K. Hinkelman, Y. Yang, W. Zuo 2023. "Design Methodologies and Engineering Applications for Ecosystem Biomimicry: An Interdisciplinary Review Spanning Cyber, Physical, and Cyber-Physical Systems." Bioinspiration & Biomimetics. 18 (2). pp. 021001. https://doi.org/10.1088/1748-3190/acb520.

Design Methodologies and Engineering Applications for Ecosystem Biomimicry: An Interdisciplinary Review Spanning Cyber, Physical, and Cyber-Physical Systems

Kathryn Hinkelman[1], **Yizhi Yang**[1], **Wangda Zuo**[1,2]

[1] Architectural Engineering, Pennsylvania State University, University Park, PA 16802, USA

[2] National Renewable Energy Laboratory, Golden, CO 80401, USA

E-mail: `wangda.zuo@psu.edu`

Abstract. Ecosystem biomimicry is a promising pathway for sustainable development. However, while typical form- and process-level biomimicry is prevalent, system-level ecosystem biomimicry remains a nascent practice in numerous engineering fields. This critical review takes an interdisciplinary approach to synthesize trends across case studies, evaluate design methodologies, and identify future opportunities when applying ecosystem biomimicry to engineering practices, including cyber systems (CS), physical systems (PS), and cyber-physical systems (CPS). After systematically sourcing publications from major databases, the papers were first analyzed at a meta level for their bibliographic context and for statistical correlations among categorical variables. Then, we investigated deeper into the engineering applications and design methodologies. Results indicate that CPS most frequently mimic organisms and ecosystems, while CS and PS frequently mimic populations-communities and molecules-tissues-organ systems, respectively (statistically highly significant). An indirect approach is most often used for mimicry at organizational levels from populations to ecosystems, while a direct approach frequently suits levels from molecules to organisms (highly significant). Dominant themes across engineering applications include symbiotic organism search algorithms for CS and ecological network analysis for CPS, while PS applications are highly diverse. For design methodologies, this work summarizes and details ten well-documented biomimetic process models among literature, which addresses an outdated concern for a lack of systematic methods for ecosystem biomimicry. In addition to the Biomimetics Standard ISO 18458, these methods include the Natural Step and Techno-Ecological Synergy framework, among others. Further, the analyses revealed future opportunities from less utilized design methods (e.g., interdisciplinary teams tackling indirect, ecosystem-level projects) to well-established engineering concepts ready for technological advancement (e.g., implementing membrane computing for physical applications). For future studies, this review provides a comprehensive reference for ecosystem biomimetic design practices and application opportunities across multiple engineering domains.

Keywords: biomimicry, design, ecosystem, engineering, methods, sustainability, systems

Submitted to: *Bioinspir. Biomim.*

December 12 2022

Nomenclature

Abbreviations

A	Actual case study
CPS	Cyber-physical systems
CS	Cyber systems
D	Direct abstraction method
ENA	Ecological network analysis
ERS	Ecogent runtime services
H	Hypothetical case study
I	Indirect abstraction method
L	Large (population-community)
M	Medium (organism)
M/S	Modeling/simulation
NICE	Nature-inspired chemical engineering
NPD	New product development
P/I	Piloting/implementation
PS	Physical systems
R	Review
S	Small (organ-organ system)
SOS	Symbiotic organism search
SoS	System of systems
T/C	Theoretical/conceptual
TES	Techno-ecological synergy
XL	Extra-large (ecosystem)
XS	Extra-small (molecule-cell-tissue)

Variables

χ^2	Chi-square statistic
df	Degrees of freedom
N	Total sample size
n	Subset/category sample size
p	Statistical probability indicator

1. Introduction

Biomimicry is typically classified at three levels: form, process, and system [1]. While form and process biomimicry have been predominant historically, system biomimicry – commonly referred as ecosystem biomimicry or ecomimicry for short – is a promising pathway to solve complex system challenges [1, 2, 3]. At the first level, form biomimicry imitates the physical shape and structure of organisms to capture functional traits, such as lizard skin for air-to-air heat exchangers [4]. At the second level, process biomimicry reflects biological processes, such as human nervous system information processing for structural health monitoring of composite bridge structures [5]. Lastly, system biomimicry reflects the principles, patterns, and strategies of natural ecosystems [1].

