Open Systems Exploration: An Example with Ecosystems Management

Masatoshi Funabashi

1 Introduction

1.1 Open Complex Systems and One-Time-Only Events

Complex systems science has been applied in various domains where theory and experiment meets with a medium of computation (e.g., [1]). Complex systems science with external observation drastically advanced laboratory measurements, and in some confined conditions succeeded to analyze the living phenomena as an augmented phenomenology, without reducing the whole process into the parts (e.g., [2]).

On the other hand, complex systems in real world cannot be fully simulated when the observation is limited from inside of the systems. When the system scale is larger than a controlled laboratory, when the sensor resolution is not sufficient to reconstruct a predictable model, and when inherent dynamics such as chaos produces principal unpredictability, we are forced to handle internal observation (e.g., [3–6]). Internal observation is not only a compromise of conventional scientific methodology but also a subjective strategy to yield an effective description of the system in dynamical functioning, where characteristic measures can only be defined on the transient configuration of many-to-many bodies systems [7].

This working hypothesis becomes especially informative when a system is open to external environment. In open complex systems (open systems in short), we cannot fully define a system's boundary as it interacts with external environment through time line. The configuration of subsystems is also fuzzy and change temporally. The systems may not be possible to model with parent-slave relation

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in closed environment. The systems are basically unpredictable in a long term by internal observers, uncontrollable depending on the fragility to external disturbance and complexity of interactions, and manifest one-time-only events that are neither fully predictable by modelling nor reproducible by the real phenomenon itself [8, 9]. Whether it be technological innovation, social order reformation, natural disasters, etc., transition of history in open systems has been always triggered by a new event of unpredictable scale [10–12].

In such open systems lie greatest challenges of complex systems science, especially those concerned with the sustainability of our civilization, that is left behind as negative legacies of the modern scientific achievement. For example, environmental problems, epidemic outbreak, life-course chronic diseases, technology-inherent breakdown of social infrastructure, climate change, and associated social-ecological transitions are predominant examples of one-time-only events that require open systems approach [13–17]. These tasks require the application of effective measure by internal observers during the operation, as it cannot be halted, analyzed, and experimented separately from the real world.

In coping with the needs of such global agenda, we need to explore novel scientific methodologies that can be applied in open complex systems. Based on the past achievement of rigorous science with external observation, we need further extend the effectiveness of internal observers' science in an open environment, where real-world problems remain untouched. In contrast to the perfection myth of science seeking the control of the system as a dominant objective, we rather need to struggle in the real-world operation where the prediction and control is not always valid. How much can we attain with incomplete observation, heterogeneous database, in unpredictable environment, with lots of new events that have never happened, but with the aid of fine mathematical theory, ubiquitous sensors, social networks of citizens, and massive computation power? What should we explore during the time-limited operation of open complex systems, in order to survive and create sustainability options in various forms?

In this article, we investigate a conceptual framework of scientific exploration in open complex systems and develop a framework of exploration interfaces taking an example in ecosystems management.

2 Open Systems and Closed Systems Approximation

Most of the natural systems can be described as open systems, and open systems science includes a proto-scientific description ranging between phenomenology and science. In a broad term, conventional science or closed systems science is an approximation of originally open systems with an artificial boundary definition that prohibits open interaction with further external environment. We need, however, to clarify what is common with conventional scientific methodology and what is new or explorable with the conception of open systems. For that purpose, we formalize the comparison between open systems and its closed systems approximation that already has specified examples in conventional science.

Table 1 Conception of open systems in contrast to closed systems approximation in dynamical systems

	Closed systems approximation	Open systems
Nature	Reproducible events	One-time-only events
Control objective	Resilient feedback to controlled state	Active transition to alternative state
Information requirement	Information quantity	Information generation
Methodology	Modelling and simulation	Exploration of management

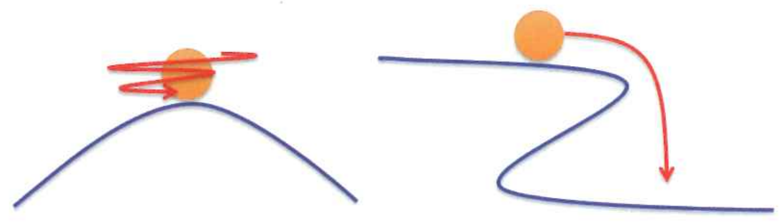

Fig. 1 Conception of open systems in contrast to closed systems approximation in dynamical systems. *Left*: Resilient feedback to controlled state in closed systems approximation. *Right:* Active transition to alternative state in open systems. *Blue lines* indicate the potential of the environment, in which systems depicted with *orange circles* are controlled and managed with *red* trajectories

2.1 Open Systems with Respect to Dynamical Systems

Dynamical systems modelling is one of the primary methods in complex systems science [18]. Table 1 and Fig. 1 compare open systems with closed systems approximation in dynamical systems perspective. Dynamical systems, when used in closed systems application, usually treat isolated systems with finite boundary conditions, in which control of reproducible events with a feedback to a desired state is the object of analysis. For such purpose, high-resolution modelling and simulation with external observation is efficient, and controlling the phenomena requires the information quantity in terms of information theory defined on a closed environment without the dynamic exchange of components with external environment.

On the other hand, open systems as it is in real world contain important dynamics in one-time-only events. Such phenomena cannot be externally controlled nor can be finely predicted from past data. Instead, we need to cope with the emerging phenomena and seek for an active transition to an alternative state with strategic adaptation that resolves the conflict. This is not a resilient feedback with a fixed definition of systems, but rather an expansion of the systems including outer environment that leads to the redefinition of the boundary with transition phenomena, in which effective information measures should be redefined. This process is associated with both the exploration and management from inside of the systems that precede modelling and simulation. The importance of exploration is not to gain the information quantity with a fixed framework of observation, but to explore an extended definition of the systems that could encapsulate necessary information for the management as a result. We call this process of extending the systems definition and evaluate the information within to cope with irreproducible events as *information generation*.

