Paper

# Assessing Coastal Sustainability: A Bayesian Approach for Modeling and Estimating a Global Index for Measuring Risk


Salvatore Vitabile[a], Alfonso Farruggia[b], Giuseppe Pernice[c], and Salvatore Gaglio[b,d]

[a]Dipartimento di Biopatologia e Biotecnologie Mediche e Forensi, University of Palermo, Palermo, Italy
[b] Dipartimento di Ingegneria Chimica, Gestionale, Informatica, Meccanica, University of Palermo, Palermo, Italy
[c] IAMC-CNR, National Research Council, Istituto per l'ambiente marino costiero, Mazara del Vallo (TP), Italy
[d] ICAR-CNR, National Research Council, Istituto di calcolo e reti ad alte prestazioni, Palermo, Italy



**Abstract—Integrated Coastal Zone Management is an emerging research area. The aim is to provide a global view of different and heterogeneous aspects interacting in a geographical area. Decision Support Systems, integrating Computational Intelligence methods, can be successfully used to estimate useful anthropic and environmental indexes. Bayesian Networks have been widely used in the environmental science domain. In this paper a Bayesian model for estimating the Sustainable Coastal Index is presented. The designed Bayesian Network consists of 17 nodes, hierarchically organized in 4 layers. The first layer is initialized with the season and the physiographic region information. In the second layer, the first-order indexes, depending on raw data, of physiographic regions are computed. The third layer estimates the second-order indexes of the analyzed physiographic regions. In the fourth layer, the global Sustainable Coastal Index is inferred. Processed data refers to 13 physiographic regions in the Province of Trapani, western Sicily, Italy. Gathered data describes the environmental information, the agricultural, fisheries, and economical behaviors of the local population and land. The Bayesian Network was trained and tested using a real dataset acquired between 2000 and 2006. The developed system presents interesting results.**



***Keywords—Bayesian Networks, Decision Support Systems, Integrated Coastal Zone Management, Sustainable Coastal Index.***


## 1. Introduction

The west coast of Sicily, Italy is an interesting local productive zone. This area is one of the main trade centers in the Mediterranean Sea, and it is a growing touristic area.

Nevertheless, the zone suffers of some problems, due its inhomogeneities. The local authorities are looking for a point of balance between various factors characterizing the area's economy, such as tourism, fishing, infrastructures, number of building, and the health of the environment, and the quality of life.

Data analysis techniques can help for modeling and reducing the above cited negative aspects through territory data processing. This makes possible to develop management tools for modeling territory's activities in order to combine and optimize socio-economic and environmental aspects.

These models have to be very sensitive to small changes of heterogeneous factors. Slight changes of environmental data such as temperature, water salinity, dissolved oxygen, the speed and direction of wind, but also the number of tourists or the percentage of buildings in the area can significantly change the sustainability of the entire region.

This work presents a Decision Support System (DSS), based on Computational Intelligent methods, for the coastal sustainability evaluation and forecasting. With more details, a Bayesian Network (BN) has been used to estimate a global index that can be used by local authorities to implement the appropriate decisions, improving the territorial economic and social activities.

The developed Bayesian Network consists of 17 nodes, hierarchically organized in 4 layers. The first layer is initialized with the season and the physiographic region information. In the second layer, the first-order indexes, depending on raw data, of physiographic regions are computed. The third layer estimates the second-order-indexes of the analyzed physiographic regions. In the fourth layer, the global Sustainable Coastal Index (SCI) is inferred.

The proposed model has been used for modeling and simulating the sustainable coastal index in the Province of Trapani area, western Sicily, Italy. The analyzed coastal area is 378.983 $km^2$ and both naturalistic and socio-economic points of views are very interesting. The Bayesian Network was trained and tested using a real dataset. Data series has been collected between 1 January 2002 and 31 July 2006 for a total of 1673 days and the measurements were daily gathered. The dataset is composed of heterogeneous data, since it contains anthropogenic factors, economic data, tourism data, infrastructure data and fishing data.

The developed model has been integrated as plug-in in a commercial Geographic Information System (GIS). The model can be used as DSS to estimate and evaluate the impact of anthropic, infrastructure, environmental changes over the coastal sustainability. The proposed system shows interesting performances when employed as DSS for coastal zone management.

The remainder of the paper is organized as follows. Section 2 presents some relevant works about DSS and automatic models use. In Section 3, the proposed model is described. Section 4 shows some experimental results. Section 5 presents the integration of the proposed model in a commercial GIS. Finally, Section 6 contains some concluding remarks.

## 2. Related Works

Nowadays, automatic models and Decision Support Systems are used for analyzing and understating the future direction of interesting application fields, such as environmental sciences, agricultural sciences, transportation systems, economic sciences, and tourism [1]–[9]. On the other hand, Computational Intelligence is an enabling discipline for developing these approaches [10]–[12].

In [1], the authors present a work to assist local authorities and policy makers of interesting regions in order to implement a mobility scheme for managing the demand in a sustainable way.

The paper [2] describes a work developed as part of a DSS. Its aim is to support an operator in his/her tasks for analyzing soft data to monitor and anticipate a geopolitical crisis.

The work presented in [3] discusses an innovative approach for measuring tourism competitiveness using eight main indicators over 200 countries. Weights for each theme are derived using confirmatory factor analysis in order to compute an aggregate index. Cluster analysis is used to group destinations according to their performance level.

In [4], the authors develop an indexing model to evaluate sustainability performance of urban settings in order to assess environmental impacts of urban development and provide an indexing model to planning agencies. The model is a DSS to be used in curbing negative impacts of urban development.

