Evaluation of the potential economic benefits of NSW-IMOS using improved ocean forecasts

F. Zhang[1]*, X.H. Wang[1] and E. Barber[2]

1. School of Physical, Environmental and Mathematical Sciences
University of New South Wales
Australian Defence Force Academy
CANBERRA, ACT. 2600

2. School of Business
University of New South Wales
Australian Defence Force Academy
CANBERRA, ACT. 2600

* Corresponding Author: Fan Zhang

Email: f.zhang@student.adfa.edu.au

Abstract

The Integrated Marine Observing System (IMOS) is an Australian national program for observing the oceans around Australia. As one of its important nodes, the New South Wales Integrated Marine Observing System (NSW-IMOS) aims to provide more accurate descriptions of the East Australian Current (EAC). The purpose of this paper is to introduce and implement a quantitative method to evaluate the economic benefits of the NSW-IMOS to the NSW ocean related sectors. To further explain the method, an example showing the potential economic benefits arising from greater prediction accuracy of factors affecting beach recreation users is provided.

Key Words: NSW-IMOS, economic benefit; evaluation; quantitative method

1. Introduction

From 2007, the Australian government and various research organizations invested approximately \$100M to establish a nationwide Integrated Marine Observing System (IMOS) for the purpose of enhancing interpretation and prediction of the oceans around Australia. A further funding of \$52M has recently been announced by the Australia government to extend and improve IMOS for the period of July 2009 to June 2013 (Moltmann, et al., 2009).

As one of the six regional nodes of IMOS, the general purpose for the establishment and maintenance of NSW-IMOS lies in providing improved data products for assimilation into and verification of ocean, wave, climate and weather prediction models. To fulfil this purpose, through installing different monitoring facilities, extracting real time or near real time observing data and publishing these data in user friendly ways to the Australian public, NSW-IMOS could provide more accurate descriptions of the latitudinal gradient in EAC (East Australian Current) effects, its separation and resultant eddy field along the coast of SE Australia and its climate impacts. The EAC, as a part of the subtropical gyre in southern Pacific, is a western boundary current flowing along the east coast of Australia and provides an important mechanism for teleconnectivity between the climates of tropical and southeastern Australia (Bhatt et al, 2010). The EAC eddy field has been related to the sudden overnight intensification of East Coast Lows (ECLs) and severe winter storms. To forecast flooding and beach erosions caused by ECLs, ocean forcing of ECL development and wave driven beach erosion are focused by NSW-IMOS during the ongoing establishment (NSW-IMOS, 2009).

Since sea level and waves are the major climate drivers affecting the coastal zone, to help understanding the ocean's impact along NSW coastal areas, NSW-IMOS will examine the coastal wind and wave climate in driving nearshore currents and northward sediment transport (NSW-IMOS, 2009). In the future, it is planned that the NSW-IMOS information will also be used to address societal concerns associated with ecosystems health and management of the marine resources of the NSW coastal waters. Predictions on biophysical response to climate changes are also expected from the observations of NSW-IMOS (NSW-IMOS, 2009). The facilities utilized by NSW-IMOS are listed and explained in Table 1. Many data streams can be obtained from these nine advanced observing facilities and are shown in Table 2.

Ocean related weather monitoring and forecasting have significant impacts on a wide range of industries as well as communities and individual activities along the coastal areas. Significant economic benefits may be experienced from the observing and forecasting information that ocean observing systems can provide. There are many ocean observing systems operating within many nations that already provide these benefits (Kite-Powell, et al., 2008; Kaiser and Pulsipher, 2004). It has been demonstrated that commercial fishing can be improved by greater knowledge about water temperature and salinity; maritime transportation could gain from pertinent information which could help decrease transit time and thus decrease shipping costs; agriculture can gain from better forecasting of seasonal conditions relating to crop planting (Adams, et al., 2000). General weather forecasting could be improved by more accurate information on water levels, wind speeds, directions, and temperatures (Lazo and Chestnut, 2002). A key benefit to Australian water supply management can be achieved by advanced climate forecasting. Medium to long term climate predictions can indicate El-Nino/La-Nina cycles, severe flooding/drought conditions, and rainfall estimates over key water catchment areas (AATSE/ WAGOOS, 2006). Beach recreational activities could be improved by more accurate weather and ocean related information (Kite- Powell and Charles Colgan, 2001).

With more accurate weather and ocean forecasting information provided by NSW-IMOS, more reasonable decisions could be made by the potential benefit related sectors. Therefore, similar to other ocean observing systems, several potential beneficiaries can be identified, which include marine tourism, coastal management, commercial fishing, recreational beach use and fishing, weather forecasting and maritime transportation.

This paper provides a new quantitative model to evaluate the potential benefits arising from the information given by the marine observing system located off the NSW coast. The model is tested with an artificially generated data set. Real data will be used in the near future to conduct a full validation of this model and to evaluate the true benefits to the NSW recreational beach users.

2. Methodology to evaluate the benefits from NSW-IMOS

In evaluating the potential benefits from advanced ocean observing systems, the unit percentage, e.g., 1% increase evaluation method has been widely used in the literature to overcome the data limitations of user values. This percentage increase evaluation method simplifies the benefits as unit percentage value increases or cost decreases (Kite-Powell, et al., 2008; Dumas and Whitehead, 2008). It provided a form of prospective break-even analysis, which can be used to check whether the benefit from a low feasible percentage improvement can cover the cost. Studies have shown that an improvement as low as 1% can significantly benefit society (Nordhaus, 1986; Kite-Powell, 2007; Lynch, et al., 2003). However, the significance of information may vary according to different beneficiaries. More accurate evaluations on the impact to these various users are needed.

A quantitative method combining impact factors analysis with Bayesian method (Berger, 1985) has been developed here to estimate the potential benefits from using information from NSW-IMOS. This method is based on the analysis of a given level of predictive accuracy in forecasting various environmental states which are important for these potential beneficiaries. The potential benefits are estimated as the difference between the expected economic benefits arising from a higher level of predicted accuracy of pertinent information and the economic benefits without using this information.

Many factors such as information, technology, and equipment could impact on the achievement of economic benefits for potential NSW-IMOS beneficiaries. Such factors are called ‘benefit impact factors’. In order to analyse how these factors could influence the benefits for NSW-IMOS potential users, “True state” has been used to express the actual conditions for these impact factors. The predicted conditions for these factors are represented by “predicted state”.

2.1. True state of benefit impact factors

We let $\tilde{\mathbf{X}} \equiv (X_1, X_2, ..., X_n)$ be a vector of factors representing the true state of these benefit impact factors. This vector might include quantities measuring the weather, the water conditions, or other impact factors relevant to potential beneficiaries' decision making processes.

As the aim of the establishment of NSW-IMOS is to supply more observation and forecasting information about the oceans around NSW, only those impact factors that can be observed and predicted by the system can be improved after the establishment of NSW-IMOS. On the other hand, almost every potential beneficiary is an ocean-related sector which relies on weather and ocean-related information. With more appropriate information, these potential beneficiaries could more effectively arrange their activities, thereby gaining more pleasure/benefits from water related activities.

Thus, NSW-IMOS could produce benefits for potential beneficiaries through improving the predicted accuracy of weather and ocean related information. Factors such as weather conditions, water temperature, wind speed and wave height for example, which could be predicted and improved by NSW-IMOS are termed the 'information-improvable factors'. These information-improvable factors are changing dramatically on a daily and seasonal basis. The forecasting accuracies of these factors are sensitive to the equipment and technology used. Information-non-improvable factors such as location, technology and travel cost could also influence the decisions that may be made by these potential beneficiaries such as commercial fishery. However, these impact factors cannot be improved by NSW-IMOS, and thus are not considered in this method.

