Information-based Network Environ Analysis: A system perspective for ecological risk assessment

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Abstract

Ecological risk assessment, aiming at evaluating a wide range of undesirable consequences initiated by a possible eco-environmental hazard, has been the center of concern for ecosystem management in recent years. However, when it comes to disturbed natural ecosystems, most models developed for ecological risk assessment are restricted to instant cause–effect computation of single factors and often ignore the indirect effects, therefore fail to implement a holistic assessment at an ecosystem scale when interactions of different risk receptors are obvious. In this study, we developed a risk-based network model based on a new control analysis termed control allocation and a conceptual conversion of flow currency in NEA. By taking a river ecosystem intercepted by dam construction as an example, risk propagation between all functional guilds of the ecosystem concerning both direct risk and integral risk dynamic were quantified and illustrated in the network model. The results of this new risk assessment showed that there were significant differences between network integral risk and input risk, and although the phytoplankton received the instantaneous impact of chromium pollution among all the functional guilds, it was the piscivorous fish which obtain the greatest overall risk threat. On the basis of the model results, we proposed the network-based indicators for assessing the system-wide risk condition and component-specific risk scenarios of disturbed ecosystems exposed to single or multiple stressors. This study could provide a novel perspective and methodology for assessing ecological risk at the system scale, and concurrently, serve as an elicitation of how we can effectively evaluate ecosystems on the same analytic basis of information-based networks.

1. Introduction

Risk science is the science of loss. It was developed to calculate the value of possible costs or damages in the face of knowable profitable outcome (Kaplan and Garrick, 1981). The conception of probabilistic risk analysis is so deeply embedded into various disciplines that it plays a crucial role in almost all safety evaluations and managements of human society involving economics (Kahneman and Tversky, 1979), politics (Slovic, 1999), engineering (Kumamoto and Henley, 1996), environmental health (Hallenbeck, 1986), etc. But the application of risk assessment for ecological theory is, comparatively, quite a recent interest. By definition ecological risk assessment (ERA) is focused on the rational appraisal of the possible damages or potential diverse effects by computing the risk values associated with possible eco-environmental hazards under uncertainty (USEPA, 1992; Freedman, 1998; Suter II, 2007). The goal of ERA is to provide information about the statistical distribution of possible ecological effects arising from exposure to one or more stressors (USEPA, 1998; Findlay and Zheng, 1999). In order to achieve this goal, three elements complete the basic profile of ERA: (1) the scenario, (2) the likelihood and (3) the consequence, or rather—what can happen; how likely things are to happen; and what are the end points from sets of occurrences (i.e., “sets of triplets” in Helton, 1993). Clear as it seems, the random and non-linear characteristics inherent in ecosystems often make it difficult to predict the precise ecological fate, furthermore, multi-process scenarios (multi-source, multi-factor and multi-receptor scenarios) are what environmental managers inevitably encounter when performing a risk analysis, all of which urge them to resort to powerful models, preferably mechanistic ones. So far, mathematical models employed for ERA includes holographic neural networks (Findlay and Zheng, 1999), Bayesian networks (Lee and Lee, 2006; Pollino et al., 2007), comprehensive aquatic systems models (DeAngelis et al., 1989; Bartell et al., 1999), and environmental contaminant dispersion models (Chen et al., 2010), etc. Helpful and instructive
as they are for guiding risk-based decision making, most of them are either restricted to the evaluation of species biology and population on the microcosm scale under circumstances of single stressors, or developed on the profile capable of limited risk receptors, therefore they have relatively poor capacity for fitting into iterative and adaptive management (Yeardley and Roger, 2000). Furthermore, the instant cause–effect type of computation might neglect the information of the indirect effect carried by the interactive components within communities or ecosystems.