The work presented in [5] examines factors influencing the sustainability of Integrated Coastal Management (ICM) projects in Philippines and Indonesia. Measures of project sustainability were developed. Primary data collected at the village level was analyzed to determine the effects of project activities and individual characteristics on ICM sustainability.

The authors of paper [6] underline the analysis and establishment of indicator-driven programs to assess change in coastal and watershed systems. The work reviews the need for and provide an assessment of important frameworks designed to foster the integration. It argues that the evolution of the Driver Pressure State Impact Response (DPSIR) framework provides an essential contribution.

In [7], the authors assert that the modeling of key environmental and socio-economic processes are a vital tools. They required to buttress coastal management institutions and practice. The proposed framework was based on a conceptual model that lays stress on functional value diversity and the links between ecosystem processes, functions and outputs of goods and services. In the work a three overlapping procedural stages for coastal resource assessment process are explained.

Article [8] discusses the potential contribution of indicators to assess the performance of the governance processes involved in integrated coastal management. They focused on the evaluation phase and on the need to complement process-oriented indicators with outcome-oriented indicators to improve adaptive management and accountability. The example of integrated management of marine protected areas is used to propose a menu of indicators of global applicability.

In [9], the authors present a sustainability indicator system based on three sub-systems: environment and resources, economic development, and society. It has been set up to evaluate the nature of development in the coastal zone in the administrative regions of the Municipality of Shanghai and Chong Ming Island.

In this work, a Decision Support System for local authorities is presented. The aim is to develop an useful model for Integrated Coastal Zone Management in order to take the appropriate decisions for improving the territorial economic and social activities and revenues. The DSS has been developed for a global index, namely Sustainable Coastal Index, evaluation and estimation.

## 3. A Four-Layer Bayesian Model

The most interesting feature of BNs, compared to decision trees or neural networks, is most certainly the possibility of taking into account prior information about a given problem, in terms of structural relationships among its features. This prior expertise, or domain knowledge, about the structure of a Bayesian Network has been used in this work.

A Bayesian Network is a particular Directed Acyclic Graph (DAG) for representing causes and effects scenarios [13]. BN variables are represented by nodes. The values assumed by nodes can be a state, or a set of probability values. Nodes are connected with edges, denoting causality relationships.

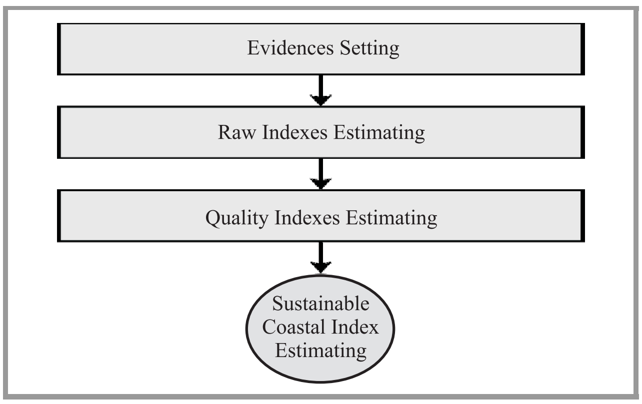


*Fig. 1.* The block diagram of the proposed model.

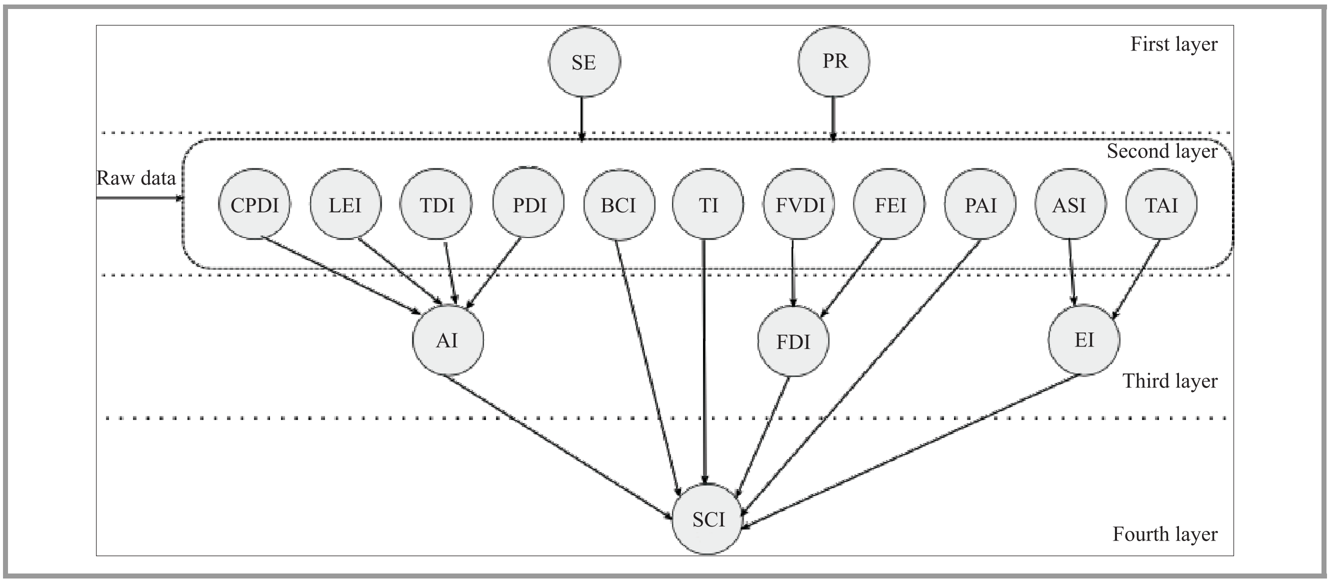


*Fig. 2.* The Bayesian Network structure is composed of 17 nodes in 4 layers. The first layer is initialized with the season and the PR information. In the second layer, the first-order indexes, depending on raw data, of PRs are computed. The third layer estimates the second-order indexes for the analyzed PRs. In the fourth layer, the global SCI is inferred.

