Developing Models using GIS to Assess Process and Economic Risk: Examples from Mineral Exploration and Wind Energy Development in New Zealand

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Introduction

Succeeding in business is as difficult as it has ever been and understanding the financial risk involved in any business venture is even more crucial. This is especially the case for mineral exploration, but also applies to other industries that depend on being able to predict outcomes using spatial information. Fortunately, there are a variety of tools and techniques now available that when used with modern GIS allow sophisticated economic risk analysis to be carried out, including assessing uncertainty (Kreuzer et al., 2007; Hronsky and Groves, 2008). Any business that works in the spatial world should consider using these techniques to improve decision making during investment for development or managing operations. The oil industry has been using these techniques successfully for a number of years. More recently, the mineral exploration industry has taken this approach further and with the help of Spatial Data Modelling in GIS can now assess the probability of exploration success in relation to project economics (e.g., Bonham-Carter 1994; Partington, 1999, Raines, 1999; Partington et al., 2002, Rattenbury and Partington 2003). Other industries are also now recognising the benefits of this approach, including wind energy generation.

Understanding Processes

Understanding how systems work is critical to developing predictive models using spatial information. We need to understand how metals form in the earths crust or what factors control the successful operation of individual wind turbines. We need to understand all the variables that affect the outcome of a model and their interrelationships to make accurate predictions of the probability of an outcome occurring. So for wind modelling we need to understand the engineering constraints of available turbines, wind speed, effects of topography on wind speed and logistical constraints. For mineral exploration we need to understand the geological processes that lead to the formation of ore deposits. Many years of university based research have gone into developing ore deposit models for most of the metals used by our industries today and these models are at the core of most mineral exploration target ranking schemes. These models include a complete array of process factors of ore-formation, including products of the mineralisation process, characteristics of the regional and local geology and structure, inferences about the tectonic setting, and grade and tonnage data (e.g., Figure 1). The critical parameters of ore deposit formation can be best described using a Mineral Systems approach, which focuses on those factors that control the generation and preservation of mineral deposits, and the processes that are involved in mobilising ore components from a source, transporting and accumulating them in more concentrated form and then preserving them throughout subsequent geological history (Wyborn et al., 1994). Applied to mineral exploration, the Mineral Systems approach requires identification at various scales of the critical ore-forming processes and mappable ingredients that characterise a particular mineral system. These diagnostic features can then be used as guides in area selection and exploration targeting.

Gold mineralisation related to granite intrusions is an example of a new style of mineralisation that was believed to be potentially present on the West Coast of New Zealand. This style of mineralisation has been found in similar rocks in Eastern Australia. A model was created for this style of gold mineralisation that included the known areas in Australia to predict where new deposits could occur in New Zealand. The gold mineralisation targeted by the Spatial Data Modelling is associated with a well defined set of geological criteria researched from known examples around the world including Eastern Australia. This has allowed the development of a well understood Mineral System model that can be used to constrain any Spatial Data Modelling (Bakke, 1995; Thompson et al., 1999; Mustard, 2001; Mustard, 2004). A GIS database containing a total of 79,000 mineral occurrences, 9,324,000 rock geochemical data analyses, 21,912,000 stream sediment geochemical data analyses, 26,360,592 soil geochemical data analyses, 109,000 drill holes and 2,537,522 km^2 of geological and geophysical data in Eastern Australia and the West Coast of New Zealand was compiled so that Spatial Data Modelling using the Weights of Evidence technique could be carried out.

