Foundations of Science
https://doi.org/10.1007/s10699-025-09975-2

An Investigation Into the Notion of Complex Systems

Fulvio Mazzocchi[1]

Accepted: 30 January 2025

Abstract
This article investigates the concept of 'complex systems'. While not searching for some necessary and sufficient conditions that are valid for all of them, it acknowledges that complex systems can take different shapes, mainly depending on the features of their internal organization and how they interact with their environment. It then advocates a networked notion of complex systems that can accommodate their rich phenomenology and the various circumstances making them, focusing on two types of these systems: (i) one that is mainly characterized by the generation of stable patterns through self-reinforcing dynamics at the lower levels (Bénard convection) and (ii) a distinct one characterized by a more complex organization that makes them 'minimally decomposable' and showing autonomy (living systems). The article also assumes that the complexity of a system is analyzable by focusing on two distinct yet interrelated aspects: (i) the features of the system itself and (ii) the relationship between the system and an observer. Its final part discusses how complex systems cannot be adequately represented by a single model or description and how this is another distinctive aspect of their complexity.

Keywords Complex systems · Dissipative structures · Organisms · Self-organization · Downward causation · Networked concept · Epistemological account of complexity · Model pluralism

1 Introduction

Complexity is an important and innovative field of contemporary science that transcends disciplinary boundaries and has implications at multiple levels. Theoretically and empirically, it has brought attention to issues such as relational patterns and nonlinear phenomena, which Newtonian science largely neglected.

✉ Fulvio Mazzocchi
fulvio.mazzocchi@cnr.it

[1] CNR - Institute of Heritage Science, Via Salaria km 29,300 - 00015, Monterotondo (Rome), Italy

The field has originated from multiple research pathways and theoretical frameworks – from the early days of dynamical systems theory founded by Poincaré in the XIX century, to the most recent complex adaptive systems theory and network theory – evolving over a long time span. A unified reading of complexity is yet to emerge. Instead, it remains an amalgam of principles, theories and methods (Alhadeff-Jones, 2008; Heylighen et al., 2007).

This situation also partially affects the way complex systems are described or defined. Usually, such descriptions or definitions depend on identifying several features that are (hypothetically) shared by all forms of complex systems and viewed as necessary and sufficient conditions for their classification as such (thus also allowing them to be distinguished from non-complex systems) (e.g. Ladyman & Wiesner, 2020; Ladyman et al., 2013). However, multiple contrasting descriptions and definitions have been formulated so far (Estrada, 2023).

This article does not aim to establish necessary and sufficient conditions for defining complex systems or to provide a 'unified' representation of them. Instead, it argues that the 'necessary and sufficient conditions' approach, usually adopted a priori, is only partially suitable in characterizing these systems, as it imposes the requirements of logical reasoning on their heterogeneous phenomenology.

Investigating the mechanisms generating complexity and how their properties combine and interact, it then advocates a 'networked' notion of complex systems, assuming the existence of several distinct 'types'. These types display differences and similarities but not a common essence, each emerging at the intersection of uniquely assembled properties. The article specifically analyzes two of them that exhibit a different degree of organizational complexity and way of interacting with their environment: (i) dissipative structures (Bénard convection) and (ii) organisms.

It also argues that the complexity of such systems can be described by focusing on two different (but interrelated) aspects: the system's features and the relationship between it and an observer.

The first descriptive strategy focuses on the systems' attributes within their vital contexts. Complex systems, as commonly understood, exist at multiple levels of organization and in various domains. One of the most paradigmatic examples is perhaps the human brain, but dissipative structures, cells, organisms, ecosystems, the Earth's climate, communication systems and human societies can also be regarded as complex systems. Most consist of manifold, closely interacting components,[1] so that the behavior of any element in the system influences and is influenced by the behavior of many others.

Additionally, what characterizes complex systems is the 'nontrivial' way their components interact with each other and the system as a whole (Richardson, 2005). Their interaction patterns are dynamic, nonlinear (e.g. characterized by the presence of multiple causal

---

[1] Complex systems can also consist of a few interacting elements. For example, a chaotic system like a simple double pendulum is considered complex, meaning it exhibits complex behaviour. However, not all chaotic systems are complex systems, nor are complex systems inherently chaotic. Although there are systems displaying complexity because of being chaotic, and even if chaotic systems and complex systems share common features (e.g. nonlinearity), they are also different in several important ways (see e.g. Bertuglia & Vaio, 2005; Rickles et al., 2007). For example, the behavior of chaotic systems, which can result from a small number of nonlinear interactions, is deterministic; however, due to extreme sensitivity to initial conditions, their trajectories diverge exponentially over time, thus becoming unpredictable. Instead, sensitivity to initial conditions plays a less critical role in complex systems. These systems are not deterministic and inherently unpredictable; they display emergent dynamical behaviors, which depend on many interacting components working as coherent units.

loops), and not fixed (i.e. with multiple variable interaction rules). Unlike merely 'aggregative systems', which can be suitably understood by focusing on their isolated parts, what primarily matters in complex systems is not their material components as such (e.g. molecules) but their organizational aspects. They display a degree of connectivity that allows them to exhibit highly complex and adaptive behaviors. [2] In fact, by joining together interacting elements at the lower levels, new structural configurations and patterns of 'relatedness' often arise.

The second descriptive strategy follows an epistemological account of complexity. It does not regard the systems per se but depends on the number of descriptions or models required to represent them.

2 A First type of Complex Systems: Dissipative Structures (Bénard Convection)

Bénard convection has been studied for decades. Ilya Prigogine (e.g. Nicolis & Prigogine, 1977), in particular, considered it a paradigm of 'stability far-from-equilibrium'. This would lead him to coin the term 'dissipative structures' and elaborate on nonlinear thermodynamics, in which entropy can become a source of order and self-organization takes place. [3]

In the early 1900s, the French physicist Henri Bénard discovered experimentally that heating a thin layer of viscous fluid can unexpectedly generate ordered structures. A source of heat is placed below a shallow vessel, and the system is in equilibrium at the beginning of the experiment. As the experiment proceeds, the heat source's temperature progressively increases, generating an energy gradient across the system that pushes it away from an equilibrium condition. When the fluid is heated uniformly from below, a constant flow of heat is established – from the bottom to the top – entailing a vertical and uniform variation in temperature that decreases with height. As long as the temperature variation is small, heat is transferred exclusively by conduction.

A fluid, when heated, expands while its density decreases. As far as the conductive state is concerned, density variations are minor and quickly dampened. However, the system is driven farther away from equilibrium as the temperature gradient increases. Once a particular critical value is reached, it becomes sensitive to small fluctuations in fluid density, which can be amplified and generate a macroscopic circular current. Conduction becomes unstable and is then replaced by convection, in which heat is transferred by the coherent motion of millions of molecules. This coherent convective motion leads to the formation of hexagonal convection cells (Bénard cells), in which the hotter parts of the fluid move upward via the cells' center, whereas its colder portions sink towards the bottom along the walls (see also Yin & Herfel, 2011).

---

[2] An example of a definition focusing on these aspects is the following: "A complex system is comprised of a large number of non-linearly interacting non-decomposable elements. The interactivity must be such that the system cannot be reducible to two or more distinct systems, and must contain a sufficiently complex interactive mixture of causal loops to allow the system to display the behaviours characteristic of such systems (where the determination of 'sufficiently' is problematic)" (Richardson, 2005, 620).

[3] The most interesting conceptual insight here is that order and disorder can be productively combined.

