Road plot section 16

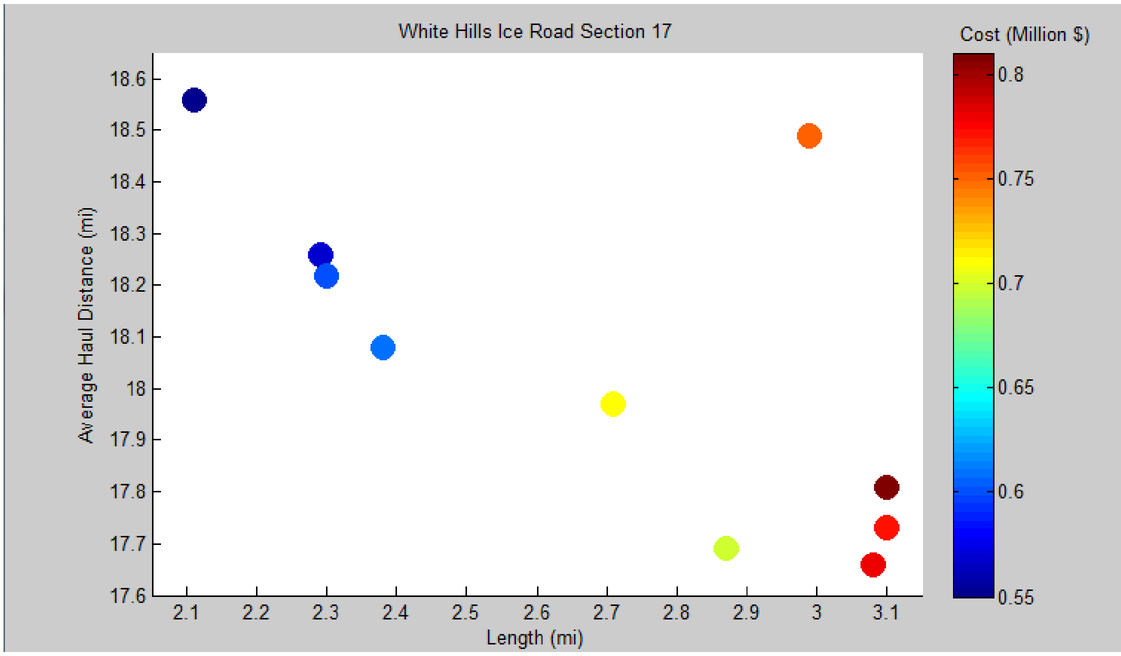

Fig. A.19. White Hills Ice Road plot section 17

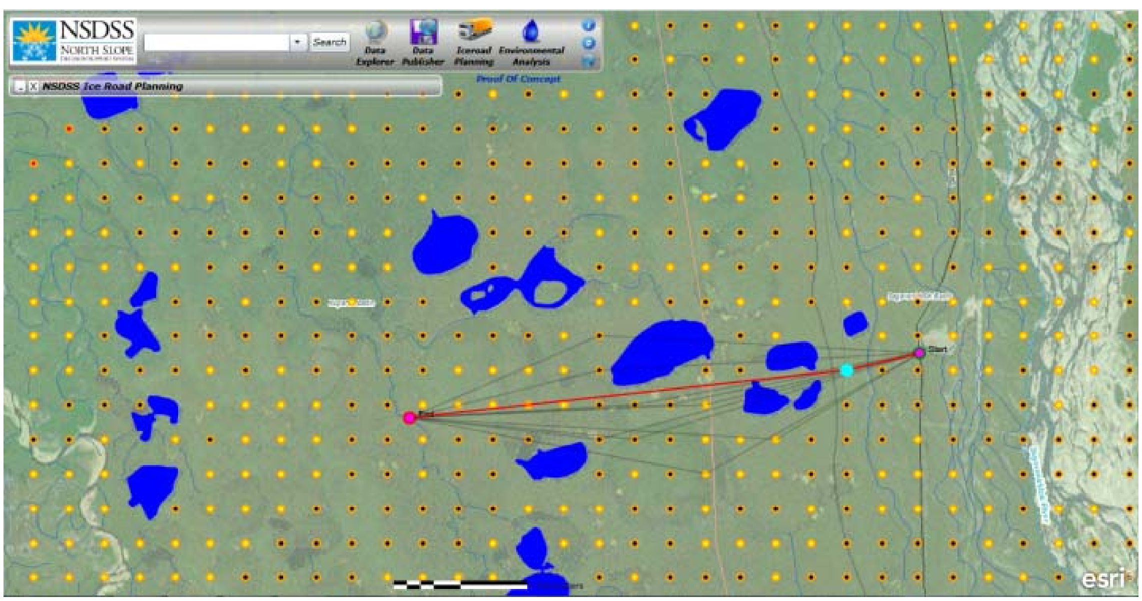

Fig. A.20. NSDSS section 1 map

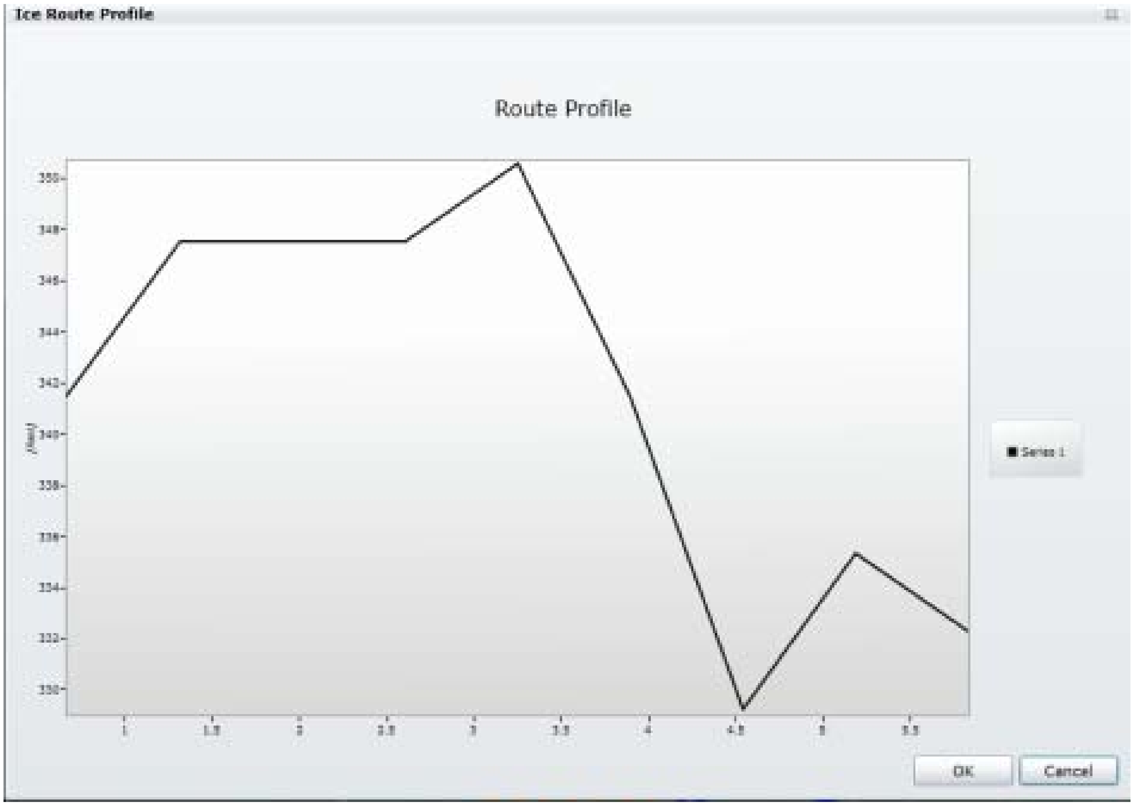

Fig. A.21. NSDSS section 1 profile

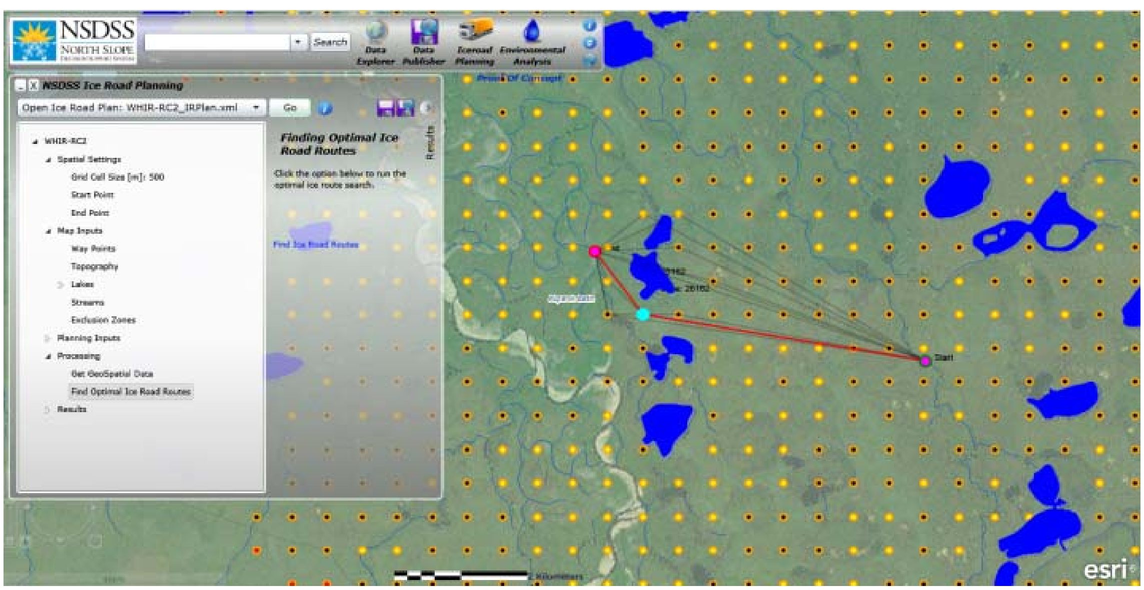

Fig. A.22. NSDSS section 2 map

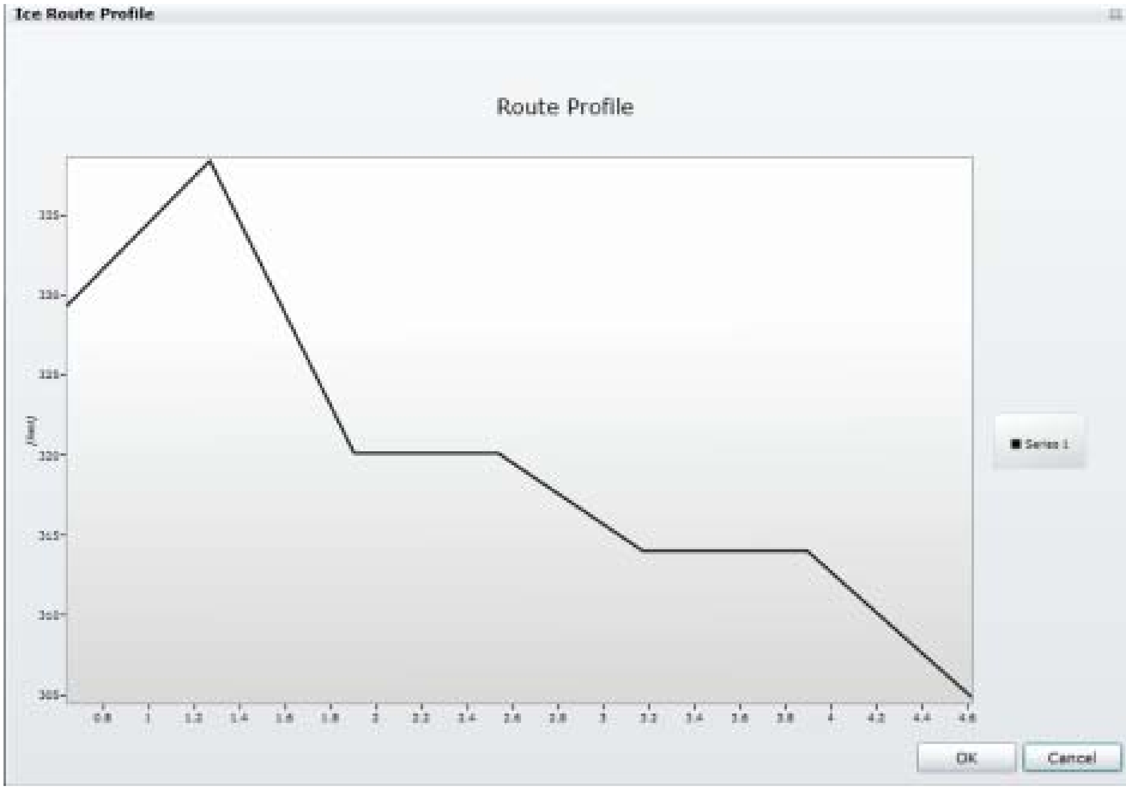

Fig. A.23. NSDSS section 2 profile

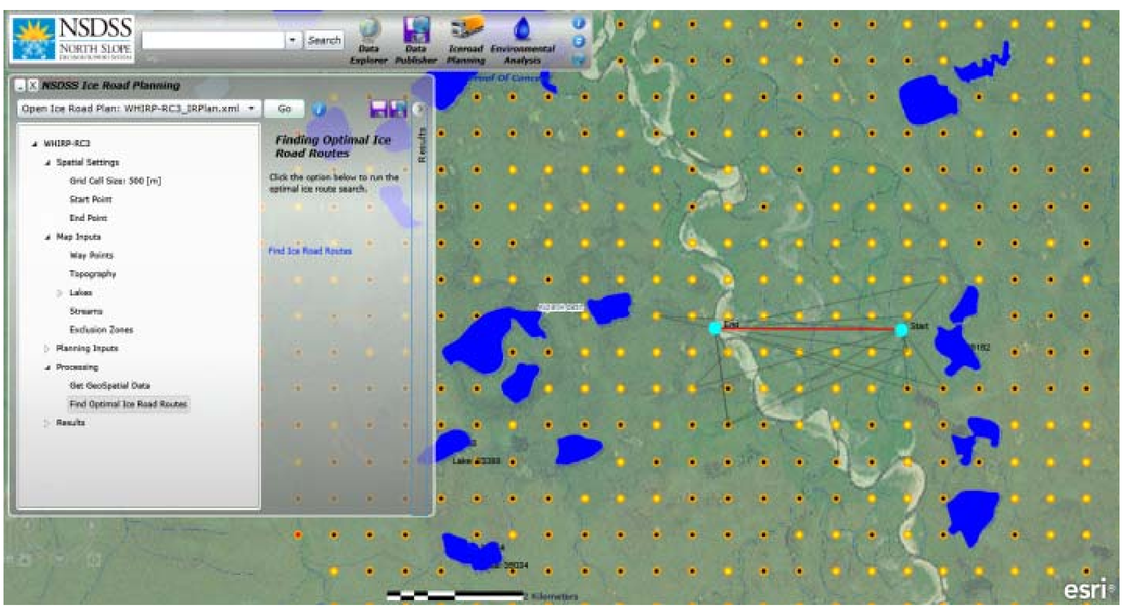

Fig. A.24. NSDSS section 3 map

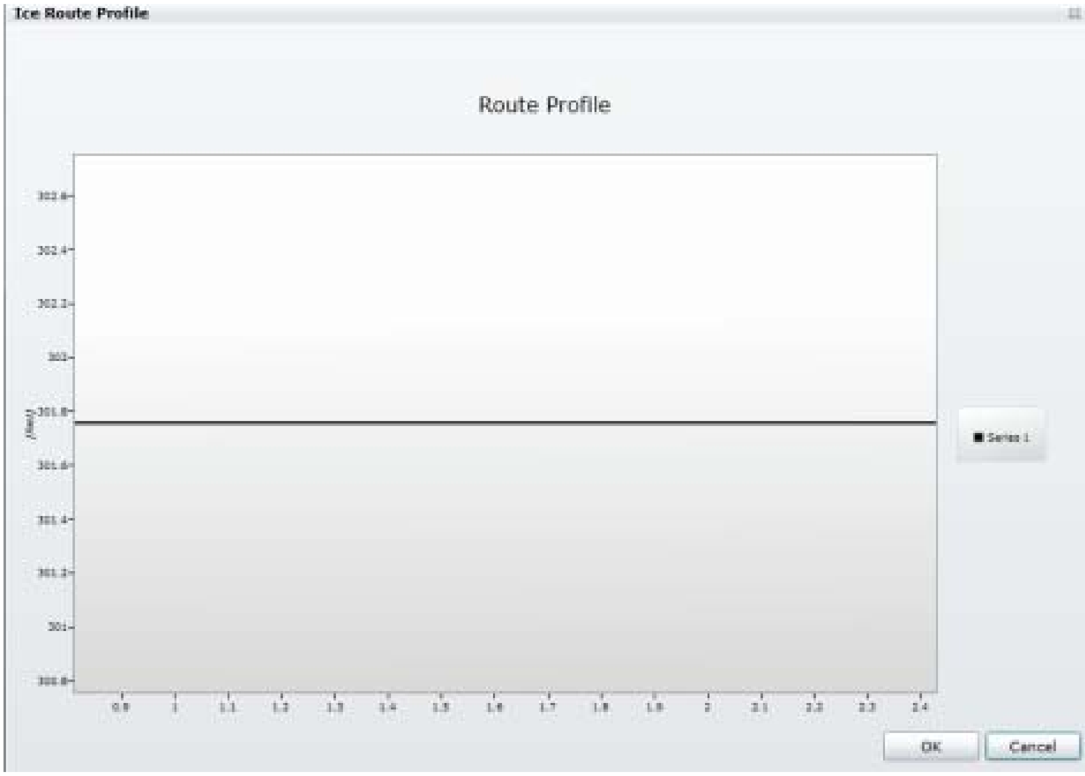

Fig. A.25. NSDSS section 3 profile

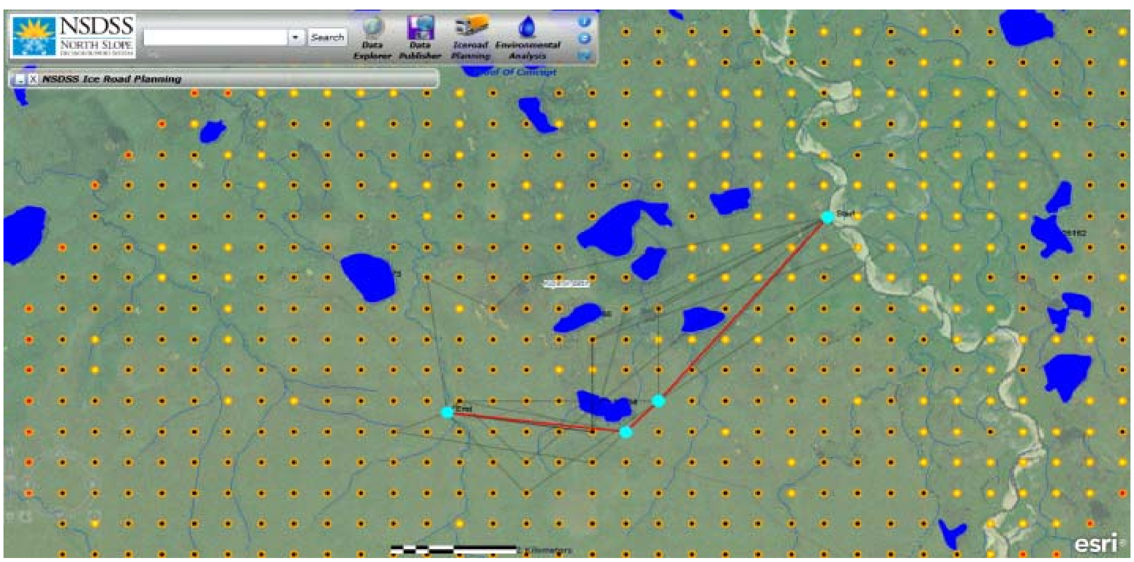

Fig. A.26. NSDSS section 4 map

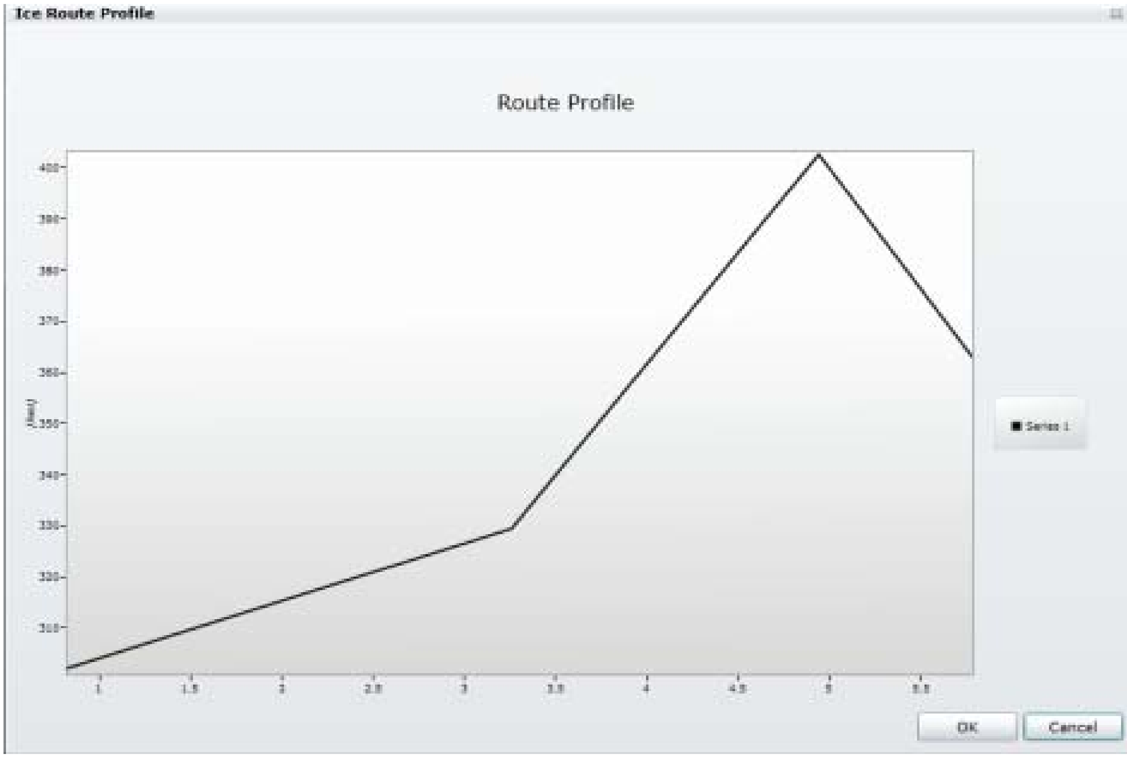