The network models the probabilistic relationships between the variables of a system, accounting their historical information. They are used to model scenarios where some information are partially unavailable or with uncertainty. Like the uncertain human reasoning, they give a representation of knowledge producing probabilistic results, given a certain degree of truth on a topic.

A feature (node) is conditionally independent from its non-descendants given its parents: $X1$ is conditionally independent from $X2$ given $X3$ if $P(X1|X2,X3) = P(X1|X3)$ for all possible values of $X1$, $X2$, $X3$ [13].

A Conditional Probability Table (CPT) can be associated to each node. It contains the probabilities of the values of the node conditioned by the values of its parent nodes. For each parent and its possible states, a new entry in the CPT is created.

The variable probability in a state, considering the actual scenario, is known as belief. In particular, a-priori beliefs are a kind of belief calculated only on a prior information. They are defined considering the CPTs, whereas the evidence is the information of a current scenario.

A different approach, which is the one considered in this paper, is to directly include in the model the relationship between raw data, intermediate indexes, and the overall index. The four-layer Bayesian model, developed with the collaboration of domain experts, allows for aggregating and processing data with different abstraction levels.

With more details, the present work describes a Bayesian Network for estimating the Sustainable Coastal Index (SCI) of 13 physiographic regions (PRs).

Figure 1 shows the block diagram of the proposed model. The designed BN consists of 17 nodes, hierarchically organized in 4 layers. The first layer is initialized with the season and the physiographic region information. In the second layer, the first-order indexes, depending on raw data, of the 13 physiographic regions are computed. The third layer estimates the second-order indexes for the analyzed physiographic regions. In the fourth layer, the global SCI is inferred.

Figure 2 shows the structure of the BN used in this work. Each Bayesian Node expresses a quality index for a productive aspect of the processed physiographic unit. It is computed considering three factors: the physiographic region, the season and the related raw data.

Table 1
Grouping class for quality index values

| Class | Range |
|---|---|
| Low | 0 – 3.333 |
| Medium | 3.334 – 6.333 |
| High | 6.334 – 10 |

In the network training phase, the required probability distributions are derived from the domain experts through the use of a mathematical model. The mathematical model produces continuous values in the [0, 10] range, where 10 is the optimal sustainability value and 0 is the most critical value. A grouping operation has been performed for mapping the range in 3 main classes, as shown in Table 1. The above classes have been used for computing the CPT associated to each node.

### *3.1. First Layer – Evidence Setting*

The first layer has two nodes for setting the season and the PR in order to start the network computation. The former node has 4 possible states, while the latter node has 13 possible states, related to the main physiographic regions in the Province of Trapani, west Sicily, Italy.

### *3.2. Second Layer – First Order Index Estimations*

In the second layer, the probability of first-order indexes, depending on raw data, of physiographic regions is computed. Considering the evidence of the BN, the appropriate table of conditioned probability has been loaded. The second layer is composed of 11 nodes, described below by the following mathematical model [14]:

**Coastal Population Density Index (CPDI)**: The CPDI deals with the population (tourists and residents) living in the coast over the surface of the coast. The CPDI is 0 if the ratio is less than or equal to 1, while it is equal to 10 if the ratio is greater than or equal to 1000. These two reference values have been interpolated with a logarithmic base 2 function:

$$CPDI = log_2\left(\frac{Kmq-surface-coast}{Total-population}\right). \quad (1)$$

**Land Exploitation Index (LEI)**: The LEI deals with the built area over the whole surface of the physiographic region. The value is calculated as follows:

$$LEI = 10\cdot\left(1-\frac{Surface-built}{Kmq-surface-PR}\right). \quad (2)$$

**Fishing Exploitation Index (FEI)**: The FEI deals with the quantity of caught fish considering the surface of the physiographic region. The values are normalized between 0 and 10, computed from:

$$FEI = \frac{Kg-fish-caught}{Kmq-surface-PR}. \quad (3)$$

**Fishing Vessel Density Index (FVDI)**: The FVDI deals with the number of fishing vessels over the surface of the physiographic region. The value is calculated as follows:

$$FVDI = \frac{Vessels}{Kmq-surface-PR}. \quad (4)$$

**Agricultural Sustainability Index (ASI)**: The ASI deals with cultivated land over the whole surface of the physiographic region. The useful cultivated land deals with the farming types. In particular, 5 crops have been considered: olive groves, orchards, vineyards, citrus groves, and woods. Each crop has a different weight (*c-weight*) in the ASI computation.

$$ASI = \sum_{cultivation=1}^{5}\frac{c-weight\cdot Kmq-surface-cult.}{Kmq-surface-PR}. \quad (5)$$

**Population Density Index (PDI)**: The PDI deals with the population density, considering the surface of the physiographic region:

$$PDI = \frac{Population}{Kmq-surface-PR}. \quad (6)$$

**Tourist Density Index (TDI)**: The TDI deals with the number of tourists in a particular season and the whole population of the PR:

$$TDI = \left(1-\frac{Tourists}{Population}\cdot\frac{1}{days-for-season}\right)\cdot 10. \quad (7)$$