Bénard convection, which is not only produced in laboratory experiments but also occurs in nature,[4] thus involves spontaneous self-organization. ‘Spontaneous’ means self-generated, not requiring outside control: it is the fluid that governs itself. The creation of convection cells depends on the local dynamics of fluid molecules and entails forming a large-scale structure that influences the behavior of fluid molecules hemselves. Prigogine remarked that internal positive feedback loops, which amplify small fluctuations, are involved in the process, and nonlinear equations are required for the study of far-from-equilibrium conditions.

Some sort of top-down or downward causation is also entailed (Bishop, 2008). As mentioned, Bénard cells arise from the motion of fluid molecules, but the total behavior of convection cells cannot be explained by focusing solely on the molecular level. Which states of motion are accessible to these molecules also depend on the collective effects of self-regulating convection patterns. In the equilibrium state, several states of motion are possible, depending only on the system’s symmetries and boundaries and other factors and forces like gravity (e.g. Busse, 1978; Cross & Hohenberg, 1993). However, in the new non-equilibrium steady state, the configurational degrees of freedom of the individual molecules are considerably reduced. Most of the states that were previously accessible are no longer so. What matters now is not only the system’s symmetries and boundaries or conservation laws as before but also the collective shaping effects of the Bénard cells on the molecules (Bishop, 2008). One way to express this is to say that the convection cells ‘constrain’ the local dynamics of the fluid molecules, providing coherence to their behavior and suppressing local deviations. These (dynamically evolving) constraints thus arise from within the system.

Bénard convection provides an example of ‘emergence’ and downward influence of the system’s large-scale structure on its constituents and their behavior. However, the interpretation of these phenomena is still debated. In some scholars’ understanding (e.g. Bedau, 2003), the new global pattern is merely ‘aggregative’: it only depends on how the lower level constituents are arranged, entailing the production of an ordered spatial pattern through self-aggregation that would be better described as a ‘self-assembly’ (Abel & Trevors, 2006). Crucially, no new genuine causal power is involved that would be able to affect the behavior of its parts. The novelty in this type of emergence is purely of a predictive kind (Bich, 2012; Crutchfield, 1994): whereas, at least in principle, the system’s behavior can be deduced from information regarding its constituents, its dynamics cannot be predicted – different directions can be taken – relying exclusively on such information. On the other hand, other scholars (e.g. Bishop, 2008) still maintain that when the behaviors of the system’s constituents, as in the case of Bénard convection, are highly coherent and intertwined, it would be mistaken to view the phenomenon involved merely as aggregative. The downward influence is instead genuine, and the behavior of individual constituents cannot be properly accounted for unless the role played by the large-scale structure is also considered.

2.1 A few Common Features of Complex Systems

Bénard convection is a system exhibiting several typical features of complexity, such as the presence of a large number of nontrivially interacting elements (already described in the introduction), self-organization, openness, far-from-equilibrium conditions, nonlinearity,

---

[4] One meteorological example is cold polar air descending and moving across the surface of a warmer sea-water (e.g. the Atlantic Ocean) (see e.g. Koschmieder, 1993).

and unpredictability. These are among the hallmarks of many complex systems. As such, they need to be described more in detail and by referring to a broader range of systems.

First, self-organization, which is widespread in the natural world and occurs in the physicochemical domain and several other domains, such as biological, psychological and social ones. It involves the generation of higher order stable patterns resulting from rich interactions of manifold elements and self-reinforcing dynamics at the lower level. As in the case of convection patterns, after reaching a particular threshold in some system's variables, something qualitatively new arises as compared to the lower levels, leading to an increase in the internal order (the system's entropy is decreased at the cost of increasing the entropy of the surroundings). Self-organizing systems spontaneously and unexpectedly arrange their components and interactions into some global adaptive structures, and they do this in the absence of an external or internal center of control or designer. Nor can such collective phenomena be predicted or inferred from local information or rules and properties: the elements in the system are usually simple and shortsighted, i.e. ignorant of the behavior of the system as a whole and the long-term effects of their actions; the only information available to them is local, but the effects of their actions can propagate and diffuse across the whole system.

To be more precise, it is only partially true that the emergence of novel ordered patterns depends exclusively on requirements that are internal to the system, i.e. manifold and highly interacting constituents. As Halley & Winkler (2008) highlight, since self-organized systems are thermodynamically open and immersed in their environments, they are necessarily constrained to some extent by external factors. However, these external factors do not correspond to key ordering mechanisms. They work primarily as 'templates' that influence and constrain internal ordering forces. For example, as mentioned earlier, convection cells necessarily depend on an external source of energy (the input of a heat source), and the direction of heat and gravity also play a role as templates. For this reason, Halley & Winkler (2008, 12) describe self-organization as

> a dissipative nonequilibrium order at macroscopic levels, because of collective, nonlinear interactions between multiple microscopic components. This order is induced by interplay between intrinsic and extrinsic factors, and decays upon removal of the energy source.

According to them, this circumstance also distinguishes self-organization from self-assembly. The two terms are often used interchangeably, as both involve manifold interactions among lower level constituents without global information. However, unlike those of self-organization, the mechanisms of self-assembly do not depend upon nonequilibrium conditions. Furthermore, due to the aggregative character of the process, self-assembled structures are considered reducible to their constituent parts. Self-assembly – involved, for example, at the molecular level in the formation of molecular crystals, colloids, and lipid bilayers (Whitesides & Boncheva, 2002) – is thus defined as

> a nondissipative structural order on a macroscopic level, because of collective interactions between multiple (usually microscopic) components that do not change their character upon integration into the self-assembled structure. This process is spontaneous because the energy of unassembled components is higher than the self-assembled

> structure, which is in static equilibrium, persisting without the need for energy input (Halley & Winkler, 2008, 14).

Self-organization relates to another highly debated (and differently interpreted) phenomenon of complex systems' behavior, namely emergence. From an emergentist standpoint, such a phenomenon, in its fuller sense, occurs when the interactions and relations between the lower level components give rise to a structure or behavior that has new qualitative properties, i.e. properties that do not display in the parts themselves (El-Hani & Emmeche, 2000). Emergent properties are believed to be neither predictable nor deducible from the properties and relationships of the lower level constituents. Moreover, the emergent higher level structure has novel and distinct causal power, which is irreducible to the causal power of the lower levels and impacts them (downward causation) (Kim, 1999). Such an idea of emergence is instead not applicable to self-assembled structures, which, as mentioned, are viewed as reducible to their parts and do not display a novel causal power.

How self-organization and emergence are linked is explained in different ways. Self-organization can be viewed as a process that causes the manifestation of emergent properties or as an emergent phenomenon itself that arises from the interactions and relations between the component parts of the system (e.g. De Wolf & Holvoet, 2005). [5]

Complex self-organizing systems can also dynamically self-regulate and reorganize in response to environmental changes (e.g. Heylighen et al., 2007). They are 'robust' or 'adaptive', meaning their order-generating mechanisms are distributed and not centrally controlled, allowing the system to preserve its overall stability under perturbations. Individual elements of the systems cannot be points of failure, as eliminating some of them does not involve the destruction of the overall structure (e.g. eliminating individual birds in a flock, the flock still persists). Besides, even systems of lower complexity, like dissipative structures, can be 'evolving'. As the flow of energy and matter that goes through them increases, dissipative structures can pass through new phases of instability, transforming into structures of greater complexity. [6]

Most complex systems are highly sensitive to small fluctuations and can undergo unexpected massive and stochastic changes in response to them. These systems can take unpredictable directions. Not only are most of them characterized by linear causal chains, which enable predictability of the system's functioning, but they also exhibit a richness of feedback loops or circular causal chains – outputs can again become inputs – both in terms of positive feedback or autocatalysis, which produces enhancing and amplifying effects (as we have seen in the Bénard convection), and negative feedback, which instead inhibits large perturbations and stabilizes the system.

