Self-organising maps for integrating data across multiple scales

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Applications of self-organising map (SOM) methods to integrated analysis of ecological data with socio-economic indices at different scales and levels are elaborated upon. The three case studies of this paper illustrate how SOM methods could be applied to analysing cross scale interactions using data from different sources, such as statistical tables with inconsistent labelling and limited prior knowledge.

Introduction

Research on methods to analyse environmental effects integrated with human activities that cause the effects, is not a new endeavour. Ecologists have made attempts to introduce new methodologies based on interdisciplinary research to better understand natural habitats since the late 1980s; literature reviewed in this regard reveals this fact. However, in recent years, the quest to better understand diverse ecosystem functioning, incorporating their biological diversity in order to improve human-environment relationship is receiving an unforeseen momentum (Environmental Protection Agency; Ministry for the Environment 2002a; Ministry for the Environment 2002b). During the last century, research on natural science became more focused on gaining in-depth knowledge, which led to the subdivision of science into many specialised fields and a fragmented image of nature (Bowler 1992). The decisions based upon knowledge, gained through such subdivisions of science are blamed for contributing significantly towards even altering the Earth's basic chemical cycles (Kirby 2000).

Global environmental issues, such as biodiversity loss, overexploitation of natural resources, fresh water scarcity, deforestation, global warming, ozone depletion and many more, caused by excessive human stress on the environment and the increasing world population growth, emphasise the wise use of natural systems for human wellbeing now and in the future (Schmitt et al. 1996). Realising this, many environmentally concerned national and international institutions have initiated monitoring programmes for the following reasons:

i. to gain more insight into diverse ecosystems,
ii. to make the general public aware of the growing environmental issues,
iii. to study the effects of urbanisation on natural habitats for developing indicators,
iv. to detect environmentally unsustainable human pressure and
v. to monitor natural habitats, in accordance with state regulations.

(Vant 1999; O'Connor and Walley 2001; National River Health Program 2002; North Shore City Council - Project care 2002; North Shore City Council - Wai Care 2002).

Despite these efforts, owing to the socio-economic trade-offs involved in developmental activities (Buckeridge 1999) and the perceived inadequacies with conventional data analysis methods, the enforcement of even sensible measures to preserve our global ecosystem has been challenging (Thrush et al. 1995). Hence, the recent studies on interdisciplinary approaches suggest for new environmental modelling methodologies to inform sustainable environment management to improve human-environment relationship (Graedel et al. 2001). With the application of such approaches natural habitat functioning including its biota could be better understood and made to sustain people as well as their activities. Conventional methods by and large fail to establish the link between the observed environmental effects and their precise cause (natural, human induced or global) making prediction of natural systems behaviour even more complex (Thrush et al. 1995; U.S. Environmental Protection Agency National Aeronautics and Space Administration 2002).

Recent research efforts in analysing environmental data are based on interdisciplinary concepts and aimed at using the recent inventions of information technology (Shanmuganathan et al. 2003b) to study the link between a cause and its effects in natural systems. One among them is the use of artificial neural networks (ANNs) based on the animal brain and nervous system structure and functioning (including human). For instance, the application of self-organising map (SOM) methods, within the connectionist paradigms of ANNs show potential to model highly complex and diverse ecosystems, incorporating their spatial and temporal variations (Shanmuganathan et al. 2003a; Shanmuganathan et al. 2003b). They can be used to improve our understanding on diverse ecosystem interactions using large volumes of dissimilar data sets even cutting across scales and are elaborated herein.

SOMs provide an excellent tool for visualising multidimensional data sets and the discovery of correlations within the analysed variables in the form of patterns and structures. They are capable of projecting multidimensional data sets onto low dimensional displays by a topology preserving mechanism. In many other disciplines, such as industrial engineering and financial data analysis, multidimensional, disparate data sets are analysed using SOMs with remarkable success. Their use in initial financial data analysis enabled analysts to gain useful knowledge on the global economic markets and the European Union (EU) countries, even before the merger. Data from standard statistical information summarised by the World Bank and the EU's (Maastrich Treaty for 1995) was used in these studies. In this paper, SOMs are applied to cause and effects analysis using the available data and indices spanning multiple scales.