**Tourist Accommodation Index (TAI)**: The TAI deals with the arithmetic average of two indicators: Kiosks Sustainability Index (KSI) and Hotel Sustainability Index (HSI). KSI is 0 if the distance between two kiosks is equal to or less than 200 meters, while it is 10 if the distance exceeds 10,000 meters. KSI will be again 10 if no kiosks are in the area. HSI is 0 if the geographic area has 200 beds per square kilometer, while HSI is 10 if no beds are in the geographic area:

$$KSI = \frac{\log_4\left(\frac{Km-coast}{(n-Kiosks)}-199\right)+\frac{Km-coast}{(685\cdot n-Kiosks)}-0.25}{2}, \quad (8)$$

$$HSI = -\frac{Beds}{20\cdot Kmq}+10. \quad (9)$$

**Balneal Coast Index (BCI)**: The BCI deals with the balneal coasts, and it is calculated as follows:

$$BCI = \frac{LengthBalnealCoast}{LengthTotalCoast}\cdot 10. \quad (10)$$

**Transportation Index (TI)**: The TI quantifies the transport infrastructures in the geographic area. It is computed considering the road surface, the stations and airports in the geographic area.

**Protected Area Index (PAI)**: The PAI is calculated considering either the surface of protected land areas and the surface of sea protected areas in the geographic area.

In the second layer, the BN computes a probability value for each state of the node. The probability values are used as inputs for the third layer of the BN.

### *3.3. Third Layer – Second Order Index Estimation*

The third layer estimates the second-order indexes. It is composed of 3 nodes: Anthropic Index, Economic Index, and Fishing Density Index. The possible states of each node are: Low, Medium, and High. The means of each node is described below:

Table 2
Conditioned Probability Table of the SCI node

| AI | BCI | FDI | PAI | EI | TI | Low [%] | Medium [%] | High [%] |
|---|---|---|---|---|---|---|---|---|
| Low | Low | Medium | Low | High | Low | 39.202 | 22.619 | 38.179 |
| | | | | | Medium | 72.692 | 24.360 | 2.948 |
| | | | | | High | 23.910 | 23.408 | 2.948 |
| | | | Medium | Low | Low | 6.496 | 25.341 | 68.163 |
| | | | | | Medium | 65.101 | 18.379 | 16.520 |
| | | | | | High | 35.209 | 22.431 | 42.360 |
| | | | | Medium | Low | 16.883 | 27.720 | 55.398 |
| | | | | | Medium | 9.319 | 55.531 | 35.150 |
| | | | | | High | 34.921 | 44.847 | 20.232 |

**Anthropic Index (AI)**: The index is produced by the following second-layer-indexes: PDI, TDI, CPDI, and LEI.

**Economic Index (EI)**: The index is produced by the following second-layer-indexes: ASI and TAI.

**Fishing Density Index (FDI)**: The index is produced by the following second-layer-indexes: FEI and FVDI.

### *3.4. Fourth Layer – Sustainable Coastal Index Estimation*

In the fourth layer, the global Sustainable Coastal Index is inferred. The BN computes the probability for the three possible states of SCI: Low, Medium, and High. If the predominant class is the High class, the related physiographic region has an high sustainability features, considering the socio-economic and environmental factors. In the same way, the Medium class and the Low class can be defined. SCI can be used by local authorities in order to take the appropriate decisions for improving the territorial economic and social activities.

## 4. Experimental Results

The Bayesian Network was trained and tested using a real dataset. The dataset refers to the Province of Trapani, western Sicily, Italy. The series was gathered between 1 January 2002 and 31 July 2006 [14].

The BN has been developed using the Norsys Netica v3.19 software [15]. The development framework allows for creating and simulating advanced bayesian belief network. Netica uses the *Message Passing* algorithm [16]–[19] for extracting probabilistic inference in a BN.

In the first phase, Netica compiles the BN into a *junction tree*. The *junction tree* is a set of Netica internal connections, and they are not visible to users. In the second phase, the Netica user inserts the evidences in the network and selects the output nodes computing the global beliefs.

The 1637-days-dataset has been split in two subsets for the training phase and the testing phase, respectively. Data series gathered from 2002 to 2004 has been used for training phase, while data series gathered from 2005 to 2006 has been used for the testing phase.

In the learning phase the Conditioned Probability Tables are carried out. As example, the CPT of the SCI node is shown in Table 2. After the training phase, the learned network has been tested using the appropriate dataset.

The proposed model performances have been evaluated comparing the network output against the findings of a group of domain experts. With more details, 120 simulation trials, with a flat distribution between the classes, have been carried out changing network inputs, i.e., time and/or physiographic unit. The confusion matrix describing the network accuracy is shown in Table 3.

Table 3
The Confusion Matrix describing the model accuracy

| | Low | Medium | High |
|---|---|---|---|
| Low | 98% | 2% | – |
| Medium | 1% | 97% | 2% |
| High | – | 2% | 98% |

In what follows, two examples, showing system functionalities, are shown. In first example, the evidence of the nodes SE, PR, CPDI, DPI, TII, BI, DBI, FI, and PAI has been superimposed. In particular, SE is *summer* and PR is *Marsala*. Netica computes the indexes for the remaining node, and, at the end, the SCI node class is inferred. Figure 3 shows the Netica network structure: the gray nodes are superimposed, while the yellow nodes are inferred. In this case, the SCI predominant probability is the High class (P(High) = 63.3%, P(Medium) = 20.8%, and