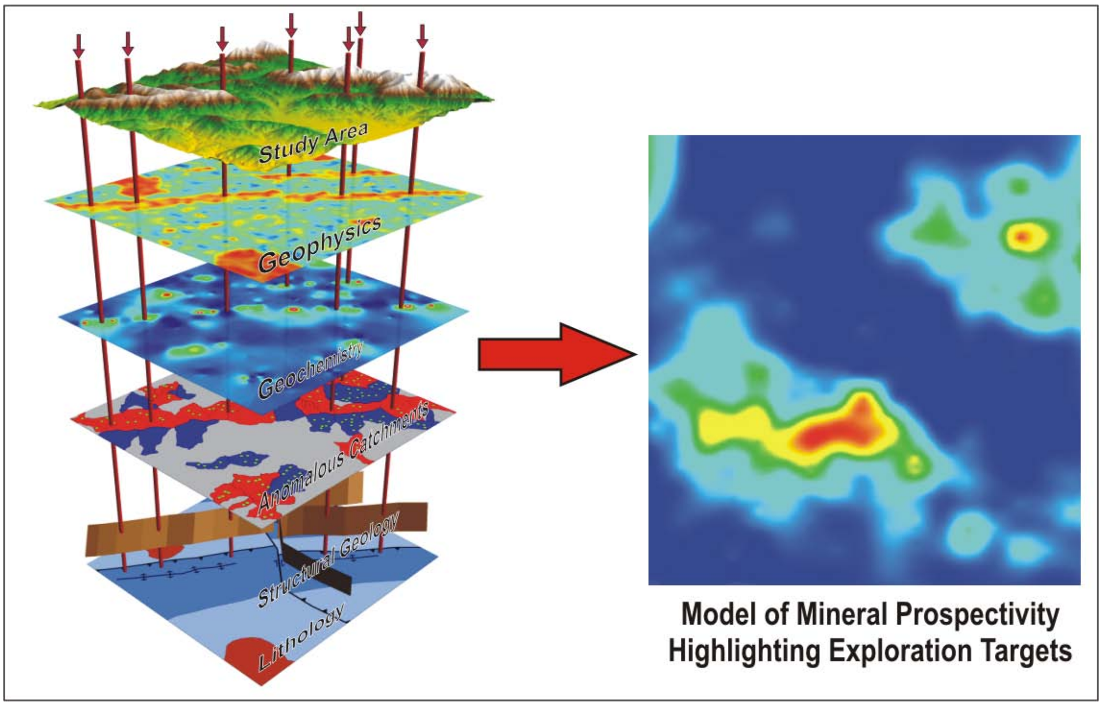

Figure 1 Types of mappable geological data used to target mineral exploration.

Wind Energy is a relatively new source of renewable energy in New Zealand and there is great potential for finding new wind farm sites that take advantage of the world class wind resource. By combining all the relevant spatial information in a GIS, Spatial Data Modelling can be used to significantly reduce the time and money needed to identify suitable sites for development. Although wind speed is the most important requirement for a successful wind farm there are many other factors that make a site suitable for development such as proximity to infrastructure, suitable topography, current land use and distance from populated areas. Again, like in the mineral exploration example, these variables can all be mapped spatially in a GIS and can be consequently used to model the probability of developing a successful wind farm. The modelling can be undertaken across entire countries for locating suitable wind farm areas, in local regions for more detailed mapping of wind farm extent, or at the wind-farm scale for assisting with turbine placement. In this example a GIS database was developed for New Zealand that consisted of a wind speed map, a DTM, detailed roads, location of transmission lines, a land use map, a map of the conservation estate, water features, population density and location of built up areas over the entire country. The database contains more than 3 gigabytes of data that had to be integrated and modelled.

Spatial Data Modelling

Although a GIS is a perfect way of visualising data and producing maps from that data, GIS also allows you to create new data using statistically based gridding techniques or predictive maps using Spatial Data Modelling techniques. Interpolation allows you to predict unknown values from within a single layer such as topography, geochemistry, hydrology or climate data. However the real power of GIS is when Spatial Data Modelling is applied to combine several maps to predict outcomes based on probability such as mineral prospectivity or wind energy production (e.g., Figure 1 and Figure 2). Spatial Data Modelling uses multiple maps related to the object being searched for to statistically predict areas where it is most likely to be found (Bonham-Carter 1994). The simplest type of predictive spatial analysis is where maps, with the chosen input variable(s) represented by a series of integer values, are combined together using arithmetic operators (Bonham-Carter 1994). This type of analysis takes no account of the relative importance of the variables being used and is based on expert opinion. Fuzzy Logic techniques address the problem of the relative importance of data being used, but this technique still relies on expert opinion to derive weights that rank the relative importance of the variable for the map combination (Bonham-Carter 1994). Weights of Evidence, in contrast uses statistical analysis of the map layers being used with training data to make less subjective decisions on how the map layers in any model are combined (Bonham-Carter 1994). Neural Network techniques have been developed to mimic the thought process of the human brain and are entirely data driven techniques that are difficult to interpret.