Alternatively, Network Environ Analysis (NEA), an important branch of network analysis first developed by Patten (1978a,b, 1982), is a system-oriented modelling technique for examining the structure and flow of materials in ecosystems (see also the pioneer works by Leontief (1951, 1966) and Hannon (1973)). NEA places great emphasis on the interactions between components rather than the characteristics of individuals, and the dynamic attributes within the system are identified and quantified via network structural and functional analytic methods (e.g., storage analysis, throughflow analysis, utility analysis, control analysis, etc.) (Fath, 1998, 2004a,b; Fath and Patten, 1998, 1999; Fath and Borrett, 2006; Kazanci, 2007; Schramski et al., 2006, 2011; Ulanowicz, 2004). Fundamentally, the underlying strength of these concepts and methods is the incorporation of direct and indirect effects which construct the whole regime of the interacted network, and that system wholeness is arguably more critical in determining the system’s behaviour than the direct effects alone, or further, the holistic picture of the concerned system can only be delineated when interactions of all lengths are clarified.

In view of these important insights, one of the most promising applications of NEA is identified as a methodology platform for modelling the integrated eco-environmental impact of natural systems under human interference (Fath, 2004a). The implication is that NEA is conceivably promising for indexing the holistic ecological risk of perturbed ecosystems. In fact, ecological network analysis (a more general version of NEA) has been proved useful as a complementary tool for assessing disturbed ecosystems in the context of system-based management. The most recent cases concerned the determination of possible ecosystem impacts of fishing on estuarine ecosystem (Manickchand-Heileman et al., 2004), the evaluation of environmental stress due to soil contamination on terrestrial ecosystem (Tobor–Kaplon et al., 2007) and the functional assessment of an estuary ecosystem exposed to eutrophication (Christian et al., 2009). Unfortunately, the fact that the model operation may encounter flow incompatibility in a material- or energy-oriented NEA remains impeditive when evaluating the adverse impact or managing the transitive risk on a system scale. In other words, energy and material, the conventionally used mediates for network synthesis, are not essentially adaptable for a system-wide ERA. A fundamental conversion of the flow currency for NEA is needed.

Herein, we presented a novel approach for holistic ecological risk assessment based on NEA. The information-based network analysis was developed to address ecological risk in which both direct and indirect effects were together considered and various risk factors and receptors were technically compatible in the same model. The reminder of this paper was arranged as follows: The general framework of the model was described in Section 2. In Section 3, the development of risk-based flow was formulated. Following that in Section 4 we illustrated the operation of risk network through a case study of a river ecosystem intercepted by dam construction. Then in Section 5, we discussed the application of information-based NEA for ecosystem management, and finally, a range of conclusions were presented in Section 6.

2. General description of the model

The information-based network model developed has three main aims:

• To assess the potential impacts of various risk factors (or stressors) via direct and indirect paths after human disturbance.
• To illustrate the effectiveness of adding NEA methodology to the existing ecosystem risk assessment.
• To provide a comprehensive tool for regulatory ecosystem management based on the network indicators elicited.

In order to achieve these ends, a comprehensive framework for picturing the holistic ERA based on information-based network analysis was constructed (Fig. 1). Numbers of stressors (signified as $S_{r1}, S_{r2}, S_{r3}, \ldots, S_{rm}$) impact the biotic system (the aggregation of all living organisms) after a specific event we call risk trigger takes place. The food web of the disturbed ecosystem is explicitly examined through field investigation, whereby all the compartments are identified and all the energy or material flows are traced and quantified in an ecological network. Based on this, the control allocation of the established network is derived, and ecological risks are distributed among different components within the ecosystem after the evaluation of different stressors. Thereafter, with the consideration of the stressor’s sensitivities to different components, the risk operating scenario from risk generation to risk distribution is achieved. Additionally, the energy/material throughflow, control flow and integral risk flow produced along the process are displayed in matrix form. Hereeto, the holistic picture of the perturbed ecosystem showing both the system-wide risk condition and the component-scale microdynamic is derived. Ultimately, with the introduction of threshold theory, the holistic ecological risk (ER) of the disturbed ecosystems is applied for ecosystem management.