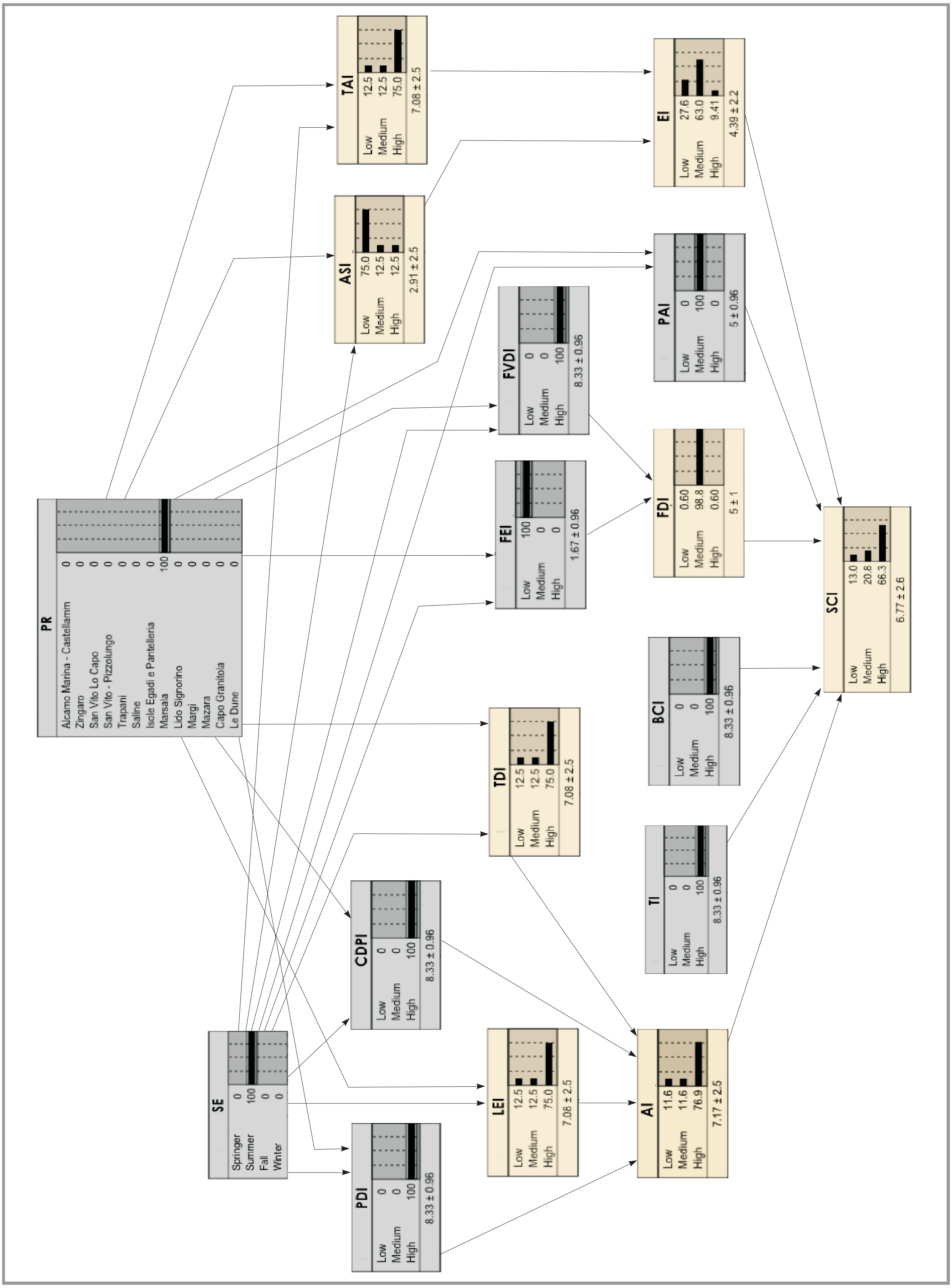


*Fig. 3.* The BN diagram extracted from the Netica software. The network is related to Marsala PR and the the summer season. The inferred SCI node shows the 63.3% of probability associated to the High value.