1 Global environmental issues

The major cause for the global ecosystem deterioration with commensurate biodiversity loss has been largely anthropogenic. "We also know that 15 per cent of the world's population accounts for 56 per cent of consumption and if everybody lived like they do we would need 2.6 additional planets to support us all…Our assessments of the state of the environment suggest we will need to innovate a transformation to sustainable production and consumption patterns in the space of just one generation" (Shrestha 2003). However, ecologists and policymakers continue to discuss the need for a comprehensive planetary health survey and the implementation of sustainable environment management.

"With 60% of the world's major fisheries being overfished, some 14 million hectares of forest disappearing each year, and habitats from wetlands to coral reefs under threat, credible guidance on how to manage these resources is invaluable… Projections suggest that, by 2030, emissions of ammonia and methane from the livestock sector of developing countries could be at least 60 percent higher than at present… Loss of biodiversity owing to agricultural methods continues unabated, even in countries where nature is highly valued and protected…Agriculture is an increasingly significant source of greenhouse gases, as well as a potential route to the mitigation of climate change through carbon storage in soils and vegetation…In the next three decades, climate change is not expected to depress global food availability, but it may increase the dependence of developing countries on food imports and accentuate food insecurity for vulnerable groups and countries… Globally, deforestation is slowing down. At the same time, the productivity of timber processing is improving, helping to meet the rising demand for wood. However, hotspots of deforestation are likely to persist, undermining biodiversity and the provision of other economic and environmental benefits from forests. The major challenge will be to improve the sustainable management of forests and to ensure equitable distribution of the benefits of forest use" (Bruinsma et al. 2002).

2 Need for new tools

Despite all these disturbing statements and predictions the implementation of sustainable environment management seems to be remote owing to lack of proper understanding on ecosystem functioning and biological diversity (Graedel et al. 2001). Indeed, gaining more insights into highly complex and diverse natural habitats to improve human-environment relationship is considered to be one among the major scientific challenges related to the environment. The need for better techniques and tools to model ecosystem interactions at different scales, (such as local, regional, national, international) and levels (such as, conceptual, communities) with a systems approach has never been so great (Osenberg and Schmitt 1996; Stewart-Oaten 1996b; Vant 1999; Interim Millennium Assessment Secretariat 2001; National Center for Environmental Research (NCER) Office of Research and Development attached to United States EPA 2001; Harris 2002). The importance of interdisciplinary methods involving data sets, computation and statistics to assess the state of an ecosystem and to predict its response to inform sustainable environmental management, has been reiterated since the late 1980s as seen in (Soule and Kleppel 1988; Buckeridge 1994; Hammond et al. 1995; Ravetz 2000; Gustavsson 2001; Harris 2002). These old and the very new studies have thrashed out interdisciplinary research ideas and concepts for scientists, policymakers and the society to make informed decisions on designing ecosystems for human use that support natural system functioning and biodiversity. However, this has not been practical; main reason being lack of quantitative methods for convincing all the professionals involved. Conventional data analysis methods do not facilitate interdisciplinary research on ecosystems and is the attitude of different professionals, who mistrust each other, showing less enthusiasm for initiating such efforts. In consideration of this fact, a number environmentally concerned research and international institutions, such as the MEA (Bierbaum et al. 2001), NCER (National Center for Environmental Research Office of Research and Development (ORD) - US Environmental Protection Agency (EPA) 2000), have initiated programmes to address the issues that are critical to continued wellbeing of humanity on this Earth.

(Graedel et al. 2001) selected topics of greatest potential for immediate investment, in response to a request from the National Science Foundation (NSF) and the National Research Council (NRC). One of them was "…to improve understanding of the factors affecting biological diversity and ecosystem structure and functioning, including the role of human activity. Important research areas include improving tools for rapid assessment of diversity at all scales; producing a quantitative, process based theory of biological diversity at the largest possible variety of spatial and temporal scales, elucidation of the relationship between diversity and ecosystem functioning; and developing and testing techniques for modifying, creating and managing habitat that can sustain biological diversity, as well as people and their activities." (Graedel et al. 2001:3).

3 Conventional data analysis methods

"We know enough about the distribution of species and ecosystems to ensure that the world's biodiversity is managed effectively….Give nature half a chance, and it will take care of itself" (Kirby 2002). However, this has not been possible as the currently used, highly complex ecological data analysis methods are seen to be incapable of detecting an environmental impact with information needed for ecosystem management purposes (Stewart-Oaten 1996a). These methods based on Before-After-Control-Impact (BACI) design with conventional univariate and multivariate analyses produce inconclusive or misleading results despite the rigor and complexity involved in them. They are not useful in analysing the relationships between environmental parameters and biological variables as they produce complex matrix of different functions, such as diversity indices, that are difficult to analyse the structure and population dynamics of an ecosystem (Giraudel and Lek 2001).