Fig. A.27. NSDSS section 4 map

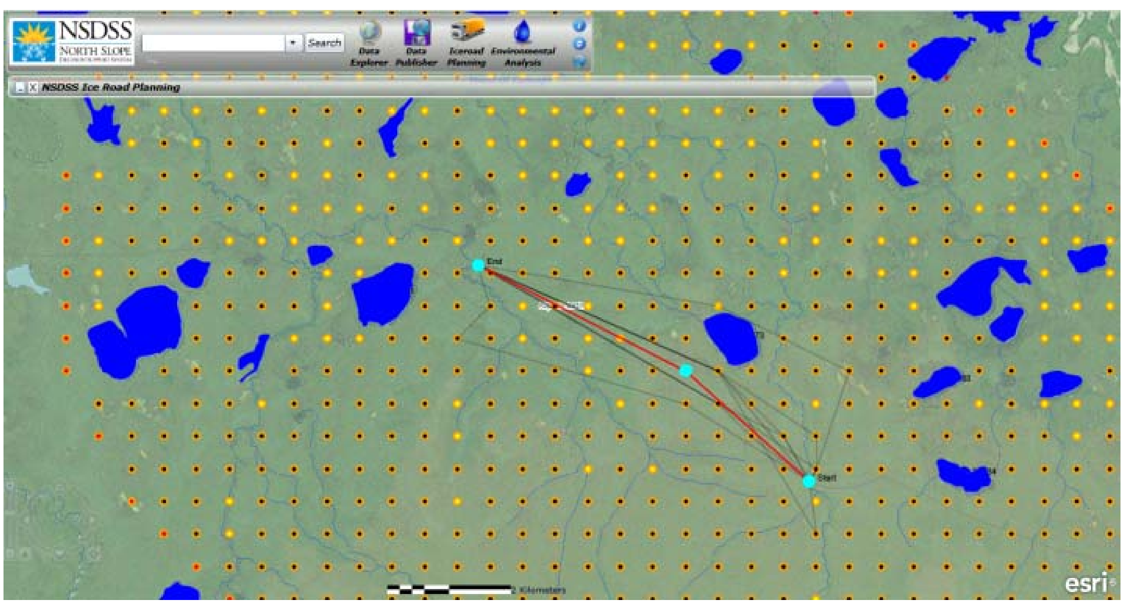

Fig. A.28. NSDSS section 5 map

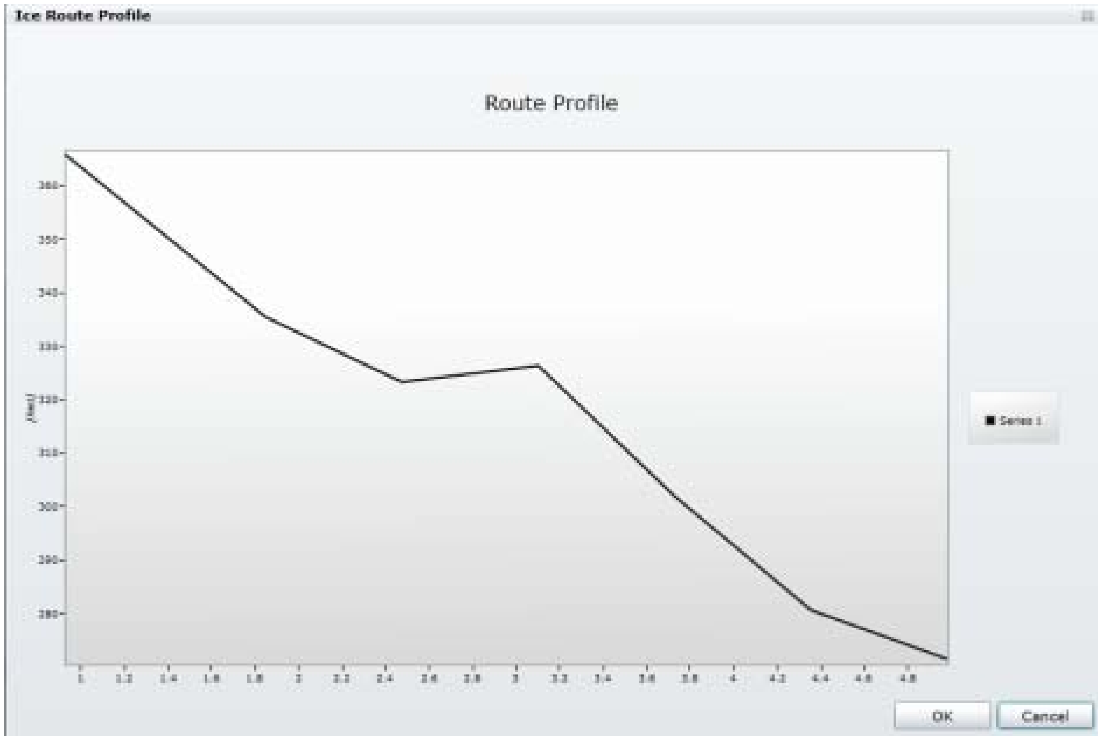

Fig. A.29. NSDSS section 5 profile

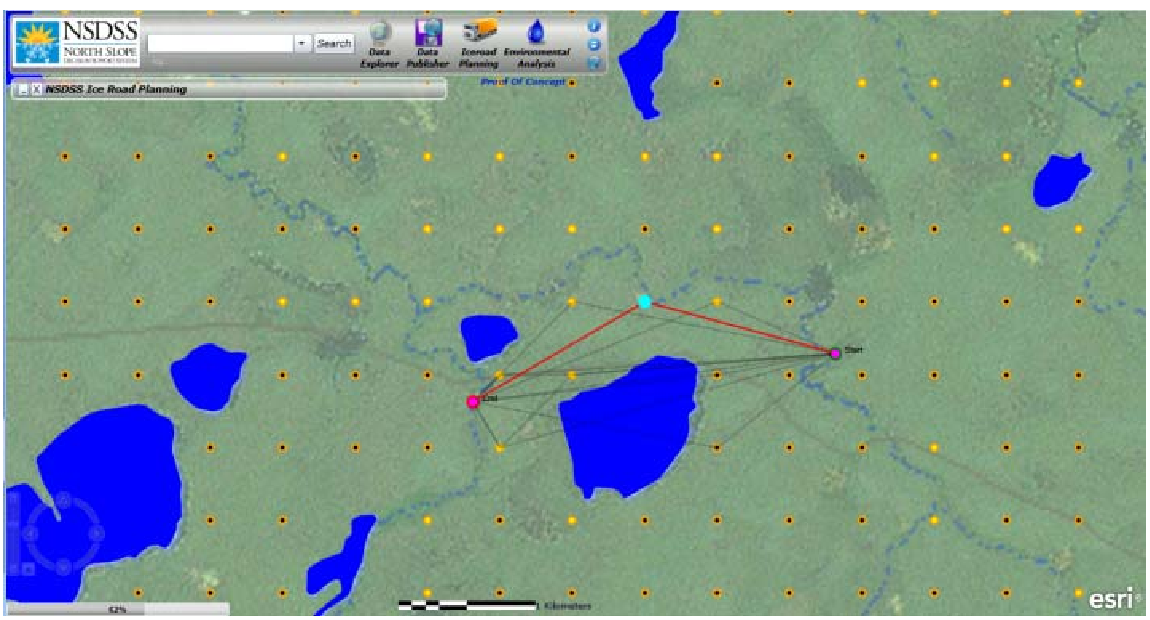

Fig. A.30. NSDSS section 6 map

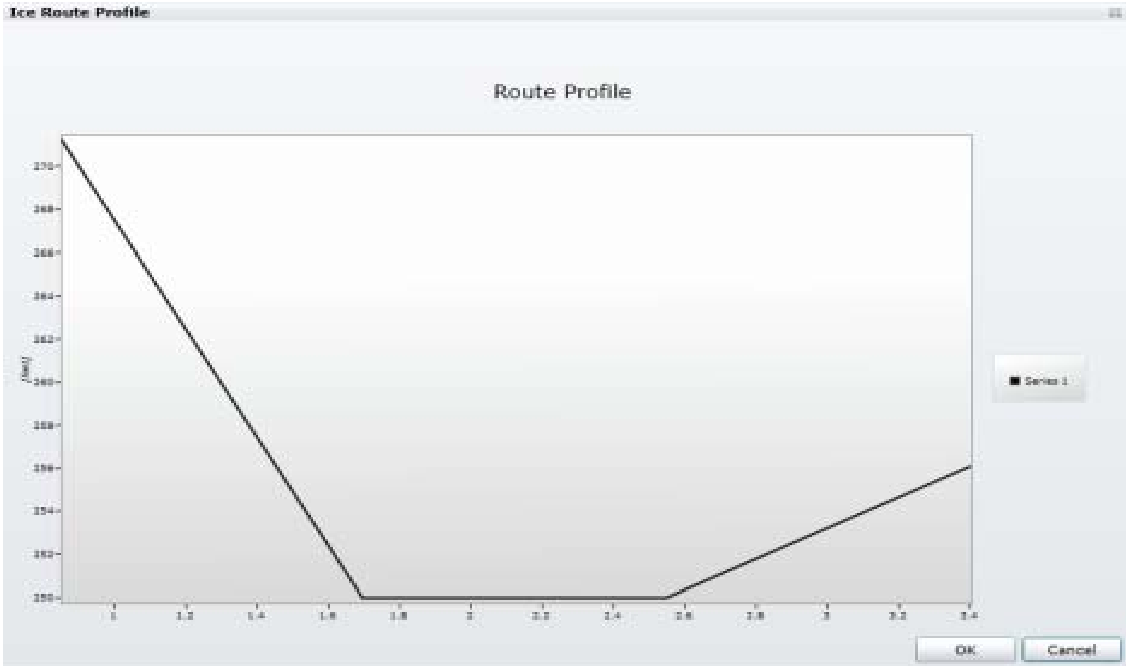

Fig. A.31. NSDSS section 6 profile

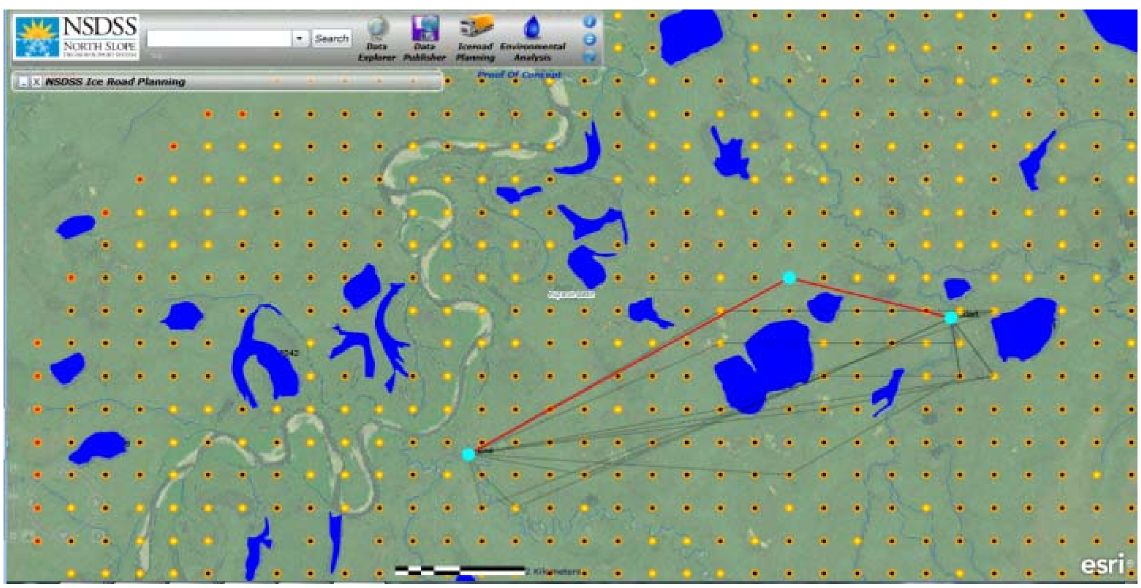

Fig. A.32. NSDSS section 7 map

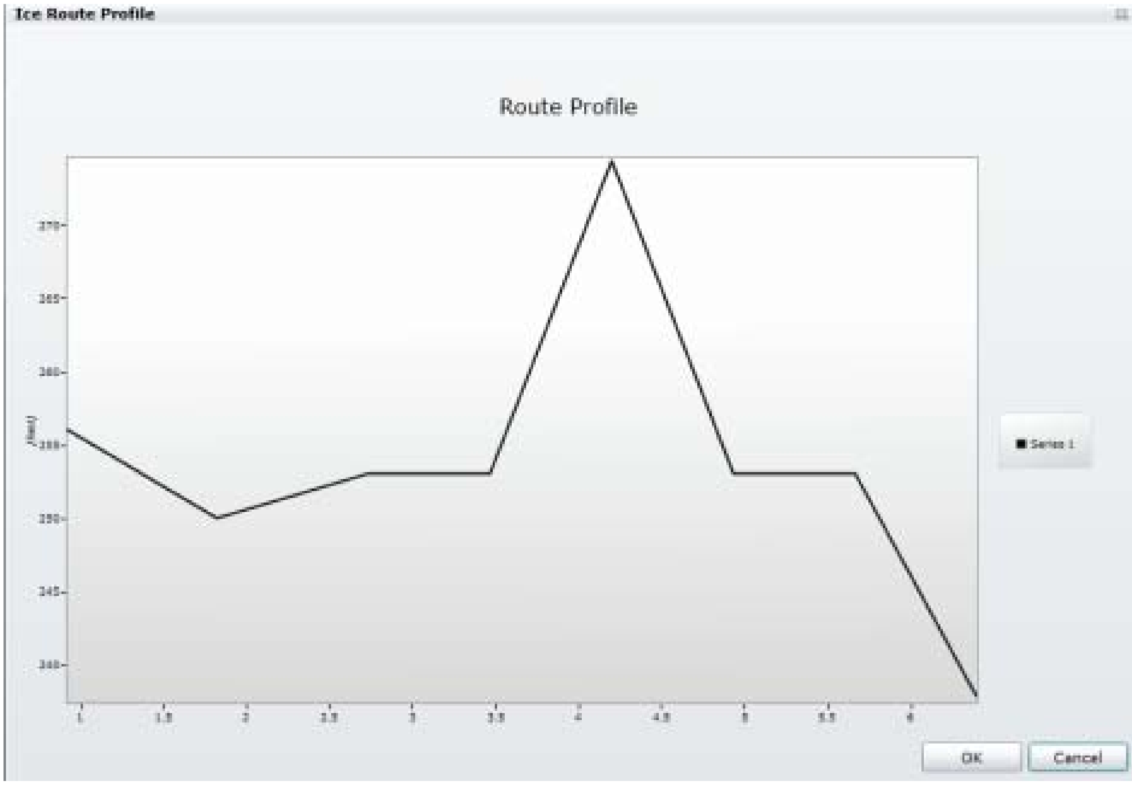

Fig. A.33. NSDSS section 7 profile

Fig. A.34. NSDSS section 8 map

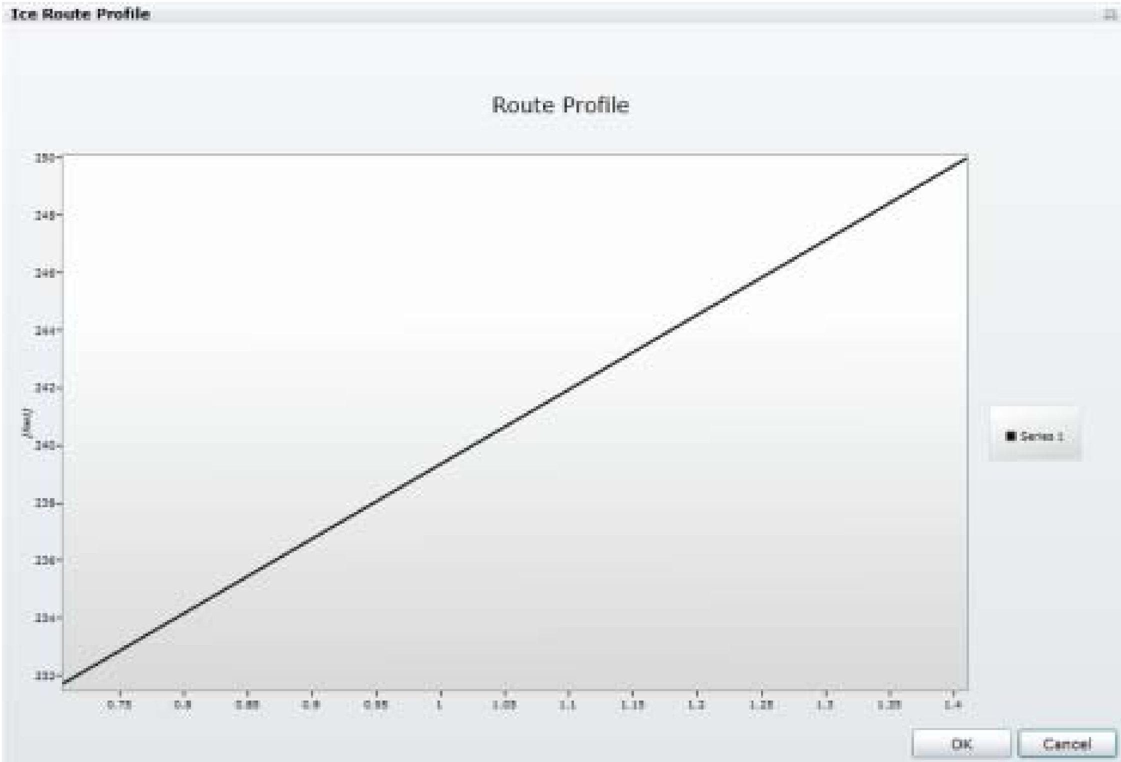

Fig. A.35. NSDSS section 8 profile

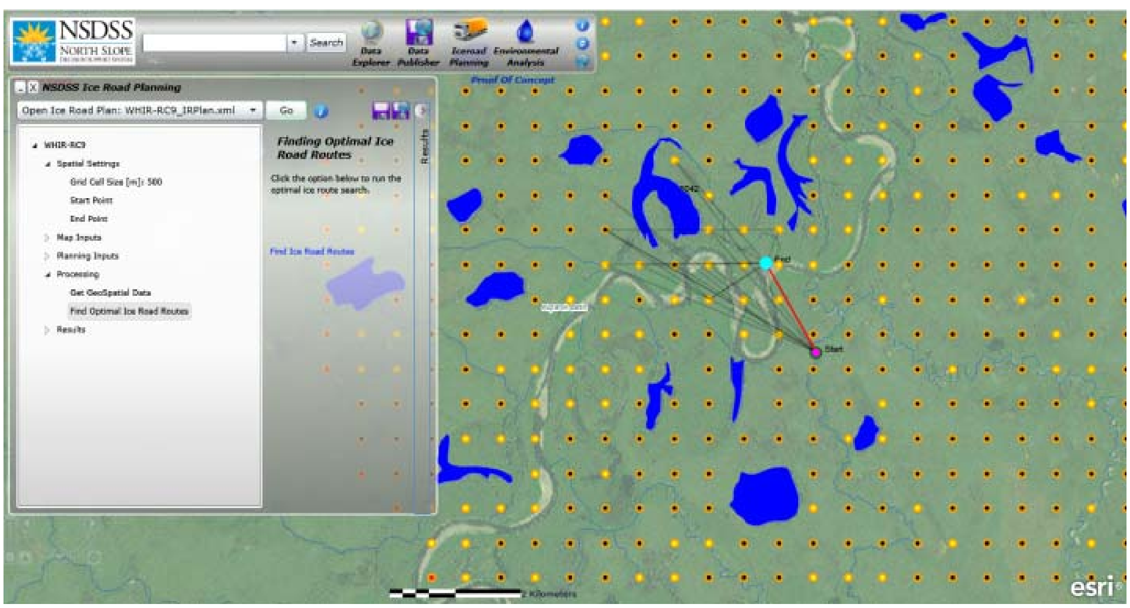