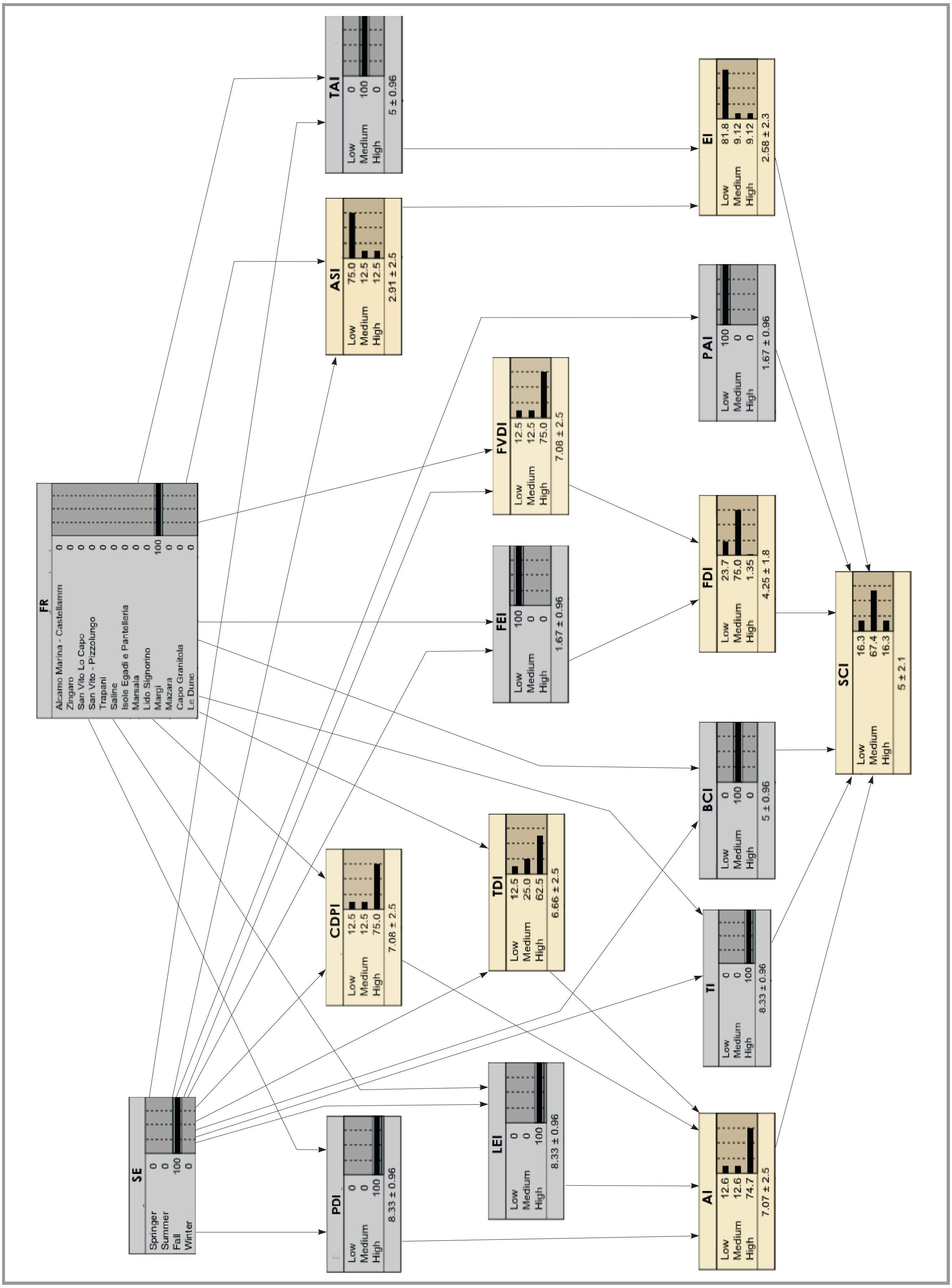


*Fig. 4.* The BN diagram extracted from Netica software. The network is related to Margi PR and the fall season. The inferred SCI node shows the 67.4% of probability associated to the Medium value.

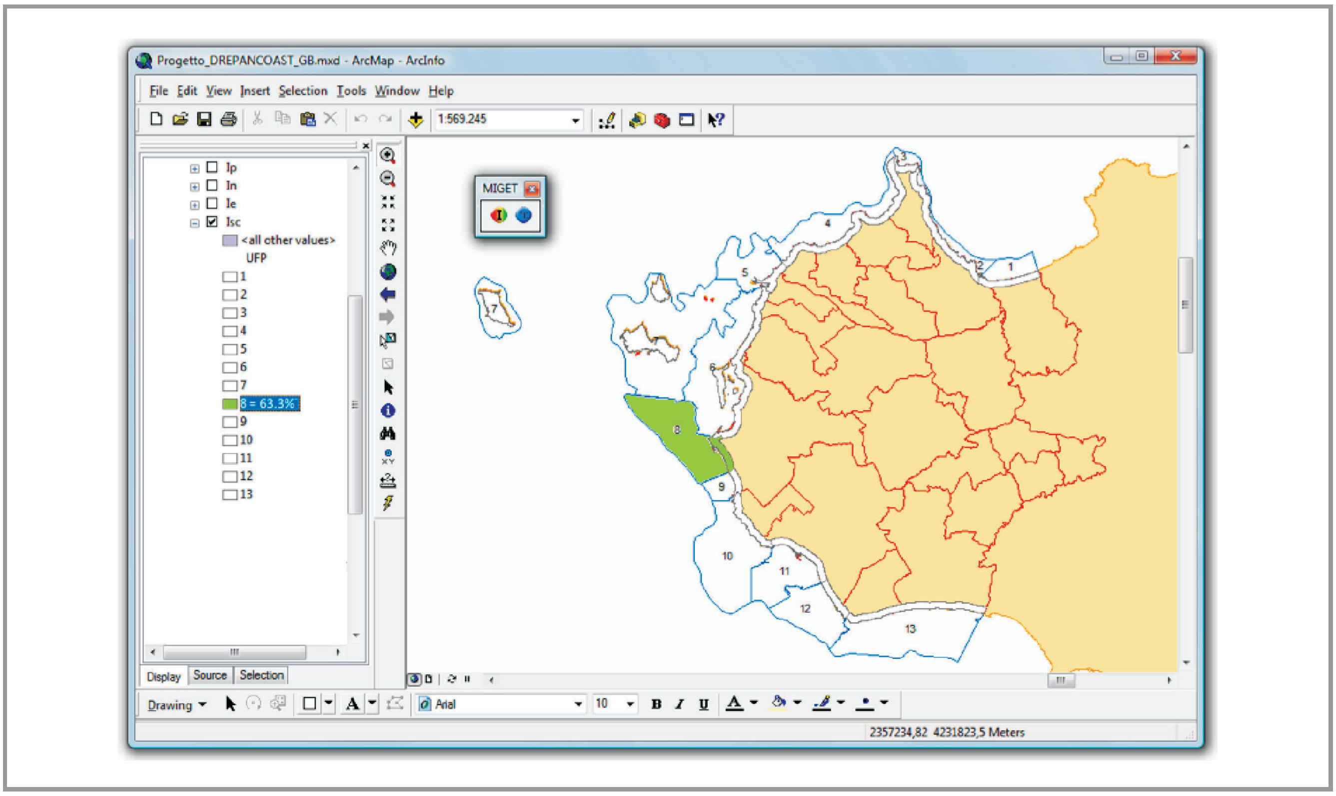


*Fig. 5.* The Bayesian model running in ERSI ArcGIS 9. The SCI has been computed for PR8 (Marsala).