3. Formulation of risk-based flow

3.1. Network control allocation

Modern perspectives have shown that there are no absolute controllers in an ecosystem or other interconnected systems (DeAngelis and Post, 1991; Fath, 2004b; Patten, 2006; Schramski et al., 2006). Instead, each element contributes to the complexity of system organization through its interactions with the other elements. In this sense, control is distributed among the system elements, characterized by the combination of these input and output environs.

As to the methodology layer, distributed control analysis was promoted by Patten (1978b) as a Network Environ Analysis based measure of control or dominance one component over another. In Patten’s control analysis (which was then improved by Patten and Auble (1981) and Fath (2004b)), network control is characterized by the ratio of pair-wise integral flows through network flow and storage analysis, representing the control each component exerts in the overall system configuration. An approach recently developed by Schramski et al. (2006, 2007) employed metrics termed control difference and control ratio to implicate the absolute open-loop control relationships between components. Based on these two measures, a modified version of distributed control index between compartments termed as control allocation (CA) was further developed in this study to formulate the control strength between components via which domination-related information is allocated and dispersed (see Eqs. (1)–(3)).

$$N = (n_{ij}) = G^0 + G^1 + G^2 + \cdots + G^m + \cdots = (1 - G)^{-1}$$  \hspace{1cm} (1)

$$N' = (n'_{ij}) = (G')^1 + (G')^2 + (G')^3 + \cdots + (G')^m + \cdots = (1 - G')^{-1}$$  \hspace{1cm} (2)
CA = (ca_{ij}) = \begin{cases} \frac{n_{ij} - n'_{ij}}{\sum_{i=1}^{m}(n_{ij} - n'_{ij})} & \text{when } n_{ij} - n'_{ij} > 0, \\ 0 & \text{when } n_{ij} - n'_{ij} \leq 0, \end{cases}

(3)

where \( G = [g_{ij}] \), \( g_{ij} = f_{ij}/T_{j} \); \( G' = [g'_{ij}] \), \( g'_{ij} = f_{ij}/T_{i} \). \( f_{ij} \) denotes energy or material flow from \( j \) to \( i \). \( T_{j} \) is the sum of flows into or out of the \( j \)th compartment, \( T_{i} \) is the sum of flows into or out of the \( i \)th compartment, and \( ca_{ij} \) signifies the control strength \( j \) exerts on \( i \).

By definition control allocation is the difference of two pairwise integral flows that normalized by the output environ of the dominator (the component that controls the other component). In this case, the transitive control originated from a component is determined by the aggregated configuration of all the ecological flows it involved. Control allocation (CA) was adapted herein as the metrics for determining the dispersion fate of a specific risk in a perturbed ecosystem conforming to the normalized control magnitudes one component allocated to each of other compartments. Consequently, the risk information is transmitted and interpreted between components via the input/output environ once the ecosystem is exposed to a specific disturbance. This information may be critical in controlling the ultimate fate of a disturbed ecosystem.

### 3.2. A conversion of flow currency in NEA

In order to adapt NEA to ERA and derive a holistic picture of the ecological risk in a dynamic way, the primary challenge was to establish a suitable transitive medium (or flow currency) for the risk network model.