Without loss of generality, we can decompose the vector $\tilde{\mathbf{X}}$ into two parts $\tilde{\mathbf{X}} = (\mathbf{X}, \mathbf{Z})$ given by (for some $k \leq n$):

$$\mathbf{X} \equiv (X_1, X_2, ..., X_k) \text{ and } \mathbf{Z} \equiv (X_{k+1}, X_{k+2}, ..., X_n). \tag{1}$$

The former vector consists of those selected impact factors that could be predicted and improved by the advanced ocean observing system (the information-improvable factors) and the latter consists of those factors that could not be improved by the improved ocean observing system (the information-non-improvable factors).

In our analysis we will consider the case where the elements of $\mathbf{X}$ have finite ranges. Without further loss of generality we suppose that X_i has range $1, 2, ..., m_i$ for all $1 \le i \le k$. This means that the number of possible outcomes of $\mathbf{X}$ is $m_1 \times m_2 \times ... \times m_k$. For example, weather conditions simply contain sunny, rainy, and cloudy.

The true state of the beach is treated as an unknown quantity and is therefore ascribed a probability distribution. This distribution is likely to be interpreted by historical statistics. We assume that $\mathbf{X} \perp \mathbf{Z}$ and we denote the mass function for $\mathbf{X}$ by:

$$\phi(\mathbf{x}) \equiv \Pr(\mathbf{X} = \mathbf{x}). \tag{2}$$

Where $\mathbf{x}$ is the value given to $\mathbf{X}$ variable. Since our analysis will not consider the information-non-improvable factors at this stage, there is no need to specify any probability distribution pertaining to these factors.

2.2. Predicted state of benefit related factors

Let $\mathbf{Y} \equiv (Y_1, Y_2, ..., Y_k)$ be predicted values of the information improvable factors. That is, the values in $\mathbf{Y}$ are predictions of the unknown values in $\mathbf{X}$. Any given prediction method will result in some conditional probability mass function for $\mathbf{Y} | \mathbf{X}, \mathbf{Z}$. We will assume that $\mathbf{Y} \perp \mathbf{Z} | \mathbf{X}$ so that the prediction is not affected by the non-information-improvable factors. We denote this mass function by the *prediction function* Δ defined by:

$$\Delta(\mathbf{y} | \mathbf{x}) \equiv \Pr(\mathbf{Y} = \mathbf{y} | \mathbf{X} = \mathbf{x}). \tag{3}$$

Where $\mathbf{y}$ is the value given to $\mathbf{Y}$ variable. When $\mathbf{x} \ne \mathbf{y}$, the predictions for these information-improvable factors differ from the true state, then there is a prediction error ε. Thus the economic benefits arising from ocean observing system would not be optimised due to the inaccuracies of the predictions;

If $\mathbf{x} = \mathbf{y}$, the predictions are identical to the true state, implying there is no error. The economic benefits could be achieved after using these accurate forecasting information to guide decisions.

The prediction function represents the predictive accuracy of the prediction method. A better prediction will give higher values on $\Delta(\mathbf{x}|\mathbf{x})$ for all possible values $\mathbf{x}$ and lower values on $\Delta(\mathbf{y}|\mathbf{x})$ for all possible values $\mathbf{y} \neq \mathbf{x}$. That means, with more accurate weather and ocean forecasting data putting into related forecasting models, the prediction accuracy of true state could be increased.

The probability values for the true and predicted states of the benefit related factors can be put into tabular form as shown in Table 3.

2.3. Benefit to potential beneficiaries

We measure the benefit to potential NSW-IMOS users through some *benefit function **B*** which is a function of both the true state of these information-improvable factors and the predicted state of these information-improvable factors. The reason that this utility function depends on both the true state and predicted state is that the former affects the user's utility of these ocean related activities while the latter affects the user's decision when and where to go to these water related activities in the first place.

Commercial fishermen decide where and when to go for fish according to water temperature and current speed and direction. More accurate prediction of this information could assist them in making better decisions about fishing areas. Fishermen' incomes are likely to increase with better decisions, and the avoidance of unnecessary trips. For recreational beach visitors, weather and ocean forecasting information will assist them to make decisions about whether or not to go to the beach. With more accurate forecasting information, they could make better choices according to the ocean and weather conditions they preferred. Therefore, both the accuracy of forecasting information and actual weather and ocean conditions will determine the benefits for NSW-IMOS users.

The potential economic benefits are evaluated by analysing to what extent the more accurate weather and sea information influence water related activities. The benefits from more accurate predicted information are most likely to be directly reflected by participation proportions of water related activities. Most people will go to beach on sunny days but the number significantly decreases if the weather is cloudy or if there are isolated showers, continual rain or heavy rain. Commercial fishermen also would like to go fishing with more accurate prediction for locations of shoal. The cost for maritime transportations can decrease by participating in optimized routes. Therefore, potential benefits can be estimated as the increase of participation proportions caused by more accurate predictions. Thus the participation proportions are used here as indicators to weigh the benefits for potential NSW-IMOS users.

The benefit to potential beneficiaries under true state $\tilde{\mathbf{X}} = (\mathbf{X}, \mathbf{Z})$ with predicted state $\mathbf{Y}$ is given by $B(\tilde{\mathbf{X}}, \mathbf{Y}) = B(\mathbf{X}, \mathbf{Y} | \mathbf{Z})$. Thus, given the previous prediction function Δ, the expected benefit conditional on $\mathbf{Z} = \mathbf{z}$ is given by:

$$\overline{B}_{\Delta} \equiv \overline{B}_{\Delta}(\mathbf{z}) \equiv \sum_{\mathbf{x}} \phi(\mathbf{x}) \sum_{\mathbf{y}} B(\mathbf{x}, \mathbf{y} | \mathbf{z}) \Delta(\mathbf{y} | \mathbf{x}). \tag{4}$$

Our analysis will compare the two different prediction methods: a base prediction method with prediction function Δ (without the improved forecasting information provided by advanced ocean observing system) and an improved prediction method with prediction function $\tilde{\Delta}$ (with the more accurate forecasting information provided by advanced ocean observing system). The gain in the expected benefit from improved forecasting information is then given by:

$$\begin{aligned} G \equiv G_{\Delta, \tilde{\Delta}}(\mathbf{z}) &\equiv \overline{B}_{\tilde{\Delta}}(\mathbf{z}) - \overline{B}_{\Delta}(\mathbf{z}) \\ &= \sum_{\mathbf{x}} \phi(\mathbf{x}) \sum_{\mathbf{y}} B(\mathbf{x}, \mathbf{y} | \mathbf{z}) \left[\tilde{\Delta}(\mathbf{y} | \mathbf{x}) - \Delta(\mathbf{y} | \mathbf{x}) \right] \end{aligned} \tag{5}$$

It can be expressed directly in terms of an expected benefit amount (as above) or a proportionate increase in expected benefits given by:

$$G_{\Delta,\tilde{\Delta}}(\mathbf{z}) \big/ \overline{B}_{\Delta}(\mathbf{z}) = \overline{B}_{\tilde{\Delta}}(\mathbf{z}) / \overline{B}_{\Delta}(\mathbf{z}) - 1 \qquad (6)$$

3. Case Study--Beach Users in NSW

To further explain the method, an evaluation of the benefits to recreational beach users in NSW is presented as a case study. Since NSW-IMOS is still being established and the data has not yet been used by most current and potential beach users, only the potential economic benefits can be evaluated at this stage.