2.2 Open Systems with Respect to Machine Learning

Machine learning incorporates a wide forms of statistical modelling in complex systems [19]. Theoretically, non-linear statistical measures can classify any kind of statistical dependency within the effective dimensions of feature space [20]. However, basic frameworks of machine learning are mostly based on closed systems approximation.

Table 2 and Fig. 2 compare open systems with closed systems approximation in machine learning perspective. While standard closed systems approaches define the format of database and observation methods, open systems reality do not always guarantee the continuity both in the definition of data items and its quality. Ubiquitous sensor network and citizen observation, for example, inevitably contain biases in various scales. This situation has a common challenge with the frame problem in artificial intelligence [21]. In the open systems reality where we do not sufficiently know how to assume the effective boundary of the systems,

Table 2 Conception of open systems in contrast to closed systems approximation in machine learning

	Closed systems approximation	Open systems
Framework of database	Fixed	Dynamically change
Protocol	Single algorithm	Workflow of algorithms
	Optimization	Exploration and optimization
Implication	Evaluation	Ontogenesis

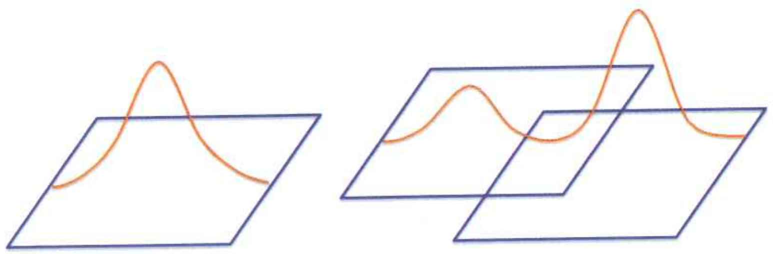

Fig. 2 Conception of open systems in contrast to closed systems approximation in machine learning. *Left:* Single algorithm optimization on a fixed database framework in closed systems approximation. *Right:* Exploration and optimization with a workflow of algorithms in open systems. *Blue rectangles* correspond to the framework of databases or observation, in which algorithmic optimizations are performed with information criteria depicted as *orange* distributions

evaluation with a single algorithm can be a blind measure with respect to the global management goal including future utility. We need to prepare a portfolio of various evaluations within available resources, with respect to a conceivable range of future scenarios, in order to set up a try-and-error workflow that can maximally avoid the operation to fail. This process is not a mere evaluation with an external algorithmic measure, but a creation of novel suitable measures for future transition, in which sense it can be represented as ontogenesis associated with *information generation*.

3 Open Systems Exploration: An Example with Ecosystems Management

Based on the above conception of open systems exploration, we develop a concrete example of the interfaces for the management of ecosystems as open systems.

3.1 Towards Dynamical Assessment of Ecosystems

Ecosystems functions and the services they provide are major sources of social-ecological sustainability [22]. Although an increasing number of literatures reveal general positive relation between biodiversity and ecosystems functions, local assessment and its utilization depend highly on local initiative and industrial inertia that devoid of appropriate scientific support [23]. We try to convert the conventional environment assessment protocol with the use of open systems science methodology in order to achieve a dynamical assessment of ecosystems.

Figure 3 and Table 3 show the comparison between typical environmental assessment and possible open systems extension. Usually, environmental assessment is performed on a basis of static, fixed scoring framework that is derived from past empirical studies [24, 25]. Current environmental studies are based on sensing parameters and index species whose score in relation to environmental quality is defined with past experience [26]. There is, however, little consideration of possible future change of base-line ecosystems, especially regime shifts in response to climate change and human perturbation in a global scale [27]: The number of index species is pre-defined and limited. Observation methods are specified that often require training by professional to assure the quality of data. By respecting the quality of reproducible observation based on the past statistics, therefore limiting the target systems in space and time, conventional assessment lacks in some aspects the accessibility to a wide public and adaptability to abrupt environmental changes where redefinition of the systems, descriptive index, and future insight should be renewed on time.

To cope with an ever-changing open systems that lies in the nature of ecosystems and associated human activities, we need to extend assessment protocols to an

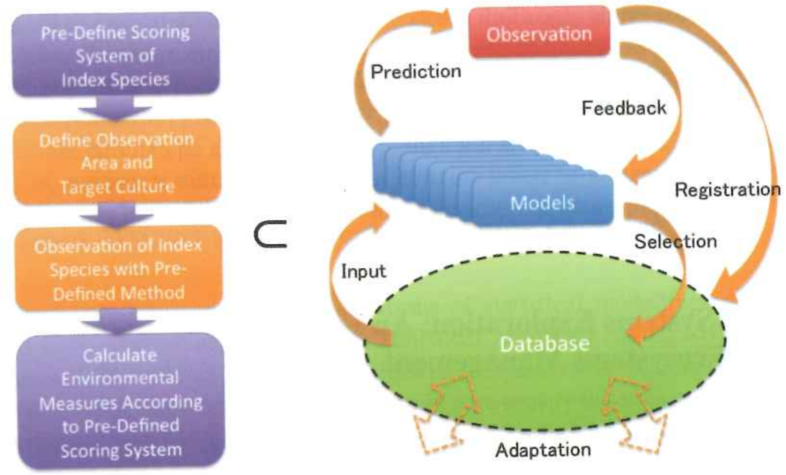

Fig. 3 Environmental assessment protocols in closed systems approximation and open systems exploration. *Left:* Typical conventional protocol with closed systems perspective (based on [24–26]). To ensure the objectivity and reproducibility of observation, *violet* processes are usually fixed based on the past assessment data. *Orange* processes need to respect pre-defined methods that usually call for training by professionals. *Right:* Dynamical assessment as a process of open systems exploration applied in ecosystems management. Hence the right protocol can include the left one by fixing the corresponding parameters