As has been noted, the flow incompatibility inherent in a material- or energy-oriented network makes it impossible to address system-wide properties in the ERA context. An alternative solution into the proper medium, naturally, comes to a conceptual conversion from the material/energy-based network to the information-based one (Fig. 2). In light of NEA theory, conventionally, an object receives materials and energy from other available compartments through its input environ, and simultaneously generates and transfer materials and energy outside via its output environ, thus completing the storage of useful energy with these continual processes. In this sense, we can define these compartments as energy entities (marked as \( E \)). In a bounded ecosystem, the existence of \( f_{ij} \) (the direct flow from compartment \( j \) to compartment \( i \)) indicates energy generated by \( E_{j} \) (could be species or other aggregated functional groups) will be transferred to \( E_{i} \) partially to support its survival or sustainability, while the opposite flow is the feedback from \( E_{i} \) to \( E_{j} \) for the regulation of the energy flow, which is an active and probably indirect feedback generally in that it completes the energy cycle and contributes to the overall network system functioning of different lengths. But if we look into the ecosystem from an information perspective, components within the interactive network should contain the transitive information carried by materials or energy flows for deciding how to behave within their ecological niches and adapt themselves to the changing environment. Similar to an energy-based network, each component should serve as an information entity (marked as \( H \)) constantly receiving and generating all kinds of information critical for their survival in the network. An ecosystem is information rich, and the operational risk information we are interested in here is responsible for the vulnerability of the ecosystem. For this, we contend that when exposed to a specific hazard, some sensitive components will suffer from it instantly and be forced to change its energy storage and dynamic attributes, and generate quantitative risks in their output environs which then exert ensuing intervention on other components they control in the ecosystem through their input environs. In this sense, all the components within the

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**Fig. 1.** Comprehensive framework of modelling the holistic ERA based on information-based network analysis.
interacting system will inevitably suffer from the influence of the hazard to some extent, either as a direct risk receptor or an indirect risk receptor. Here, we marked the risk flow from information entity $H_j$ to $H_i$ as $I_{fij}$, indicating the risk which $H_j$ exerts on $H_i$. Feedback also operates in the information-based network from $H_i$ to $H_j$. Different from energy-based networks, it expresses itself in a passive manner in that it retransfers a certain risk back to the first component from where it receives the risk originally and even exacerbates the information state of that component.

3.3. Development of risk flow

Risk flow, as has been introduced, is not an energy- or mass-based interaction but an information one, theoretically negative and basically undesirable for nature. The existence of a risk flow indicates that the donor discharge a risk it generated previously, while the receptor suffers the risk from the donor with which it naturally linked. Ecological risk is generally defined as the undesired probability event with the possible occurrence of certain potential harms or damages to ecosystems it exposes. According to the fundamentals of risk measurement (Nath et al., 1993; Bolger, 1997), risk flow is generally formulated by combining the undesirable change magnitude of a risk factor with its probability of occurrence, but here we added the component-specific sensitivity towards a certain degree before transferring them to other components through an indirect pathway (Bartell et al., 1992, 1999; Knoben et al., 1998). Hereafter, the development risk-based flow is parsed into two different situations, i.e., risk flow from the external environment and risk flow within the system.

In terms of input risk value to compartment $i$ from the environment, three parameters—the risk intensity, its corresponding probability and the compartment-specific sensitivity together determine the input risk value ($R_i$), which is formulated as follows:

$$R_i = R_{ix} \cdot P_x \cdot S_i, \quad 0 \leq R_i \leq 1$$

in which, $R_{ix}$ refers to the risk intensity resulting from a certain change in risk factor $x$, $P_x$ refers to its probability of occurrence, while $S_i$ represents the sensitivity of compartment $i$. Specifically, the risk intensity is computed as:

$$R_{ix} = \frac{|I_{ex} - I_{ox}|}{\max(I_{ex}, I_{ox})}, \quad 0 \leq R_{ix} \leq 1$$

where $I_{ex}$ represents the value of a measurable environmental indicator at a certain time point $t$ of interest after the occurrence of the hazard (e.g., a month, a year, or a century following the hazard), and $I_{ox}$ represents the background value of the indicator, which could be the value of an adjacent ecosystem with almost the same habitat but free from effects of the hazard or an previous state exactly before the risk. And the probability is further formulated as:

$$P_x = P_{ox} \cdot P_x, \quad 0 \leq P_x \leq 1$$

where $P_{ox}$ is the existence probability of the hazard event $x$, referring to how likely the hazard is going to happen at all, which is calculated by dividing the total number of times by the number of hazard striking times. $P_x$ is the operating probability of the hazard, indicating the actual operating extent providing the existence of the ecological hazard, which can be parsed into as follows:

$$P_x = \begin{cases} P_{ox} & \text{if } N_x \geq 1, \\ 0 & \text{if } N_x < 1, \end{cases}$$

where $N_x$ stands for the number of susceptible components involved in the risk operating process (i.e., risk receptors) within the concerned ecosystem. Hereto, the input risk was defined in a dimensionless form by using the ratio of the change magnitude associated with the hazard to the background value (on account that probability and sensitivity per se are dimensionless). In this way, we are technically capable of evaluating stressors of different units on the common basis of measurement.

Further, the risk flow that travelled through system components was formulated. Bartell et al. (1999) pointed out that risk analysis should be processed by expressing the toxic effects factors as statistical distributions. As has been elaborated in their risk assessment system, each modelled population has a specific distribution of toxic effects for each chemical contaminant assigned to it. The implication of this decentralized effect for system organization, we contend, also holds for other risk factors. On the other hand, with respect to the environmental flow distribution, Patten and Witkamp (1967) discovered that the distribution of a radionu-

![Fig. 2. The conceptual conversion of NEA: from energy-based flow (shown in solid lines) (a) to risk-based flow (shown in dashed line) (b).](image)
The integral risk matrix can be computed as below:

$$
F = \begin{bmatrix}
0 & 24 & 0 & 75 & 0 \\
35 & 0 & 1510 & 42 & 495 \\
0 & 0 & 0 & 0 & 2780 \\
0 & 67 & 210 & 0 & 0 \\
64 & 1991 & 1060 & 160 & 0
\end{bmatrix}
$$

**Fig. 3.** The energy flow digraph and its flow matrix ($F$) ($kJ \cdot m^{-2} \cdot y^{-1}$).

4. **Operation of risk-based network**

4.1. **Background of the case study**

Natural ecosystems, once exposed to a certain stressor or even a set of specific risk factors triggered by an abrupt alteration of their habitats, will inevitably suffer conceivable risks which compel them to corresponding risk processes. Herein, we took the reservoir river ecosystem intercepted by Manwan dam of Lancang River (N24°25′−24°40′; E100°05′−100°25′) as an example of such ecosystems subjected to human interference. It has been well documented that dam construction results in influences on hydrology, river flow pattern, and habitats, therefore disturbing the organisms that reside in the changed environment (Tiffan et al., 2002; Wu et al., 2003; He et al., 2006; Tomsica et al., 2007). Among these changes, downstream water quality, especially the heavy metal levels show a tendency to increase (Zhang et al., 2005; Zhai et al., 2010). An investigation into the environmental changes was conducted in Manwan in 1994 (a year after dam construction), serving as the basic data source of this case study. Four system components, or so called functional guilds (i.e., piscivorous fish, detritus, phytoplankon and zooplankton) were selected to analyze their conditions after exposure to an increased heavy metal contamination. Piscivorous fish, phytoplankon and zooplankton were regarded as the main components directly sensitive to heavy metal contamination, and detritus is a necessary node for connecting other susceptible organisms concerned.

4.2. **Results of model operation**

Based on the field investigation and relevant literatures, we structured the energy flows between all components of the river ecosystem quantitatively based on ecological food web analysis (referring to Fath et al., 2007). The natural river bank within the reservoir area serves as the system’s boundary. All the input flow, output flow and throughflow of the four selected compartments were examined a year after dam construction. The energy-based network model of the four functional guilds (i.e., four energy entities: E1 (piscivorous fish), E2 (detritus), E3 (phytoplankon) and E4 (zooplankton)) extracted from Manwan reservoir ecosystem after dam construction is shown in the form of flow digraph and matrix ($F$) (Fig. 3). The control allocation matrix (CA) among these interactive compartments is derived to reveal the influence one compartment exerts on another within this biosystem (Fig. 4).

