

# Application of sensitivity and uncertainty analyses for the validation of an integrated systems model for coastal zone management

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**Abstract:** RaMCo (Rapid Assessment Model for Coastal Zone Management) is a decision support system, which encompasses a number of sub-models, namely, marine fisheries, catchment hydrology, land-use/land-cover changes, marine hydrodynamics, and coastal ecology. The model has been developed by a multidisciplinary team including researchers from various institutions in the Netherlands and Indonesia. The coastal zone area of South-West Sulawesi (Indonesia) serves as the study area. Limited calibration of the model has been conducted due to the scarcity of data, and extensive expert knowledge was used to fill that lack. Though validation is essential prior to any practical implementation of the model it has not been done yet. Presently, with newly collected data on socio-economic, land use and land cover changes, we are on the way to validate that model. Our ultimate goal is to obtain a generic methodology for validation of complex integrated systems models like RaMCo. In this paper, we present the analysis on the problem of integrated systems model validation, i.e. concept, difficulties, research questions, general framework of validation. Besides, the results of sensitivity and uncertainty analyses using a screening design are shown. The analyses and the framework of validation of the present model indicate an important role of the sensitivity and uncertainty analyses throughout the whole process of validation of an integrated systems model.

**Keywords:** *Validation; Decision support system; Integrated systems model; Coastal zone management; Sensitivity and uncertainty analyses*

## 1. INTRODUCTION

The Netherlands Organization for Advancement of Tropical Research (WOTRO) launched a multidisciplinary research program in 1984. The aim of the project was to develop a scientific framework of analysis for coastal zone management. In the view of the project's theme, scientists from various fields (i.e. ecology, hydrology, oceanography, anthropology, economics, system dynamics etc.) gathered together, in search for a scientific methodology to support coastal zone management. The ultimate product of their efforts is RaMCo (Uljee et al., 1996; De Kok and Wind, 2002). Previously, each sub-model of RaMCo had been calibrated separately, using the maximum available field data from Southwest Sulawesi (Indonesia), expert knowledge and data obtained from literature. However the validation of RaMCo as a whole system model has not been conducted yet.

There have been an increasing number of examples adopting an integrated systems approach, especially in the fields of modeling climate change and natural resources management. Researches are often involved with the design and application of a number of

integrated models. However, these models are not completely validated in a systematic manner. The reason may be attributed to the lack of a methodology or a framework for validating these types of models. The following five factors are thought to form an obstacle to the validation of integrated systems models:

- Lack of a generally agreed definition of validation
- Lack of conventional criteria for model validity
- Complexity of integrated systems models
- Difficulty in obtaining test data
- Large model and data uncertainties

Although the literature on validation is abundant the issue is still controversial (see Rykiel, 1996). In the present paper, an attempt is made define validation for integrated systems models. Based on that definition, it tries to set up a methodology to validate the RaMCo model. Before arriving at a definition of validation, it is necessary to point out some remarks that help to separate validation from other processes.

- Calibration is the process of specifying the values of the model parameters with which model behavior and real system behavior are in good agreement.
- Verification is the process of substantiating that the computer program and its implementation are correct, i.e., debugging the computer program.
- Validation can be implemented after the model-building phase, but it is not the end of the model life cycle (i.e. a model is always in need of improvement, and validation facilitates the iterative improvement process). So the term “examine” can be used interchangeably with the term “validate”.
- The domain of model applicability is relevant to the validity of a model.

From these points set above, we define validation of an integrated systems model as: “the process of examining the ability of a model to represent a real integrated system within the model’s domain of applicability”

Therefore, the process of model validation involves answering the following questions:

- i) Is the structure of the model, underlying assumptions, and parameters contradictory with their counterparts observed in reality and/or with those obtained from expert knowledge?
- ii) To what extent is the behavior of the model system in agreement with the observed and/or hypothesized behavior of the real system?
- iii) To what degree does the model fulfill its designated tasks or serve its intended purpose?