The NSW marine tourism industry is the largest marine industry in the NSW region. It contributed $4.4 billion in value added to the NSW economy during 2002-2003 and employed more than 70,000 people (The Allen Report, 2004). NSW coastal areas received nearly 41million visitors in year 2008, and 13% of these visitors went to the beach for recreational activities (Tourism NSW, 2008). As stated above, the provision of more accurate information could help increase the participation rates of water related activities, thereby adding income to the NSW tourism industry. In this case study, the increase in the proportion of tourists to the beach is termed ‘visitor proportion’, which is the percentage of visitor numbers based on various predicted and actual weather and ocean conditions, and which has been used in the benefit function as an indicator to show the potential benefits for beach users.

3.1 Potential benefits for beach visitors from NSW-IMOS

According to the literature, there are six kinds of beach visitors likely to benefit from more accurate forecasting information (Adams, et al., 2000; Dumas and Whitehead, 2008; Kite- Powell and Charles Colgan, 2001):

(1) swimmers who may be impacted by wave, weather and water conditions;

(2) walkers who may be impacted by weather conditions, storm and wind speeds;

(3) recreational surfers who may be affected by wave, weather and water conditions;

(4) serious surfers who are likely to consider only wave conditions;

(5) recreational fishermen who may be influenced by water temperature and ocean current’s speed and direction;

(6) recreational boaters who may want to avoid hazardous water and weather conditions.

As outdoor activities are always weather and climate-dependent, more accurate forecasting of weather and sea conditions could possibly increase the beach visitor proportions due to increasing the number of beach visits as well as increasing the enjoyment (economic utility) of the beach visit.

For recreational fishermen and boat users, as stated by Kite-Powell and Charles Colgan (2001), greater utility is related to ocean currents and water temperature. The fishing experience can be enhanced by increasing probabilities of catching fish as a result of more accurate information. The enjoyment of recreational boating could be increased by allowing boat users to identify weather and sea conditions that are favourable for boating, thus encouraging additional activities. For the other four kinds of beach users, the benefits from using ocean observing data is the product of a net increase in the number of days engaged in beach recreation activities (Dumas and Whitehead, 2008); As stated before, each kind of beach visitor may be interested in different weather or sea conditions. By following the forecast relevant to their specific interests, beach visitors can decide whether to go to the beach, or when and where to go to increase their enjoyment.

Greater utility can also be gained by decreasing the risk of danger during recreational activities. Based on the analysis conducted by O’Connor (2008), about 17% of all recreational boating fatalities in Australia have been caused by environmental factors, such as hazardous wind or sea conditions (storms) and restricted visibility. In 2009, at Bondi beach, one of Sydney’s most famous beaches, four persons drowned as they were surfing. Therefore, with more accurate weather and sea forecasting information, recreational boaters and surfers are more likely to avoid such dangerous conditions, thus promoting more visitors.

3.2 Evaluation the benefits of beach visitors from improved information from ocean observing systems

3.2.1 Apply the general methodology

In this case study we will make a number of simplifying assumptions in order to reduce the complexity of the model and allow calculation for the benefits evaluation for beach visitors. These assumptions are made to overcome the data limitations of benefit impact factors.

For all $1 \le i \le k$ we define the vector $\phi^{(i)} \equiv \left(\phi_1^{(i)}, \ldots, \phi_{m_i}^{(i)}\right)$ where $\phi_x^{(i)} \equiv \Pr\left(X_i = x\right)$. We assume that the true states of each of the factors are independent of one another so that:

$$\begin{aligned} \phi(\mathbf{x}) &= \prod_{i=1}^{k} \Pr\left(X_i = x_i\right) \\ &= \prod_{i=1}^{k} \phi_{x_i}^{(i)} \end{aligned} \tag{7}$$

For all $1 \le i \le k$ we also define the matrix $\Delta^{(i)} \equiv \left[\Delta_{x,y}^{(i)}\right]$ where $\Delta_{x,y}^{(i)} \equiv \Pr\left(Y_i = y \middle| X_i = x\right)$. We assume that each of these information-improvable factors are predicted independently of one another and are dependent only on the corresponding true factor values so that the prediction function becomes:

$$\begin{aligned} \Delta(\mathbf{y}|\mathbf{x}) &= \prod_{i=1}^{k} \Pr\left(Y_i = y_i \middle| X_i = x_i\right) \\ &= \prod_{i=1}^{k} \Delta_{x_i, y_i}^{(i)} \end{aligned} \tag{8}$$

Aware that the assumption of factor independence may influence the accuracy of this evaluation, correlation analysis should be conducted to verify this assumption when data is sufficient.

Finally, as expressed above that the benefit function can be decomposed into the product of parts which depend only on the true and predicted states of each information-improvable factor. That is, we suppose that the benefit can be decomposed as:

$$B(\mathbf{x}, \mathbf{y}|\mathbf{z}) = \prod_{i=1}^{k} B_{x_i, y_i}^{(i)}\ , \tag{9}$$

where $B_{x_i,y_i}^{(i)} \equiv B_{x_i,y_i}^{(i)}(\mathbf{z})$ is the multiplicative element for the $i\,th$ factor for all $1 \le i \le k$. The specific benefit functions could be given according to various potential beneficiaries. Without loss of generality, we give the above generic benefit function here.

Under these assumptions the expected benefit under a given prediction method becomes:

$$\overline{B}_{\Delta} \equiv \overline{B}_{\Delta}(\mathbf{z}) = \sum_{\mathbf{x}} \sum_{\mathbf{y}} \prod_{i=1}^{k} \phi_{x_i}^{(i)} B_{x_i,y_i}^{(i)} \Delta_{x_i,y_i}^{(i)} . \tag{10}$$

The gain in expected benefit after using improved ocean and weather information then becomes:

$$G(\mathbf{z}) = \sum_{\mathbf{x}} \sum_{\mathbf{y}} \prod_{i=1}^{k} \phi_{x_i}^{(i)} B_{x_i,y_i}^{(i)} \left[\tilde{\Delta}_{x_i,y_i}^{(i)} - \Delta_{x_i,y_i}^{(i)} \right]. \tag{11}$$

So, for each possible combination of values $(\mathbf{X}, \mathbf{Y})$ we calculate the product of the relevant probabilities and the benefit elements and we sum this over all possible combinations. (The range of possible values for $\mathbf{X}$ and $\mathbf{Y}$ consists of $m_1 \times m_2 \times ... \times m_k$ elements so that the range of possible combinations of $(\mathbf{X}, \mathbf{Y})$ will have $m_1^2 \times m_2^2 \times ... \times m_k^2$ elements.)

To evaluate the potential benefits for beach users, based on the combination analysis of the data streams provided by NSW-IMOS and the main impact factors that could influence potential beach visitor decisions, three kinds of weather and ocean related parameters are chosen as the main information-improvable factors for benefits evaluation: weather, water and wave conditions. The weather conditions are classified as sunny, rainy and cloudy; water conditions are classified as good water quality, that is water is clean and suitable for swimming and surfing in, and poor water quality that is water is unsuitable for swimming and surfing; wave conditions are classified as those suitable for swimming and surfing, and those which are not.