Fig. A.36. NSDSS section 9 map

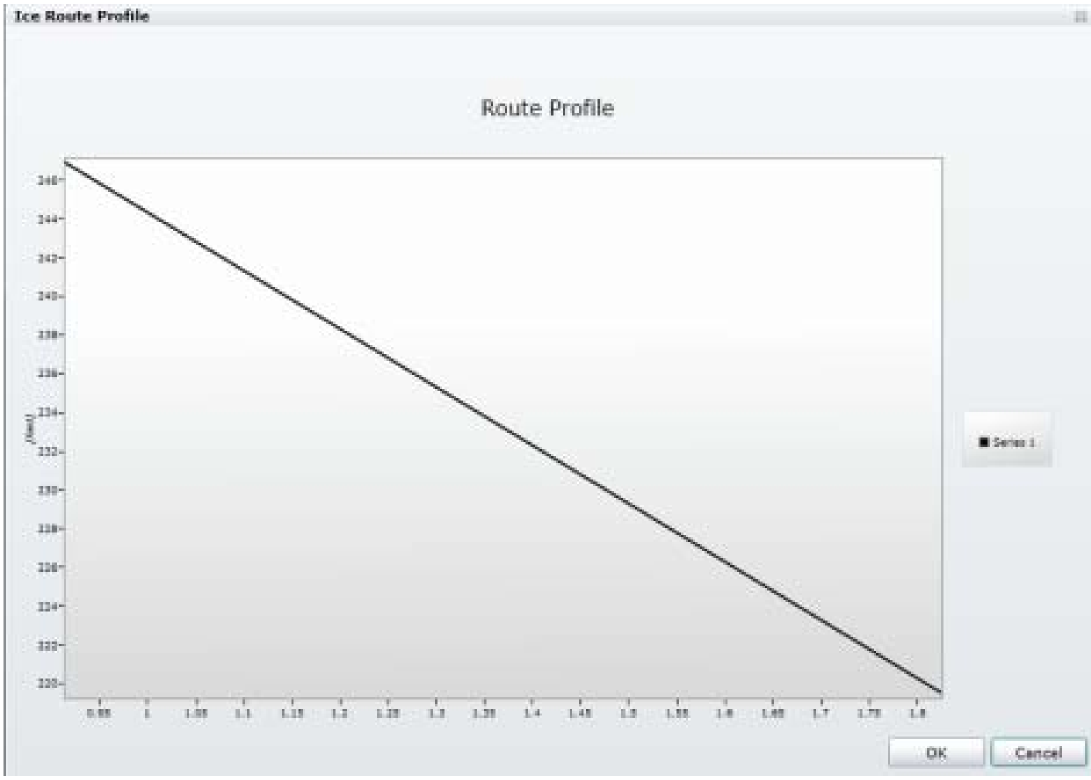

Fig. A.37. NSDSS section 9 profile

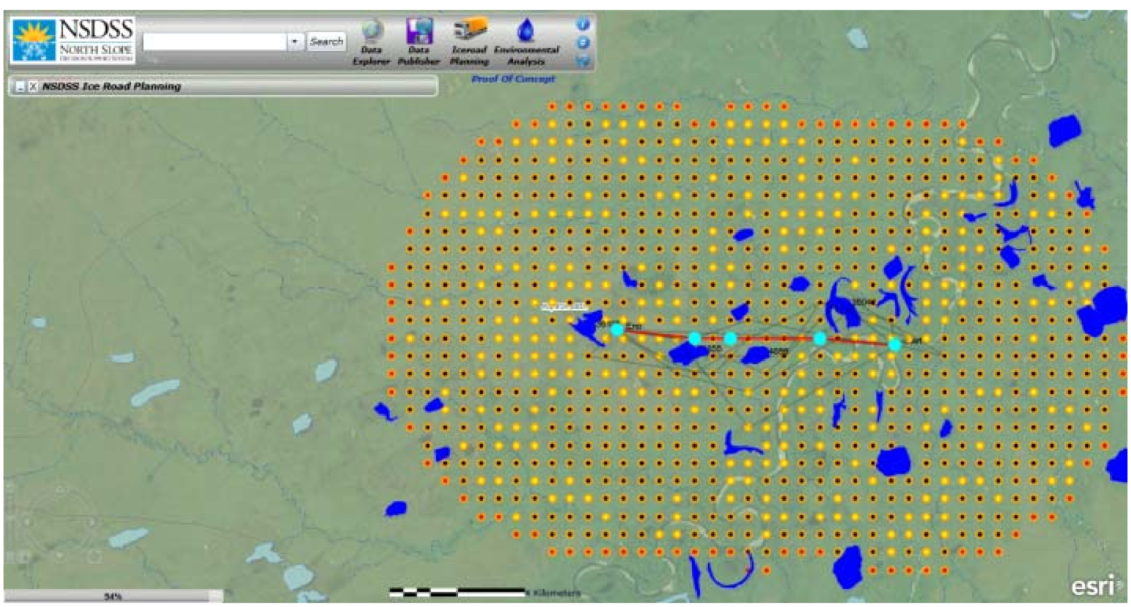

Fig. A.38. NSDSS section 10 map

Fig. A.39. NSDSS section 10 profile

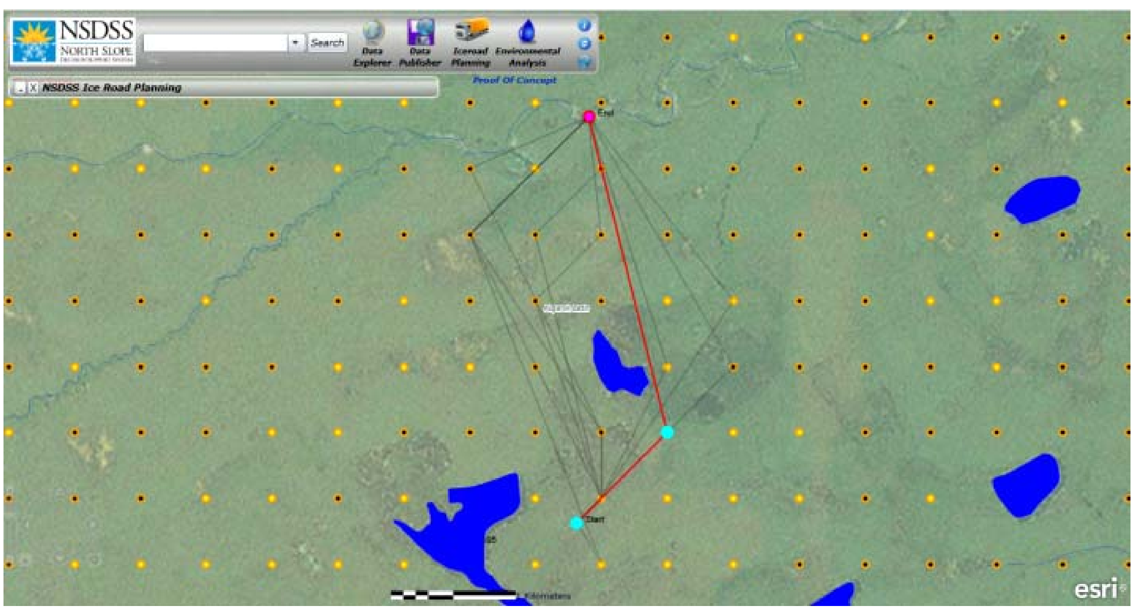

Fig. A.40. NSDSS section 11 map

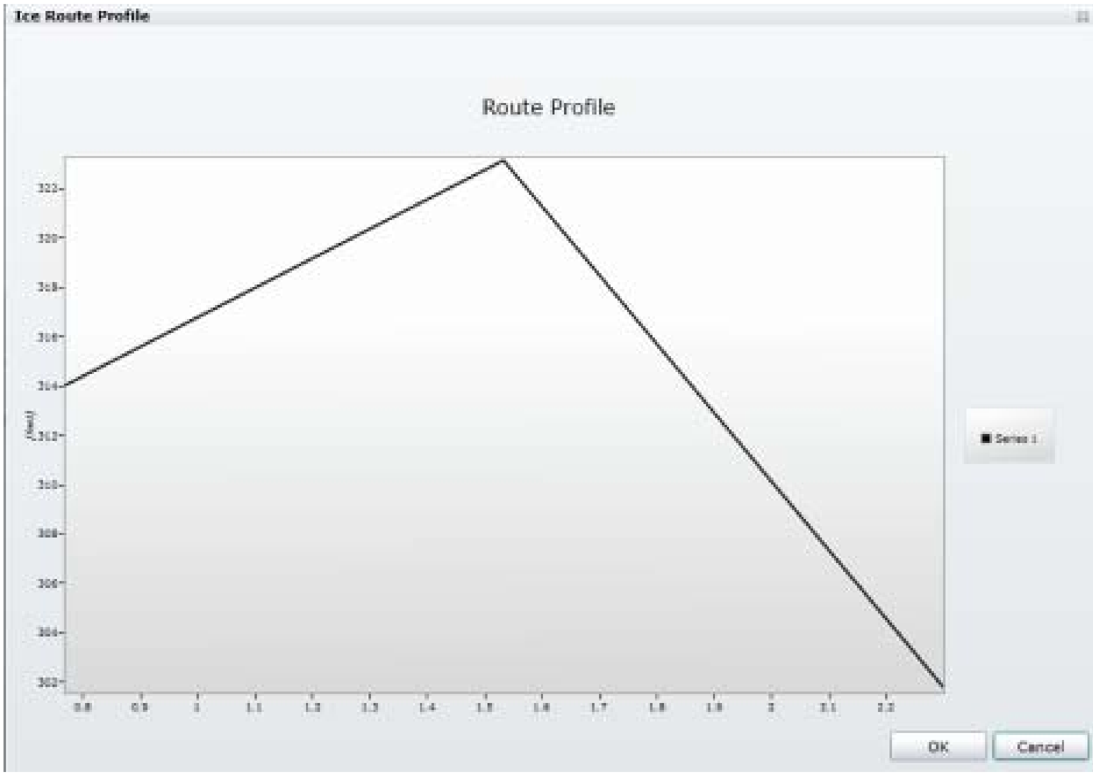

Fig. A.41. NSDSS section 11 profile

Fig. A.42. NSDSS section 12 map

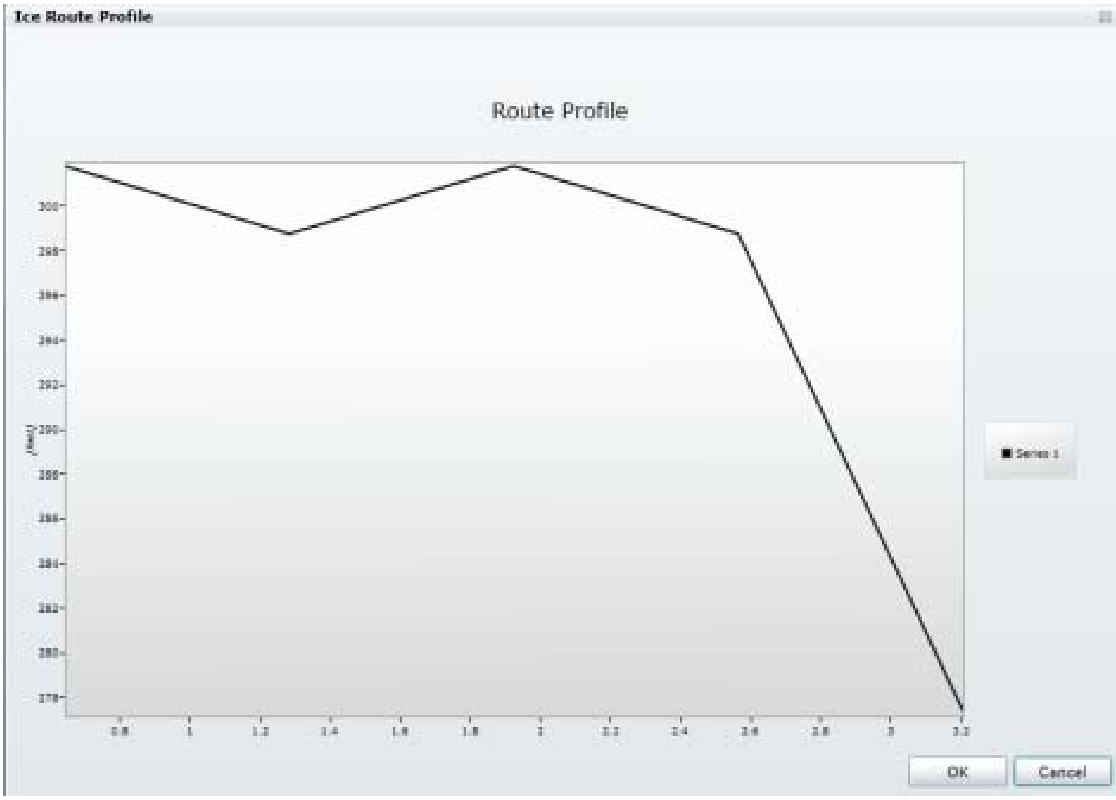

Fig. A.43. NSDSS section 12 profile

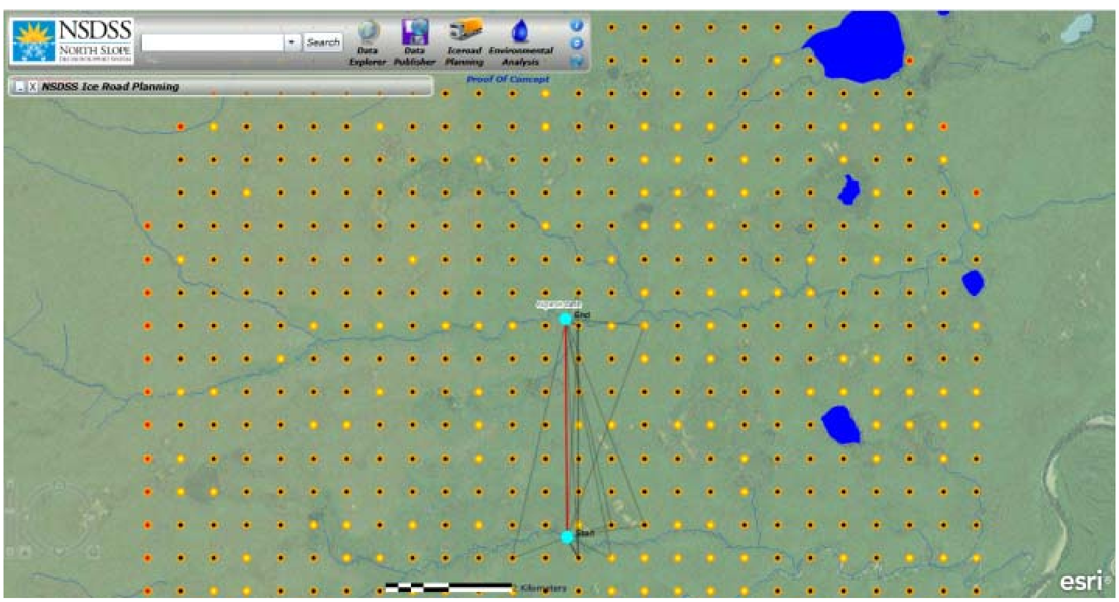

Fig. A.44. NSDSS section 13 map

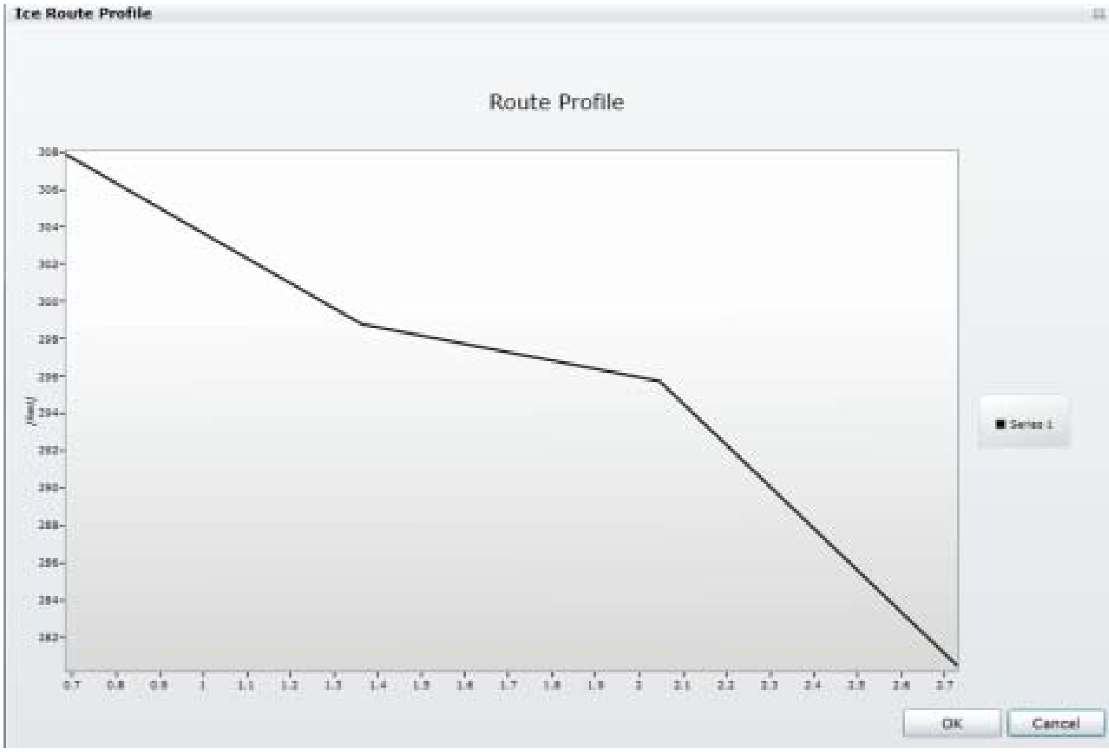

Fig. A.45. NSDSS section 13 profile

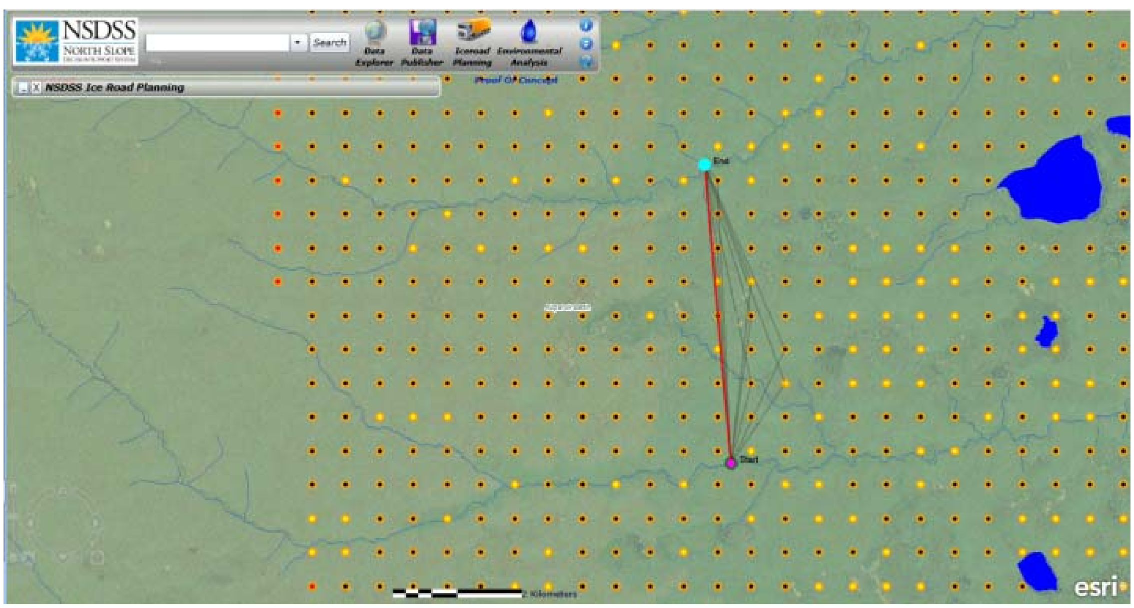