5 Digital data

Technological advances of the late last century enabled ecologists to capture and store data on digital formats easier than the pre-digital era, which in turn led to innovations in analysing the data. The digital data explosion that began in the middle of the last century kept on adding more to the mountains of data left untapped. This and the perceived inadequacies with conventional data analysis methods led ecologists to experiment with the latest intelligent information processing methodologies for ecological data mining; now referred to as ecological informatics. Of these methodologies, the use of artificial neural networks (ANNs) based on the brain's cognitive and functioning-elucidation models has been significant in unravelling often, cryptic ecosystems.

5 Artificial neural networks

ANNs are biologically inspired approaches to intelligent information processing methodologies. They provide a means to introduce innovations and flexibility into conventional computing to solve real world problems (Amari 1995). Complex problems of modern day (Kasabov 1999; Kasabov 2000) and human expectations from computers (Aleksander 2000) continue to demand innovations in this rapidly changing field.

The ANN computational methods have a fundamental difference to the traditional 'conventional computing methods' that basically consist of sequential programming. Conventional computing methods are successfully applied to solving highly laborious, repetitive tasks such as, complex mathematical calculations or 'rote things', without making any mistakes similar to that are characteristic of humans, due to fatigue. However, conventional computers cannot solve what are simple problems for humans, such as remembering patterns, relating and using them for future processing, especially for recognising images and figures that can be handled effortlessly even in low order animal brains (Anderson and McNeill 1992).

One of the many breakthroughs achieved in neurology is to understand how patterns of information are stored in biological nerve cells. Based on such understandings innovative ANN computational methodologies are developed for storing information in the neuronal structure and networks that can be trained through parallel processing. During the training process depending on the neuron type, network architecture and the training algorithm used, the necessary information is transferred into the network in the form of weights and connections, which are later used to solve specific problems; generally found to be impossible by conventional methods. ANNs provide a means to incorporating heuristics into computational algorithmic processing, associated with them are a set of terms, such as behave, react, adapt, self-organise, learn, generalise, and forget.

6 Self-organising maps

A SOM is a two-layered feed forward neural network that uses an unsupervised training algorithm to perform non-linear, non-parametric regression. Through a process called self-organisation the network configures the output data into a display of topological representation, where similar input data are clustered near each other. At the end of the training SOM enables analysts to view novel relationships, patterns or structures in the input vectors. The topology preserving mapping nature of SOM algorithm is useful in projecting multidimensional data sets onto low dimensional displays, generally one- or two-dimensional planes (Deboeck and Kohonen 1998).

The SOM techniques are successfully applied to visualising and clustering of large volumes of complex statistical data sets, thereby solving many real world problems, such as pattern recognition, image analysis, process monitoring and control, and fault recognition (Deboeck and Kohonen 1998). In this paper, SOMs are applied to integrated analysis of environmental and socio-economic data, across scales. As SOM methods are based on an unsupervised training algorithm they could be used for data clustering without knowing the class membership of the input data (Simula et al. 1999). Traditional methods, such as simple statistical methods that are useful in summarising low-dimensional data sets (mean value, smallest and highest values), are less effective in visualising multidimensional, such as multivariate, data sets (Deboeck 1998; Deboeck and Kohonen 1998).

7 SOM in integrated data analysis

The following three case studies illustrate how SOM methods could be applied to analysing cross scale interactions using data from statistical tables:

i) New Zealand's annual gross domestic product (GDP) composition with household consumption and housing patterns from year 1988 to 2001.
ii) World Bank's rural development, GDP and biodiversity indices for year 1980 and 2000
iii) Ozone hole area and minimum ozone with greenhouse gas release from year 1979 to 2001.