Table 3 Characteristics of environmental assessment protocols in closed systems approximation (current environmental assessment) and open systems exploration (dynamical assessment)

	Current environmental assessment	Dynamical assessment
Interface	Static, fixed scoring framework	Interactive, dynamical, on-the-fly ICT
Index	Pre-defined and limited	Can be expanded and renewed by observation
Observation method	Fixed	Can be modified, various
Accessibility	Mainly for trained professionals	Open to wide public without training
Evaluation	Based on the past experience	By renewal of the observation scheme according to the focused change

interactive and dynamical interface that can treat on-the-fly modification of the protocol itself. The acceleration of information sharing, processing, and augmentation of interactivity can further modify the way of environmental assessment, and contribute to the readiness of the management. Information communication technology (ICT) is expected to bring more dynamic and reflexive dimension in citizen science, allowing to fill the gap between crude, diverse data, and refined governance on multifunctional ecosystems [28]. Since model-based prediction from physical to biological diversity still confronts complexity of ecological response [4],

direct biodiversity measurement with human observation still plays an essential role. The distributed measurement of biodiversity with interactive ICT has a potential to shift the modality of indexing and scoring of species, from stable qualitative description to dynamic quantitative data-driven assessment in real time. This approach will expand current assessment in its observation network, data quantity, and analytic tools on an integrated design of distributed ICT. By means of the on-the-fly observation, reflexive redefinition of index species and its environmental score becomes possible. Such dynamic reconfiguration of assessment criteria would introduce more flexibility for rapidly adapting to changing situation. For that purpose, we propose an iterative framework that comprises database, models, and observation that can modify its relationship according to the actual change of situation.

Observation of multi-scale systems such as society and ecosystems is internal observation in principle. We cannot rely on empirical external measurement in terms of data efficiency and analytical predictability [4]. Rather, we need to assure a diversity of strategies to allow multiple actors to explore possible scenarios that are rich enough to mitigate unpredictable change. Open systems exploration in ecosystems management may not realize the reproducibility or predictability on what will happen, but should seek for the capacity of exploration on what could happen for a flexible planning of strategy portfolio. In short, we may fail to predict rigorously but should succeed to survive in any possible situation. This is a common principle with ICT-mediated citizen science in the roadmap of complex systems science [28].

With this respect, structural design of exploratory simulation tools should have emphasis on the diversity of the models, their parameters, and reflexive evaluation of substantive variables for dynamic adaptability. Figure 3 (right) shows conceptual framework of open systems exploration in ecosystems management: Distributed measurements including the sensing of ecosystem agents collect massive data with multiple and fluctuating criteria. A copious combination of analytical and numerical simulators produce possible predictions in the background, which are given feedback by the on-going measurement to evaluate the efficacy of each model and weight the data variable in a reflexive workflow with multiple time scale. Not only the effect of single variable but also synergetic effects between variables can be explored with a variety of model functions. The observation network should be reconfigured according to the efficiency of the actual management, in order to assure sufficient diversity of substantive variables by eliminating useless ones and investing for novel exploration. Here, the frame problem of determining sufficiently diverse and effective subset of variables is a consistent task to resolve. Cloud computing resource and parallel-processed simulators would play essential role for the on-site implementation.

For the example, data-driven assessment of biodiversity and associated environmental quality can be realized with this framework. Taking environmental variables and biodiversity as a database, a wide range of possible definitions of index species and their environmental scores can be generated from simulators, which will be selected to extract high-resolution assessment scheme as actual measurement continues. Steep change of biodiversity, environment, and observation network can be immediately reflected to the assessment protocol by producing new possibilities of scoring system with new inputs. We develop basic interfaces and models of such protocol in the next chapters.

3.2 *Example of Data Interface: Multi-partite Graph Exploration*

We develop prototypical interfaces for open systems exploration applied in ecosystems management. As a testbed we use an ecological database developed in Synecoculture project [29]. The database comprises biodiversity observation in various Synecoculture farms and surrounding environment in Japan. To assess these environments in open systems perspective, one needs to diversify the observation until it can attain the saturation of the biodiversity measures related to the management principles.

For this purpose, extensive link of data and related information is useful as an initial hands-on interface. Figure 4 shows a multi-partite graph visualization of biodiversity records. The observation of plants and insects species are linked according to the geographical cooccurrence with taxonomical relationships and observation places. The users can explore on this graph to seek concurrent and/or allied species, that could extend their observation activity and learn related ecological information. This model can support extensive search for data registration within the framework of cumulative past experience. It represents a simplest model for prediction in which all past cooccurrences are superimposed.

Management requires wider choice in response to a change. Ecosystems dynamics under human perturbation is especially irregular and difficult to harness [30]. By combining further information source such as climate data and ecological literature, multi-partite links can provide wider choice triggered by actual observation when a new data is recorded and connected in the web of multi-partite relations. The real-time development of complex network of observation with automated link to relevant information is a primary interface that complex systems science can offer to open systems exploration. The evolution of complex network autonomously combines observation and related knowledge, and extends the framework of possible observation to provide collective suggestion between users.