Thus, following the methodology of this paper, the number of main information-improvable factors k equals to 3, and true state functions can be rewritten as:

$$\phi(\mathbf{x}) = \prod_{i=1}^{3} \phi_{x_i}^{(i)} = \phi_{x_1}^{(1)} \phi_{x_2}^{(2)} \phi_{x_3}^{(3)} \tag{12}$$

The prediction function becomes:

$$\Delta(\mathbf{y}|\mathbf{x}) = \prod_{i=1}^{3} \Delta_{x_i, y_i}^{(i)} = \Delta_{x_1,y_1}^{(1)} \Delta_{x_2,y_2}^{(2)} \Delta_{x_3,y_3}^{(3)} \tag{13}$$

Thus, the benefit function can be expressed as:

$$B(\mathbf{x}, \mathbf{y}|\mathbf{z}) = \prod_{i=1}^{3} B_{x_i, y_i}^{(i)} = B_{x_1,y_1}^{(1)} B_{x_2,y_2}^{(2)} B_{x_3,y_3}^{(3)} \tag{14}$$

Incorporating with the three main information-improvable factors we have chosen, we can see that the above benefit function can be decomposed as $B(\mathbf{x}, \mathbf{y}|\mathbf{z}) = B_{x_1,y_1}^{(1)} B_{x_2,y_2}^{(2)} B_{x_3,y_3}^{(3)}$ where $B^{(1)}$ is the benefit multiplication factor from the weather (rainy, sunny, cloudy), $B^{(2)}$ is the benefit multiplication factor from the wave conditions (suitable for surfing and swimming, unsuitable for surfing and swimming) and $B^{(3)}$ is the benefit multiplication factor from the water quality (good or poor).

To date, we have not yet obtained actual data to determine the prediction functions for the base case and for the improved case with the NSW-IMOS system. However, in order to elucidate the methodology in principal, we can use artificially generated values of these quantities that mimic real scenarios in beach usage. For example, it is reasonable that no prediction could be 100% correct, thus we assume that the new prediction method using the NSW-IMOS information could reduce the error of prediction. Therefore, we assume that the reduction in the probability of wrong prediction is error ε $(0 < \varepsilon < 1)$ due to more accurate information from NSW-IMOS. For example, if $\varepsilon = 75\%$, the probability of each incorrect prediction is reduced to 75% of its previous value.

With this assumption it can easily be shown that for all $1 \le i \le 3$ we have:

$$\tilde{\Delta}_{x,y}^{(i)} = \begin{cases} 1-(1-\Delta_{x,x}^{(i)})\varepsilon & \text{for } x = y \\ \varepsilon\,\Delta_{x,y}^{(i)} & \text{for } x \neq y \end{cases} \tag{15}$$

Under this assumption the expected benefit under the new prediction method becomes:

$$
\begin{aligned}
\overline{B}_{\tilde{\Delta}} \equiv \overline{B}_{\tilde{\Delta}}(\mathbf{z}) &= \sum_{\mathbf{x}}\sum_{\mathbf{y}}\prod_{i=1}^{3}\phi_{x_i}^{(i)}\tilde{\Delta}_{x_i,y_i}^{(i)}B_{x_i,y_i}^{(i)} \\
&= \sum_{\mathbf{x}}\left(\prod_{i=1}^{3}\phi_{x_i}^{(i)}B_{x_i,x_i}^{(i)}\right)\left(\prod_{i=1}^{3}\tilde{\Delta}_{x_i,x_i}^{(i)}\right)+\sum_{\mathbf{x}\neq\mathbf{y}}\left(\prod_{i=1}^{3}\phi_{x_i}^{(i)}B_{x_i,y_i}^{(i)}\right)\left(\prod_{i=1}^{3}\tilde{\Delta}_{x_i,y_i}^{(i)}\right) \\
&= \sum_{\mathbf{x}}\left(\prod_{i=1}^{3}\phi_{x_i}^{(i)}B_{x_i,x_i}^{(i)}\right)\left(\prod_{i=1}^{3}\left(1-\varepsilon+\varepsilon\,\Delta_{x_i,x_i}^{(i)}\right)\right)+\sum_{\mathbf{x}\neq\mathbf{y}}\left(\prod_{i=1}^{3}\phi_{x_i}^{(i)}B_{x_i,y_i}^{(i)}\right)\left(\varepsilon^{3}\prod_{i=1}^{3}\Delta_{x_i,y_i}^{(i)}\right) \\
&= \sum_{\mathbf{x}}\left(\prod_{i=1}^{3}\alpha_i\right)\left(\prod_{i=1}^{3}(1-\varepsilon+\varepsilon\beta_i)-\varepsilon^{3}\prod_{i=1}^{3}\beta_i\right)+\varepsilon^{3}\overline{B}_{\Delta}(\mathbf{z})
\end{aligned}
\tag{16}
$$

where $\alpha_i \equiv \phi_{x_i}^{(i)}B_{x_i,x_i}^{(i)}$ and $\beta_i \equiv \Delta_{x_i,x_i}^{(i)}$. The gain in expected benefit for beach users after using NSW-IMOS then becomes:

$$
\begin{aligned}
G(\varepsilon) \equiv G_{\Delta,\tilde{\Delta}}(\mathbf{z}) &= \overline{B}_{\tilde{\Delta}}(\mathbf{z})-\overline{B}_{\Delta}(\mathbf{z}) \\
&= \sum_{\mathbf{x}}\left(\prod_{i=1}^{3}\alpha_i\right)\left(\prod_{i=1}^{3}(1-\varepsilon+\varepsilon\beta_i)-\varepsilon^{3}\prod_{i=1}^{3}\beta_i\right)-\left(1-\varepsilon^{3}\right)\overline{B}_{\Delta}(\mathbf{z})
\end{aligned}
\tag{17}
$$

Since this expression is a product of linear functions of ε, it will be a polynomial function of ε with degree equal to $k=3$. Therefore the function can be written as:

$$
G(\varepsilon)=\sum_{i=0}^{3}a_i\varepsilon^{i} \tag{18}
$$

Where the coefficient values a_0, a_1, a_2, a_3 depend on the various probability values and benefit factors. Then the benefits for beach visitors from improved weather and ocean information can be expressed as:

$$
\begin{aligned}
G(\varepsilon) &= \sum_{\mathbf{x}}\left(\prod_{i=1}^{3}\alpha_i\right)\left(\prod_{i=1}^{3}\left(1-\varepsilon+\varepsilon\,\Delta_{x_i,x_i}^{(i)}\right)-\varepsilon^{3}\prod_{i=1}^{3}\Delta_{x_i,x_i}^{(i)}\right)-\left(1-\varepsilon^{3}\right)\overline{B}_{\Delta}(\mathbf{z}) \\
&= \sum_{i=0}^{3}a_i(\mathbf{x})\varepsilon^{i}
\end{aligned}
\tag{19}
$$

where the coefficients are given by:

$$
a_0(\mathbf{x}) \equiv \sum_{\mathbf{x}}\prod\alpha_i-\overline{B}_{\Delta}(\mathbf{z}) \tag{20}
$$

$$
a_1(\mathbf{x}) \equiv -\sum_{\mathbf{x}}\left(\prod\alpha_i\right)\sum(1-\beta_i) \tag{21}
$$

$$
a_2(\mathbf{x}) \equiv \sum_{\mathbf{x}}\left(\prod\alpha_i\right)\left[\sum(1-\beta_i)-\sum\nolimits_{i\neq j}\beta_j(1-\beta_i)\right] \tag{22}
$$

$$
a_3(\mathbf{x}) \equiv \overline{B}_{\Delta}(\mathbf{z})-\sum_{\mathbf{x}}\left(\prod\alpha_i\right)\left[\prod(1-\beta_i)-\prod\beta_i\right] \tag{23}
$$

3.2.2 Data analysis using artificial data

For the purpose of demonstrating the above methodology, we have made the following assumptions, in which, the reduced error probability for the three information-improvable factors are ε. Details of the assumed prediction accuracies for weather conditions, water qualities, and wave heights are listed in Tables 4 to 9.