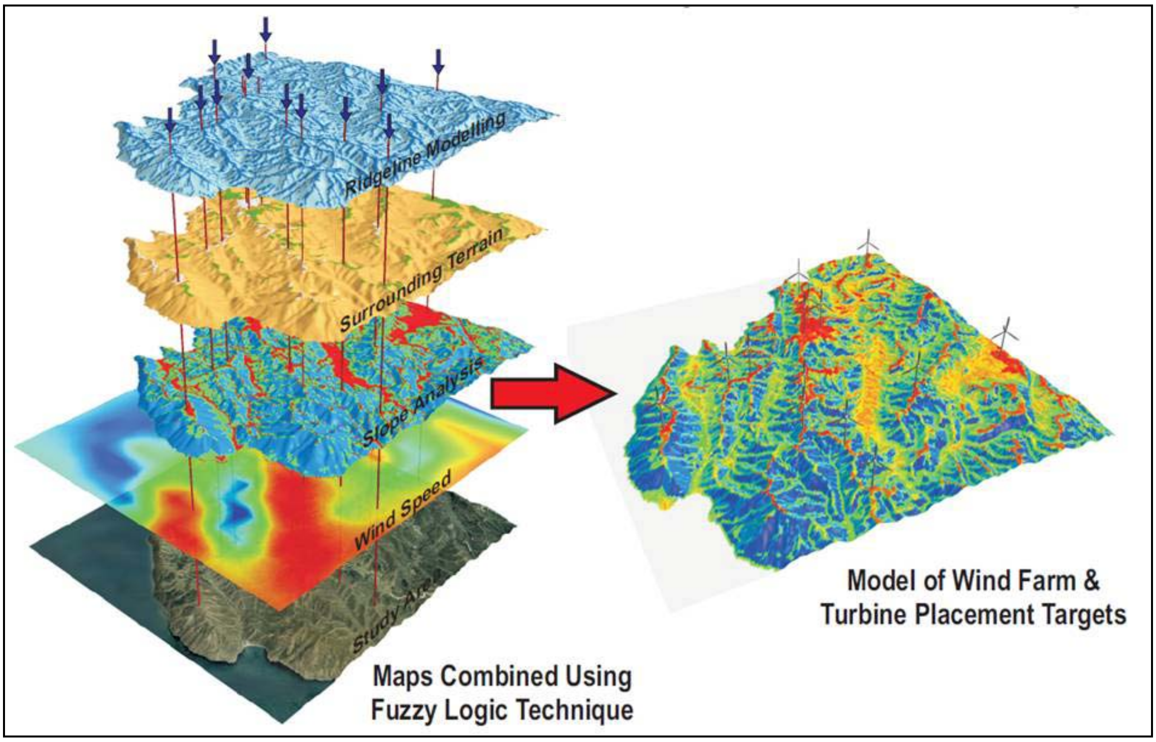

Figure 2 Types of mappable data used to target wind energy.

The Weights of Evidence technique was used to develop the granite gold model because of the data driven approach and transparency of results compared to Fuzzy Logic and Neural Network techniques (e.g., Bonham-Carter, 1994; Partington and Sale, 2004). The Weights of Evidence model for granite related gold mineralisation in New Zealand was created using predictive maps that represent all stages of the mineral system model (Figure 3). The predictive maps were generated using GIS techniques such as buffering, map intersections, interpolation using inverse distance weighting or density algorithms. Statistical analyses of all geophysical, geological and geochemical data were completed using probability and percentile plots to identify anomalous populations to help with the reclassification of the base data sets.