3.3 *Example of Suggestion Tool: Integration of Environmental and Biodiversity Data with Symbolic Dynamics Analysis*

Integration of biodiversity and sensor data is a fundamental task in data-driven environmental management. While current studies try to integrate biodiversity

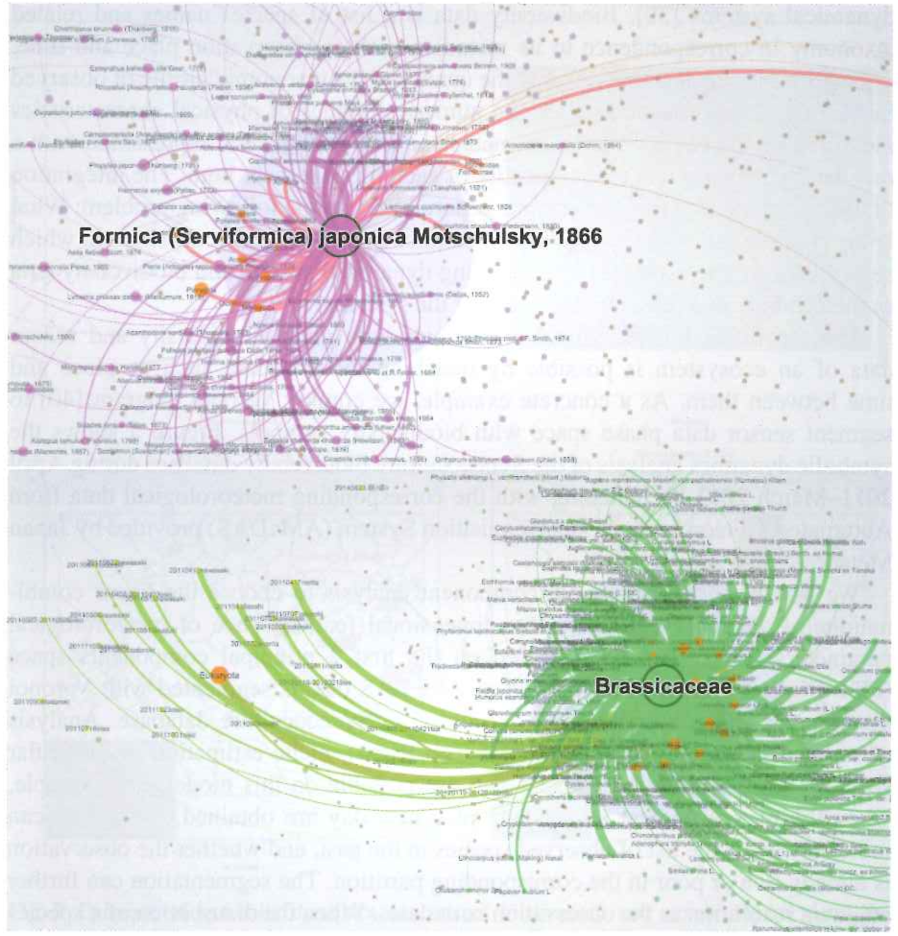

Fig. 4 Snapshots of multi-partite graph between plants (*green*), insects (*magenta*), biological taxonomy (*orange*), and observation place (*yellow*). The links represent the total cooccurrence in the database (Synecoculture CMS [29])

records with remote sensing databases [31, 32], little has been investigated on a local scale under direct effect of management. For example, in agricultural land, sensor-based measurement and control of precision agriculture [33] is not connected with local biodiversity observation. Natural farming practices based on local biodiversity, on the other hand, rely merely on human observation and have little introduced sensor technology [34, 35]. In actual management of farmland with both yield and biodiversity promotion, one needs to consider the integrated aspects of biodiversity and environmental conditions [36–38].

We propose a general framework to integrate biodiversity data based on human observation and sensor data in general with the use of symbolic dynamics in dynamical systems [39]. Biodiversity data is a list of species names and related taxonomy in correspondence to its metadata such as observation place and time. This is a symbolic data that refers to the quality of the taxonomic profile of observed biota. In contrast, sensor data are the numerical values of physical characteristics measured on the environment with metadata. This is in general represented with a real data type that refers to the quantity of each measurement item. The integration of biodiversity and sensor data can be generalized into the following problem: What is the characteristics of the symbolic dynamics of a measured ecosystem, in which sensor data are the estimates of underlying dynamical system and biodiversity data as the symbols that represent the states of the systems?

The reconstruction of symbolic dynamics with given biodiversity and sensor data of an ecosystem is possible by matching the metadata such as place and time between them. As a concrete example, we employ Voronoi diagram [40] to segment sensor data phase space with biodiversity symbols. Figure 5 shows the symbolic dynamics analysis of the Synecoculture biodiversity database during April 2011–March 2013 by matching with the corresponding meteorological data from Automated Meteorological Data Acquisition System (AMeDAS) provided by Japan Meteorological Agency [41].

We first performed principal component analysis to choose the linear combinations of the most distinctive two-dimensional feature space of meteorological parameters (Fig. 5 Top Left). Based on the first 2 principal components space (PC1–PC2), 30 previous days mean of AMeDAS data is segmented with Voronoi diagram for each observation date recorded in Synecoculture database. Analysis of observable species diversity (Fig. 5 Top Right), niche estimation of particular species (Fig. 5 Bottom Left and Right) are possible on this model. For example, when the meteorological sensor data of a new day are obtained, the model can indicate what is the list of observed species in the past, and whether the observation is already rich or poor in the corresponding partition. The segmentation can further augment resolution as the observation cumulates. When the distribution of a species is confined in a subspace of the Voronoi diagram, it is possible to estimate its niche boundary by an interpolation. Significant correlation between estimated niches (e.g., order-wise correlation [42]) can provide suggestions that there might be underlying ecological dependence between those species.

Theoretically, infinite sequence of finite biodiversity symbols can specify any arbitrary trajectory of meteorological data with real-value precision, if the system is deterministic and the partition is "generating" in terms of symbolic dynamics [43]. To enrich the suggestion based on the spatio-temporal structure, this model is further accessible to mathematical analysis of symbolic dynamics that can treat complex trajectories in dynamical systems including chaos.