This, of course, contributes to their nonlinearity, which is intended here as no proportionality between inputs and outputs. As Ladyman et al. (2013) point out, even the nonlinearity of interactions cannot be viewed, strictly speaking, as a necessary (and even less sufficient)

---

[5] Self-organization is primarily considered in connection to emergence. However, self-organization can also exist without emergence, and emergence can exist without self-organization (for a discussion on this see De Wolf & Holvoet, 2005). From this brief analysis, it should have become clear that, due to historical stratifications and various interpretations, there is a significant degree of ambiguity regarding the concept of complex systems and several other notions (e.g. self-organization, emergence, self-assembly) used for its characterization.

[6] For some authors (e.g. Halley & Winkler, 2008), notions like 'adaptive' and 'evolving' should be reserved only for the biological domain.

feature of a complex system, as some complex systems are subject to linear dynamics (at least in a mathematical sense; e.g. MacKay, 2008). However, it is a highly distinctive and recurring attribute.

Another key feature is openness. Differently from the objects of Newtonian science, which are closed or isolated systems, most complex systems are embedded in and constantly interact with their (especially neighbouring) environment, which is ever-changing and made up of many other systems. While a change in the system might impact its surroundings, a change (even slight) in the environmental conditions can affect the system, whose survival, as in the case of organisms, often depends on a healthy interaction with it. Besides, the environment partakes in creating the system's identities; it is, in fact, often difficult to draw boundaries and separate what is inside the system from what is part of its environment. When studying complex systems, rather than focusing exclusively on internal factors, it is therefore crucial to consider the environment's role (see also Chu, 2011).

Of course, there are systems that, albeit sharing many features of dissipative structures, are much more complex. Additional features should be considered to grasp the specificity of these systems of higher complexity, such as biological ones, focusing especially on the architecture of their internal organization and their more complex relationship with their environment.

3 A Second type of Complex Systems: Organisms

Biological systems are epitomes of a higher level complexity. Their features are also taken to question or circumscribe the legitimacy of reductionism in studying a complex system. This section explores the issue further, especially from this perspective.

While reductionism is still viewed as an important and successful heuristic device, it is also acknowledged that, in many cases, it is not sufficient or even inappropriate. Reductionism is adopted especially as a methodological procedure: the most suitable way of scientifically investigating a system is concentrating on its constituent parts (usually, albeit not necessarily, at the lowest possible level). Specific reductive methods like decomposition typically obtain such parts, which are then studied in isolation, i.e. in settings different from in situ such as laboratory conditions (e.g. Kaiser, 2011). It is believed that studying the parts is sufficient to understand the system as a whole and that the properties of parts are basically unaffected by the context in which they are placed. [7]

Methodological reductionism can be apt here to investigate systems that are nearly closed or isolated and 'highly decomposable' (Bechtel & Richardson, 2010), i.e. the relational context plays a minor role in determining how the system's parts function (and interactions between these parts usually occur in linear ways). However, in systems like Bénard convection and many others, it is evident that the behavior of the system's parts also depends on interlevel relations and is affected by the broader context. Even the biochemical structures of simpler organisms involve many interacting chemical pathways, and the operations of the subsystems are coordinated among them (Bechtel, 2012). Methodological reduction-

---

[7] For some scholars like Herbert Simon, most natural systems are "nearly decomposable", i.e. the interactions between their subsystems are weak and, in the short run, the behaviour of any component part is "approximately independent" from the behaviour of the other parts, whereas, in the long run, it depends on them in "only an aggregative way" (Simon, 1962, 198).

ism hence becomes inadequate and is even more unsuitable for studying more complex living systems, which are only 'minimally decomposable' (Bechtel & Richardson, 2010): they are made of 'strongly interacting' parts (Strevens, 2005) in a way that the constituents' properties and behavior are greatly influenced or codetermined – e.g. some possibilities are allowed or triggered, whereas others are restrained or inhibited – by the presence of the other constituents, the higher levels, and the system as a whole, which together form the overall organization.

In such cases, studying the behavior of a system by decomposing it and focusing on its parts in isolation is misleading, as it leads to faulty models and fallacious interventions (as if the system were decomposable). Depending on whether they are integrated into the system they are part of (in situ) or studied in isolation and separately from such a system (e.g. in vitro), the system's constituents can exhibit different properties and behaviors (Chong & Ray, 2002; Cornish-Bowden et al., 2004). Such is the case, for example, of the gene expression of certain bacteria, in which some groups of genes are differentially expressed in vivo and in vitro (e.g. Talaat et al., 2004). Moreover, the findings of in vitro experimentations do not frequently apply to the physiological conditions of the system (Bruggeman et al., 2002). Indeed, the more its component parts are interrelated and interdependent, the less suitable are reductionist approaches.

We have already encountered some sort of downward causation in dissipative structures. However, the organizational and causal complexity of living systems far exceeds that of convection patterns. This complexity is intricately woven into the fabric of these systems, which are typified by a strong internal interconnectedness and the presence of stable, multilevel hierarchical structures with mutually dependent processes and pathways, many control mechanisms, and intertwining feedback loops (between levels of organization, too). Each level can be governed by laws that do not manifest at lower levels. Moreover, the parts of organisms are often, per se, complex systems. For instance, cells are highly organized wholes, consisting of millions of interacting macromolecules and many interrelated regulatory feedback loops (e.g. Karsenti, 2008).

Another key issue characterizing biological systems is their interconnectedness and interdependence with their environment. Their behavior is the outcome of a long history of interactions and adjustments. Organisms and their environment mutually transform and co-evolve. According to Lewontin (2000), organisms are the result of complex interactions between internal (genetic) factors and external (environmental) influences; not only do they adapt to their environment, but in turn, they contribute to creating and modifying it. Moreover, organisms live in ecosystems, in which the biotic and abiotic parts interact through nutrient cycling and energy flow, and each species contributes to maintaining the overall functioning.

It is especially in virtue of the aforementioned internal complexity that biological systems acquire the property of being 'autonomous', which is their most distinguishing feature (e.g. Hofmeyr, 2007). For Ruiz-Mirazo et al. (2004, 330), autonomous is in fact

> a far-from-equilibrium system that constitutes and maintains itself establishing an organizational identity of its own, a functionally integrated (homeostatic and active) unit based on a set of endergonic-exergonic couplings between internal self-constructing processes, as well as with other processes of interaction with its environment.

Living systems are thus integrated wholes that are able to ‘produce’ themselves. Whereas they are sensitive to environmental inputs and highly responsive to signals, constantly reacting to external and internal stimuli, meanwhile, they exhibit internal ‘systemic closure’, i.e. the elements and processes occurring within the system operate to maintain its identity and integrity in the face of environmental perturbations and internal fluctuations. This makes them adaptable and capable of self-modifying and modifying their environment, as well as assessing these modifications, thus enhancing their viability and survival (see also Bich et al., 2016; Montevil & Mossio, 2015).

It is worth spending a few words on better specifying the meaning of ‘to cause’ when related to downward causation. First, as Hulswit (2005) points out, it is still debated what this verb means when applied to the influence of the higher levels on the constituents, phenomena and states at the lower levels, having been used in the scientific and philosophical literature, to indicate restrain, determine, govern, bind, structure, delimit and so on. Such terms and notions are, of course, all interrelated and overlapping but not equivalent.