In other words, a system can be defined as a set of elements or components working together towards a common purpose, while a process involves a set of actions or steps to meet a given aim, and two things of the same form look like each other. Systems often contain both forms (physical) and processes (physical, information, chemical, etc.). It is also important to note that there are at times overlapping cases between different kinds of biomimicry, as the levels are not mutually exclusive [6]. Nonetheless, while the form and process levels have found to not necessarily lead to sustainable solutions due to their imitation of only a few select features, many consider the ecosystem level a necessity for biomimicry to shift paradigms for sustainability [7, 3, 8, 9]. From henceforth, we refer to the system-level biomimicry as *ecosystem biomimicry*.

In spite of its high value potential, ecosystem biomimicry remains a nascent practice in many engineering fields, as exemplified in review studies by Hayes et al. [10] (infrastructure systems), Austin et al. [11] (buildings), Wijegunawardana and de Mel [12] (automobiles), Roni et al. [13] (electrical power systems), and Bhasin and McAdams [14] (physical engineering products). As such, it is unclear to what degree the existing biomimetic design methods are suitable for ecosystem-level applications (more background on the existing methods in section 2). To proliferate ecosystem biomimicry practices across multiple disciplines with real-world impact capabilities, this paper conducts an interdisciplinary review of ecosystem biomimicry across engineering applications, including cyber systems (CS), physical systems (PS), and cyber-physical systems (CPS). The review targets three principal objectives:

(1) to discern trends for ecosystem biomimicry across multiple engineering applications;

(2) to synthesize and evaluate design methodologies employed in previous case studies; and

(3) to identify future opportunities for biomimicry practitioners based on open research questions and literature patterns.

To address these objectives, the rest of this paper is organized as follows. Before assessing design practices for ecosystem biomimicry, the first step is to establish the baseline for best practices. Thus, section 2 provides background on the biomimetic design process and common variations among the approach. Section 3 presents the methodology followed for the systematic literature review. The results of the review are presented in section 4. This includes both contextual and statistical analyses, followed by deeper dives in engineering applications and design methodologies. The findings are discussed in section 5. Lastly, section 6 presents concluding remarks.

2. Background

Biomimetic design can take many forms in engineering practice. In both bio-inspired and traditional engineering design practices, designers have at their disposal structured procedural methods and unstructured toolbox style methods [15, 16]. Procedural methods provide a step-by-step process from conceptualization to implementation, often with iterations between steps. Examples of procedural methods include both *technology pull* and *biology push* [17], to be discussed further shortly. On the other hand, toolbox style methods provide an unstructured collection of resources for designers to select at their disposal, such as the collections of biological strategies on the online database *AskNature* [18]. While both procedural and toolbox methods are effective individually, design toolboxes often augment procedural methods by providing a wide range of selectable methods or concepts within steps (e.g., [18]), or vice versa, by informing designers about the variety of procedural methods available for different scenarios (e.g., [15]).

Although numerous biomimicry process models are available in literature (several are reviewed in [21]), all typically represent variations of the New Product Development (NPD) process. Generically, NPD is a process by which designers create a product, service, or system that end users will adopt and use [16]. The process typically involves seven iterative steps: (1) opportunity recognition, (2) idea creation, (3) idea selection, (4) idea development, (5) idea testing, (6) idea implementation, and (7) idea expansion and adoption [16]. Through this process, teams decompose the high-level idea into its parts before integrating the detailed design features back into the whole for end use. Waves of divergent/convergent ideation within individual steps also aid the NPD process [22]. In Figure 1, we summarized and mapped two