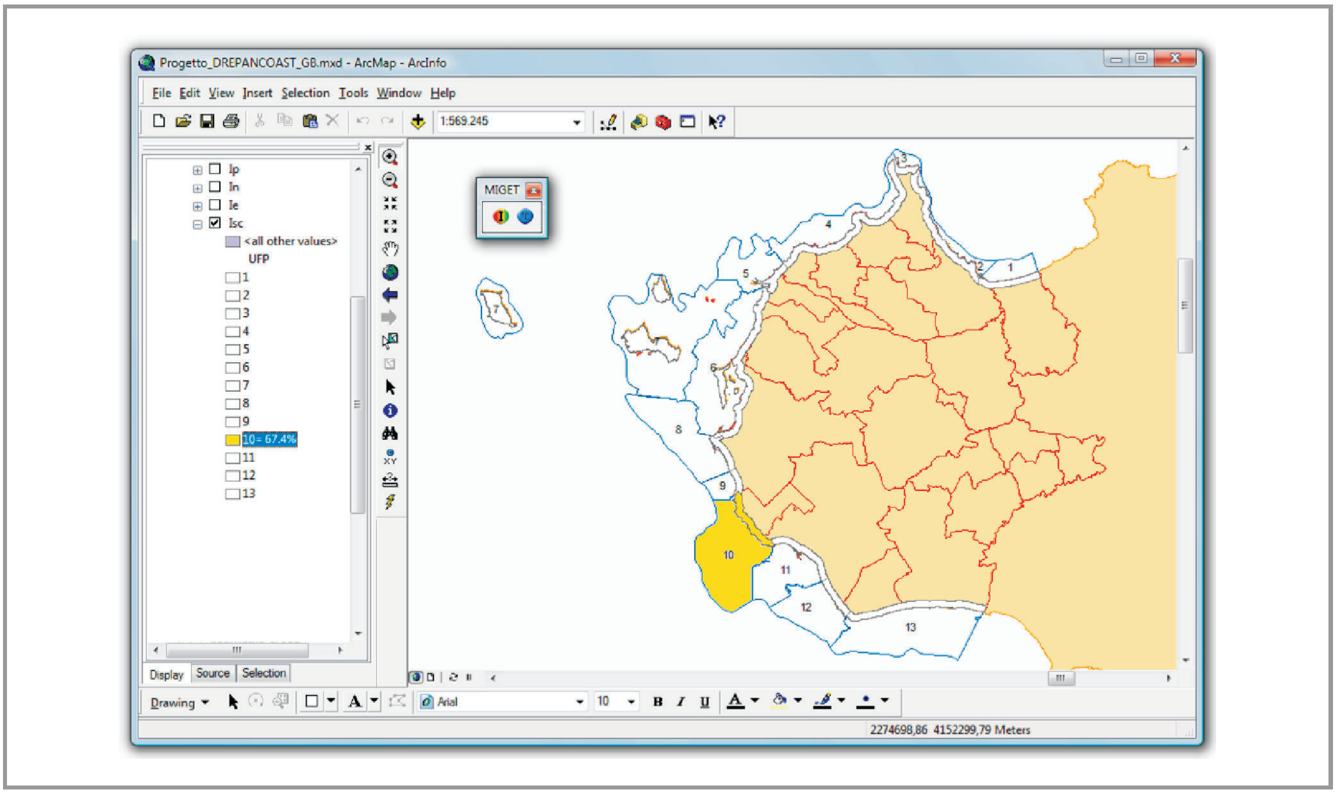


*Fig. 6.* The Bayesian model running in ERSI ArcGIS 9. The SCI has been computed for PR10 (Margi).

P(Low) = 13.0%). In the second example, the evidence of nodes SE, PR, DPI, ELI, TII, BI, FI, PAI, and ATI has been superimposed. In particular, SE is *fall* and PR is *Margi*. Figure 4 shows the Netica network structure. The gray nodes are superimposed, while the yellow nodes are inferred. In this case, the SCI predominant probability is the Medium class (P(High) = 16.4%, P(Medium) = 67.4%, P(Low) = 16.3%). Similar results can be obtained selecting different physiographic units and/or seasons.

## 5. Integrating GIS and Bayesian Network

The presented Bayesian model has been also integrated in the ESRI ArcGIS 9 Desktop [20]. ArchGis is a set of integrated software tools for the Geographic Information System management. It is based on a shared library of GIS components, namely ArcObjects.

ESRI provides a set of development tools, namely ArcGIS Developer Kit. This framework is useful for creating standalone applications, based on ESRI ArcGIS Engine, as well as for extending the capabilities of existing software, such as ArcMap. The programming environments used for developing the present work are the .Net SDK, Visual Basic, C++ and Java.

Netica v3.19 environment allows for exporting the Bayesian network using the appropriate APIs. The APIs allow for exporting the code of the developed BN in several programming languages, such as Java, C, C++, and C#.

Due to the previous features, an ad-hoc plug-in was developed for the SCI estimating.

The proposed ArcGIS plug-in consists of a toolbar linked to the Netica library. This toolbar is loaded into ArcMap software and integrated in the ArcGIS user interface, becoming part of the original software tool.

Two screenshots of the running system are shown in Figures 5 and 6. The plug-in associates the red color to the Low class, the yellow color to the Medium class and the green color to the High class.