Their use also relates to the ‘type’ of cause believed to be involved and its relative ‘force’. The present article does not delve into the distinction between the strong, medium and weak meaning of downward causation (e.g. Emmeche et al., 2000; Wilson, 2016). However, whereas causes are mostly interpreted as efficient causes, a call to distinguish between efficient and formal causation (intended in an Aristotelean sense) or at least to identify some sort of causal influence not explainable in terms of efficient cause, has resurfaced in the discussions on self-organization and downward causation (e.g. El-Hani & Pereira, 2000; Emmeche et al., 2000). Moreno & Umerez (2000, 109), for example, hold that DNA molecules are “informational components” that act as the formal cause of proteins, in the sense that “their sequence of nucleotides convey the ‘idea’ or ‘form’ of the latter”. Self-organization too has been depicted as entailing downward formal causation (e.g. De Lorenzana, 1998). Downward causation, on the other hand, is often described as the higher levels forming ‘constraining’ conditions for the relations and processes, including efficient causation, at the lower levels (El-Hani & Emmeche, 2000; Hooker, 2013). Campbell (1974, 80), for example, believes that the processes at the lower level are “restrained by and act in conformity to” the laws – i.e. organizational principles that basically function as formal causes (see also Moreno & Umerez, 2000) – of the higher levels. For their part, Emmeche et al. (2000, 25) point out that the fact that the higher levels constrain the processes at the lower levels entails that they also constrain “which higher level phenomenon will result from a given lower level state.”

In Montevil & Mossio’s (2015) view, even the autonomy and self-determination of living systems depend on how they realize a ‘closure of constraints’, in which the constraints within the system are mutually determined. Bich & Bechtel (2022, 99) further specify that

> A system realizing closure of constraints is able to maintain its dynamical organization despite the constant transformations and turnover at the level of components (…) This does impose further requirements on the types of material components that can perform the needed functions (membranes, catalysts, etc.), but these requirements are generated top-down in terms of the functional activity they must perform, not derived from the material constitution of a given organism.

Another area of discussion concerns the causal relata: what kind of things (i.e. the higher and lower level entities) are linked by causation? Are they substances (e.g. molecules, cells) or processes (e.g. interactions) (Hulswit, 2005)? Different metaphysical stances can be at work here, whose discussion is beyond the scope of the present article. [8]

Returning to the limitations of reductionist approaches, focusing exclusively on the parts in isolation cannot shed light on how they behave in situ. Hence, such approaches are very limited in explaining the behavior of a complex system as a whole. For this reason, in the biological field, there has been a rediscovery of holistic and noninvasive experimental methods to study the structures and behavior in cells and organisms under physiological conditions (e.g. Mazzocchi, 2012).

Network theory too is especially suitable for investigating complex systems that are minimally decomposable (Rathkopf, 2015; see also Green et al., 2018). The use of methods like decomposition is avoided, privileging a methodologically holistic and mathematically grounded approach: "[r]eductionism deconstructed complex systems, bringing us a theory of individual nodes and links. Network theory is painstakingly reassembling them, helping us to see the whole again" (Barabási, 2012, 15). Network theory, which links together models of network structures and notions that emerged in statistical physics (e.g. phase transition and self-organized criticality), represents complex systems as networks and their properties as networks' properties, i.e. basically topological ones (Huneman, 2010) like modularity, scale free and small world properties (see also Barabási & Albert, 1999).

On the other hand, the limitations of holistic or network approaches are that they usually focus mostly or exclusively on the relational context and whole system, overlooking the role of the component parts. Indeed, it is not enough to focus exclusively on the whole, just as it is not enough to focus solely on its parts (Bich & Bechtel, 2022). It is not enough to consider exclusively downward causation (due to the causal influence of the higher levels) or exclusively upward causation (due to the causal influence of the lower levels). Both sides should be taken into account, acknowledging the reciprocal action of the system's organization and its constituents (see also Powell & Dupré, 2009).

This also fits well with Estrada's (2023) definition of a complex system: a system can be "said to be complex if there is a bidirectional nonseparability between the identities of the parts and the identity of the whole. Then, not only the identity of the whole is determined by the constituent parts, but also the identity of the parts is determined by the whole due to the (…) nature of their interactions".

4 A Networked Notion of Complex Systems

Many complex systems have been mentioned so far, which can, *prima facie*, be grouped into various distinct types. Focusing on two robust examples provided a glimpse of their phenomenological variety. Several other types can be identified, such as ecosystems and human societies (and, more generally, sociocultural systems). While the article does not attempt to elaborate a comprehensive typology of complex systems, this section briefly explores the

---

[8] For example, Juarrero (2002) describes complex systems as 'structures of processes', i.e. they constantly change and evolve, almost in agreement with Heraclitus' idea that the world is in continual flux (see also Nicholson & Dupré, 2018).

potential for further exploration into the producers of such a variety, i.e. how their properties combine and interact.

First, several complex systems' properties act as 'generators of complexity' (a term borrowed from Chu et al., 2003). As mentioned, defining necessary and sufficient conditions based on a structured essence or universal set of properties that apply to all types of complex systems is more than questionable. However, there are meaningful areas of overlap stemming from the fact that a set of properties (e.g. a large number of nontrivially interacting elements, self-organization, emergent properties, robustness, nonlinearity, openness) is shared by *most* complex systems. This shared set can be seen as a *weak* common denominator, consisting of 'nearly unerasable' attributes that only partially resemble necessary conditions. [9] Instead, a combination of 'necessary' and 'sufficient' conditions is not only unattainable but also misleading in the context of complex systems. This approach results in a closed set of attributes where none can be erased or added.

At the same time, various factors contribute to diversifying complex systems. On the one hand, there are properties peculiar to given types (e.g. autonomy in organisms). On the other hand, even shared properties can combine differently, taking different shapes and relative importance in distinct types. For example, feedback loops are present in both dissipative structures and organisms; however, only in organisms do they combine with a multilevel hierarchical structure, contributing to interlevel relations and increasing the ability of self-regulation.

Among the generators of complexity, the system-environment relationship should be included, considering that it too can take different shapes, from an environment basically setting up constraints (as in the case of dissipative structures) to a dynamic system-environment coevolution (as in the case of living systems). Furthermore, complexity generators can also be placed at the epistemological level (i.e. the system's irreducibility to a single model's representation), as discussed in the next section.

A 'networked' notion emerges of complex systems. Such a notion refers to a large ensemble of types connected in many different ways. Each emerges at the intersection of many properties distinctively assembled for that type.

Here, the genus-species model, linked to essentialism, is only partially applicable. Such a model gives rise to hierarchical trees by connecting, at multiple levels, a genus with its species (e.g. animals-mammals). The genus-species relation is characterized by the inheritance of properties – any property of the genus must also be attributable to the species – and works by adding (to the genus) further distinctive features (to obtain the species of that genus).

However, the notion of complex systems is not portrayable in this way. No strict genus-species relation links the different types with the general category or between themselves (instead, long-standing taxonomic traditions exist internally to given types like organisms). Despite the aforementioned weak common denominator, the types of complex systems do not stem from a genus fixing a common structured essence for all of them. Rather, the broader notion of complex systems itself emerges from an intricate, networked ensemble of types with their properties.

Such a networked notion is also representable as a multidimensional space. In such a space, depending on several factors, each type occupies a specific locus and is placed at a relative distance from the other types, which is not fixed but varies according to perspective. There are, of course, hierarchical components and different levels (e.g. organizational) of

---

[9] 'Unerasable' here means that if that property is deleted, the system cannot exist.

complexity. However, instead of a single spectrum reflecting an axis of progressive complexity and considering a single dimension for comparison, there are multiple ways to order this space. For example, the brain, the Earth's climate, cities, and human societies are all highly complex systems, each in its particular way; it makes little sense to one-sidedly establish which one is at a higher or lower grade of complexity.