As beach visitor numbers could be significantly influenced by weather conditions, the visitor proportion, when both the actual and predicted weathers are "sunny", is assumed to be 1.0. If the prediction is wrong, some visitors may assume the weather is not suitable for beach visiting and, therefore, the visitor proportion will decrease. Further, if the actual weather conditions are not good, the visitor numbers are likely to decrease. The influence of weather conditions on visitor proportion and their predictions are listed in Table 10.

Ocean conditions, such as wave height, will also influence visitor numbers. The number of visitors will be significantly less if there is either, or is likely to be, dangerous wave heights near the beach. The influence of wave heights on visitor proportion and their predictions are listed in Table 11.

Water qualities also significantly influence visitor proportions at beaches as these people are mainly looking for clean, warm water for recreational activities. The influence of water quality on visitor proportion and their predictions are listed in Table 12.

In constructing Tables 10-12, we assume that greater benefit accrues under improved predictions, and a lesser benefit accrues under any less accurate predictions, which means the benefits from improved weather and ocean information can only be achieved when the prediction states are the same or close to the true state. Thus, we assume that the visitor proportion for the scenario when the prediction is correct must be higher than the scenario when prediction is incorrect under the same subset of information-improvable factors (see Tables 10-12).

To simplify our calculations, we also assume that this is a constant reduction applying to all possible true states of the beach and all possible prediction errors, so that each error probability is reduced by the same proportion. Appendix 1 shows one calculation example when $\varepsilon = 40\%$.

3.3 Results

As calculated from Tables 4 to 12, the possibilities of information forecasts (with or without NSW-IMOS data) and the visitor proportion for each possible combination can be computed. Using the equation (6) the expected proportional increase in the number of beach users which is the potential benefit from advanced NSW-IMOS information is evaluated.

In order to analyze the relationship between the various probabilities for prediction errors and the proportionate changes in the number of beach users, the sensitivity of visitor proportion to the reduction in probabilities of wrong predictions is examined. As shown in Figure 1, a decrease in the probability of wrong prediction increases the percentage of beach visitors under the favourable conditions.

4. Conclusion

In this paper, a quantitative model to evaluate the potential economic benefits for the NSW-IMOS using improved ocean observing and forecasting information has been introduced. The method has been applied to estimate the potential economic benefits for NSW recreational beach users from NSW-IMOS information using fabricated data.

The evaluation method analysing the improved ocean forecasts focuses on the improved accuracy of the information provided, which is obviously a positive gain arising from the NSW- IMOS. Since the participation proportions and accuracies of different prediction methods could be determined either by observations or surveys, the indicators and information-improvable factors assumed in this paper are all determinable. Therefore, evaluating the potential economic benefits from NSW-IMOS is likely to provide closer estimates than the widely used 1% constant percentage increase method. Future research is currently underway and is expected to validate our model using actual beach user data.

Acknowledgement

Deepest gratitude goes to Professor Paulo Augusto Nunes for his kind help and very useful suggestions for my research.

Special thanks go to Dr. Ben O’Neill for this great help in mathematics.

Grateful thanks go to Mrs. Denise Russell and the All Unit staff in UNSW@ADFA for their editorial assistance.

List of Tables

Table 1. Nine facilities deployed by the NSW-IMOS in Australian waters.

Name	Acronym	Purpose of the facility
Argo Australia	Argo	Blue Water and climate observation
Enhanced Measurements from Ships of Opportunity	SOOP	Blue Water and climate observation
Southern Ocean Time Series	SOTS	Blue Water and climate observation
Australian National Facility for Ocean Gliders	ANFOG	Coastal currents and water properties observation
Australian National Mooring Network	ANMN	Coastal currents and water properties observation
Australian Coastal Ocean Radar Network	ACORN	Coastal currents and water properties observation
Australian Acoustic Tagging and Monitoring System	AATAMS	Coastal ecosystems observation
Australian National Autonomous Underwater Vehicle	AUV	Coastal ecosystems observation
Satellite Remote Sensing	SRS	Coastal and blue water sea surface observations
eMarine Information Infrastructure	eMII	Process all the IMOS data to the public

Sources: NSW-IMOS (2009)

Table 2. NSW-IMOS data streams and the facilities that provide each stream.

Parameter	Facility
Sea Temperature	
Skin temperature	SRS,SOOP
Surface temperature	SOOP,ANMN
Sub surface temperature	ANMN, AATAMS,AUV
Vertical temperature profiles	ARGO,SOTS, ANFOG,ANMN,SOOP
Sea Conductivity/Salinity	ARGO,SOTS,ANMN,ANFOG,SOOP
Dissolved Oxygen	ARGO,SOTS ANFOG,ANMN
Radiation Flux	SOOP,SOTS, ANMN
Meteorology	SOOP,SOTS,ANMN
pCO2	SOOP,SOTS
Optical, Fluorescence	ANMN,SOTS ANFOG, AUV,SOOP
Optical, Turbidity	ANMN,SOTS, ANFOG, AUV,SOOP
Optical, CDOM	ANFOG, AUV
Chlorophy II	SOOP, SRS
Optical, Clarity	ANMN
Current Measurement	ANMN,ACORN,AUV,ARGO,ANFOG
Biogeochemical	ANMN
Biological	AATAMS, SOOP,ANMN
Bathymetry	AUV
Stereo imagery and sizing	AUV
Wave climate	ACORN, ANMN

Sources: IMOS (2008)

Table 3. Probability values for the true and predicted states

		True State				
		$X_i = 1$	$X_i = 2$	$X_i = 3$	$\cdots$	$X_i = m_i$
		$\phi_1^{(i)}$	$\phi_2^{(i)}$	$\phi_3^{(i)}$	$\cdots$	$\phi_{m_i}^{(i)}$
Predicted State	$Y_i = 1$	$\Delta_{1,1}^{(i)}$	$\Delta_{1,2}^{(i)}$	$\Delta_{1,3}^{(i)}$	$\cdots$	$\Delta_{1,m_i}^{(i)}$
	$Y_i = 2$	$\Delta_{2,1}^{(i)}$	$\Delta_{2,2}^{(i)}$	$\Delta_{2,3}^{(i)}$	$\cdots$	$\Delta_{2,m_i}^{(i)}$
	$Y_i = 3$	$\Delta_{3,1}^{(i)}$	$\Delta_{3,2}^{(i)}$	$\Delta_{3,3}^{(i)}$	$\cdots$	$\Delta_{3,m_i}^{(i)}$
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
	$Y_i = m_i$	$\Delta_{m_i,1}^{(i)}$	$\Delta_{m_i,2}^{(i)}$	$\Delta_{m_i,3}^{(i)}$	$\cdots$	$\Delta_{m_i,m_i}^{(i)}$

Table 4. Weather conditions $\phi_{x_1}^{(1)}$ with prediction accuracy $\Delta_{x_1,y_1}^{(1)}$ (without NSW-IMOS).