7.1 SOM in national data analysis

Initially, the composition of New Zealand's annual GDP along with household consumption and housing patterns are analysed. These measures are considered as indirect indicators of environmental stress based on a pressure-state-response (PSR) framework model (Environmental Statistics Team 2002). The human pressure on the environment cannot be measured in terms of population increase, as it is non-linear to the stress imposed by humans on the environment. However, patterns within the stated indirect pressure indices are described to be reflective of this stress. Hence, population growth, structure and distribution are considered to be the important aspects of environmental stress, in the sense that every individual's needs for basic necessities of water, food, clothing shelter and energy could affect the ecosystems directly or indirectly. Similarly, consumption of resources, production of goods and services and generation of waste can be analysed from patterns within household consumption, technologies employed and educational levels. In consideration of this fact, a SOM is created with 100 nodes and all other map parameters set to default values (using a commercial software based on Kohonen's SOM algorithm) to see the patterns in these indirect pressure variables; annual GDP composition data table that consists of agriculture, forestry and logging, fishing, mining, manufacturing, electricity, gas and water supply, construction, transport and storage, other services, and unallocated GDP values. The household consumption data table consists of food and beverages, clothing and footwear, housing, household goods and services, health and medical goods and services, transport, leisure and education, hotels and restaurants, and other goods and services. The housing pattern data consists of housing type (house or flat) and occupancy details.

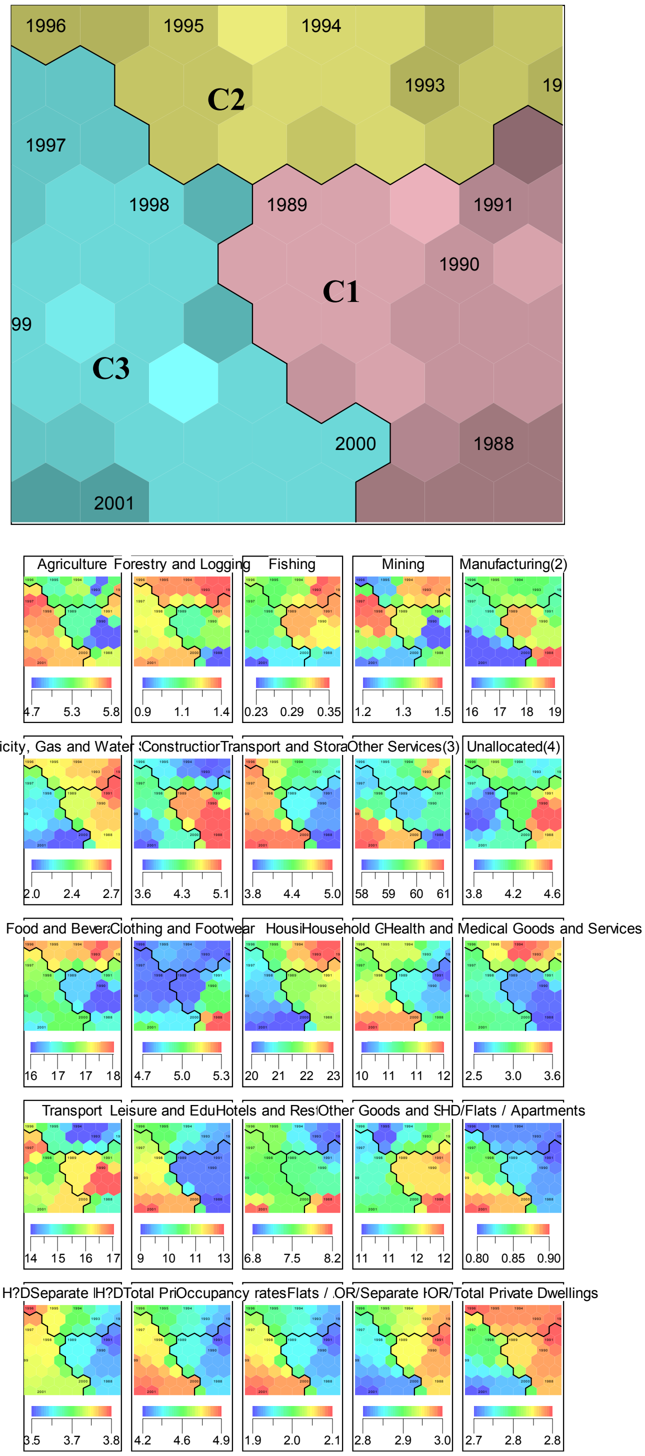


Figure 1 a & b: SOM created with New Zealand's national GDP, household consumption and housing pattern data.