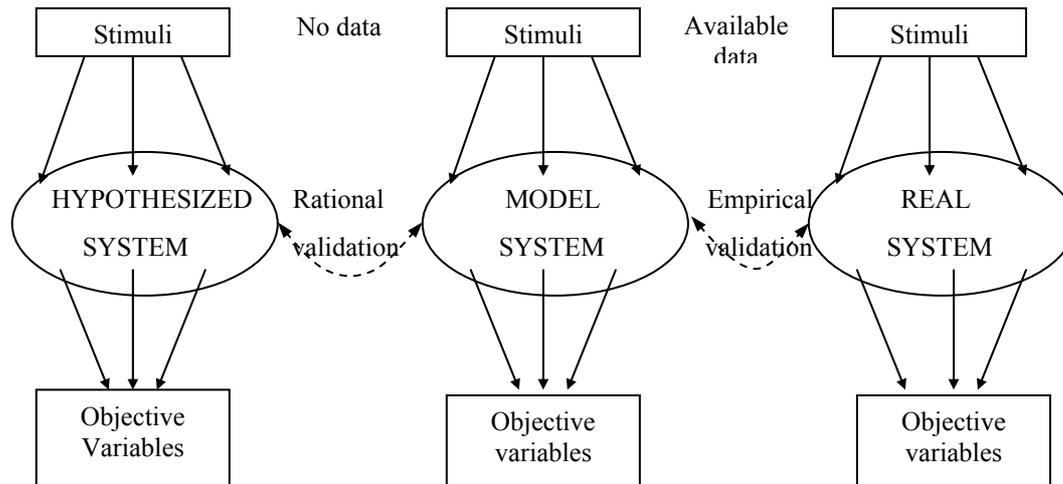
Consequently, the main purpose of validation is to show transparently both strong and weak points of the model to the potential users. The potential users could be the decision makers, analysts, or the model builders themselves (Uljee, 1996). To the model builders, validation can reveal flaws in the model, from which they may see a need to improve or rebuild the model. To the analysts, validation can provide the necessary information to facilitate the process of calibration for other applications, and analysis of the results before transferring them to the decision makers. Finally, to the decision makers, validation informs them of the degree of confidence in using the model results to support their decision-making processes.

## 2. GENERAL FRAMEWORK OF ANALYSIS

It is necessary to distinguish three systems (figure 1) that will be frequently mentioned later. The *real system* includes existing components, interactions, causal linkages between those components and the resulting behavior of the coastal system in reality. We do not have enough knowledge of the real system in most cases. The *model system* is the system built by the modelers to simulate the real system, which can help managers in decision-making processes. The *hypothesized system* is the counterpart of the real system, which is constructed from hypotheses. The hypothesized system is created from the available knowledge of experts on the real system through the process of observation and reasoning. With the above classification, we can carry out two categories of tests, namely, empirical tests and rational tests with and without real field data (figure 1).

We define the empirical tests as those tests that are conducted directly from the comparison between model outcomes and real field data. Empirical tests are conducted to examine the ability of the model to match historical data (hindcasting), future data (forecasting), and other qualitative behaviors (e.g. frequency, mode) of the real system. Where no data are available, the hypothesized system is used to conduct a series of rational tests, such as: extreme condition tests, boundary adequacy tests, and extreme policy tests (Forrester et al., 1980). These tests are called rational tests since they can be conducted with the available expert knowledge and through reasoning. Real data needed for empirical testing is usually, if not always, lacking and its accuracy uncertain. Hence rational tests are an important part of the model validation process.

In figure 1, there are three systems as mentioned previously. The same stimuli as inputs of each system produce different values of objective variables as outputs. The differences are caused by the lack of knowledge of the real system and/or others (e.g. errors of field data measurements, computational errors). Model builders always want the model behavior to be as close to the behavior of the hypothesized and real systems as possible. Where no data are available, we have to assume that the hypothesized system made up by experts is a better presentation of the real system than the model system created by modelers. To get a higher degree of confidence, one would conduct the validation of expert knowledge as in the case of data validation (Sargent, 1991) by using expert group meetings and the Delphi technique (Shannon, 1975).



**Figure 1.** Framework of analysis for validation of RaMCo

### 3. FRAMEWORK DETAILS

As mentioned in the first section, one of the reasons that make validation of an integrated model difficult is the complexity of an integrated model. In order to overcome it, a general framework should be realized in systematic steps. The following are 16 steps ordered in four phases describing the whole process of model validation.

#### 3.1. Phase 1. Specifying relevant components

Step 1: Selecting the most important Management Objective Variables (MOVs) of the Decision Support System (DSS) from preferences of the local decision makers.