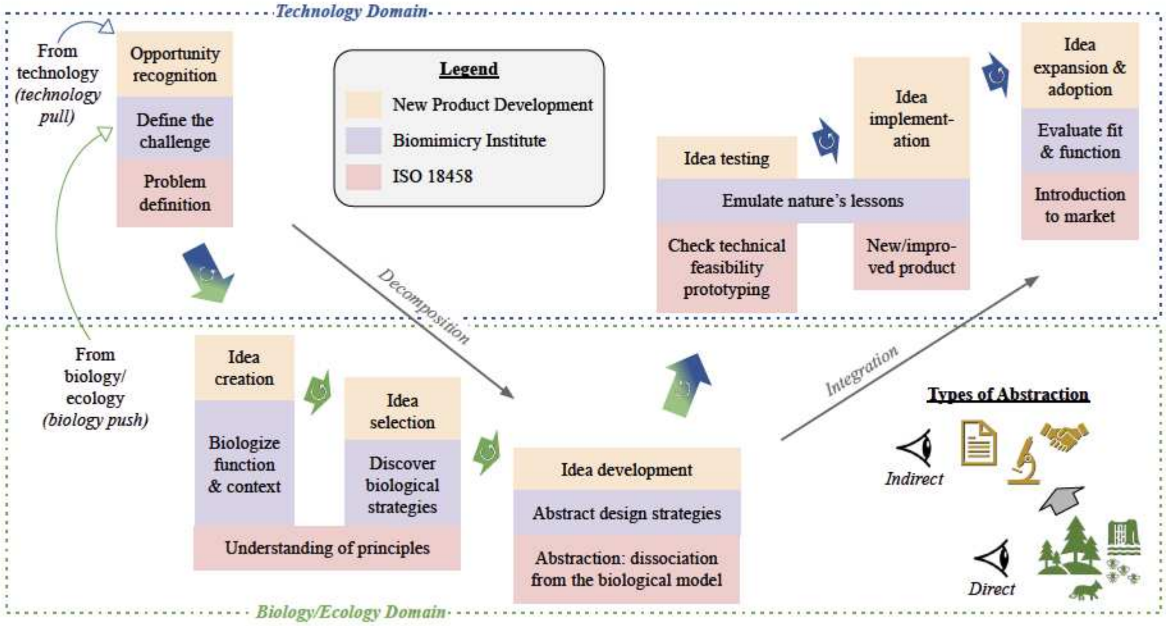


Figure 1: Typical biomimetic design processes with variants for opportunity recognition (technology pull, biology push) and abstraction (direct, indirect). We correlate the major design steps from three sources: NPD [16], the Biomimicry Institute [19], and ISO 18458 [20].

common biomimicry models to the NPD framework. These two models are the Biomimicry Institute design process [19] and the Biomimetics Standard ISO 18458 [20]. Distinguishing it from other product development processes such as NPD, a key aspect of biomimetics is the *intentional abstraction* of biological and ecological systems to technological solutions [20]. As such, biomimicry moves between technology and biology/ecology domains. The source of the recognized opportunity is distinguished as arising from technology (technology pull) or biology/ecology (biology push); within the biology domain, the type of abstraction can either be direct or indirect (more details to follow).

Technology pull and biology push represent the two major procedural design approaches for biomimicry and are the terminology adopted by ISO 18458 [20], but these terms vary across literature. The technology pull approach [20] – also commonly referred as problem-based [17], problem-driven [23], challenge to biology [24], or top down [25] – starts with recognizing a technical problem opportunity and seeks for a practical solution from the natural world. Because this approach most closely follows standard problem-solving processes, it is most commonly adopted by industry practitioners [21]. The second approach is biology push [20] (i.e., solution-based [17], solution-driven [23], biology to design [24], or bottom up [25]). This approach starts with the identification of a phenomenon or design feature in the natural world and then seeks to find a suitable application. Examples include fish swimming and leaping studies for future bioengineering applications [26] and plant stem studies to inspire technical textiles [27].