Component	C 1: 1989, 1991, 1990, 1988	C 2: 1996, 1995, 1994, 1993, 1992	C 3: 1997, 1998, 1999, 2000, 2001
Agriculture	5.222771	5.259909	5.694109
Forest & Logging	1.101665	1.341325	1.259064
Fishing	0.308207	0.31355	0.266168
Mining	1.298866	1.331572	1.330472
Manufacturing	18.01848	17.28686	16.37737
Electricity, Gas & Water Su	2.570233	2.584055	2.154615
Construction	4.846069	3.776741	3.969373
Transport & Storage	3.965869	4.505566	4.912953
Other Service	58.96777	59.57524	60.1027
Unallocated	4.428326	4.146841	3.977442
Food & Beverages	16.36897	17.34357	16.75825
Cloth & Footwear	4.978258	4.754966	4.823911
Housing	21.89897	22.18611	20.0704
Household G & Services	10.78759	11.22431	11.63696
H& Medi Goods & Services	2.607985	3.393614	2.938322
Transport	16.20295	15.11398	16.27534
Leisure & Education	9.067035	10.10612	11.89916
Hotels & Residence	7.481782	7.188151	7.633473
Other Goods & Services	11.86159	11.14292	11.15649
Housing Flats /Apart	0.8	0.8	0.9
S Houses	3.5	3.8	3.7
Total P Dwell	4.2	4.6	4.9
O rates Flats/ Apart	1.9	2	2.1
S Houses	3	2.9	2.8
Total P Dwelling	2.8	2.8	2.7

Figure 1 c: SOM cluster details of NZ national GDP, household consumption and housing data.

The interpretations derived from the SOM are:

i) The three SOM clusters (of figures 1 a, b & c) consist of the following years; cluster 1 (1988-1991), cluster 2 (1992-1996) and cluster 3 (1997-2001).

ii) In figure 1 c, GDP from Agriculture, mining and other services show a steady increase over the years; unless measures to preserve habitat biodiversity are taken this is not a good trend. If left unchecked it could possibly lead to increase in the pressure on natural habitats. Manufacturing and unallocated categories show a steady decrease.

iii) In the household consumption, household goods and services, and leisure and education show a steady increase; Increase in GDP for education is described to be good as it makes the population aware of environmental issues.

iv) GDP through fishing, forestry and logging shows a steady decrease. This could be a good indication as far as natural resources use is concerned.

v) Flat/ apartment dwelling in housing patterns and occupancy has increased. This is not a good trend as far as ecosystem services and disposal of waste materials are contented.

7.2 SOMs in integrated analysis of global data

Data on rural development, urbanisation and threaten species, classified as pressure-state-response indicators of biodiversity are collectively analysed with a SOM to see the patterns in them.