Step 2: Searching for the most influential combinations of measures, scenarios, and inputs (i.e. stimuli) on the above MOVs by doing sensitivity and uncertainty analyses.

Step 3: Selecting the State Variables (SVs, i.e. outputs of sub-models) that link stimuli to MOVs.

Step 4: Identifying the sub-models and/or clusters describing the links from stimuli to MOVs.

#### 3.2. Phase 2. Collecting and evaluating validation data

Step 5: Collecting field data relevant to the most influential stimuli (measures, inputs, scenarios), SVs, MOVs found from steps 1 to 4.

Step 6: Evaluating the accuracy, sufficiency, and appropriateness of the data collected from step 5 *considering the purpose of the model*.

Step 7: Formulating hypotheses based on the results from step 4 and the evaluation of field data from step 6. (Hypotheses are validation data).

Step 8: Evaluating the validity of the hypotheses created from step 7 *considering the purpose of the model*.

#### 3.3. Phase 3. Testing

Step 9: Determining the appropriate tests (examples: t-tests and extreme condition tests) for each sub-model or cluster specified in step 4 based on phase 2 *considering the model purpose*.

Step 10: Determining the norm (validity criterion) for each test in step 9 *considering the purpose of the model* and the nature of the test.

Step 11: Carrying out the tests

Step 12: Representing the tests results in graphical forms and tables.

#### 3.4. Phase 4. Assessment and documentation

Step 13: Quality assessing model validity

Step 14: Discussing the usefulness of the model

Step 15: Recommending for model improvement *considering the purpose of the model*.

Step 16: Documenting and reporting.

In the above steps, “purpose of the model” has been repeated many times to emphasize that the purpose of the model decides the framework of validation as well as the details of most steps. RaMCo was designated as a link between measures, scenarios, and MOVs to support rapid decision-making processes. This means that

point-by-point matching is generally not the target of RaMCo since it is not a predictive model in strict sense. The consistency between the trend of model behavior and the behavior of the real system is more important.

#### 4. IDENTIFICATION OF INFLUENTIAL FACTORS USING MORRIS METHOD

One of the most important steps in phase 1 is to identify the most influential measures, scenarios, parameters and inputs (all together are called factors in the analysis) on selected MOVs. When dealing with a complex model like RaMCo (totally includes 309 factors), selection of which sensitivity and uncertainty analyses to use is very crucial. Following the guideline set up by (Morgan et al. 1990), the present study adopts the Morris method (Morris, 1991) to find out the factors that have important effects on the MOVs.

Depending on which definitions of sensitivity analysis and uncertainty analysis used, the Morris method can be categorized as either sensitivity or uncertainty analysis. According to Morgan et al. (1990) "Uncertainty analysis is the method for comparing the importance of the input uncertainties in terms of their relative contributions to uncertainties in the outputs. Meanwhile sensitivity analysis is the method for computing the effect of changes in inputs on the model prediction". In regard to this definition, the Morris method belongs to the uncertainty analysis category. Therefore, the term "sensitivity and uncertainty analyses" is taken here to denote uncertainty analysis as defined by Morgan et al. (1990) and sensitivity analysis as used by Morris (1991).

##### 4.1. Morris method

Morris (1991) made two significant contributions to sensitivity analysis. First, he proposed the concept of elementary effect,  $d_i(x)$ , attributable to each input  $x_i$ . An elementary effect can be understood as the change in an output  $y$  induced by a relative change in an input  $x_i$  (e.g. the increment of 300 kg BOD/day of the total BOD load to the coastal sea is induced by decreasing 33 % water treatment plant's capacity).