Weather conditions	Sunny	Cloudy	Rain
State possibility	0.7	0.2	0.1
Predicted sunny	0.8	0.2	0.1
Predicted cloudy	0.1	0.6	0.1
Predicted rainy	0.1	0.2	0.8

Table 5. Wave heights $\phi_{x_2}^{(2)}$ with prediction accuracy $\Delta_{x_2,y_2}^{(2)}$ (without NSW-IMOS).

Wave heights	Normal	High
State possibility	0.75	0.25
Predicted suitable	0.8	0.2
Predicted unsuitable	0.2	0.8

Table 6. Water qualities $\phi_{x_3}^{(3)}$ with prediction accuracy $\Delta_{x_3,y_3}^{(3)}$ (without NSW-IMOS).

Water qualities	Good	Poor
State possibility	0.7	0.3
Predicted good	0.6	0.4
Predicted poor	0.4	0.6

Table 7. Weather conditions $\phi^{(1)}_{x_1}$ with prediction accuracy $\tilde{\Delta}^{(1)}_{x_1,y_1}$ (with NSW-IMOS).

Weather conditions	Sunny	Cloudy	Rain
State possibility	0.7	0.2	0.1
Predicted sunny	1- 0.2 ε	0.2 ε	0.1 ε
Predicted cloudy	0.1 ε	1-0.4 ε	0.1 ε
Predicted rainy	0.1 ε	0.2 ε	1-0.2 ε

Table 8. Wave heights $\phi^{(2)}_{x_2}$ with prediction accuracy $\tilde{\Delta}^{(2)}_{x_2,y_2}$ (with NSW-IMOS).

Wave heights	Normal	High
State possibility	0.75	0.25
Predicted suitable	1-0.2 ε	0.2 ε
Predicted unsuitable	0.2 ε	1-0.2 ε

Table 9. Water qualities $\phi^{(3)}_{x_3}$ with prediction accuracy $\tilde{\Delta}^{(3)}_{x_3,y_3}$ (with NSW-IMOS).

Water qualities	Good	Poor
State possibility	0.7	0.3
Predicted good	1-0.4 ε	0.4 ε
Predicted poor	0.4 ε	1-0.4 ε

Table 10. Visitor proportion $B^{(1)}_{x_1,y_1}$ based on weather conditions with prediction accuracy .

Weather conditions	Sunny	Cloudy	Rain
Predicted sunny	1.0	0.4	0.1
Predicted cloudy	0.5	0.5	0.1
Predicted rainy	0.2	0.1	0.2

Table 11. Visitor proportion $B^{(2)}_{x_2,y_2}$ based on wave heights with prediction accuracy.

Wave heights	Normal	High
Predicted suitable	1.0	0.5
Predicted unsuitable	0.5	0.6

Table 12. Visitor proportion $B^{(3)}_{x_3,y_3}$ based on water qualities with prediction accuracy.

Water qualities	Good	Poor
Predicted good	1.0	0.6
Predicted poor	0.6	0.7

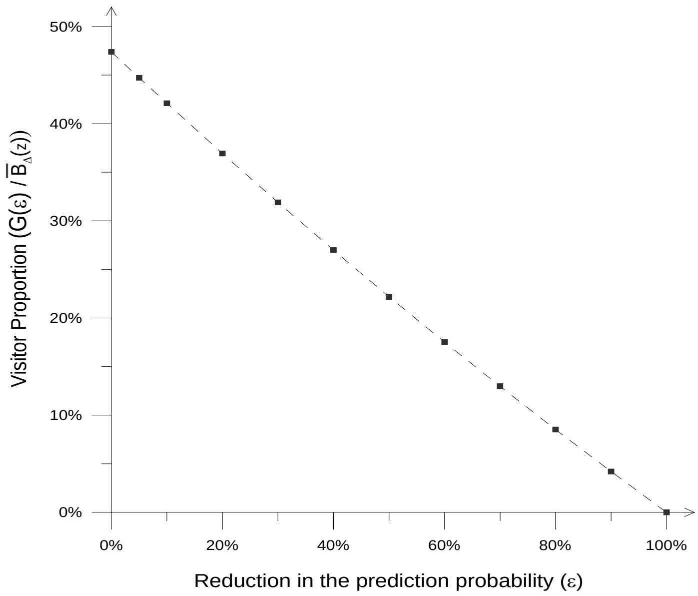

Figure 1. Sensitivity of visitor proportion to the reduction in the probabilities of wrong predictions**.**

References

AATSE/WAGOOS (Australian Academy of Technological Sciences and Engineering/ the Western Australian Global Ocean Observing Inc.), 2006. Economics of Australia's sustained ocean observation system, benefits and rationale for public funding, online, http://www.ioc-goos.org/component/option,com_oe/task,viewDocumentRecord/docID,2481.

Adams, R., Brown, M., Colgan, C., Flemming N., Kite-Powell, H., McCarl, B., Mjelde, J., Solow, A., Teisberg, T., and Weiher, R., 2000. The economics of Sustained Ocean Observations: benefits and rationale for public funding. Report.Washington D.C.: National Ocean and Atmospheric Administration and Office of Naval Research.

Berger, James O., 1985. Statistical Decision Theory and Bayesian Analysis. Springer Series in Statistics (Second edition). ISBN 0-387-96098-8.

Bhatt, V., Wang, X.H., Morrison, J., 2010. Seasonal variability of the East Australian Current: the role of JEBAR, J. Geophys. Res., (submitted).

CoastalCOMS, 2010. People Counting Data Report, Cronulla Beach, 15th November 2009 to 26th April, 2010.

Dumas, C.F., Whitehead, J.C., 2008. The Potential Economic Benefits of Coastal Ocean Observing Systems: The Southeast Atlantic Region. Coastal Management 36 (2), 146-164.

IMOS, 2008. National overview of Node Science and Implementation Plans. Report.

Kaiser, M.J., Pulsipher, A.G., 2004. The potential value of improved ocean observing systems in the Gulf of Mexico. Marine Policy 28, 469-489.

Kite-Powell, H., Colgan, C., Weiher, R., 2008. Estimating the economic benefits of regional ocean observing systems. Costal Management 36, 125-145.

Kite-Powell, H., 2007, Estimating Economic Benefits from NOAA PORTS information: A Case Study of Houston/Galveston, The Port of Houston Authority.Report.

Kite-Powell, H., Colgan, C.S., 2001. The potential economic benefits of coastal ocean observing systems: the Gulf of Marine. Report. National Oceanic and Atmospheric Administration, Office of Naval Research, Woods Hole Oceanographic Institution, joint publication.

Lazo, J.K, Chestnut, L.G., 2002. Economic value of current and improved weather forecasts in the U.S. household sector. Executive summary. Prepared for the National Oceanic and Atmospheric Administration. Stratus Consulting Incorporation.

Lynch,T., Harrington.J., O'Brien,J.J., 2003. Economic impact analysis of coastal ocean observing systems in the Gulf coast region, online, http://www.cefa.fsu.edu/nopp_study.pdf.

Moltmann,T., 2009. IMOS five year strategy. Report. Australian Government Department of Innovation Industry, Science and Research. University of Tasmania.

Nordhaus,W.D., 1986. The value of information. In Richard Krasnow, ed., Policy Aspects of Climate Forecasting, Resources for the Future, Washington, pp. 129-133.

NSW-IMOS (New South Wales Integrated Marine Observing System), 2009. IMOS Node Science and Implementation Plans. Report.