Sixty-seven different predictive maps were developed and tested for their spatial correlation with the training data in the mineral exploration example. The key geological concepts tested included: relationship to granite lithology, granite texture, granite series, granite age, granite geochemistry, proximity to major faults and relationship to fault orientation, correlation with density of quartz veins, proximity to aplite or pegmatite dykes or veins and correlation with As, Au, Bi, Cu, Mo, Sn, U and W geochemistry. Most of the data were reclassified to produce binary predictive maps, but data like geology were reclassified into multi-class predictive maps. The predictive maps used in the final model were chosen from those with the highest positive weights. Some of the predictive maps with high weights had similar map patterns, for example granite age and granite type. In this case only one predictive map was used in the model to attempt to reduce potential conditional dependence. The model was developed using Arc-SDM software through Spatial Analyst in ArcGIS 9.2 (Sawatzky et al., 2008).

The resulting prospectivity model consisted of a raster grid containing the intersection of all of the input maps as a single integer raster (Figure 3). Each row of the raster attribute table contains a unique row of input map values, the number of training points, area in unit cells, sum of weights, posterior logit, posterior probability, and the measures of uncertainty. Importantly, the raster grid can be mapped by any of the fields in the attribute table, giving important information on the data influencing the result and missing information. The final stage of the modelling was to reclassify the model grid to map high priority exploration targets for intrusion related mineralisation. This was done by using the prior probability as lower cutoff and the post probability values calculated for known economic mines such as Timbarra and Kidston as an upper threshold. Target areas above the lower threshold were considered for tenement acquisition and targets with post probability values greater than known mines were prioritised for immediate follow-up exploration.

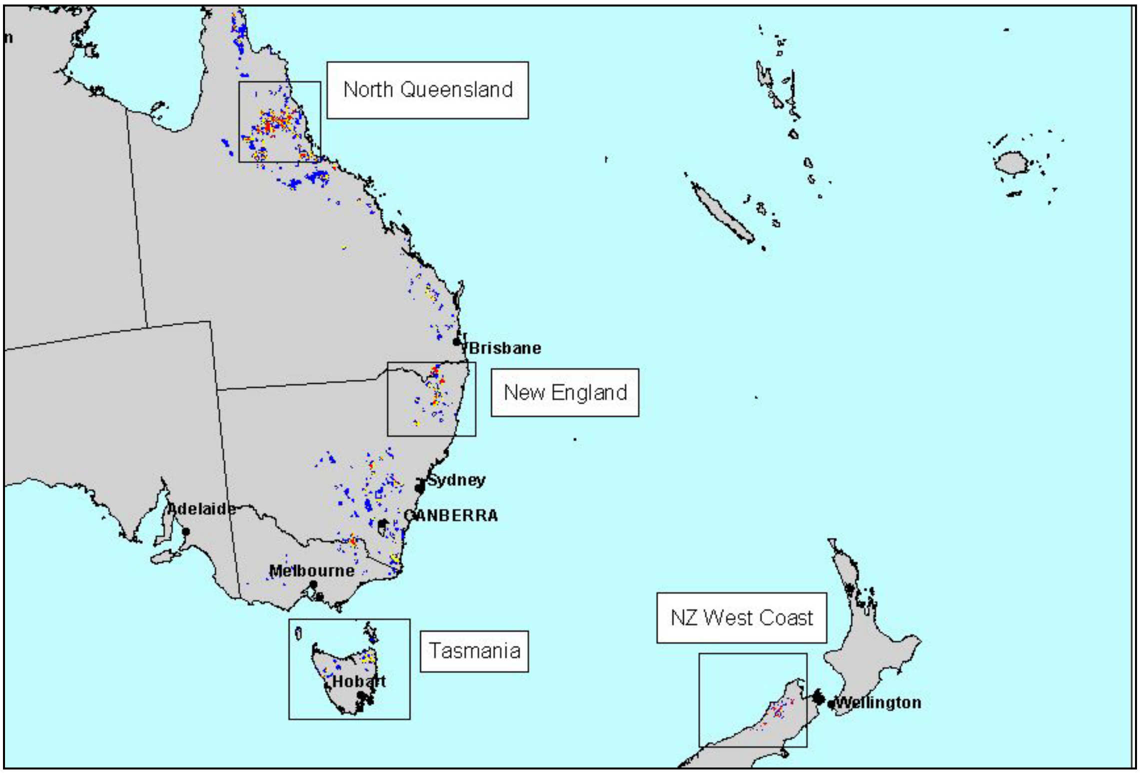

Figure 3 Prospectivity model for granite gold mineralisation showing areas highly prospective for gold mineralisation in red, confirming that the West Coast of the South Island of New Zealand has similar potential for gold mineralisation as Eastern Australia.