5 Complex Systems are not Representable by a Single Model

The second descriptive strategy shifts the focus from the system's properties to the features of the interaction between the system and the (e.g. scientific) observer, paying attention to the modeling relation. The complexity of the real world is often so vast that a reduction of its complexity is needed to allow natural phenomena to become objects of scientific investigation. It is precisely here that the usefulness of models resides.

Rosen (1987) depicts complexity as the property of a natural system corresponding to the difficulty in representing and modeling it: whereas a single description can adequately characterize a 'simple' system, there is no single formalism able to capture all the properties of a complex system; many of them can instead be needed, which are neither derivable from each other nor reducible to a more comprehensive model. [10] The complexity of a system can thus be said to depend on how many separate descriptions are needed to comprehensively analyze it. Here, the observer plays a key role in attributing a system the feature of being 'complex'.

Rosen's thesis rests on the assumption that creating a model entails establishing a meaningful connection between a natural system and a formal system. More precisely, it entails encoding the former into the latter, thus establishing a parallel between causal relations and implicative relations between propositions describing them.

In the modeling process, it is, however, impossible to include all the system's components and factors that would be able to provide meaningful information; researchers have to make choices, and some of them will necessarily be disregarded. All models, whatever their type – e.g. mathematical or descriptive – are thus inherently incomplete. There will always remain a gap between the real system and the representations we make of it. For example, the mathematical models constructed to represent network structures in complex systems usually involve simplifications – to create 'manageable' versions of many-elements systems – and idealizations – which neglect to consider the empirical nature of the individual nodes. Modelers might have to choose what variables to consider as relevant to their mathematical treatment. For instance, Bishop (2012, 11) notes that

> (…) the fluid equations governing Rayleigh–Bénard convection require the imposition of a constant temperature along the bottom plate of a container holding fluid so that a temperature difference can be established. In an idealized mathematical model of this situation, there is a very serviceable pragmatic choice to make for where to draw the boundary and what factors to consider as relevant to the model. However, when these same fluid equations are applied to model atmospheric weather there is no

---

[10] Even simple objects can be described from different perspectives, always discovering new aspects and attributes. However, in the case of complex systems, using multiple representations is presented here as the *only* suitable epistemic strategy to capture their complexity.

> obvious choice for where to place the cut between weather system and other systems as well as for what the relevant versus irrelevant factors are.

An aspect that is much less considered is that, in the modeling process, it is also infeasible to include all the system-environment interactions:

> Every definition of a system partitions the world into two parts, namely the system and its ambiance. Importantly, the idealization process that leads to a model does not only involve the simplification of the internal dynamics of the system, but also an idealization of the system-ambiance interactions either by ignoring them all together, or by modelling them in terms of sinks (output) or sources (input). No equivalent of ambiance can be present in the model as ambiance. If it were, it would simply have comprised an extra element of the system, enlarging the system boundaries (Chu et al., 2003, 23).

The idealization of the system-environment relationship can depend on the amplitude of the context considered, e.g. where the cut that identifies what is 'environment' for that system is placed (thus also what external elements the system is considered connected and casually related to). Researchers should not only restrain the focus to 'proximate' factors or events. For instance, to comprehend and address climate change, it is crucial to investigate the impact on the Earth's climate, beginning with the Industrial Revolution, of the human-induced release of substantial amounts of carbon dioxide and other greenhouse gases into the atmosphere. It also requires understanding how surpassing a critical threshold in the global average temperature could set off a series of self-reinforcing feedback loops in the interconnected Earth system, potentially leading to a domino effect with massive consequences at the ecological and socioeconomic levels, too (Steffen et al., 2018). Furthermore, it involves considering how much broad transformative changes, such as decarbonization scenarios, would contribute to its mitigation.

Models are thus the result of idealization processes and inherently involve a reduction of the system's complexity, necessitating consideration of the observer's role. Before going further, something more should be said about this role. Indeed, even the process of 'worlding', which precedes modeling, depends on the observer. Our perceived reality is a product of how we partition the world into systems, subsystems, and environments. This partitioning is not fixed or pre-existing in the world but is also influenced by the boundary-drawing practices of an observer, who plays an active role in shaping it (see also Barad, 2007). Particularly in the case of a complex system, it is challenging to establish – univocally and permanently – its boundaries, distinguishing it from the environment, or neatly identifying the hierarchies and subsystems forming it (Cilliers, 2005). It might be argued that certain systems (i.e. *observed* entities) exist because certain *observing* entities place borders in some specific ways. In the words of second-order cybernetics (which is still part of the complexity tradition), the mind and the world thus dynamically co-emerge, mutually specifying each other (Maturana & Varela, 1980).

In modeling, the observer's role is, in a sense, further amplified. However, it frequently occurs that the modeling process is forgotten, and the model as such is mistakenly viewed as if it were the real-world system (Mikulecky, 2000). Several modeling approaches to complex systems also assume that a single structure exists underlying complex real-world phenomena and systems, which can, apart from any possible lack of information, be fully and objectively represented by graph-theoretic models or other tools like cellular automata and multiagent simulation. Network theory, for example, characterizes the structure of complex systems in terms of nodes, corresponding to the system's elements, and edges, corresponding to the relationships or interactions between them. Nonetheless, under different research situations, what is identified as a node or a connection and the way of representing them might vary (e.g. Baker, 2013).

Generally speaking, the same complex system can be modeled differently using alternative approaches. Modeling is influenced by the researchers' theoretical or disciplinary viewpoint, research interests, and the aim of modeling. It also depends on the material and contextual conditions, including the financial and computational resources available. All these factors will contribute to determining what aspects the models focus on and what instead are disregarded. The adequacy of a modeling enterprise will thus depend on how properly it represents the complex system in question and on how satisfactorily it is able to fit the researcher's purpose in undertaking it.

Moreover, nature (or what we perceive as such) can itself, in a sense, be 'polymorphous'. Not only are complex systems constantly changing and evolving, together with their boundaries, but they are also highly nested and entangled, i.e. their parts and elements are interconnected and interrelated to one another in manifold ways. They usually include multiple, often overlapping pathways and feedback loops, making the interactions between the component parts, between the parts and the whole system and between the system and its environment very rich and dynamic.

On the one hand, the number of factors, interactions and relations to study and measure is almost countless and computer simulation can only approximate real-world situations. On the other, thinking about the brain, living systems, ecosystems, and societies, which are made up of a highly entangled structure of parts and subsystems – e.g. neurons and synapses, cells and protein pathways, organisms and ecological niches, social agents and structures – it is unlikely that they can be partitioned in a single way. Instead, multiple crosscutting joints can usually be found (e.g. Dupré, 1993). This is another reason why there is not necessarily only a single type of mathematical network that can be built for the same system or a single interpretation.

For example, the cell is made up of highly interconnecting and interacting subsystems and parts, including proteins that themselves tend to form complexes and pathways, clustering into highly interconnected networks and subnetworks (Parrish et al., 2007; Schwikowski et al., 2000). Depending on which structural and dynamical elements are considered, different networks can be created to study the cell and identify the genes and proteins that play a key role in cellular processes. For instance, Klein et al. (2012) point out that, in metabolic networks, nodes can be metabolites or reactions, and edges can be, respectively, reactions or shared metabolites. Several other networks can be built, such as gene regulatory networks (where nodes correspond to transcriptional regulators and their targets, which are linked together by arcs) and protein–protein interaction networks (where nodes are proteins and edges indicate their physical interactions). Likewise, just as the factors and aspects considered conceptually and empirically can vary, even the importance of a node is appraisable in several different ways. Notably, Klein et al. (2012, 421) depict the cell as a "network of networks" in which complex and continuous interactions occur, even between different levels. It is thus important to build integrated models (e.g. modeling metabolism and gene regulation together) to investigate them. In their view, the cell is also a highly dynamic environment, in which “regulatory connections and feedbacks change the network’s connectivity depending on the physiological state” (ibid., 426), and the properties of genes and proteins often change too. In this framework, the different models and networks might somehow turn out to be ‘integrable’, but there is still enough room to study the cell in multiple ways and produce not only complementary but also divergent outcomes.