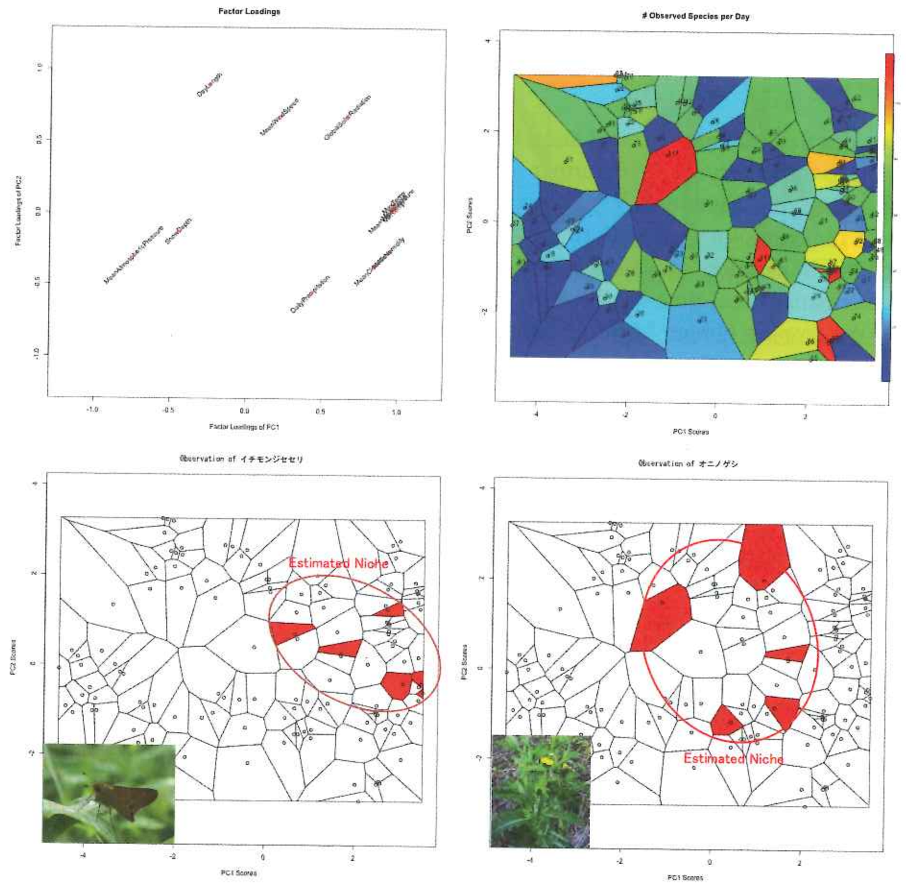

Fig. 5 Example of symbolic dynamics analysis of biodiversity and meteorological data. *Top Left*: Factor loading of principal components analysis (PC1 and PC2) of 11 daily meteorological parameters (mean/maximum/minimum temperature, daily precipitation, day length, global solar radiation, mean wind speed, mean vapour pressure, mean atmospheric pressure, mean humidity, mean cloud cover, and snow depth) in AMeDAS data. *Top Right*: Voronoi segmentation of AMeDAS data PC1–PC2 space with Synecoculture biodiversity database for each 30 days mean. The *color* represents the number of species observed in the same partition. *Bottom Left*: Example of niche estimation of *Parnara guttata guttata (Bremer et Grey, 1852)* (*in picture*) on the symbolic dynamics analysis. *Bottom Right*: Example of niche estimation of *Sonchus asper (L.) Hill* (*in picture*) on the symbolic dynamics analysis. Partitions where the species appeared are filled with *red*

3.4 *Example of Model Selection: Seasonal Segmentation and Prediction of Biodiversity Observation*

Besides the data interface and integration model that can provide interactive suggestions to the observation, we further consider how to select a better predictive model in a changing situation. We take an example of biodiversity prediction combined with meteorological data in time development. This is again a prototypical model for the integration of sensor and biodiversity data, but with consideration to the refinement of real-time feedback on observation based on the model selection.

We employ hidden Markov model (HMM) as a primitive example of seasonal segmentation of meteorological data [44]. We applied the standard forward–backward algorithm for the inference of hidden states from the past AMeDAS data, and the Viterbi algorithm to inversely infer hidden states with new data for each observation. Figure 6 Top shows an example of seasonal segmentation of AMeDAS data. Hidden states with the highest probability was chosen to associate the observed species in Synecoculture database in the same day. The species diversity associated with each hidden state is expressed as a discrete distribution on a set of observed species name, with cumulative occurrence probability. Each time new species is observed, the model acquires additional list of species for the corresponding hidden state. The discrete probability distribution of species occurrence associated with each hidden state can be used as a prediction model, when a new observation is estimated to be in the same hidden state.

Based on the estimated models with the hidden states number ranging from 2 to 10, we performed a numerical experiment to evaluate the prediction capacity of each HMM with respect to each 30 observations mean (Fig. 6 Middle). Each model was evaluated with the standard likelihood function of discrete probability distribution with respect to the observed species. The results show a dynamical trend in the number of hidden states that gives the best prediction model. For example, in Fig. 6 Bottom, the initial phase during April 2011–January 2012 shows an increase of the number of hidden state for the best model, which implies an increase of model resolution for seasonal segmentation. Observation of new species also tends to saturate as it is in winter time. Between February 2012 and October 2012, as the summer time reactivates the ecosystems, new species records become more frequent which leads to the decrease of the model resolution (hidden states number of the best model). The models go through a heuristic learning process of biodiversity change with low likelihood for estimation, until it regains the resolution and relative likelihood in the next winter time around November 2012–March 2013. Since likelihood of the models monotonously decreases as the list of observed species expands, relative increase/decrease of likelihood is important to characterize the model resolution. When the relative increase of likelihood is associated with the increase of the number of hidden states in the best model, model resolution is considered to increase. During the observation, the diversity of observation is maintained sufficiently high without producing statistical bias on new species