O'Connor P.J., 2008, National Assessment of Boating Fatalities in Australia 1999-2004. Report. Prepared for the National Marine Safety Committee Inc.

Samonte-tan, G.P.B., White, A.T., Tercero, M.A., Diviva, J., Tabara, E., Caballes, C., 2007. Economic valuation of coastal and marine resources: Bohol Marine Triangle, Philippines. Coastal Management 35, 319-338.

The Allen Report, 2004. The Economic Contribution of Australia's Marine Industries. 1995-96 to 2002-03. Report to the National Oceans Office.

Tourism New South Wales, 2008. International Visitor Survey and National Visitor Survey. Annual report.

Appendix 1 Possibility and expected visitor proportion of each possible combination

	Weather	Predicted weather	Wave height	Predicted wave height	Water quality	Predicted water quality	Possibility without NSW-IMOS	Possibility with NSW-IMOS	Visiting ratio
1	sunny	sunny	suitable	suitable	good	good	0.14112	0.261284	1
2	sunny	sunny	suitable	suitable	good	poor	0.09408	0.049768	0.6
3	sunny	sunny	suitable	suitable	poor	good	0.04032	0.021329	0.6
4	sunny	sunny	suitable	suitable	poor	poor	0.06048	0.111979	0.7
5	sunny	sunny	suitable	unsuitable	good	good	0.03528	0.02272	0.5
6	sunny	sunny	suitable	unsuitable	good	poor	0.02352	0.004328	0.3
7	sunny	sunny	suitable	unsuitable	poor	good	0.01008	0.001855	0.3
8	sunny	sunny	suitable	unsuitable	poor	poor	0.01512	0.009737	0.35
9	sunny	sunny	unsuitable	suitable	good	good	0.01176	0.007573	0.5
10	sunny	sunny	unsuitable	suitable	good	poor	0.00784	0.001443	0.3
11	sunny	sunny	unsuitable	suitable	poor	good	0.00336	0.000618	0.3
12	sunny	sunny	unsuitable	suitable	poor	poor	0.00504	0.003246	0.35
13	sunny	sunny	unsuitable	unsuitable	good	good	0.04704	0.087095	0.6
14	sunny	sunny	unsuitable	unsuitable	good	poor	0.03136	0.016589	0.36
15	sunny	sunny	unsuitable	unsuitable	poor	good	0.01344	0.00711	0.36
16	sunny	sunny	unsuitable	unsuitable	poor	poor	0.02016	0.037326	0.42
17	sunny	cloud	suitable	suitable	good	good	0.01764	0.01136	0.5
18	sunny	cloud	suitable	suitable	good	poor	0.01176	0.002164	0.3
19	sunny	cloud	suitable	suitable	poor	good	0.00504	0.000927	0.3
20	sunny	cloud	suitable	suitable	poor	poor	0.00756	0.004869	0.35
21	sunny	cloud	suitable	unsuitable	good	good	0.00441	0.000988	0.25
22	sunny	cloud	suitable	unsuitable	good	poor	0.00294	0.000188	0.15
23	sunny	cloud	suitable	unsuitable	poor	good	0.00126	8.06E-05	0.15
24	sunny	cloud	suitable	unsuitable	poor	poor	0.00189	0.000423	0.175
25	sunny	cloud	unsuitable	suitable	good	good	0.00147	0.000329	0.25
26	sunny	cloud	unsuitable	suitable	good	poor	0.00098	6.27E-05	0.15
27	sunny	cloud	unsuitable	suitable	poor	good	0.00042	2.69E-05	0.15
28	sunny	cloud	unsuitable	suitable	poor	poor	0.00063	0.000141	0.175
29	sunny	cloud	unsuitable	unsuitable	good	good	0.00588	0.003787	0.3
30	sunny	cloud	unsuitable	unsuitable	good	poor	0.00392	0.000721	0.18
31	sunny	cloud	unsuitable	unsuitable	poor	good	0.00168	0.000309	0.18
32	sunny	cloud	unsuitable	unsuitable	poor	poor	0.00252	0.001623	0.21
33	sunny	rain	suitable	suitable	good	good	0.01764	0.01136	0.2
34	sunny	rain	suitable	suitable	good	poor	0.01176	0.002164	0.12

35	sunny	rain	suitable	suitable	poor	good	0.00504	0.000927	0.12
36	sunny	rain	suitable	suitable	poor	poor	0.00756	0.004869	0.14
37	sunny	rain	suitable	unsuitable	good	good	0.00441	0.000988	0.1
38	sunny	rain	suitable	unsuitable	good	poor	0.00294	0.000188	0.06
39	sunny	rain	suitable	unsuitable	poor	good	0.00126	8.06E-05	0.06
40	sunny	rain	suitable	unsuitable	poor	poor	0.00189	0.000423	0.07
41	sunny	rain	unsuitable	suitable	good	good	0.00147	0.000329	0.1
42	sunny	rain	unsuitable	suitable	good	poor	0.00098	6.27E-05	0.06
43	sunny	rain	unsuitable	suitable	poor	good	0.00042	2.69E-05	0.06
44	sunny	rain	unsuitable	suitable	poor	poor	0.00063	0.000141	0.07
45	sunny	rain	unsuitable	unsuitable	good	good	0.00588	0.003787	0.12
46	sunny	rain	unsuitable	unsuitable	good	poor	0.00392	0.000721	0.072
47	sunny	rain	unsuitable	unsuitable	poor	good	0.00168	0.000309	0.072
48	sunny	rain	unsuitable	unsuitable	poor	poor	0.00252	0.001623	0.084
49	cloudy	sunny	suitable	suitable	good	good	0.01008	0.006492	0.4
50	cloudy	sunny	suitable	suitable	good	poor	0.00672	0.001236	0.24
51	cloudy	sunny	suitable	suitable	poor	good	0.00288	0.00053	0.24
52	cloudy	sunny	suitable	suitable	poor	poor	0.00432	0.002782	0.28
53	cloudy	sunny	suitable	unsuitable	good	good	0.00252	0.000564	0.2
54	cloudy	sunny	suitable	unsuitable	good	poor	0.00168	0.000108	0.12
55	cloudy	sunny	suitable	unsuitable	poor	good	0.00072	4.61E-05	0.12
56	cloudy	sunny	suitable	unsuitable	poor	poor	0.00108	0.000242	0.14
57	cloudy	sunny	unsuitable	suitable	good	good	0.00084	0.000188	0.2
58	cloudy	sunny	unsuitable	suitable	good	poor	0.00056	3.58E-05	0.12
59	cloudy	sunny	unsuitable	suitable	poor	good	0.00024	1.54E-05	0.12
60	cloudy	sunny	unsuitable	suitable	poor	poor	0.00036	8.06E-05	0.14
61	cloudy	sunny	unsuitable	unsuitable	good	good	0.00336	0.002164	0.24
62	cloudy	sunny	unsuitable	unsuitable	good	poor	0.00224	0.000412	0.144
63	cloudy	sunny	unsuitable	unsuitable	poor	good	0.00096	0.000177	0.144
64	cloudy	sunny	unsuitable	unsuitable	poor	poor	0.00144	0.000927	0.168
65	cloudy	cloudy	suitable	suitable	good	good	0.03024	0.068161	0.5
66	cloudy	cloudy	suitable	suitable	good	poor	0.02016	0.012983	0.3
67	cloudy	cloudy	suitable	suitable	poor	good	0.00864	0.005564	0.3
68	cloudy	cloudy	suitable	suitable	poor	poor	0.01296	0.029212	0.35
69	cloudy	cloudy	suitable	unsuitable	good	good	0.00756	0.005927	0.25
70	cloudy	cloudy	suitable	unsuitable	good	poor	0.00504	0.001129	0.15
71	cloudy	cloudy	suitable	unsuitable	poor	good	0.00216	0.000484	0.15
72	cloudy	cloudy	suitable	unsuitable	poor	poor	0.00324	0.00254	0.175
73	cloudy	cloudy	unsuitable	suitable	good	good	0.00252	0.001976	0.25
74	cloudy	cloudy	unsuitable	suitable	good	poor	0.00168	0.000376	0.15