$$d_i(x) = \frac{y(x_1, x_2, \dots, x_i + \Delta, \dots, x_k) - y(X)}{\Delta}$$

In the above equation,  $X$  is a vector containing  $k$  inputs or factors ( $x_1, \dots, x_i, \dots, x_k$ ). A factor  $x_i$  can randomly take a value in an equal interval set  $\{x_i^1, x_i^2, \dots, x_i^p\}$ , each with equal probability. In this set of real number,  $x_i^1$  and  $x_i^p$  are minimum and maximum values of the uncertainty range of factor  $x_i$ , respectively. Symbol  $p$  denotes number

of levels chosen for each factor. For the sake of technical convenience, each element of vector  $X$  is assigned a rational number (Morris, 1991) or a natural integer number (Campolongo et. al, 1997) in the Morris design. Therefore, transformations, after the design, of these factors to real numbers are necessary for model computations. Symbol  $\Delta$  denotes a predetermined increment of an input  $x_i$ , whose value is chosen in such a way that  $x_i + \Delta$  is still within the uncertainty range of  $x_i$ . The frequency distribution  $F_i$  constructed by randomly selecting  $r$  elementary effects of each input  $x_i$  tells us about the degree and nature of the influence of that input on the specified output. For instance, a combination of a relatively small mean  $\mu_i$  with a small standard deviation  $\sigma_i$  indicates a "negligible" effect of the input  $x_i$  on the output. A large mean  $\mu_i$  and a large standard deviation  $\sigma_i$  indicates a strong nonlinear effect or strong interaction with other inputs. A large mean  $\mu_i$  and small standard deviation  $\sigma_i$  indicates a strong linear and additive effect. Second, he designed a highly economical numerical experiment to extract  $k$  samples of elementary effects; each has size  $r$  ( $k$  is the number of analyzed factors and  $r$  is the number of elementary effects constructing one  $F_i$ ). The total number of model runs is in the order of  $k$  (rather than  $k^2$ ). To save space of this article, the full description of the design is skipped. Refer to Morris (1991) and Campolongo et al. (1997) for details. The following are steps that were applied to this particular model to arrive at the results described in the next section.

First, three outputs of the model - live coral reef area, total BOD load to the coastal sea, and sediment transported to the reservoir - after 5 years, 10 years, and 25 years of simulation were selected to be the quantities of interest. Second, model factors were grouped and the representative factors for each group were selected manually. As the result from this step, the number of factors to be analyzed reduced from 309 to 137 ( $k = 137$ ). Third, the quantitative ranges of parameters and inputs were specified using historical data analyses, literature, and expert knowledge. Fourth, the Morris design is applied with the number of level for each factor equal four ( $p = 4$ ), the increment of  $x_i$  to compute elementary effects  $d_i(x)$ ,  $\Delta = 1$  (see Campolongo et al., 1997). The selected size of each sample  $r = 9$ . A total of 1142 model evaluations were performed ( $N = r(k + 1)$ ). Finally, the two measures indicating the importance of each factor's contribution to the uncertainty in the outputs,  $\mu$  and  $\sigma$  are computed and plotted. The inferences from those plots are discussed in the following section.

## 4.2. Results

Figure 2 to figure 4 show the two measures of influence of 137 factors on the three selected outputs after 5 years of simulation. Only the important factors are numbered in these figures. Table 1 contains a description of each factor. It is worth noting that the purpose of the Morris method is to determine which inputs have important effects on the outputs. Care should be taken when interpreting order of importance for each input. The results serve to highlight the factors we should pay most attention to when collecting data since these have the most influences on the model outputs.

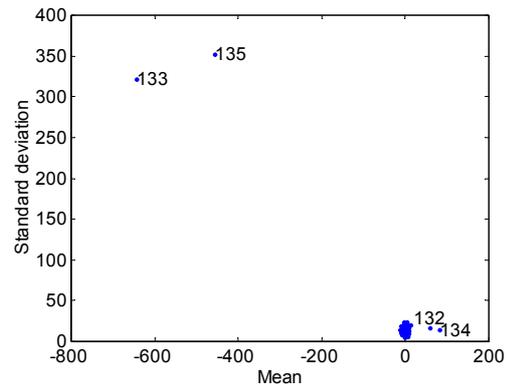
From figure 2 it can be inferred that preventing blast fishing on coral reefs would play a dominant role in the survival of the coral reefs in the study area. This conclusion was compared with expert knowledge to confirm qualitatively the ability of the model system to mimic the real system.

In figure 3, the most influential factor on total BOD load discharged to the coastal sea is pollution from shrimp culture, not pollution from residential uses or industry. Since the value of parameter 124 (BOD load generated by 1 kg of shrimp) was roughly estimated from few measurements (large uncertainty), it suggests a need to spend more effort on investigating this factor during data collection and validation of the model.