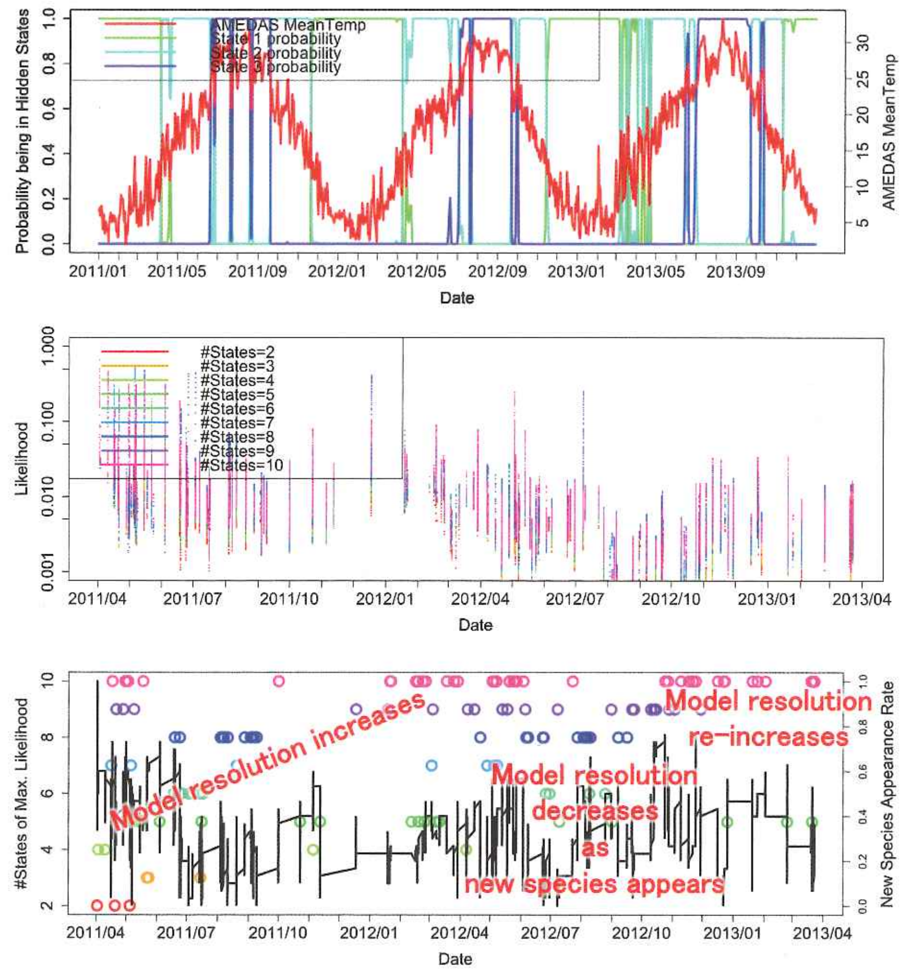

Fig. 6 Example of model selection on an integrated model of biodiversity and sensor data with hidden Markov model (HMM). *Top*: Example of seasonal segmentation of AMeDAS daily mean temperature data with 3 hidden states. Estimated probability of each state is plotted with corresponding color. *Middle*: Numerical experiment of model selection based on the likelihood of HMMs with hidden states 2 to 10, for each 30 observations mean. Likelihood of each HMM is depicted as dots with colors that corresponds to the number of hidden states. *Bottom*: Time development of new species appearance rate for each 30 observations and number of hidden states of selected HMM giving maximum likelihood for prediction. Dynamic trend of model selection and learning occur with the real-time feedback of observation

appearance rate (data not shown). Therefore, the numerical experiments imply a dynamic model selection process during the real-time learning, in which the system manages to select the best-in-time prediction model by compromising between the adaptability to new observation and reproducibility of past statistics.

4 Conclusion

4.1 *Components Evaluation of Dynamical Assessment*

We have conceptualized the methodology of open systems exploration based on open systems science, and developed prototypical interfaces with models taking an example in ecosystems management, namely dynamical assessment. Basic properties of the example systems in view of incorporation into dynamical assessment are summarized in Table 4. By generalizing these properties such as data processing mode from batch to real-time, parameter segmentation type from simple superposition to spatio-temporal segmentation, and model selection range from single to group selection, respectively, these systems can be further developed and integrated to augment a whole cycle of dynamical assessment.

The correspondences between the processes in Fig. 3 (Right) of dynamical assessment and the utilization of each example model are summarized in Table 5.

The *information generation* proposed as the essential dynamics of open systems exploration in Table 1 can further be explored in the following contexts:

Table 4 Achievement of basic system properties of three example models, multi-partite graph (MPG), symbolic dynamics model (SDM), and hidden Markov model (HMM) for the integration in dynamical assessment

Properties	MPG	SDM	HMM
Ex.1 Data processing mode	Batch	Batch	Real-time
Ex.2 Parameter segmentation type	None	Spatial	Temporal
Ex.3 Model selection range	Single	Single	Group

Table 5 Correspondence between dynamical assessment process in Fig. 3 (Right) and multi-partite graph (MPG), symbolic dynamics model (SDM), and hidden Markov model (HMM)

Process in Fig. 3 (Right)	Process in example models
Input	AMeDAS and Synecoculture database
Prediction	Links in MPG
	Suggestion from SDM
	Prediction with HMM
Feedback	Selection of effective information in MPG
	Selection of time window in SDM
	Parameters selection in HMM
Selection	Selection of AMeDAS variables in SDM and HMM
	Geographical and time window selection of Synecoculture database
Registration	Modification of actual observation
	Introduction of new observation method
	Setting of new sensors

- Multi-partite graph: Exploration of links and validation by observation
- Symbolic dynamics model: Field exploration of suggested species diversity, niche condition, and its validation
- Hidden Markov model: Exploration of wider parameter spaces, model selection with a real-time observation likelihood during operation

4.2 *Example of Assessment Result: Generative Index Species Scoring Systems*

By gradually introducing the suggestion from prototypical models, environmental assessment in Synecoculture project started to operate the initial steps of dynamical assessment. Data-driven lists of index species candidates are obtained from the field practice between August 2014 and July 2015 as in Table 6. These generative index species, when connected with other database that refers to the quality of environment such as yield, will serve as timely reconfigurable measures of environmental quality in an ever-changing open systems surrounding the practice and management.