In addition, two types of abstraction – *direct* and *indirect* – can be adopted in either technology pull or biology push approaches. With the direct method, a specific example in biology or ecology is selected and studied, and design strategies are abstracted. The selection can be on any scale (from molecule to biosphere), but the defining feature is that the selection is explicit. Examples include marine invertebrates such as the tubeworm (*Phragmatopoma californica*) inspiring water-compatible adhesives [28] or the leaves of the Bird-of-Paradise flower (*Strelitzia reginae*) inspiring building façades that are adaptable, hinge-less, and louvered [29]. Conversely, the indirect approach uses general principles from nature. In this case, one cannot explicitly point to an example from nature, but reference known properties, lessons learned, and observed best practices from successful organisms and ecosystems on Earth. These general principles include self-organization, incorporating diversity, water-based chemistry, and self-similarity, among others. As an example, self-similarity is a principle found in nature that at smaller scales, there exists a smaller piece of the object or feature that is similar to that which exists at a larger scale; or defined simply, a self-similar pattern does not vary with spatial scale [30]. For more examples of indirect abstractions, Life's Principles from Biomimicry 3.8 [31] is an oft-referenced set of design guidelines gathered by biologist, engineers, and designers for numerous applications.

Lastly, it is worth noting that biomimetic design can be applied at any level in biology's organizational hierarchy. Biologists classify nature into structural levels in order to define part-whole relationships and effectively study different systems. These levels range from molecule to biosphere, and higher levels are composed of components of the lower level. In the context of engineering design, the organizational level represents the level at which the biological phenomenon was observed, abstracted, and translated for adoption in the technical product. Previous literature shows that the organ and organism levels have most frequently been mimicked in the past [14]. Meanwhile, studies at the ecosystem level are limited, and there is increased likelihood of translating high-level biological principles to products with high novelty [14]. This review addresses this important ecosystem-level opportunity gap across multiple engineering domains.

3. Methodology

The aim of this review is to synthesize engineering applications and design methodologies across multiple domains in order to identify opportunities for future research and sustainable technologies. To encompass the wide variety of engineering applications of ecosystem biomimicry, we include CS, PS, and CPS in the scope. Because of this wide scope, care must be taken to select search criteria that capture a significant number of publications that are relevant to engineering applications yet not exclusionary to individual disciplines. For example, the term "biomimicry" is most common in the United States, while "bionics" is often used in Europe [7]. Several previous ecosystem biomimicry reviews produced suggestions for search terms [3, 32]. Starting with these suggestions, the following search terms produced the most meaningful results after evaluating multiple combinations of key words and phrases:

> ecosystem AND (biomim* OR bionic* OR bio-inspir*) AND (system* OR cyber OR physical) AND engineering.

With these selected terms, this review aimed to emphasize ecosystem-level biomimicry case studies by including "ecosystem" explicitly, while including either "system*", "cyber", or "physical" expands the application scope. Further, "engineering" was a required term to concentrate the focus on technical and science-based applications as opposed to more artistic design domains (e.g., architecture, landscape design). In contrast to engineering applications, artistic design spaces have more commonly adopted ecosystem biomimicry [7, 33].

These search terms were applied in two major publication databases (Scopus and Web of Science) and across three fields (title, keywords, and abstract)‡. The database searches yielded 88 publications. Seventeen publications were duplicates between the two databases, leaving 71 unique papers. Next, a preliminary review of titles and abstracts eliminated some publications that were not relevant. For example, some publications were not biomimicry (e.g., pure scientific studies without translation to technology), while others did not involve any variety of engineering (e.g., self-declared as "not engineering", yet the term still appeared). Finally, full documents were sourced for the remaining 54 publications to be included in the detailed analyses.

For unbiased contextual analysis, we adopted the CorTexT Manager platform [34]. CorTexT is a free, online bibliometric tool for data analysis and visualization. Because two separate database sources were included, we imported the review dataset as a csv file before creating the corpus database. A terms extraction algorithm ranked the top 100 terms across all publications based on their specificity and frequency, with specificity computed as a chi-square (χ^2) score using the standard formula

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}, \tag{1}$$

where O is the observed value and E is the expected value. Per statistical methods, E is the probability of an event multiplied by the number of times the event happens. When referring to *terms* in this review, these are multi-word terms extracted from fields of title, keywords, and abstract. Monograms were excluded because they tend to produce less insightful results [34]. With CorTexT, network mapping was selected to visualize the time evolution and regularity of term co-occurrences across the publications. In addition to terms, organizational level was selected as a second category. In the map results, the nodes represent commonly occurring terms in the publications, the clusters represent the organization levels, and the edge lengths describe the regularity in which the terms/organizational levels co-occur. The number of time slices and structure of the slices (regular or homogeneous) were iteratively selected to produce the best insights regarding the time evolution of terms.