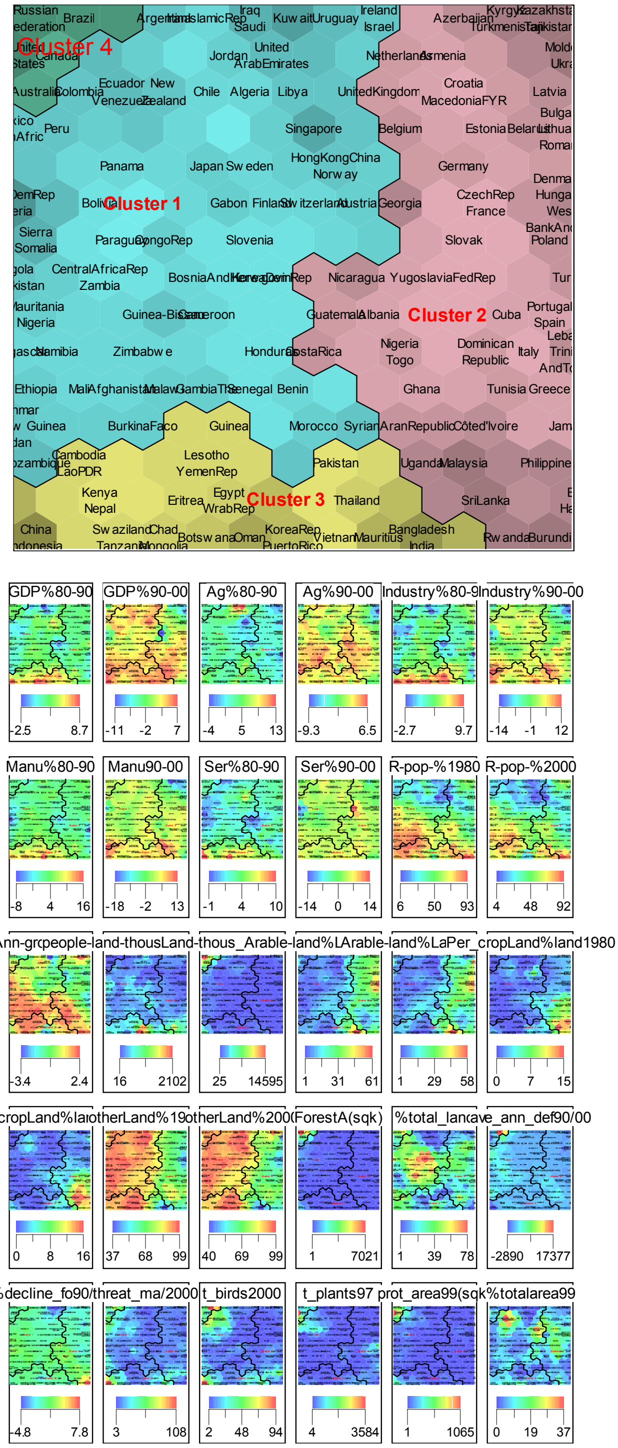


Figure 2 a: SOM of development and biodiversity data with 100 nodes and all other map parameters set to default values. b: Components of SOM

Component	C 1	C 2	C 3	C4
GDP%80-00	1.93	2.16	5.84	3.12
GDP%90-00	2.79	0.83	4.62	1.68
Ag%80-90	2.93	0.79	3.33	2.67
Ag%90-00	2.35	0.34	2.61	0.12
Industry%80-90	1.9	2.55	7.33	2.56
Industry%90-00	2.27	0.18	5.79	0.14
Manufacturing%80-90	2.17	2.3	9.56	2.29
Manufacturing90-00	2.06	-0.43	6.12	2.67
Services%80-90	2.1	2.85	6.26	3.31
Services%90-00	2.27	2.57	4.9	2.27
R-pop-%1980	53.53	48.78	75.18	27.15
R-pop-%2000	43.72	41.68	63.31	22.35
AAG'80-00%	0.809	0.206	1.167	0.215
People/land-1000sqk'99	271	268	737	51
Land 1000 sqkm'99	687	214	944	9761
%Aland/ tot l'80	6.88	28.16	15.08	9.08
%A land/tot l'99	7.39	26.47	15.24	8.74
%cropL/totl'80	0.92	4.93	1.28	0.43
%cropL/totl'00	1.02	5.41	1.75	0.43
%otherLand'80	92.1	66.9	84	90.5
%otherLand'00	91.5	68.1	83.3	90.8
ForestA(sqk)	194	40	210	3895
%total_land	31.78	23.57	23.82	37.86
aa_def90/00	1081	93	123	3471
%decl for90/00	0.228	0.483	0.236	0.075
threat_ma/2000	17.7	11.8	28.8	46.1
t_birds2000	15.4	8	25.6	51.1
t_plants97	195	175	178	1677
prot_area99(sqk)	44	13	73	674
%totalarea99	8.11	8.63	7.02	7.47

Figure 2 c: SOM cluster details of GDP, rural development and biodiversity data.

GDP, rural development data (World Bank Report 2002) and biodiversity indices are analysed in this example. The following are the interpretations derived from this map (figures 2 a & b):

i) Cluster 4 consisting of Russian Federation, Brazil, United States, Canada and Australia show medium to low GDP and average annual percentage growth of agriculture, industry, manufacturing and Services in 1980 to 1990 and 1990 to 2000 time periods. They also show medium to high numbers of threatened mammal, higher plant and bird species. It can also be seen that they have large areas of protected land, but when converted into percentage of total land area these countries have low percentages. Percentage decline in forestation is low in this cluster that is because of their high total land area.

ii) Cluster 3 countries show high GDP (for 1980-90 and 1990-2000), agriculture, manufacturing, rural population, people/1000sqk land (which is, 737 maps highest), average annual growth in rural population and percentage of decline in forest (1990-2000). The cluster also has high values of threaten species for all three categories.

iii) Within this cluster 3, China and Indonesia in one node show the highest GDP values and highest rates of threatened species of both mammals and birds in the year 2000. These two countries also have enjoyed the highest GDP for both years with high industry, manufacturing and percentage of average annual deforestation (1990/2000). This indicates that their GDP growth would have achieved at the expense of their biodiversity.

iv) Cluster 2 countries show low to medium GDP, agriculture, industry, services, rural population, forest and total land. However, they have higher (268) people/1000sqm land (1999), compared with that of cluster 1's 51.

v) Cluster 1 counties show low to average values for the attributes analysed.