Table 7 gives the list of observed species in Table 6. As an example of scoring system generation, the environmental score of these species is calculated from the

Table 6 Numbers of generative candidates of index species extracted from dynamical assessment in Synecoculture project

Date	Place	Suggestion	Observation	Consistent index	Past index	Novel index
2014/8/7	Todoroki (Tokyo)	16	23	12	4	11
2014/9/13	Todoroki (Tokyo)	36	35	22	14	13
2014/9/14	Oiso (Kanagawa)	33	31	23	10	8
2014/11/22	Oiso (Kanagawa)	17	16	8	9	8
2014/12/21	Oiso (Kanagawa)	21	14	3	18	11
2015/3/28	Todoroki (Tokyo)	22	21	4	18	17
2015/4/25	Todoroki (Tokyo)	22	18	6	16	12
2015/5/2	Oiso (Kanagawa)	62	26	22	40	4
2015/5/30	Todoroki (Tokyo)	16	25	5	11	20
2015/6/13–14	Ise (Mie)	96	64	23	73	41
2015/6/27	Todoroki (Tokyo)	37	21	9	28	12
2015/7/19	Todoroki (Tokyo)	37	24	11	26	13
2015/7/25	Oiso (Kanagawa)	36	21	14	22	7
2014/8–2015/7	Total	229	147	80	190	99

The numbers indicate the number of species that were suggested from the prototypical models, observed on field, and classified as consistent/past/novel index species according to the inclusion and exclusion relationships between suggestion and observation: Consistent index species commonly appeared in both suggestion and observation, while past and novel index species only appeared in either suggestion or observation, respectively

Table 7 List of observed species and its environmental score based on the edible species diversity during the observations between August 2014 and July 2015

Academic name	Score	Category
Morella rubra Lour.	37	C
Ficus carica L.	37	C
Zanthoxylum ailanthoides Siebold et Zucc.	37	C
Megacopta punctatissima (Montandon, 1894)	37	C
Popillia japonica Newman, 1844	37	C
Graphosoma rubrolineatum (Westwood, 1873)	37	C
Mimela splendens (Gyllenhaal, 1817)	37	C
Microcerasus tomentosa (Thunb.) G.V.Eremin et Yushev	37	C
Ipomoea batatas (L.) Poir.	37	C
Ficus erecta Thunb. var. erecta	37	C
Lycaena phlaeas daimio (Matsumura, 1919)	37	C
Orthetrum albistylum speciosum (Uhler, 1858)	37	N
Rubus fruticosus	37	N
Ziziphus jujuba Mill. var. inermis (Bunge) Rehder	37	N
Cyanococcus	37	N
Hyla japonica	37	N
Papilio protenor	37	N
Locusta migratoria Linnaeus, 1758	37	N
Uroleucon nigrotuberculatum	37	N
Aronia melanocarpa	37	N
Eumeta japonica Heylaerts, 1884	37	N
Actinidia polygama (Siebold et Zucc.) Planch. ex Maxim.	37	N
Hydrangea serrata (Thunb.) Ser. var. thunbergii (Siebold) H.Ohba	37	N
Camellia sinensis (L.) Kuntze	37	N
Citrus limon (L.) Osbeck	37	N
Oleandraceae	37	N
Eurema hecabe (Linnaeus, 1758)	37	N
Allium chinense G. Don (variant Shimarakkyo)	37	N
Elaeagnaceae	37	N
Prunus avium	37	N
Fragaria x ananassa Duchesne ex Rozier	37	N
Epilachna vigintioctomaculata Motschulsky, 1857	37	N
Diptera Linnaeus, 1758	37	N
Metaplexis japonica (Thunb.) Makino	37	N
Neoscona adianta (Walckenaer, 1802)	37	N
Vitis spp	30.66666667	N
Paederia scandens (Lour.) Merr.	29.5	C/N
Aralia cordata	27.5	N
Acca sellowiana (O.Berg) Burret	27.5	C/N
Trifolium repens L.	26.5	N
Rosa multiflora Thunb.	24.5	C/N

(continued)

Table 7 (continued)

Academic name	Score	Category
Vitis ficifolia Bunge	23.66666667	C/N
Lycopersicon esculentum Mill.	23.33333333	C/N
Acrida cinerea (Thunberg, 1815)	23.33333333	C/N
Solidago altissima L.	23	C
Morus	22.66666667	N
Perilla frutescens (L.) Britton var. crispa (Thunb.) H.Deane	22	N
Smilax china L.	22	C
Ginkgo biloba L.	22	C
Rubus hirsutus Thunb.	22	N
Angelica keiskei (Miq.) Koidz.	22	C
Polistes rothneyi iwatai van der Vecht, 1968	22	N
Gonista bicolor (de Haan, 1842)	22	C
Ampelopsis glandulosa (Wall.) Momiy. var. heterophylla (Thunb.) Momiy.	22	C
Scolia (Scolia) histrionica japonica Smith, 1873	22	C
Lycoris radiata (L'Hér.) Herb.	22	N
Momordica charantia var. pavel	22	N
Artemisia indica Willd. var. maximowiczii (Nakai) H.Hara	22	C/N
Diaea subdola	21.66666667	N
Houttuynia cordata Thunb.	21.4	C/N
Asteraceae	19.83333333	C/N
Colocasia esculenta (L.) Schott	19.8	C/N
Commelina communis L.	19.5	C
Formica (Serviformica) japonica Motschulsky, 1866	19.5	C/N
Dioscorea japonica Thunb.	19.25	C/N
Allium fistulosum L.	18.5	C/N
Allium tuberosum Rottler ex Spreng.	18.42857143	N
Coccinella septempunctata Linnaeus, 1758	18.25	C/N
Pieris (Artogeia) rapae crucivora Boisduval, 1836	18	C/N
Daucus carota L. subsp. sativus (Hoffm.) Arcang.	18	C/N
Eurydema rugosa Motschulsky, 1861	17.66666667	C/N
Brassicaceae	17.54545455	C/N
Cucumis sativus L.	17.5	C/N
Poaceae	17.5	C/N
Equisetum arvense L.	17.4	C/N
Ericaceae	17	C
Parnara guttata guttata (Bremer et Grey, 1852)	17	C
Nonarthra cyanea Baly, 1874	17	C
Portulaca oleracea L.	17	C
Eurydema dominulus (Scopoli, 1763)	17	C
Arctium lappa L.	17	N