Taking the potential contamination of a heavy metal Cr in the downstream ecosystem as a case study, we then quantified the input risk scenario within the information network (shown in...
Table 1. Input risk values of four components in Manwan downstream ecosystem.

<table>
<thead>
<tr>
<th>Component</th>
<th>S_i</th>
<th>P_ecr</th>
<th>P_oer</th>
<th>R_i</th>
<th>E_i</th>
</tr>
</thead>
<tbody>
<tr>
<td>Piscivorous fish</td>
<td>0.20</td>
<td>0.66</td>
<td>1.00</td>
<td>0.41</td>
<td>H1</td>
</tr>
<tr>
<td>Detritus (E2)</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Phytoplankton (E3)</td>
<td>0.50</td>
<td>0.66</td>
<td>1.00</td>
<td>0.41</td>
<td>H2</td>
</tr>
<tr>
<td>Zooplankton (E4)</td>
<td>0.20</td>
<td>0.66</td>
<td>1.00</td>
<td>0.41</td>
<td>H3</td>
</tr>
</tbody>
</table>

Notes: S_i refers to the Cr content a year after dam construction; P_ecr and P_oer refer to the existence probability and the operation probability of the Cr contamination; S_1, S_2, and S_3 stand for the species sensitivity of E_1, E_3 and E_4, respectively.

Fig. 4. The control allocation digraph and its matrix (CA).

Fig. 5. The direct risk flow digraph and matrix (RF). Notes: To distinguish the risk flow from the material or energy flow, dashed line was utilized in the risk flow digraph. Arrows of different colors indicate risk flows initiated from different components (different source), also different colors in the matrix have the same implication. The last row of the matrix indicates the instant input risk of each information entity. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)
formulation. The proportions of different risk sources composing the received risk of four components were also identified in the integral risk network (Fig. 7). The result showed that almost all components had multiple risk sources rather than solely received from the instant input value (except H3, who only gave off risks but never receive one from other components within this biosystem). That is to say, components that receive the largest risk instantly do not necessarily suffer the most in consideration of the entire system organization. As indicated by Dale et al. (2008), ERA techniques at high organization levels (i.e., community, habitat, and ecosystem scales) will be useful for revealing indirect ecological effects of disturbed ecosystems. In terms of the network metric as developed, the system-wide risk dynamic and the component-scale microdynamics displayed a totally different picture from the conventional assessment both in the qualitative and quantitative aspects. In this sense, the information-based NEA is instructive for unveiling the system-wide risk dynamic and the component-scale microdynamics displayed a totally different picture from the conventional assessment both in the qualitative and quantitative aspects. In this sense, the information-based NEA is instructive for unveiling the

5. Network indicators for risk management

It is a series of risk factors rather than a single hazard an ecosystem has to face most of the time, under which circumstance the existing ERAs fail to work effectively (Yeardley and Roger, 2000; Xu et al., 2004), also, the impact on one component may induce chain effects on others in a complex fashion. In this context, the major challenges faced by risk modellers and assessors are to acquire the proper kind of multi-factor environmental data for interpreting to efficient risk formulation, and to quantify the multi-process risks in an ecosystem-based and direct-viewing manner for future environmental protection activities (Bradbury et al., 2004; Hope, 2006).

Herein, in order to provide a candidate paradigm and methodology to address these challenges based on the developed information-based network, we made use of threshold theory to index the judgment of holistic risk condition for ecosystem evaluation. We parsed the present risk assessment into two scenarios according to different situations of risk factors and proposed some network indices for supporting system-wide ERA.