7.3 SOM in integrated analysis across scales

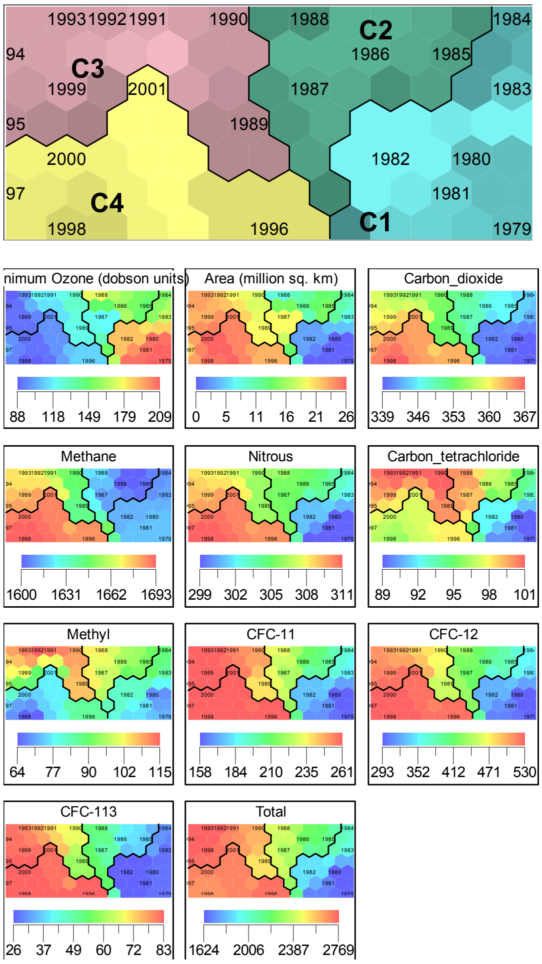
Finally, a SOM is created with annual greenhouse gas release, the cause and ozone hole area (millions sqm), minimum ozone (dobson unites), the effects to see the trends between the two within the period of 1979-2001. The example illustrates how SOM methods could be applied to data analysis across scales. The interpretations derived from the map (figures 3 a, b, c and d) are:

i) The SOM clusters classified the years in the following manner based on the ozone depletion gas release patterns: c 1 (1981-84), c 2 (1985-88), c 3 (1989-95 and 1999) and c4 (1996-98 and 2000-01). This indicates the major trends and changes in greenhouse gas release over the analysed time period.

ii) The ozone hole area or the minimum ozone is not proportionate to the total gases analysed herein. This indicates that certain gases, such as CFC 12 and 113, (which show a similar pattern to the ozone hole area and minimum ozone in figure 3 b) contribute more towards the depletion process than the others. Reduction in volumes in the release of these gases from 2000 onwards shows changes of direction in ozone hole attributes; also enforce the fact that these gases contribute more towards ozone depletion.

iii) Methane gas release shows a remarkable increase since 1985 figure 3 d.

In figure 3 e, a SOM was created with simulated values for high ozone hole area and minimum ozone layer (worse case scenario data) to see how SOMs could be used in ecological prediction models.



Figures 3 a & b: SOM and component planes of ozone hole area, minimum ozone and greenhouse gases.

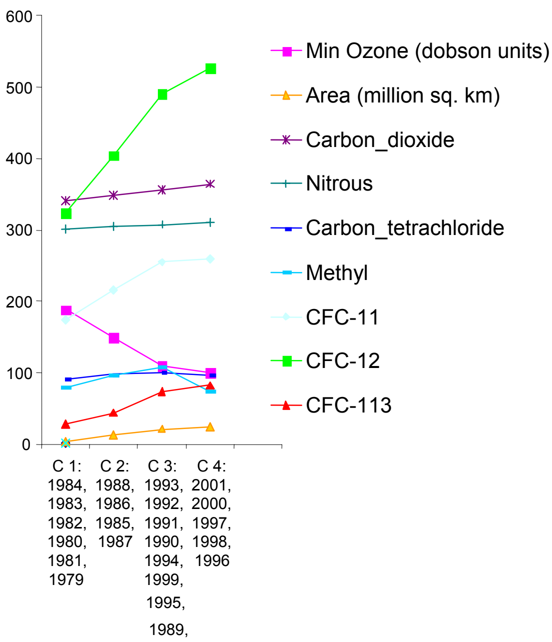


Figure 3 c: Graph showing the cluster details of greenhouse gases released 1979-2001.