(continued)

Table 7 (continued)

Academic name	Score	Category
Menochilus sexmaculatus (Fabricius, 1781)	17	N
Solanum tuberosum L.	17	C/N
Eriobotrya japonica (Thunb.) Lindl.	17	C
Amygdalus persica L.	17	C
Cichorium intybus	17	N
Eucalyptus globula Labill.	17	N
Formicidae	16.8	C/N
Brassica oleracea L. var. capitata L.	16.6	C/N
Glycine max (L.) Merr. subsp. max	16.5	C
Rubus trifidus Thunb.	16.25	C/N
Aedes (Stegomyia) albopictus (Skuse, 1894)	16	C/N
Apis mellifera Linnaeus, 1758	16	C/N
Capsicum annuum "grossum"	16	N
Nerium oleander L. var. indicum (Mill.) O.Deg. et Greenwell	16	C
Armeniaca mume (Siebold et Zucc.) de Vriese	16	N
Promachus yesonicus Bigot, 1887	16	C
Setaria viridis (L.) P.Beauv.	16	N
Cynara scolymus L.	15.66666667	N
Papilio machaon hippocrates C. et R.Felder, 1864	15.66666667	C/N
Dolycoris baccalum (Linnaeus, 1758)	15.66666667	C
A. officinalis	15.6	N
Atractomorpha lata (Motschulsky, 1866)	15.5	C
Aphididae	15.5	C/N
Polistes jadwigae jadwigae Dalla Torre, 1904	15.5	C
Mentha suaveolens	15.5	N
Cornus controversa Hemsl. ex Prain	15.5	N
Akebia quinata (Houtt.) Decne.	15.5	N
Solanum nigrum L.	15.33333333	C
Rutaceae	15.33333333	C
Mentha canadensis L. var. piperascens (Malinv. ex Holmes) H.Hara	15.2	N
Helianthus annuus L.	15	C
Capsicum annuum L.	15	N
Nephotettix cincticeps (Uhler, 1896)	15	N
Lavandula officinalis Chaix.	15	N
Colias erate poliographus Motschulsky, 1860	15	N
Melissa officinalis	15	N
M. pumila	14.75	N
Nysius plebejus Distant, 1883	14.66666667	C
Brassica oleracea L. var. italica Plenck	14.66666667	C/N
Solanum melongena L.	14.66666667	N

(continued)

Table 7 (continued)

Academic name	Score	Category
Petroselinum neapolitanum	15	N
Rosmarinus officinalis	14.66666667	N
Pisum sativum L.	14.6	C/N
Zingiber mioga (Thunb.) Roscoe	14.5	C
Raphanus sativus L.	14	C
Aphis craccivora craccivora Koch, 1854	14	C
Vicia faba L.	14	C
Dolerus similis japonicus Kirby, 1882	14	C
Coccinellidae	14	C
Fabaceae	14	C
Canna	14	N
Phytomyza horticola (Goureau, 1851)	13.66666667	C
Eruca vesicaria	13.5	N
Aulacophora femoralis (Motschulsky, 1857)	13	C
Nephila clavata	13	N
Gryllidae	13	C
Xanthophthalmum coronarium (L.) P.D.Sell	13	C
Diospyros kaki Thunb.	13	C/N
Brassica rapa L. var. perviridis L.H.Bailey	13	C
Illeis koebelei koebelei Timberlake, 1943	13	N
Veronica persica Poir.	12	N
Takydromus tachydromoides (Schlegel, 1838)	12	N
Armadillidium vulgare	10	N
Cycas revoluta Thunb.	10	N
Camellia japonica	10	N
Citrus japonica Thunb.	10	N

The category refers to *C* consistent index, *N* novel index, and *C/N* consistent or novel index depending on the observation place in Table 6

number of edible species observed in the same date and place as an indicator of the productivity. The environmental score of each species was calculated as follows:

1. Calculate the observation-wise environmental score of each species as the number of edible species for each observation.
2. Take mean value of all observation to obtain the overall environmental score of each species.

These environmental scores will evolve as the observation continues and can serve as a data-driven predictor of edible species diversity. Although the scores are not yet fine-grained due to the limit of observation numbers, future observations can be evaluated using the generated scoring systems of index species, further refine the scores and expand the list. The conditions such as time scale of the database that generates a better scoring system can then be selected to optimize the predictability at that moment. The scoring systems can also enrich exploration process since species with similar scores are susceptible of efficient exploration to entail more comprehensive observation. When sufficient diversity of observation is assured in the loop of dynamical assessment, the scoring systems are expected to yield an effective measure with available means, timely reflecting ever-changing conditions of open systems. *Information generation*, a crucial requirement for open systems exploration, can therefore be evaluated by the dynamical reconfiguration of the generative index species scoring system in response to environmental change.

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