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# 3 Task 4.7: Assessment of error in habitat mapping and how it affects map interpretation

For habitat maps, there are two types of errors that may be assessed: spatial and attribute error. This discussion is related to attribute error only, as spatial accuracies of base data (eg. bathymetry) in the marine environment are generally imposed by commercial or governmental survey standards. There is great deal of work on spatial error and error propagation in maps within the GIS literature. This section covers a very basic overview of how a couple of concepts and methods can be considered for use for the marine habitat maps created within this and previous milestones developed for the coastal CRC.

**Traditional error reporting**
Habitat map error is traditionally assessed using error (confusion) matrices which describe the misclassification rate across classes, or by global statistical measures, such as overall or kappa accuracy. Generally speaking, error matrices are used when the modelling method used is predicting multiple classes and overall and kappa accuracies are also calculated.

An overall statistical measure provides some understanding of error across an entire map, but often obfuscates the differences in misclassification rates by class. Especially when a class is rare, then the overall map can have very high global accuracies, but can have very poor predictions for a single class.

Error matrices are useful in that they provide further information on the predictability of each class. Two sets of accuracy are provided in an error matrix: the user's and the producer's accuracy. The user's accuracy (number of sites correctly classified / total number of sites attributed to that class) provides information for the map user on how likely it is that a single site on the ground is actually the class ascribed to it by the map. In other words, it provides information on the *probability* that, at any given site, the user will find the class described by the map. This information is very useful to the user in the context of further field assessment, and is helpful for map interpretation.

For individual species or group predictions, kappa or Area Under the receiver operator Curve (AUC) are used to assess map accuracy. AUC is considered to be superior to kappa, because it is a measure of the accuracy of the probability prediction across the range of values and thus is a non-threshold measure. Kappa, on the other hand, requires thresholding the probability prediction to a binary outcome for assessment. This type of assessment provides global error information for each predicted class (as shown in Table 4-1, reproduced from Milestone CB 6.03, Task 3.6).

**Spatial error reporting**
However, none of these methods provides a spatial representation of the habitat map error. Spatial representations can be created using the statistical error from predictive models. Figure 4-1 shows the spatial variation in prediction error based on the kriging

variance for a seagrass model at Owen Anchorage, WA. Thus, this shows the error inherent in model fit, which is different than classification accuracy or any uncertainty propagated from base data. For other modelling methods, the standard errors on the model fit can also be spatially predicted and used as a supplementary map.

**Table 3-1. Table describing the prediction accuracy of substrate and biotic groups based on classification tree models, Point Addis MP (reproduced from Milestone CB 6.03, Task 3.6).**