75	cloudy	cloudy	unsuitable	suitable	poor	good	0.00072	0.000161	0.15
76	cloudy	cloudy	unsuitable	suitable	poor	poor	0.00108	0.000847	0.175
77	cloudy	cloudy	unsuitable	unsuitable	good	good	0.01008	0.02272	0.3
78	cloudy	cloudy	unsuitable	unsuitable	good	poor	0.00672	0.004328	0.18
79	cloudy	cloudy	unsuitable	unsuitable	poor	good	0.00288	0.001855	0.18
80	cloudy	cloudy	unsuitable	unsuitable	poor	poor	0.00432	0.009737	0.21
81	cloudy	rain	suitable	suitable	good	good	0.01008	0.006492	0.1
82	cloudy	rain	suitable	suitable	good	poor	0.00672	0.001236	0.06
83	cloudy	rain	suitable	suitable	poor	good	0.00288	0.00053	0.06
84	cloudy	rain	suitable	suitable	poor	poor	0.00432	0.002782	0.07
85	cloudy	rain	suitable	unsuitable	good	good	0.00252	0.000564	0.05
86	cloudy	rain	suitable	unsuitable	good	poor	0.00168	0.000108	0.03
87	cloudy	rain	suitable	unsuitable	poor	good	0.00072	4.61E-05	0.03
88	cloudy	rain	suitable	unsuitable	poor	poor	0.00108	0.000242	0.035
89	cloudy	rain	unsuitable	suitable	good	good	0.00084	0.000188	0.05
90	cloudy	rain	unsuitable	suitable	good	poor	0.00056	3.58E-05	0.03
91	cloudy	rain	unsuitable	suitable	poor	good	0.00024	1.54E-05	0.03
92	cloudy	rain	unsuitable	suitable	poor	poor	0.00036	8.06E-05	0.035
93	cloudy	rain	unsuitable	unsuitable	good	good	0.00336	0.002164	0.06
94	cloudy	rain	unsuitable	unsuitable	good	poor	0.00224	0.000412	0.036
95	cloudy	rain	unsuitable	unsuitable	poor	good	0.00096	0.000177	0.036
96	cloudy	rain	unsuitable	unsuitable	poor	poor	0.00144	0.000927	0.042
97	rain	sunny	suitable	suitable	good	good	0.00252	0.001623	0.1
98	rain	sunny	suitable	suitable	good	poor	0.00168	0.000309	0.06
99	rain	sunny	suitable	suitable	poor	good	0.00072	0.000132	0.06
100	rain	sunny	suitable	suitable	poor	poor	0.00108	0.000696	0.07
101	rain	sunny	suitable	unsuitable	good	good	0.00063	0.000141	0.05
102	rain	sunny	suitable	unsuitable	good	poor	0.00042	2.69E-05	0.03
103	rain	sunny	suitable	unsuitable	poor	good	0.00018	1.15E-05	0.03
104	rain	sunny	suitable	unsuitable	poor	poor	0.00027	6.05E-05	0.035
105	rain	sunny	unsuitable	suitable	good	good	0.00021	4.7E-05	0.05
106	rain	sunny	unsuitable	suitable	good	poor	0.00014	8.96E-06	0.03
107	rain	sunny	unsuitable	suitable	poor	good	0.00006	3.84E-06	0.03
108	rain	sunny	unsuitable	suitable	poor	poor	0.00009	2.02E-05	0.035
109	rain	sunny	unsuitable	unsuitable	good	good	0.00084	0.000541	0.06
110	rain	sunny	unsuitable	unsuitable	good	poor	0.00056	0.000103	0.036
111	rain	sunny	unsuitable	unsuitable	poor	good	0.00024	4.42E-05	0.036
112	rain	sunny	unsuitable	unsuitable	poor	poor	0.00036	0.000232	0.042
113	rain	cloudy	suitable	suitable	good	good	0.00252	0.001623	0.1
114	rain	cloudy	suitable	suitable	good	poor	0.00168	0.000309	0.06

115	rain	cloudy	suitable	suitable	poor	good	0.00072	0.000132	0.06
116	rain	cloudy	suitable	suitable	poor	poor	0.00108	0.000696	0.07
117	rain	cloudy	suitable	unsuitable	good	good	0.00063	0.000141	0.05
118	rain	cloudy	suitable	unsuitable	good	poor	0.00042	2.69E-05	0.03
119	rain	cloudy	suitable	unsuitable	poor	good	0.00018	1.15E-05	0.03
120	rain	cloudy	suitable	unsuitable	poor	poor	0.00027	6.05E-05	0.035
121	rain	cloudy	unsuitable	suitable	good	good	0.00021	4.7E-05	0.05
122	rain	cloudy	unsuitable	suitable	good	poor	0.00014	8.96E-06	0.03
123	rain	cloudy	unsuitable	suitable	poor	good	0.00006	3.84E-06	0.03
124	rain	cloudy	unsuitable	suitable	poor	poor	0.00009	2.02E-05	0.035
125	rain	cloudy	unsuitable	unsuitable	good	good	0.00084	0.000541	0.06
126	rain	cloudy	unsuitable	unsuitable	good	poor	0.00056	0.000103	0.036
127	rain	cloudy	unsuitable	unsuitable	poor	good	0.00024	4.42E-05	0.036
128	rain	cloudy	unsuitable	unsuitable	poor	poor	0.00036	0.000232	0.042
129	rain	rain	suitable	suitable	good	good	0.02016	0.037326	0.2
130	rain	rain	suitable	suitable	good	poor	0.01344	0.00711	0.12
131	rain	rain	suitable	suitable	poor	good	0.00576	0.003047	0.12
132	rain	rain	suitable	suitable	poor	poor	0.00864	0.015997	0.14
133	rain	rain	suitable	unsuitable	good	good	0.00504	0.003246	0.1
134	rain	rain	suitable	unsuitable	good	poor	0.00336	0.000618	0.06
135	rain	rain	suitable	unsuitable	poor	good	0.00144	0.000265	0.06
136	rain	rain	suitable	unsuitable	poor	poor	0.00216	0.001391	0.07
137	rain	rain	unsuitable	suitable	good	good	0.00168	0.001082	0.1
138	rain	rain	unsuitable	suitable	good	poor	0.00112	0.000206	0.06
139	rain	rain	unsuitable	suitable	poor	good	0.00048	8.83E-05	0.06
140	rain	rain	unsuitable	suitable	poor	poor	0.00072	0.000464	0.07
141	rain	rain	unsuitable	unsuitable	good	good	0.00672	0.012442	0.12
142	rain	rain	unsuitable	unsuitable	good	poor	0.00448	0.00237	0.072
143	rain	rain	unsuitable	unsuitable	poor	good	0.00192	0.001016	0.072
144	rain	rain	unsuitable	unsuitable	poor	poor	0.00288	0.005332	0.084