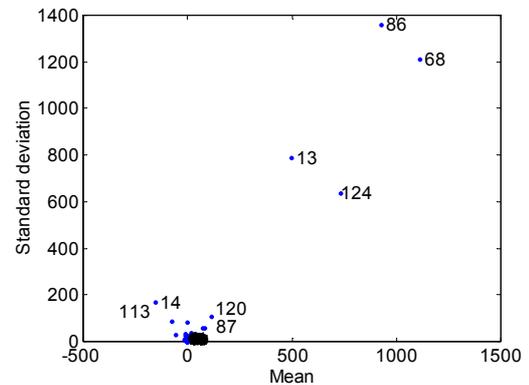
Figure 4 shows the most influential factors on the amount of sediment transported into the reservoir. Since agriculture is the most sensitive land-use to erosion, factor 28 (cover and management factor C for agriculture) and factor 33 (support practice factor P for agriculture) have the highest means and standard deviations. A recent examination of these two parameters shows that the authors over estimated the initial uncertainty range of parameter 33. It would be adjusted to reduce the uncertainty in the output.

A dense cluster of points lying away from horizontal axis in figure 4 can be explained by the existence of a stochastic rainfall-generating module employed in RaMCo.

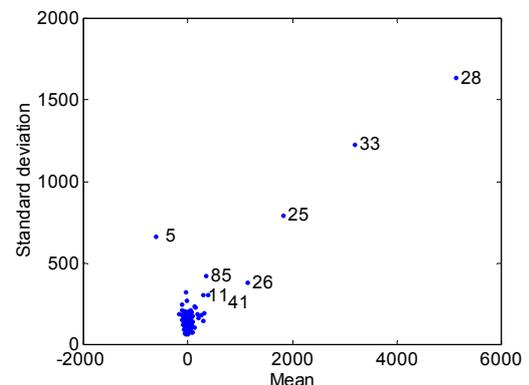
Results of Morris analyses after 10 and 25 years of simulation (not shown here) are similar to the three figures shown for 5 years of simulation. The most influential factors remain the same but the order of the importance is slightly different. Specifically, for the sediment transported into the reservoir, factor 81 (natural spatial growth rate of forest) appears to be an influential one only after 25 years of simulation. It reflects the fact that the importance of each factor can change with time in a system dynamics model.



**Figure 2.** Means and standard deviations of the distributions of elementary effects of 137 factors on live coral reef area.



**Figure 3.** Means and standard deviations of the distributions of elementary effects of 137 factors on total BOD load.



**Figure 4.** Means and standard deviations of the distributions of elementary effects of 137 factors on sediment transported to the reservoir.

**Table 1.** Descriptions of the most influential factors on 3 MOVs resulted from Morris analysis

Factor's label	Description
133	Damaged surface area of coral reef per fish blast
135	Average number of fish blasts per year
134	Recovery rate of damaged coral reef
132	Natural colonization rate of coral reef
68	Spatial extension growth rate of shrimp culture
86	Yield of intensive shrimp culture
124	BOD load generated by 1 kg of shrimp
13	Relative growth rate of price of intensive shrimp culture
14	Relative growth rate of cost of intensive shrimp culture
113	Purification capacities of water treatment plant
120	BOD concentrations before entering water treatment plant
87	Yield of extensive shrimp culture
28	Cover and management factor C for agriculture
33	Support practice factor P for agriculture
25	Adjustment coef. for rainfall amount
26	Slope length
5	Reforestation factor
41	Sediment delivery ratio for sub-catchment 4
11	Growth coef. of price for agriculture
85	Agriculture yield
81	Natural spatial extension of forest

## 5. CONCLUSIONS

A new framework and its realization for validation of integrated systems model has been presented. It originated from a desire to establish a general methodology to validate any models of the same type. Though the final results have not been completed, the authors want to show the initial findings toward a practical framework for validation of an integrated systems model. In addition, the application of the Morris method to

the present problem confirms the three important roles of sensitivity and uncertainty analyses throughout the process of validation. First, it helps to pinpoint those parameters, inputs, and measures that need more investigations in the process of model validation. Second, it allows end-users of the model to judge qualitatively the validities of the hypotheses embedded in a model. Finally, it helps to find the backbone of a model with which validation should be based on. It is also the next step of the present research.

## 6. ACKNOWLEDGEMENTS

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