The Fuzzy Logic technique was used to model potential wind farm locations in New Zealand because there was no information on which wind turbines operating in New Zealand were economically successful that would have allowed a training dataset to be created. Each dataset to be used in a Fuzzy Logic model is weighted using a fuzzy membership function that expresses the degree of importance of the map layer as a predictor of the feature under consideration. Predictive maps are combined by a variety of fuzzy combination operators (e.g. fuzzy AND, fuzzy OR, fuzzy gamma; Bonham-Carter, 1994). The output from the fuzzy logic model is a map showing feature favourability after combining the effects of all of the input spatial data (Figure 4).

Advanced analysis of satellite data provided by Aurecon was used to develop national meso-scale wind speed maps, which provide continuous detailed coverage of wind speed and wind direction. The modelling is based on advanced three-dimensional meteorological models that simulate airflow over complex terrain at a range of resolutions and elevations. There is usually a variance of only 0.7–0.85% between the meso-scale results and actual wind mast readings in areas where the modelling has been used to date; consequently the technique is very reliable and ideal for use in Spatial Data Modelling. Once the models have been run, wind speed and direction information can be extracted for any point in the area covered. The national-scale models generate results for heights 80 metres above the ground that allow analysis of the wind speed at turbine hub heights. The wind speed and direction data is analysed and classified into ranges suitable for different classes of modern turbines and regional economic constraints of the study region.

Advanced terrain modelling techniques are used to integrate digital elevation data to determine slope, aspect to the main wind direction, complexity of surrounding terrain, ridgelines and upwind terrain effects. Maps of these five terrain parameters are created using GIS modelling tools and each represents a key element that can effect local wind speeds and turbulence, and are crucial when positioning wind turbines. This advanced analysis can also be completed over smaller detailed regions to allow planning of turbine placement at individual wind farm sites. The wind farm model also takes into account other factors that could affect the suitability of a site for wind farm development. These include infrastructure, social, land use and environmental variables. The layers that are used in the model will depend on the specific requirements and economic conditions in place in the country or region being modelled and also on the digital data that is available over the area.

At a country or state-wide scale the output probability map can be used to target new wind farm sites and rank them in order of favourability for follow-up field investigation. At the regional or wind farm scale of modelling it can define the potential extent of an individual wind farm, be a guide for monitoring mast placement and even assist with locating turbine sites and managing development.