Fig. A.46. NSDSS section 14 map

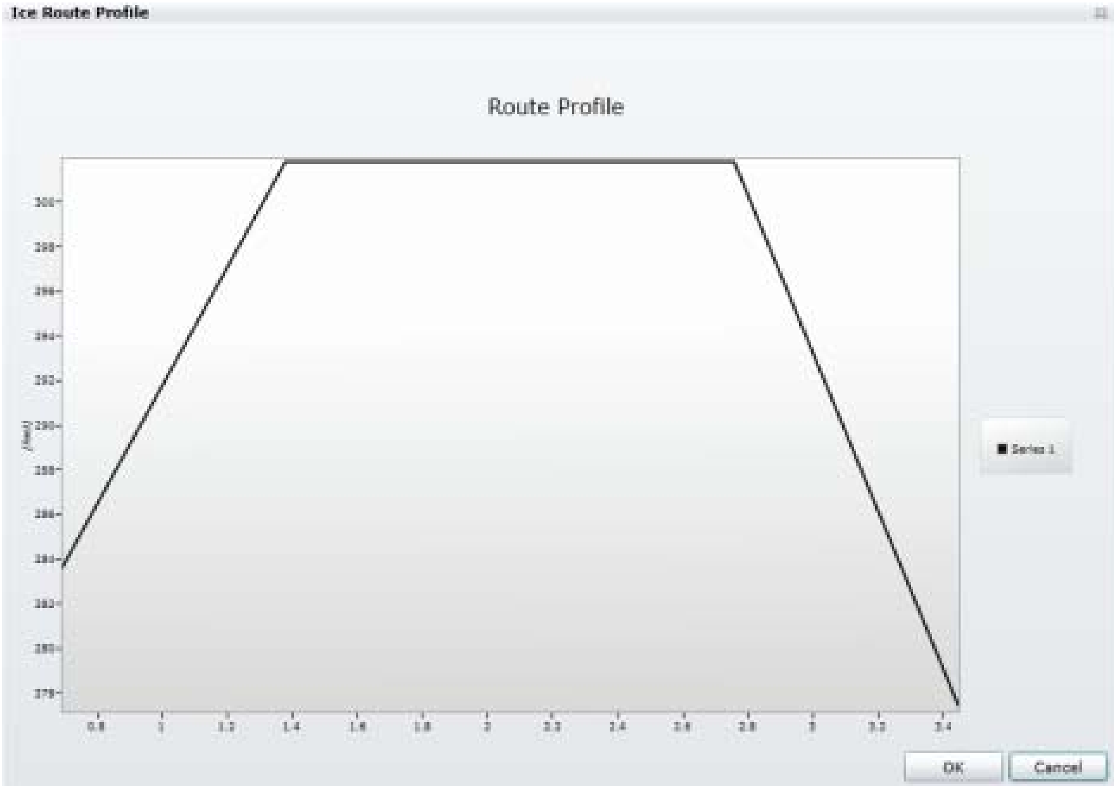

Fig. A.47. NSDSS section 14 profile

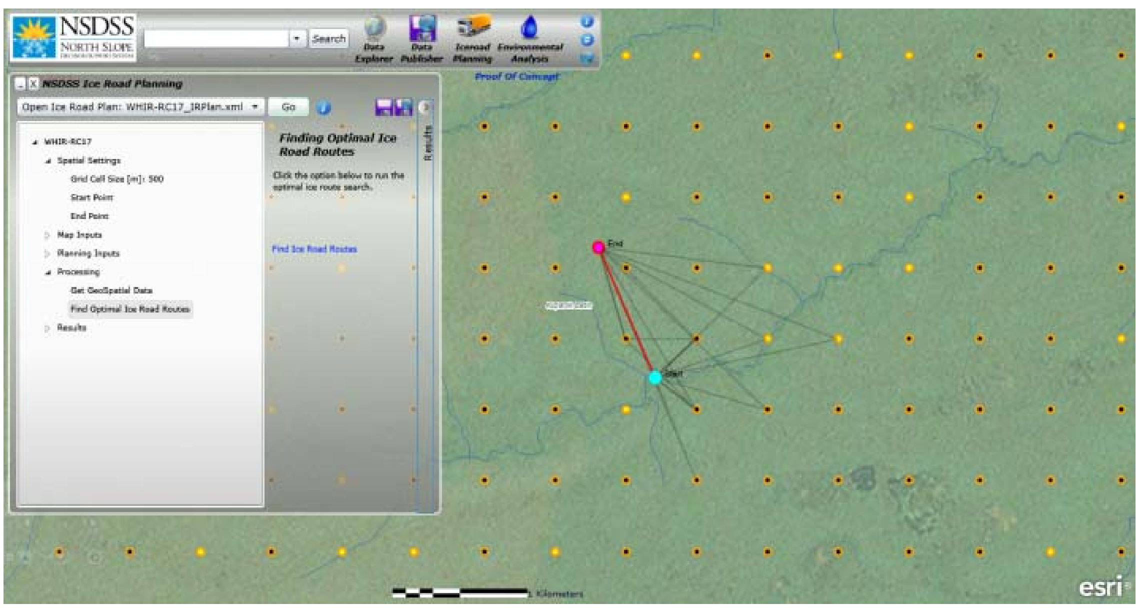

Fig. A.48. NSDSS section 15 map

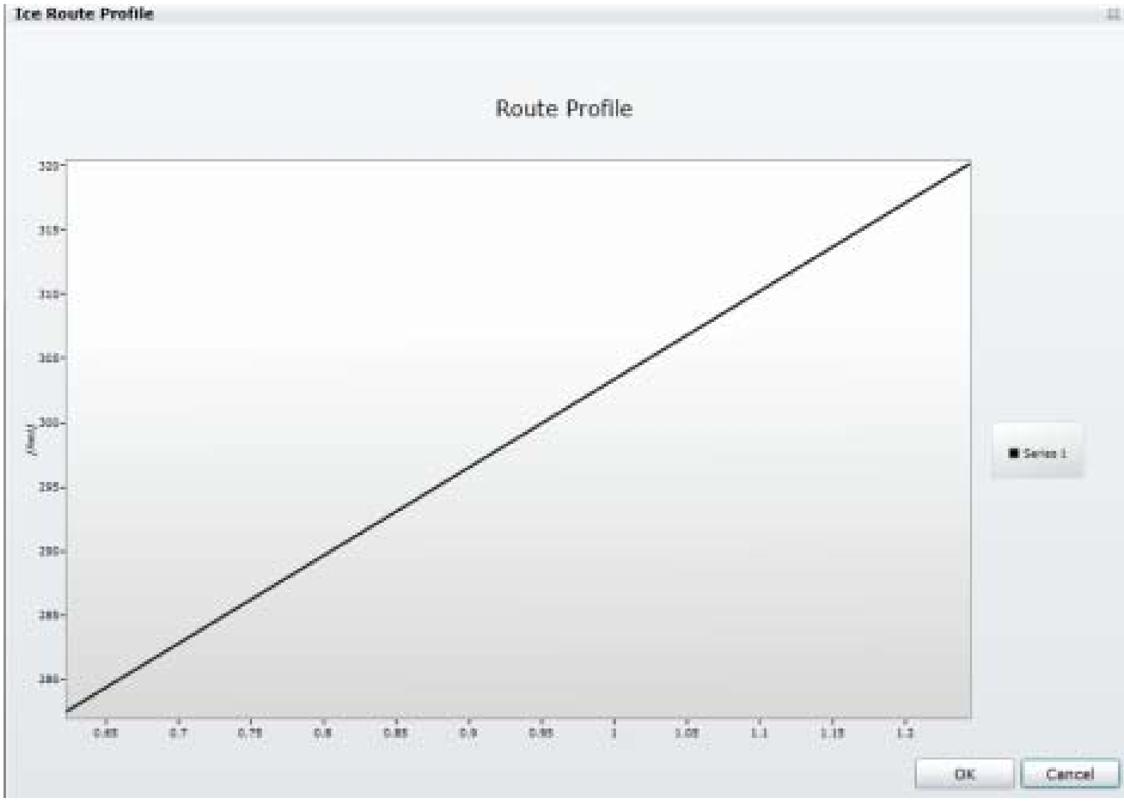

Fig. A.49. NSDSS section 15 profile

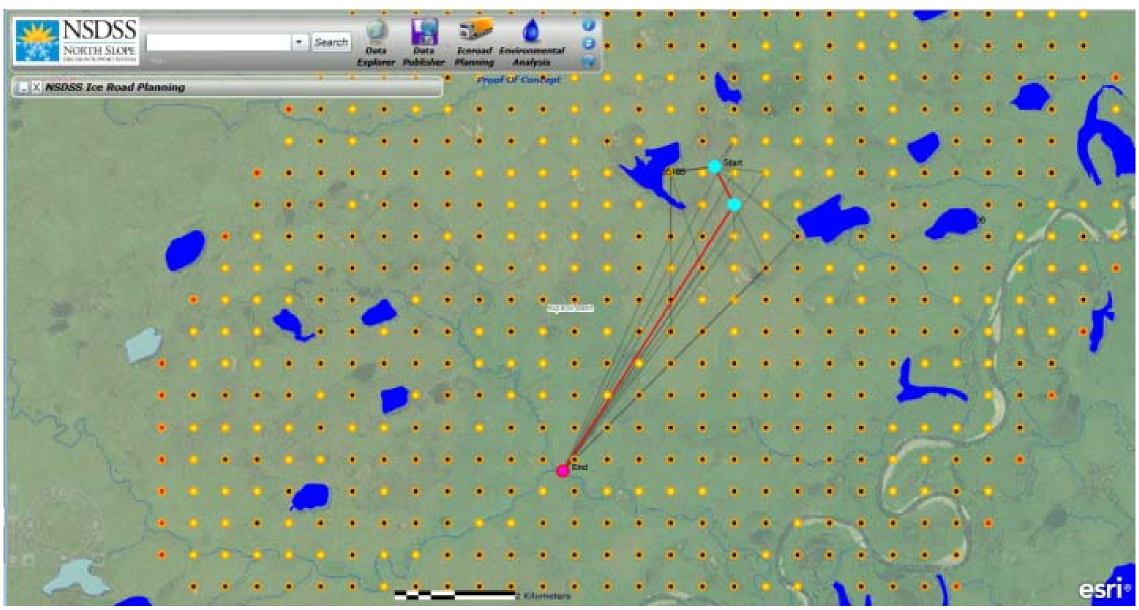

Fig. A.50. NSDSS section 16 map

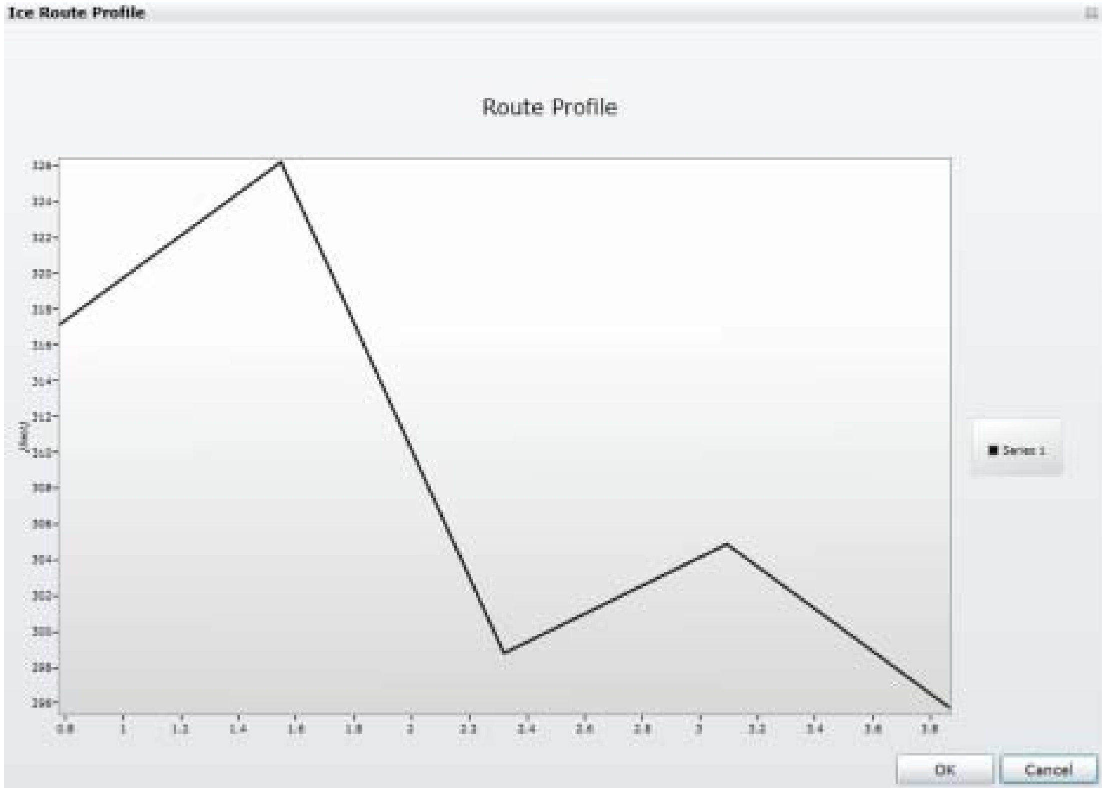

Fig. A.51. NSDSS section 16 profile

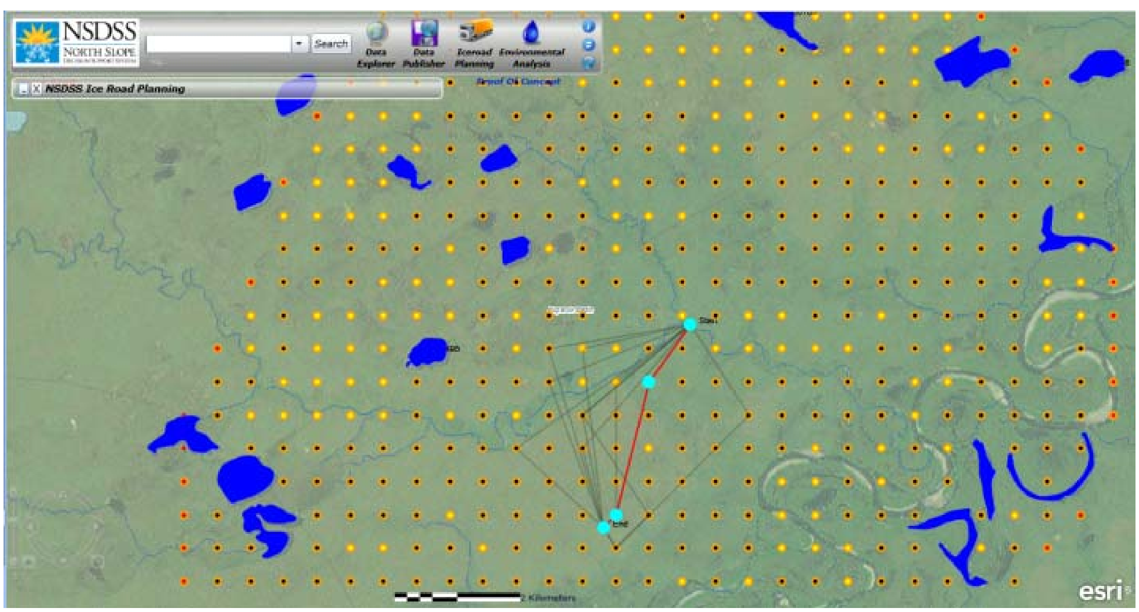

Fig. A.52. NSDSS section 17 map

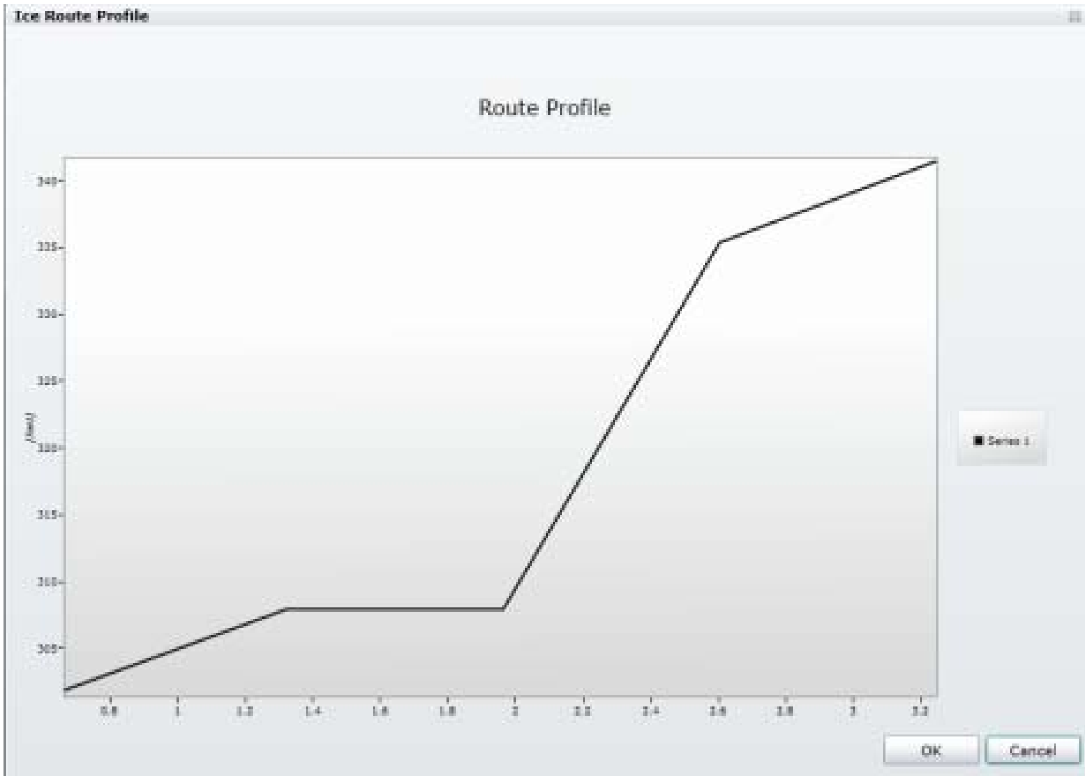

Fig. A.53. NSDSS section 17 profile

Table A.1. White Hills Ice Road Lakes Data