Even beyond the modeling relation *strictu senso*, studying complex systems through a single mode of description, or concentrating on a single organizational level, is rarely suitable. As noted earlier, a combination of bottom-up and top-down approaches is required in the case of minimally decomposable systems. In brain research, for example, instead of focusing exclusively on individual neurons as structural and functional units of nervous systems – thus neglecting to consider neuron-neuron interactions – or on the interconnections between the neurons (represented by neural network models) – therefore overlooking the intraneural processes – it is necessary to include both (Yuste, 2015). Systems biology also uses multiscale research strategies and modelling. These strategies integrate information at different lengths and time scales (e.g. Martins et al., 2010) or, more generally, study biological systems from multiple viewpoints by simultaneously implementing bottom-up and top-down methods at various levels (De Backer et al., 2010).

6 Conclusion

The article has not dwelt on searching for a unified definition that, based on a common essence, would apply to all forms of what is usually termed ‘complex systems’ or to account for them based on a common mechanism, as discovered by some sort of general theory of complexity (Taborsky, 2014). The issue is not only whether such a common essence or universal laws of complexity exists or not and, if so, what they can explain, but also what view of science they reflect: a view that likely grounds on the premise that, behind the (superficial) multiplicity and complexity of phenomena, reality is essentially ‘simple’ (Chu et al., 2003). In a sense, as Morin (2007) highlights, complexity is recognized but ‘decomplexified’ at the same time. The alternative hypothesis that an inherent dynamic complexity underlies the world is not considered (e.g. Richardson, 2005).

It is worthwhile for scientific interest to investigate if and how diverse phenomena and issues, disconnected at first sight, are explainable based on a common theoretical approach. Complexity grounds in physics, whose tendency is to seek the underlying connections and similarities that unite broad ranges of phenomena, usually looking for simplicity within the complex. It might be incidental that no comprehensive laws have yet been discovered, although some putative principles, e.g. the ‘edge of chaos’ and ‘self-organized criticality’, have been suggested.

However, rather than only drawing parallels between very different systems, a complementary strategy is also needed. The ‘right level of abstraction’ (Holland, 1994) to describe complexity is the one that can accommodate the various conditions making up complex systems and their rich phenomenology. Indeed, despite some common features (e.g. nonlinear behavior, self-organization, radical openness), different types can be identified. Dissipative structures (Bénard cells) and living systems have been analyzed as examples of such types.

The article's purpose was not to formulate a typology of complex systems. Instead, it was to investigate the mechanisms generating complexity and heterogeneity, focusing on the properties empirically characterizing them and how they combine and interact. A networked notion of complex systems has been advocated, which refers to a broad ensemble of types and forms related to each other in multiple ways.

At the same time, the article also honed in on the epistemic role of an observer in grasping and studying complexity. It highlighted that complex systems, especially those with highly entangled parts, cannot be suitably represented by a single model or description. Multiple models or descriptions (even beyond physics) are often needed to reach a broader understanding of a complex system or to address specific contextual needs. While these models or descriptions may overlap, they are not necessarily consistent or integrable. Each is relative to a particular vantage point, such as a given theoretical view or research interest, which focuses on specific aspects of the system and can involve distinct ways of interacting with and decomposing it. Each has its blind spots and cannot provide a complete account of a complex system (e.g. Mitchell, 2003). However, combining them might complement each other, allowing researchers to acquire comprehensive knowledge. In this context, a pluralist approach is thus a highly valuable research strategy, fostering the accomplishment of broader scientific findings about complex systems.

To conclude, it makes sense to scrutinize whether some minimal 'distinguishing' feature is attributable to complex systems of all types, i.e. sort of basic generator of complexity. It should be neither an 'essence' (in the sense discussed so far) nor something trivially applicable yet incapable of offering new insight into the nature of these systems. For example, in his definition of a complex system, Estrada (2023), following Morin's (1992a), suggests focusing on the particular nature of the interactions between the system's elements. Specifically, interactions are "transformers of the nature of the interacting objects and of the whole formed by them". To put it simply, "interactions transform interactors". Similarly, Strevens (2005, 532), describing them as nondecomposable systems, argues that in complex systems, "parts sometimes interact in ways that have potentially radical consequences for the interactors".

Morin (2007) also remarks that the term 'complex' originates from the Latin *complexus*, indicating what is 'woven together'. Here, it is suggested that a basic condition for complexity is 'organized relatedness' to readapt a term of the British emergentist Lloyd Morgan (1923). In this regard, an 'internal' and (some sort of) 'external' aspect should be distinguished. The internal one corresponds to how the system's parts are interconnected and depend on each other and the kinds of interactions and processes occurring in the context of this relatedness. Along with that, complex systems are usually deeply interconnected and interdependent with their environment, corresponding to the external aspect. Both aspects notably impact (sometimes transform) all the 'interactors' involved at all levels.

At a very basic level, a key difference compared to 'non-complex' systems – including 'complicated' systems – resides in this notion of organized relatedness, which applies to both Bénard cells and living systems. Even a complicated system (e.g. a mechanical system like an aircraft) can consist of many elements that interact (sometimes nonlinearly). However, unlike a complex one, a complicated system is externally controlled. It lacks the degree of internal interconnectedness and control that would be required to generate collective adaptive behaviours (e.g. Van de Vijver et al., 2003).

From a certain point of view, the degree of complexity depends on the shape taken by this distinguishing feature that, focusing now on its internal aspect, can also be viewed as a kind of 'coherence' (from the Latin *co-haerere*). The elements and component parts of a complex system are, in fact, not just aggregated but closely 'tied together', according to some rule, to form a cohesive unity. In principle, the higher the internal coherence, the more the relatedness is organized, the more complex the system is.[11,12]

Only when its elements are entangled in such a way can a complex system come to exist as such, in some cases acquiring the property of being autonomous. In biological systems, such a property depends on a dynamic and flexible coherency of processes and operations governed by internal information. This ensures that the system preserves its integrity and organization in response to environmental and internal variations. In other words, the 'systemic closure' mentioned before allows biological systems to maintain their coherence while living in interaction with their environment, with which they are strongly interconnected and co-evolve.

From the generation of stable patterns to the condition of being autonomous, all the systems involved can be said to belong to the same class of complex systems. However, it should be acknowledged that such a class is diversified – there are not only one but several ways to be a complex system – and, in a way, still evolving.

Author Contributions Fulvio Mazzocchi is the unique author of this manuscript.

Funding Open access funding provided by Consiglio Nazionale Delle Ricerche (CNR) within the CRUI-CARE Agreement.

Data Availability No datasets were generated or analysed during the current study.

Declarations

Competing Interests The authors declare no competing interests.

---

[11] Significantly, among the criteria for quantitatively measuring a system's level of complexity, together with logical depth and algorithmic complexity (e.g. Ladyman et al., 2013), proposals focused on its internal connectivity, i.e. the more interconnections between its component parts, the greater its complexity (Goguen & Varela, 1979). At any rate, as noted in Sect. 4, establishing the complexity level in an absolute sense proves problematic.