| | Area Under the Curve (AUC)** | p for AUC-critical | Misclassification Rate | Correct Classification Rate | False Negative Rate (1 - sensitivity) | False Positive Rate (1-specificity) | P-KAPPA |
|---|---|---|---|---|---|---|---|
| ***SUBSTRATE*** | | | | | | | |
| **Reef, undiff.*** | 0.869664 | < 0.0001 | 16.27% | 83.73% | 17.12% | 15.68% | 0.2725 |
| Reef Structure: solid (continuous) | 0.79545 | < 0.0001 | 20.06% | 79.94% | 37.11% | 13.68% | 0.26 |
| Reef Structure: vertical (> 70 deg) | 0.711525 | > 0.05 | 0.98% | 99.02% | 87.50% | 0.00% | 0.625 |
| **Sediments, undiff.** | 0.77447 | < 0.05 | 13.74% | 86.26% | 8.18% | 47.06% | 0.805 |
| Sediment Texture: coarse grained | 0.84144 | < 0.0001 | 17.11% | 82.89% | 37.24% | 11.97% | 0.23 |
| Sediment Structure: coarse ripples | 0.81775 | < 0.0001 | 19.35% | 80.65% | 31.42% | 13.76% | 0.24 |
| Sediment Structure: fine ripples | 0.766634 | < 0.01 | 15.43% | 84.57% | 64.38% | 2.82% | 0.7875 |
| **Cobbles** | 0.63004 | > 0.05 | 16.97% | 83.03% | 89.39% | 0.52% | 0.7375 |
| ***BIOTA*** | | | | | | | |
| **Algae, undiff.** | 0.932853 | < 0.0001 | 11.22% | 88.78% | 9.76% | 12.21% | 0.2875 |
| Brown Algae, undiff | 0.908548 | < 0.0001 | 13.60% | 86.40% | 6.83% | 15.58% | 0.165 |
| Kelp, undiff. | 0.878999 | < 0.0001 | 14.73% | 85.27% | 30.61% | 10.60% | 0.29 |
| *Ecklonia* | 0.867738 | < 0.0001 | 16.55% | 83.45% | 36.11% | 11.60% | 0.215 |
| Red Algae, undiff. *** | 0.75485 | < 0.05 | 20.34% | 79.66% | 45.52% | 13.91% | 18.50% |
| Rhodoliths | 0.63004 | > 0.05 | 16.97% | 83.03% | 89.39% | 0.52% | 0.7375 |
| **Sessile Invertebrates, undiff.** | 0.595651 | > 0.05 | 40.53% | 59.47% | 37.54% | 43.28% | 0.6 |
| Ascidians | 0.63653 | > 0.05 | 7.15% | 92.85% | 91.18% | 2.95% | 0.095 |
| Sponges | 0.5207 | > 0.05 | 58.77% | 41.23% | 21.29% | 73.58% | 0.2125 |

*Undifferentiated

*** Rhodoliths not included.

** Hosmer and Lemeshow (2000):
AUC = 0.5 No discrimination; 0.7 < AUC < 0.8 Acceptable; 0.8 < AUC < 0.9 Excellent; AUC > 0.9 Outstanding

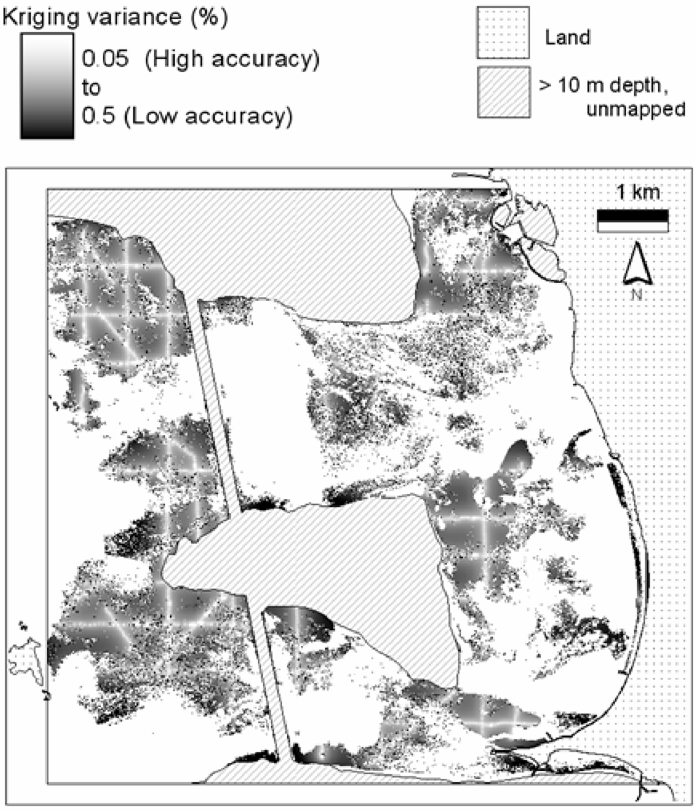

**Figure 3-1. Map showing the spatial distribution of error based on kriging variance, Owen Anchorage, WA.**

### Propagated error when combing individual class predictions

For a map created by combining two classes predicted independently, as shown in Figures 2-1 and 2-2, the accuracy can be computed by simple mathematical methods and depends mainly on the logical or mathematical operator used.