Chevron Lake Number	NSDSS Lake Number	R and RTS Lake Names	Latitude	Longitude	Surface Area (acres)	Max Depth (ft.)	Total Volume (mil. Gal)	Recommended Max Withdrawal (mil. Gal.)	Sensitive Fish Species	Resistant Fish Species	Permitted Amount (mil. Gal.)
W1*	32055	R0616	69.71525	-148.81441	242.792	5.7	244.616	0.166	No	Yes	0.17
W47*	26162	R0644	69.71849	-149.0118	61.899	8.2	57.055	0.927	No	Yes	0.93
W11*	33388	R0619	69.70518	-149.2059	62.084	6.3	85.312	1.701	No	Yes	1.7
W5*	35034	R0620	69.69136	-149.19412	81.49	8.7	147.134	9.522	No	Yes	9.52
W6*	36673	R0622	69.7155	-149.30338	147.379	18	264.645	19.366	No	Yes	19.37
W12*	31711	R0630	69.71954	-149.45123	185.545	7.5	301.811	12.788	No	Yes	12.79
W7*	31346	R0629	69.71679	-149.54281	362.287	5.9	344.567	0.836	No	Yes	0.84
W8*	35042	R0633	69.71688	-149.75425	97.868	13.4	127.976	6.587	No	Yes	6.59
W17*	34856	R0626	69.7022	-149.80878	71.842	10.2	109.629	4.662	No	Yes	4.66
W18*	34855	R0625	69.70143	-149.86223	138.176	7	196.774	0	Yes	Assumed	19.10 (ice only)
W3*	36105	R0624	69.71143	-149.9393	110.614	8.2	178.889	35.778	No	No	35.78
W25*	32849	R0640	69.68222	-150.15894	59.048	7.1	103.678	20.736	No	No	20.74
W24*	36495	R0641	69.6607	-150.08464	54.032	11	78.764	2.12	No	Yes	2.12
W4*	33047	R0634	69.61899	-150.02983	52.28	5.9	66.523	0.078	No	Yes	0.08
W20*	27647	R0635	69.61208	-150.00548	83.848	11.3	149.851	11.188	No	Yes	11.19