With respect to single risk factors, the ecological risk is assessed as follows:

\[
\hat{R}_i = \sum_{j=0}^{n} r_{ij} < R_{i,\text{max}} \tag{10}
\]

\[
\hat{R}_F = \sum_{i=1}^{n} \hat{R}_i < \sum_{i=1}^{n} R_{i,\text{max}} \tag{11}
\]

Let \( P_{ex} = P_{ox} = 1 \), \( R_{i,\text{max}} = R_{k,\text{max}} \cdot P_{ex} \cdot P_{ox} \cdot S_j = R_{k,\text{max}} \cdot S_j \) (12)

where \( \hat{R}_i \) refers to the received risk of \( H_i \), of which \( j = 0 \) means the risk flow from the environment (i.e., \( R_j \) ); \( r_{ij} \) refers to the integral risk flow from \( H_j \) to \( H_i \); \( R_{k,\text{max}} \) refers to the total single-factor risk level of the whole system; \( R_{k,\text{max}} \) refers to the maximum risk flow of \( H_i \) (the maximum risk flow of compartments are different due to the sensitivity disparity), in which situation the risk intensity.

![Fig. 6.](image-url) The integral risk flow digraph and matrix (RN). Notes: To make a distinction from the direct risk flow, crooked lines are employed to signify the pathways of integral risk flow.

![Fig. 7.](image-url) The proportions of different risk sources composing the received risk of \( H_i \) in the integral risk network (\( \varnothing \) represents the external environment).

**Table 2**

A comparison among input risk, direct risk and integral risk condition of \( H_i \)

<table>
<thead>
<tr>
<th>Risk condition</th>
<th>( H_1 )</th>
<th>( H_2 )</th>
<th>( H_3 )</th>
<th>( H_4 )</th>
<th>Pathways number</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_i )</td>
<td>0.0546</td>
<td>0.2471</td>
<td>0.2614</td>
<td>0.0724</td>
<td>3</td>
</tr>
<tr>
<td>( \hat{R}_i )</td>
<td>0.1135</td>
<td>0.0015</td>
<td>0.1366</td>
<td>0.0737</td>
<td>3 + 9</td>
</tr>
<tr>
<td>( R_{i,\text{max}} )</td>
<td>0.0209</td>
<td>0.0546</td>
<td>0.0015</td>
<td>0.1135</td>
<td>3 + 9 + 3</td>
</tr>
</tbody>
</table>

Notes: \( R_i \) denotes the input risk to component \( i \), \( \hat{R}_i \) denotes the risks of component \( i \) received from its input environ in direct risk network (RF), \( R_{i,\text{max}} \) denotes the risks of component \( i \) received from its input environ in integral risk network (RN). 3 \( \varnothing \) represents the total number of direct risk pathways (pathway length = 1) in RF, and 9 \( \varnothing \) represents the number of indirect risk pathways (pathway length > 1) uncovered in RN.
formulated as follows: Let $R_{\text{max}}$ be the maximum level of risk generated by a single stressor and $P_{\text{ex}}$ the operating probability of the hazard event. Then, $R_{\text{max}}$ indicates the maximum endurable change of risk factor $x$ from background value beyond which will induce species extinction to a specific functional guild theoretically, while maximum $P_{\text{ex}}$ and $P_{\text{op}}$ mean the hazard happen continually and operationally during the investigation period.

According to the formulation, the total integral risk value of a compartment that received from its environ is regarded acceptable if it is lower than the maximum risk it can bear with. Furthermore, the perturbed ecosystem will not be counted as a well-functioning system unless the gross risk of ecosystem is below the sum of the maximum risk all sensitive components can ever generate. Consequently, the ecosystem which satisfies the requirements of Eqs. (10) and (11) at the same time is deemed to be sustainable despite its exposure to the stressor. $R_{\text{max}}$ and $\sum R_{\text{max}}$ therefore serve as the thresholds for single compartments and the whole ecosystem respectively, crossing which the functional guilds or the whole ecosystem will be endangered. These thresholds, technically, can be derived through empirical or theoretical vulnerability assessments of the specific hazard (see e.g., De Lange et al., 2010; Masashi and Wataru, 2008; USEPA, 1992).