Mathematical operations have received the greater attention within GIS studies of attribute error propagation (Heuvelink et al. 1989). These are generally easier to examine, because their probability distribution functions (pdfs) are either known or assumed to be normal (as needed for stochastic simulation), or they can be approximated with first or second order Taylor series. Relational or logical operations are much more difficult to study, because their error distributions are not as simple to quantify (Heuvelink et al. 1989). However, for predictive habitat modelling, overlay with relational and logical decision-making is the most common tool for developing output. For example, univariate overlay is when a single spatial data layer is manipulated to create a new spatial data layer, as in the case of using a threshold on a spatial distribution map of a single class (based on optimised kappa) to convert the map to a binary presence and absence map (as demonstrated in Milestone 6.03, Task 3.6).

Depending on the type of operation, output of a layer operation can result in an equal, lower, or higher accuracy than that of the input layers (Veregin 1989). As with mathematical operations, some logical operations inherently reduce errors while others inherently increase them. For example, the OR operation can lead to an output data set with much higher accuracy than the least accurate data set. For the AND operation, the result depends more on the spatial correlation of the errors (Arbia et al. 1998), because decision-making requires the consideration of all data layers included in the operation. A common Boolean AND statement would be "if class A and class B are both present, then set class C to present".

For a Boolean AND where the errors are uncorrelated, the resulting accuracy can be determined by multiplying the overall accuracy values of the two input layers (Lanter and Veregin 1992). Clearly, this can lead to significant reduction in the estimate of the overall accuracy of the output layer. If the errors are correlated, then that must be considered in the calculation. The probability that a correct point in the first layer will also be correct in the second layer is then used in the calculation (Lanter and Veregin 1992). If a data set has more than two classes, then the equation has to take into account the probability of all other combinations.

The overall accuracy of the output for the predictive map of reef and sediment co-occurrence (shown in Figure 2-1) can be calculated given this information. From Table 4-1, undifferentiated reef overall accuracy (correct classification) is 83.73%, and undifferentiated sediment overall accuracy is 86.26%. Given independence in the errors, the overall accuracy for the combined model is 72.23%.

However, it is unlikely that the errors are uncorrelated, given that both maps were created from the same base data layers (eg bathymetry and its derivatives). In this case, the correlation between the errors from the field data points must be used to assess the predictions that are of interest. For the combined sediment-reef map, if we assume that the probability that a site that was correctly classified by the sediment map was also correctly classified by the reef map is 0.71, then the overall accuracy of the map of co-occurrence of reef and sediment becomes 61.24%. If the probability is 0.92, then the overall accuracy becomes 79.36%.

### Integration of spatial error in habitat maps

A problem, however, with the discussion above and the map shown in Figure 4-1, is that the spatial error is either a global value or a separate map. If the spatial error is not incorporated into the data map itself, then it is less likely that it will be taken into consideration by decision makers. For predictions of a single class, group or species, the upper and lower confidence intervals, associated with the model fit, can be used to create a transitional membership map (Van Niel 2003). A transitional membership map can display the sites of presence, absence, and the gradient between the two, based on any confidence level (eg. 95%) using the *t* critical value. For predictions of a combined class, the output from individual predictions above can be used to create combined presence, absence and transitional zones for presence of both classes.

## References

Arbia, G., D. Griffith, and R. Haining. 1998. Error propagation and modelling in raster GIS: overlay operations. International Journal of Geographical Information Science **12**:145-167.

Heuvelink, G., P. Burrough, and A. Stein. 1989. Propagation of errors in spatial modelling with GIS. International Journal of Geographical Information Science **3**:303-322.

Lanter, D., and H. Veregin. 1992. A research paradigm for propagating error in a layer-based GIS. Photogrammetric Engineering and Remote Sensing **58**:825-833.

Van Niel, K. 2003. Geographical issues in predictive vegetation modelling: Error and uncertainty in GIS data, methods, and models. PhD thesis. The Australian National University, Canberra.

Veregin, H. 1989. Error modeling for the map overlay operation. Pages 3-18 *in* M. Goodchild and S. Gopal, editors. The Accuracy of Spatial Databases. Taylor and Francis, London.