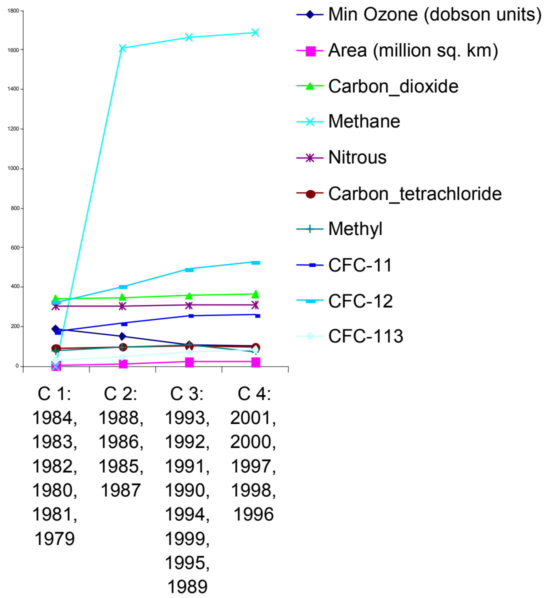


Figure 3 d: Graph showing the cluster details of greenhouse gas (including methane) released during 1979-2001.

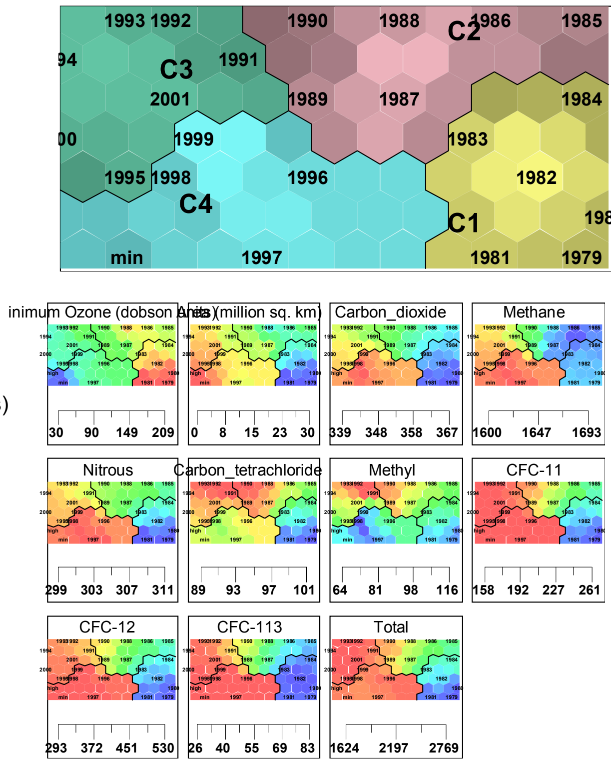


Figure 3 e: SOM created with simulated values.

The following are the interpretations arrived from the SOM (figure 3 e):

i) Cluster 4 consists of years 1996-1999 and the worse case scenario data. Years 2000-2001 in cluster 3, with year 1991-1994 data show signs of improvements in the situation.

ii) The SOM shows a reduction in CFC12 and CFC 113 (512.9, 80.88 total 2750) for 2000-

2001 than in 1996-1999 where, CFC12 and CFC113 (525.7 and 82.06 total 2689) despite the former years showing high total release. This also shows that CFC gases contribute more towards ozone depletion. The increase values in total gas in 2000-2001might have caused from increased methane.

Conclusion

Despite the hard fact that humans cause significantly excessive stress on natural habitats and the realisation of a need to improve human-environment relationship, possible implementation of sustainable environment development seems to be hampered owing to lack of ecosystem understanding and quantitative analyses for modelling the widely available ecological data with socio-economic indices. The paper illustrated how SOM methods could be applied to integrated analysis of dissimilar data sets with inconsistent labelling, to study cross scale interactions; the links between causal processes and their environmental effects, which is found to be complex and difficult with conventional data modelling methodologies and limited prior knowledge on ecosystem understanding of natural habitats.

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