[12] Internal coherence is not incompatible with internal conflict. A complex system cannot be understood unless the dialectic between harmony and conflict is considered. Von Bertalanffy (1950, 153–154.) already argued that "Every whole is based upon the competition of its elements, and presupposes the 'struggle between its parts' (…) The latter is a general principle of organisation in simple physio-chemical systems as well as in organisms and social units". Morin (1992b) uses 'organizational antagonism' instead, remarking how internal antagonism and conflict play a role in the overall organization and how the very idea of organization involves the ability to connect the differences into a unity without eliminating them: 'everything that forms transforms' (the parts and differences are transformed into elements of an organized whole).

References

Abel, D. L., & Trevors, J. T. (2006). Self-organization vs. self-ordering events in life-origin models. *Physics of Life Reviews*, *3*, 211–228.

Alhadeff-Jones, M. (2008). Three generations of complexity theories: Nuances and ambiguities. *Educational Philosophy and Theory*, *40*, 66–82.

Baker, A. (2013). Complexity, networks, and non-uniqueness. *Foundations of Science*, *18*, 687–705.

Barabási, A. L. (2012). The network takeover. *Nature Physics*, *8*, 14–16.

Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks. *Science*, *286*, 509–512.

Barad, K. (2007). *Meeting the universe halfway. Quantum physics and the entanglement of matter and meaning*. Duke University Press.

Bechtel, W. (2012). Explanation: Mechanism, modularity, and situated cognition. In P. Robbins, & M. Aydede (Eds.), *Cambridge handbook of situated cognition* (pp. 155–170). Cambridge University Press.

Bechtel, W., & Richardson, R. C. (2010). *Discovering complexity: Decomposition and localization as strategies in scientific research*. MIT Press.

Bedau, M. (2003). Downward causation and autonomy in weak emergence. *Principia*, *6*, 5–50.

Bertuglia, C. S., & Vaio, F. (2005). *Nonlinearity, chaos and complexity: The dynamics of natural and social systems*. Oxford University Press.

Bich, L. (2012). Complex emergence and the living organization: An epistemological framework for biology. *Synthese*, *185*(2), 215–232.

Bich, L., & Bechtel, W. (2022). Organization needs organization: Understanding integrated control in living organisms. *Studies in History and Philosophy of Science*, *93*, 96–106.

Bich, L., Mossio, M., Ruiz-Mirazo, K., & Moreno, A. (2016). Biological regulation: Controlling the system from within. *Biology and Philosophy*, *31*(2), 237–265.

Bishop, R. C. (2008). Downward causation in fluid convection. *Synthese*, *160*, 229–248.

Bishop, R. C. (2012). Fluid convection, constraint and causation. *Interface Focus*, *2*(1), 4–12.

Bruggeman, F. J., Westerhoff, H. V., & Boogerd, F. C. (2002). BioComplexity: A pluralist research strategy is necessary for a mechanistic explanation of the 'live' state. *Philosophical Psychology*, *15*, 411–440.

Busse, F. (1978). Non-linear properties of thermal convection. *Reports on Progress in Physics*, *4*, 1929–1967.

Campbell, D. T. (1974). Downward causation in hierarchically organized biological systems. In F. Ayalaand, & T. Dobzhansky (Eds.), *Studies in the philosophy of biology* (pp. 179–186). University of California Press.

Chong, L., & Ray, L. B. (2002). Whole-istic Biology. *Science*, *295*(5560), 1661.

Chu, D. (2011). Complexity: Against systems. *Theory in Biosciences*, *130*(3), 229–245.

Chu, D., Strand, R., & Fjelland, R. (2003). Theories of complexity: Common denominators of complex systems. *Complexity*, *8*, 19–30.

Cilliers, P. (2005). Knowledge, limits and boundaries. *Futures*, *17*, 605–613.

Cornish-Bowden, A., Cardenas, M. L., Letelier, J. C., Andrade, S., J., & Guíñez Abarzúa, F. (2004). Understanding the parts in terms of the whole. *Biology of the Cell*, *96*, 713–717.

Cross, M., & Hohenberg, P. (1993). Pattern formation outside of equilibrium. *Reviews of Modern Physics*, *65*, 851–1112.

Crutchfield, J. P. (1994). Is anything ever new? Considering emergence. In G. A. Cowan, D. Pines, & D. Meltzer (Eds.), *Complexity: Metaphors, models and reality* (pp. 515–533). Westview.

De Backer, P., De Waele, D., & Van Speybroeck, L. (2010). Ins and outs of systems biology vis-à-vis molecular biology: Continuation or clear cut? *Acta Biotheoretica*, *58*, 15–49.

De Lorenzana, J. M. A. (1998). Self-organization and self-construction of order. In Van de G. Vijver, G. S. N. Salthe, & M. Delpos (Eds.), *Evolutionary systems* (pp. 67–78). Kluwer Academic.

De Wolf, T., & Holvoet, T. (2005). Emergence versus self-organisation: Different concepts but promising when combined. In S. A. Brueckner, Di G. Marzo, A. Serugendo, Karageorgos, & R. Nagpal (Eds.), *Engineering Self-Organising systems* (pp. 1–15). Springer.

Dupré, J. (1993). *The disorder of things: Metaphysical foundations for the disunity of science*. Harvard University Press.

El-Hani, C. N., & Emmeche, C. (2000). On some theoretical grounds for an organism-centered biology: Property emergence, supervenience, and downward causation. *Theory in Biosciences*, *119*, 234–275.

El-Hani, C. N., & Pereira, A. N. (2000). Higher-level descriptions: Why should we preserve them? In P. B. Andersen, C. Emmeche, N. O. Finnemann, & P. V. Christiansen (Eds.), *Downward causation: Minds, bodies and matter* (pp. 118–142). Aarhus Universitetsforlag.

Emmeche, C., Køppe, S., & Stjernfelt, F. (2000). Levels, emergence, and three versions of downward causation. In P. B. Andersen, C. Emmeche, N. O. Finnemann, & P. V. Christiansen (Eds.), *Downward causation: Minds, bodies and matter* (pp. 13–34). Aarhus Universitetsforlag.

Estrada, E. (2023). What is a complex system, after all? *Foundations of Science*. https://doi.org/10.1007/s10699-023-09917-w

Goguen, J. A., & Varela, F. J. (1979). Systems and distinctions; duality and complementarity. *International Journal of General Systems*, *5*(1), 31–43.

Green, S., Şerban, M., Scholl, R., Jones, N., Brigandt, I., & Bechtel, W. (2018). Network analyses in systems biology: New strategies for dealing with biological complexity. *Synthese*, *195*(4), 1751–1777.

Halley, J. D., & Winkler, D. A. (2008). Consistent concepts of self-organization and self-assembly. *Complexity*, *14*(2), 10–17.

Heylighen, F., Cilliers, P., & Gershenson, C. (2007). Complexity and philosophy. In J. Bogg, & E. Geyer (Eds.), *Complexity, science and society* (pp. 117–134). Radcliffe Publishing.

Hofmeyr, J. H. S. (2007). The biochemical factory that autonomously fabricates itself: A systems biological view of the living cell. In F. Bruggeman, F. C. Boogerd, J-H-S. Hofmeyr, & H. V. Westerhoff (Eds.), *Systems biology: Philosophical foundations* (pp. 217–242). Elsevier.

Holland, J. H. (1994). Echoing emergence: Objectives, rough definitions, and speculations for ECHO-class models. In G. A. Cowan, D. Pines, & D. Meltzer (Eds.), *Complexity: Metaphors, models, and reality* (pp. 309–333). Addison-Wesley.