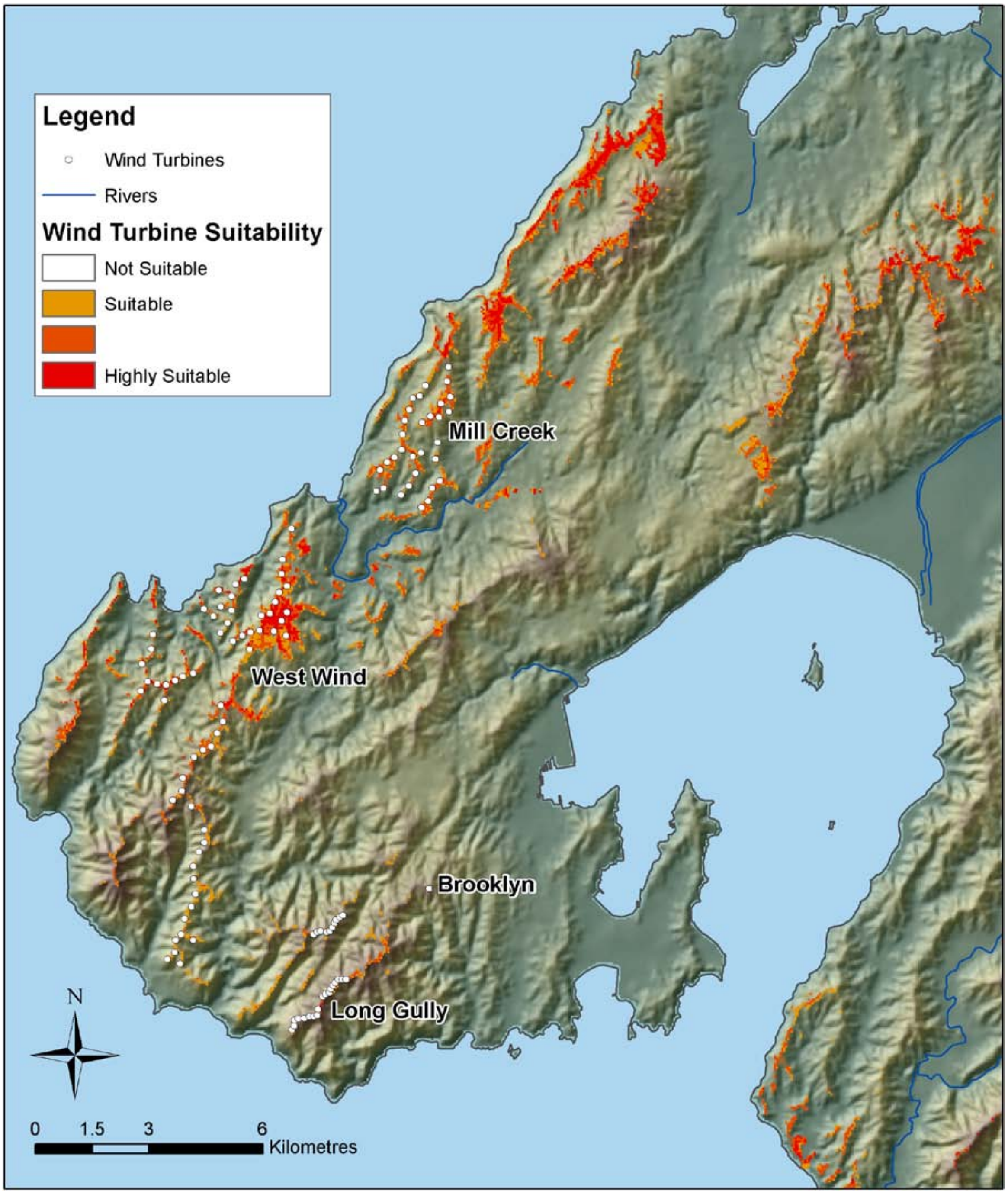

Figure 4 Fuzzy logic wind farm target model for part of the Wellington Region of New Zealand.

Estimating Economic Risk

The Spatial Data Modelling provides a measure of the probability of occurrence for a variety of targets in both examples, but does not take into account financial cost and return on any follow-up work or development; consequently the full risk of development is unknown. It is possible to calculate the development risk by combining the probability of occurrence with the cost and reward from development (e.g., Kreuzer et al., 2007; Groves and Horonsky, 2008). This can be done for each target defined by the spatial data modelling to develop a district or nation wide risk profile for each target area. In the granite related gold example the probability of geological success has been calculated by the Weights of Evidence modelling, the probability of discovering a target tonnes and grade can be calculated from grade and tonnage data from grade tonnage curves and cost and revenue data can be derived from historic information updated for current costs and metal prices. The exploration risk can be calculated by multiplying the cost of exploration and development by the probability of failure and subtracting this from the Net Present Value (NPV) of the project times the probability of success (Kreuzer et al., 2007). This allows the identification of the highly prospective targets that have the best returns in an exploration portfolio. It is these targets that should be given the highest priority for exploration investment. The economic risk analysis assumes minimum, likely and maximum input variables which when simulated allow the calculation of the uncertainty of the outcome.

The wind farm targets can be analysed in a similar manner. The target areas can be created using a probability cut-off defined by probability values from currently operating wind farms. Potential NPV values for new targets can be calculated by taking the area covered by the target and calculating the possible number of turbines that can be located within the defined area (Table 1). This gives an idea of potential power production and consequently revenue. Development and running costs can be estimated from logistical factors such as distance from grid, topography, distance from roads and potential consenting issues. The final product is a database of target areas that can be sorted according to a variety of factors including economic performance and chance of meeting corporate targets. The Fuzzy Logic technique, unlike Weight of Evidence does not calculate a measure of uncertainty for the wind energy model, which does limit the risk analysis to some degree.