Figure 5 shows the computed SCI for PR 8 (Marsala). The left bar shows the green SCI probability value (63.3%) of the highlighted physiographic region (in right side). Figure 6 shows the computed SCI for PR 10 (Margi). The left bar shows the yellow SCI probability value (67.4%) of the highlighted PR.

## 6. Conclusions

Integrated Coastal Zone Management (ICZM) is an emerging research area. Computational Intelligence methods and Geographic Information can be successful used to estimate and forecast the impact of environment and anthropic actions and strategies.

In this work a Decision Support System, based on a Bayesian Network, for Sustainable Coastal Index evaluation and forecasting has been presented. Local authorities can use the developed model in order to take the appropriate decisions for improving the economic and social activities and revenues of target area.

The Bayesian Network was trained and tested using a real dataset. The dataset used has been acquired between 2000 and 2006 in the Province of Trapani, western Sicily, Italy. Model results are very interesting and they have been validated by a group of domain experts.

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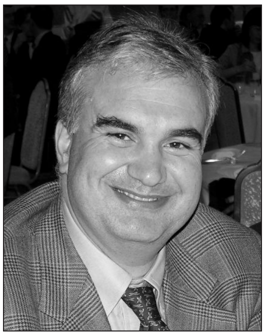
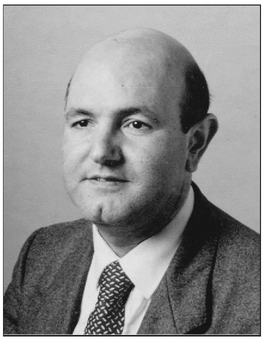


**Salvatore Vitabile** received the Laurea degree in Electronic Engineering and the Ph.D. degree in Computer Science from the University of Palermo, Italy, in 1994 and 1999, respectively. He is currently an assistant professor with the Department of Biopathology, Medical and Forensic Biotechnologies, University of Palermo, Italy. In 2007, he was a visiting professor in the Department of Radiology, Ohio State University, Columbus, USA. His research interests include computational intelligence, biometric authentication systems, architecture design and prototyping, real-time driver assistance systems, multi-agent system security, and medical data processing and analysis. He is also the Editor in chief of the International Journal of Adaptive and Innovative Systems, Inderscience Publishers, and a member of the board of directors of SIREN (Italian Society of Neural Networks).

E-mail: salvatore.vitabile@unipa.it
Dipartimento di Biopatologia e Biotecnologie Mediche e Forensi
University of Palermo
Via Del Vespro 129
90127 Palermo, Italy

**Alfonso Farruggia** is a post doctoral fellow with the University of Palermo, Italy. He received the Computer Engineer M.Sc. degree from the Polytechnic of Turin, Italy and the Ph.D. degree in Computer Engineer from the University of Palermo, Italy in 2008 and 2011, respectively. During the Ph.D. course, he has conducted his research on issues related to anomaly detection in Wireless Sensor Networks using Machine Learning and Computer Intelligence methods. His research interest include Wireless Sensor Networks, Computer Intelligence methods, and Information Retrieval in healthcare.

E-mail: alfonso.farruggia@unipa.it
Dipartimento di Ingegneria Chimica, Gestionale, Informatica, Meccanica
University of Palermo
Viale delle Scienze
90128 Palermo, Italy



**Giuseppe Pernice** received his M.Sc. degree in Nuclear Engineering from the University of Palermo, in 1972. He also obtained a fellowship at the Central Bureau for Nuclear Measurements (CBNM) of EURATOM in Geel and at the United Kingdom Atomic Energy Authority (UKAEA) in Harwell. He was a researcher at the CNEN (National Committee for Nuclear Energy) since 1975, where he performed research activities in the field of fast reactors safety, and then he worked at ENEA (Italian National Agency for New Technologies, Energy and the Environment), where he worked in the field of renewable sources of energy and of environmental protection. Since 2001 he is Senior Researcher at CNR (National Research Council), at the IAMC (Institute for Coastal Marine Environment) where he is involved in the field of forecasting models for the integrated management of coastal areas. He has also developed research projects aimed to the safeguard the Sicilian coast. He is currently Coordinator of the "Observatory of Fisheries of the Mediterranean", that is a NGO of scientific-technical support to the Sicilian Region and to the Production District Fishing in marine fisheries. He is also author of scientific papers, technical reports and publications in the field of integrated coastal zone management (ICZM), renewable energy sources, energy conservation and marine fisheries.

E-mail: giuseppe.pernice@cnr.it
IAMC-CNR, National Research Council
Istituto per l'ambiente marino costiero
Via Vaccara 61
91026 Mazara del Vallo (TP), Italy

**Salvatore Gaglio** graduated in Electronic Engineering at the University of Genoa, Genoa, Italy in 1977. In 1977 he was awarded a Fulbright scholarship to attend graduate courses in USA, and in 1978 he received the M.S.E.E. degree from the Georgia Institute of Technology, Atlanta, USA. From 1979 to 1981 he has been Assistant Professor of electronic communications and from 1981 to 1986 associate professor of artificial intelligence at the University of Genoa, Italy. From 1986 he is Professor of Computer Science and artificial intelligence at the University of Palermo, Italy. From 2002 he is the head of the Palermo brand of the High Performance Computing and Networking Institute (ICAR) of the Italian Research Council (CNR). He has been member of various committees for projects of national interest in Italy and he is referee of various scientific congresses and journals. His present research activities are in the area of artificial intelligence and robotics. He is a member of IEEE, ACM, and AAAI.

E-mail: salvatore.gaglio@unipa.it
Dipartimento di Ingegneria Chimica, Gestionale, Informatica, Meccanica
University of Palermo
ICAR-CNR, National Research Council of Italy
Viale delle Scienze
90128 Palermo, Italy