Hooker, C. A. (2013). On the import of constraints in complex dynamical systems. *Foundations of Science*, *18*(4), 757–780.

Hulswit, M. (2005). How causal is downward causation? *Journal for General Philosophy of Science*, *36*(2), 261–287.

Huneman, P. (2010). Topological explanations and robustness in biological sciences. *Synthese*, *177*(2), 213–245.

Juarrero, A. (2002). Complex, dynamical systems and the problem of identity. *Emergence*, *4*, 94–104.

Kaiser, M. I. (2011). The limits of reductionism in the life sciences. *History and Philosophy of the Life Sciences*, *33*, 453–476.

Karsenti, E. (2008). Self-organization in cell biology: A brief history. *Nature Reviews Molecular Cell Biology*, *9*, 255–262.

Kim, J. (1999). Making sense of emergence. *Philosophical Studies*, *95*, 3–36.

Klein, C., Marino, A., Sagot, M. F., Mileu, V., P., & Brilli, M. (2012). Structural and dynamical analysis of biological networks. *Briefings in Functional Genomics*, *11*(6), 420–433.

Koschmieder, E. L. (1993). *Bénard cells and Taylor vortices*. Cambridge University Press.

Ladyman, J., & Wiesner, K. (2020). *What is a complex system?* Yale University Press.

Ladyman, J., Lambert, J., & Wiesner, K. (2013). What is a complex system? *European Journal for Philosophy of Science*, *3*, 33–67.

Lewontin, R. C. (2000). *The triple helix: Genes, organism, and environment*. Harvard University Press.

Lloyd Morgan, C. (1923). *Emergent evolution*. Williams and Norgate.

MacKay, R. S. (2008). Nonlinearity in complexity science. *Nonlinearity*, *21*, T273.

Martins, M. L., FerreiraJr, S. C., & Vilela, M. J. (2010). Multiscale models for biological systems. *Current Opinion in Colloid & Interface Science*, *15*(1–2), 8–23.

Maturana, H., & Varela, F. (1980). *Autopoiesis and cognition. The realization of the living*. Reidel Publishing Company.

Mazzocchi, F. (2012). Complexity and the reductionism-holism debate in systems biology. *Wiley Interdisciplinary Reviews: Systems Biology and Medicine*, *4*(5), 413–427.

Mikulecky, D. (2000). Robert Rosen: The well-posed question and its answer– why are organisms different from machines? *Systems Research and Behavioral Sciences*, *17*, 419–432.

Mitchell, S. (2003). *Biological complexity and integrative pluralism*. Cambridge University Press.

Montevil, M., & Mossio, M. (2015). Biological organisation as closure of constraints. *Journal of Theoretical Biology*, *372*, 179–191.

Moreno, A., & Umerez, J. (2000). Downward causation at the core of living organization. In P. B. Andersen, C. Emmeche, N. O. Finnemann, & P. V. Christiansen (Eds.), *Downward causation: Minds, bodies and matter* (pp. 99–117). Aarhus Universitetsforlag.

Morin, E. (1992a). From the concept of system to the paradigm of complexity. *Journal of Social and Evolutionary Systems*, *15*(4), 371–385.

Morin, E. (1992b). *Method, 1: The nature of nature*. P. Lang.

Morin, E. (2007). Restricted complexity, general complexity. In C. Gershenson, D. Aerts, & B. Edmonds (Eds.), *Worldviews, science and us: Philosophy and complexity* (pp. 5–29). Singapore World Scientific.

Nicholson, D. J., & Dupré, J. (2018). *Everything flows: Toward a processual philosophy of biology*. Oxford University Press.

Nicolis, G., & Prigogine, I. (1977). *Self-organization in nonequilibrium systems*. Wiley.

Parrish, J. R., Yu, J., Liu, G., Hines, J. A., Chan, J. E., Mangiola, B. A., Zhang, H., Pacifico, S., Fotouhi, F., DiRita, V. J., Ideker, T., Andrews, P., Russell, L. F., & Jr, R. L. (2007). A proteome-wide protein interaction map for Campylobacter jejuni. *Genome Biology*, *8*(7), R130.

Powell, A., & Dupré, J. (2009). From molecules to systems: The importance of looking both ways. *Studies in History and Philosophy of Biological and Biomedical Sciences*, *40*, 54–64.

Rathkopf, C. (2015). Network representation and complex systems. *Synthese*, *195*, 55–78.

Richardson, K. (2005). The hegemony of the physical sciences: An exploration in complexity thinking. *Futures*, *37*(7), 615–653.

Rickles, D., Hawe, P., & Shiell, A. (2007). A simple guide to chaos and complexity. *Journal of Epidemiology and Community Health*, *61*, 933–937.

Rosen, R. (1987). On complex systems. *European Journal of Operational Research*, *30*, 129–134.

Ruiz-Mirazo, K., Peretó, J., & Moreno, A. (2004). A universal definition of life: Autonomy and open-ended evolution. *Origins of Life and Evolution of the Biosphere*, *34*(3), 323–346.

Schwikowski, B., Uetz, P., & Fields, S. (2000). A network of protein-protein interactions in yeast. *Nature Biotechnology*, *18*, 1257–1261.

Simon, H. A. (1962). The architecture of complexity: Hierarchic systems. *Proceedings of the American Philosophical Society*, 106, 467–482.

Steffen, W., Rockström, J., Richardson, K., Lenton, T. M., Folke, C., Liverman, D., Summerhayes, C. P., Barnosky, A. D., Cornell, S. E., Crucifix, M., Donges, J. F., Fetzer, I., Lade, S. J., Scheffer, M., Winkelmann, R., & Schellnhuber, H. J. (2018). Trajectories of the Earth system in the Anthropocene. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(33), 8252–8259.

Strevens, M. (2005). How are the sciences of complex systems possible? *Philosophy of Science*, *72*, 531–556.

Taborsky, P. (2014). Is complexity a scientific concept? *Studies in History and Philosophy of Science*, *47*, 51–59.

Talaat, A. M., Lyons, R., Howard, S. T., & Johnston, S. A. (2004). The temporal expression profile of Mycobacterium tuberculosis infection in mice. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(13), 4602–4607.

Van de Vijver, G., Van Speybroeck, L., & Vandevyvere, W. (2003). Reflecting on complexity of biological systems: Kant and beyond? *Acta Biotheoretica*, *51*(2), 101–140.

von Bertalanffy, L. (1950). An outline of general system theory. *British Journal for the Philosophy of Science*, *1*, 134–165.

Whitesides, G. M., & Boncheva, M. (2002). Beyond molecules: Self-assembly of mesoscopic and macroscopic components. *Proceedings of the National Academy of Sciences of the United States of America*, *99*(8), 4769–4774.

Wilson, J. (2016). Metaphysical emergence: Weak and strong. In T. Bigaj, & C. Wüthrich (Eds.), *Metaphysics in contemporary physics* (pp. 251–306). Brill.

Yin, G., & Herfel, W. (2011). Constructing post-classical ecosystems ecology. In C. Hooker (Ed.), *Philosophy of complex systems* (pp. 389–420). Elsevier.

Yuste, R. (2015). From the neuron doctrine to neural networks. *Nature Reviews Neuroscience*, *16*(8), 487–497.

Fulvio Mazzocchi biologist and philosopher, is a senior researcher at the Institute of Heritage Science of the CNR (Italy). His research activity is focused on philosophical issues of scientific research, epistemic pluralism, philosophy of cultural heritage, and knowledge organization.