ID	Area	Type	No	MW	Efficiency	P(Wind)	NPV	Risk	NPV >0	Risk >0
WF1	6.44	Large	38	95.0	87%	0.913	$79.45	$57.93	96.0%	91.8%
WF2	3.94	Medium	23	34.5	95%	0.865	$47.98	$33.07	99.5%	97.7%
WF3	1.52	Medium	9	13.5	95%	0.892	$18.79	$14.12	99.5%	98.2%
WF4	4.15	Medium	25	37.5	95%	0.885	$52.23	$38.51	99.8%	98.4%
WF5	3.73	Medium	22	33.0	95%	0.885	$45.91	$33.84	99.5%	98.3%
WF6	1.13	Large	6	15.0	95%	0.885	$21.24	$15.75	99.5%	98.5%
WF7	1.73	Large	10	25.0	95%	0.885	$35.49	$26.35	99.7%	98.5%
WF8	1.39	Large	8	20.0	95%	0.862	$28.39	$19.58	99.7%	98.2%
WF9	97.6	Medium	589	883.5	95%	0.885	$1,230	$907	99.5%	97.8%
WF10	1.23	Medium	7	10.5	87%	0.830	$8.45	$3.80	95.3%	81.2%
WF11	2.89	Medium	17	25.5	87%	0.842	$20.57	$10.05	95.7%	83.5%
WF12	3.01	Medium	18	27.0	78%	0.845	$7.49	-$1.19	75.4%	45.7%
WF13	2.24	Large	13	32.5	78%	0.845	$9.91	-$0.54	77.3%	48.6%
WF14	2.05	Medium	12	18.0	95%	0.824	$25.03	$14.94	99.6%	96.2%
WF15	2.26	Large	13	32.5	78%	0.845	$9.90	-$0.55	78.0%	49.0%

Table 1 Example of the economic analysis from the wind energy model. The targets can now be sorted according to various factors that take account of economic and location risk.

Conclusions

The aim of using Spatial Data Modelling techniques in both examples was to shorten development time consequently reducing costs. The mineral exploration model has confirmed the prospectivity of the West Coast of the South Island for gold mineralisation similar to historic gold mines in Eastern Australia that are worth billions of dollars. The discovery of a gold deposit of this type would have a significant impact on the economy of New Zealand and the economic modelling of targets generated by the spatial data model has allowed a database to be developed of ranked targets that can be prioritised so that those targets with the lowest geological and economic risk can be explored first. The modelling in the wind energy example shows how quickly a developer can cost effectively target and rank new wind farm opportunities and define the potential extent of an individual wind farm. It allows for easy approximation of the number of turbines that the wind farm can hold, can be a guide for turbine and monitoring mast placement, and can be used to identify the land owners that need to be approached early on in the development process. The modelling also provides a pipe-line of projects that can be worked on sequentially allowing those with the lowest risk to be developed first. Other benefits that come from carrying out Spatial Data Modelling include effective data compilation, QC of digital data, understanding of the critical factors that can be used to target more effectively, ranking of targets allowing more effective management, understanding of risk, and cost reduction.

The Weights of Evidence technique is a particularly useful Spatial Data Modelling tool as it is possible to derive a range of data that contribute to any area with high probabilities from the final map. It is possible to identify those data variables that contribute most to any model and the combination of factors that influence the final result. Weights of Evidence also allows the calculation of uncertainty within the model due to missing data. More importantly, the technique allows the identification of missing data in areas of lower probabilities that if collected could increase the prospectivity of the area. All Spatial Data Modelling techniques need to be combined with economic factors to allow a complete understanding of risk to be measured. This allows targets with differing local spatial variables to be compared and prioritised.

The most important outcome from the modelling work is that it is now possible to assess the location and value of important resources that could contribute significantly to New Zealand's economic well being. It is also possible to assess the risk of investing capital to develop these opportunities. This should lead to increased investment in developing these resources and provide a framework for their future development. This is critical when considering future land access, investment in infrastructure and land management at a national scale.

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