Accordingly, in terms of multiple factors, the ecological risk is formulated as follows:

\[
\sum_{j=0}^{n} R_{ij} < \sum_{x=1}^{m} R_{\text{max}}^{(x)} \quad (13)
\]

\[
\sum_{i=0}^{n} R_{ij} < \sum_{x=1}^{m} \left( \sum_{i=1}^{n} R_{\text{max}}^{(x)} \right) \quad (14)
\]

where $R_{\text{max}}^{(x)}$ refers to the maximum risk flow of $Hi$ initiated by risk factor $x$, also under which circumstance risk intensity reaches its maximum level and both the existence probability ($P_{\text{ex}}$) and the operating probability ($P_{\text{op}}$) of the hazard reach 1. Here, $R_{ij}$ represents the gross multi-factor risk level of the whole ecosystem.

Analogously, the disturbed ecosystem which satisfies the requirement of Eqs. (13) and (14) at the same time, i.e., all compartments within the ecosystem live under the total maximum bearable risk originated from all stressors and the gross integral risk is lower than the maximum risk value all sensitive compartments can ever generate, is regarded sustainable after all the exposures of the risk factors, without crossing the risk threshold.

The monitoring of indices could be more useful if environmental modellers use a risk-based approach to address important problems rather than simply tracking the changes of indicators (Suter II, 2001). The evaluation of the disturbed ecosystem from a network point of view urges modellers to probe into the indirect effects of the risk flow within ecosystem dynamics, and the risk-based networks and their indices we defined here provides an overall yet succinct metric for doing so. Following the implication of the proposed network-oriented indices, the component-scale and ecosystem-wide risk information inherent in ecological networks can be extracted and formulated as potential metrics for risk assessment and management. Taking the downstream ecosystem disturbed by dam construction for example again, there is a pragmatic need to manifest the possible impacts on the overall river ecosystem before making management decisions, not only the impacts on single aquatic organisms but also their interactions crucial for risks dispersing. By turning to network analysis as proposed, managers are able to obtain the important knowledge on which species and whether the ecosystem are crossing the safety threshold and consequently endangered. In this sense, the information-based NEA meets this very request for ecosystem management of river ecosystem both before and after dam construction. The follow-up work of this case should focus on the construction of a comprehensive environmental database of dam construction incorporating monitoring information of different scales (i.e., species, community and ecosystem), whereby a system-wide evaluation based on the newly developed network can be enhanced.

6. Conclusions

The network perspective has been recognized by general ecological interest and proved critical for deriving a deeper insight into ecosystem processes, especially the integral impact of disturbances involving vital environmental flows (DeAngelis et al., 1989; Gattie et al., 2006; Manickchand-Heileman et al., 2004; Neubert and Caswell, 1997; Tobor-Kaplon et al., 2007). In this study, we introduced a system methodology for the holistic ERA by employing a novel network analysis. In order to achieve this end, a conceptual conversion from the original energy-based network to the present information-based network was proposed. Also, a new distributed control metric termed control allocation (CA) was developed based on the existing control analysis. By taking a disturbed downstream ecosystem as a case study, we demonstrated the usefulness of risk-based networks in the unveiling of indirect effect embedded in the ecosystem dynamics, based on which, we explored some network-based indicators for ecosystem management that are promising for assessing both system-wide integral condition and component-scale microdynamic risk scenarios. In essence, as with energy and materials, the tracking of information flow also plays a same important role, if not a prior, in ecosystem assessment and management for combined human-natural systems. By turning to the information-based NEA, modellers can handily derive a straight picture accompanied by applicable indicators to track the processing and operation of vital signals associated with system self-organization so long as the risk networks are established. In view of these, this study may serve as an inception of advancing the conventional NEA to a more compatible stage on which information-based networks are available in assessing ecosystems.

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