W54**	35222	RTS07145	69.61333	-149.9355	18.44	9	22.33	0.84	No	Yes	0.84
W19*	36308	R0636	69.5892	-150.02213	65.867	14	105.588	6.317	No	Yes	6.32

Table A.1 Continued

W58	Not in Database		RTS07149	69.58691	-149.87111	too shallow	0.5	-	0				
W55**	Not in Database		RTS07146	69.58444	-149.8611	8.15	10	13.74	0.81	No	Yes		0.81
W57**	Not in Database		RTS07148	69.56431	-150.02356	21.98	5	21.98	0	No	Yes	2.20 (ice)	
W56**		34306	RTS07147	69.55079	-150.02342	49.29	5.5	41.49	0	No	Yes	4.15 (ice)	
W52*		26531	R0656	69.80352	-149.58639	130.544	14	263.738	6.365	Yes	Yes		6.37
W2*		36107	R0623	69.83994	-149.72224	108.411	6.8	495.203	13.797	No	Yes		13.8
W30*		28552	R0663	69.99486	-150.01745	197.118	6	253.787	1.373	No	Yes		1.37
W31*		34299	R0664	70.01754	-149.97973	66.189	8.1	108.047	3.327	No	Yes		3.33
W32*		35588	R0665	70.02497	-149.9269	136.771	8.3	216.557	5.982	No	Yes		5.98
W33*		36681	R0666	70.01984	-149.8527	77.086	8.2	77.278	0.271	No	Yes		0.27
W34*		30987	R0667	70.0169	-149.82987	181.854	6.5	250.729	2.2	No	Yes		2.2

VITA

Name:	Walter Miller McDonald
Address:	Zachary Department of Civil Engineering Wisenbaker Engineering Research Center Room 205-R 3136 TAMU College Station, TX 77843-3136
Email Address:	waltermcdonald@tamu.edu
Education:	B.S. Civil Engineering, Texas Tech University, 2010 M.S. Civil Engineering, Texas A&M University 2012