Following the contextual analysis, all publications were then statically analyzed to determine correlations among eight categorical variables (Table 1). These eight categories span both engineering application and design methodology dimensions. With respect

‡ For Web of Science, the topic (TS) field was used, which includes the title, abstract, author keywords, and keywords plus.

Table 1: Eight discrete classification categories included in the literature review.

Category name	*Included variable keys †*	*Description*
System type	CS, PS, CPS	Scope of technological innovation achieved
Case study type	A, H, R	Description of the test case(s)
Organizational level	XS, S, M, L, XL	Scale mimicked and translated into technology
Interdisciplinary team	Yes, No	Authors from uniquely different disciplines
Type of abstraction	D, I	Principles abstracted from biology/ecology
Research stage	T/C, M/S, P/I, R	Furthest stage achieved in case study
Biomimetic process rank	0, 1, 2 ‡	Method presented in paper or referenced citation
Engineering process rank	0, 1, 2 ‡	Method presented in paper or referenced citation

† See Nomenclature section or section 3 text for abbreviation definitions.

‡ Ranks include 0: no reference, 1: weak reference, 2: strong reference.

to engineering applications, the publications were classified by biological sources and application fields. The classification categories included system type: cyber systems (CS), physical systems (PS), or cyber-physical systems (CPS); case study type: actual (A), hypothetical (H), or review (R); and organization level: molecule through biosphere. For system types, there are at times blurred lines between CS and CPS applications, as implementations of CS in the real world often require physical components as well. To distinguish between these two categories, the systems were classified based on the technological innovation achieved in the current paper rather than future implementations. For complex systems in particular, case studies often mimicked biology at more than one organizational level. Because of this, levels were grouped in pairs or triplets and papers were assigned to the appropriate category. Acronyms ranging from extra-small (XS) to extra-large (XL) were assigned to aid conceptualization as

(1) molecule-cell-tissue (XS),

(2) organ-organ system (S),

(3) organism (M),

(4) population-community (L), and

(5) ecosystem (XL).

In addition to the above categories, the biological source of inspiration and the primary innovation related to the engineering application were identified.

Among the eight discrete categorical variables listed in Table 1, Pearson's χ^2 tests of independence [35] were performed to statistically determine differences between categories (Equation 1). This statistical test is highly useful because it informs not only the significance of any observed differences (e.g., in a given population, peoples' height and shirt color are statistically correlated), but also which categories account for the differences (e.g., people taller than 2m are statistically likely to wear red shirts). While the height/shirt color example is clearly fictitious, it illustrates how χ^2 tests allow us to quantitatively determine the relationships (or lack there of) between discrete categories in an unbiased way. As an indicator for statistical significance (i.e., whether the observed differences are real or only due to chance), $p-$values were calculated based on χ^2 and the degrees of freedom (df). Alpha was set at 0.05 for all statistical analyses, with $p \leq 0.001$ for highly significant differences, $0.001 < p \leq 0.01$ for significant differences, and $0.01 < p \leq 0.05$ for weakly significant differences. As an example, $p \leq 0.05$ indicates that there is strong evidence that the observed differences are not due to chance (i.e., there is less than a 5% probability that the observed results are random).

With respect to design methodologies, the analysis included categorization of approaches, ranking of robustness with respect to both engineering and biomimetic design process methodologies, and documenting of procedural design steps, when applicable. Classification categorization included design approach: technology pull or biology push; research stage: theoretical/conceptual (T/C), modeling/simulation (M/S), piloting/implementation (P/I), or review (R); and type of abstraction: direct (D) or indirect (I). The quality of documentation of the engineering and biomimetic design methodologies varied across studies. Thus, ranks were assigned from 0 to 2 based on the strength of the referenced documentation to the methodological process, with 0 corresponding to no reference, 1 to weak/minimal reference, and 2 to strong reference. To gain insight into the most promising design methodologies, the strongly-referenced biomimetic methods (rank of 2) from the literature were further detailed, including their defining features, their procedural steps (when applicable), and their use case example(s).

4. Results

All publications were first analyzed at a meta level for their bibliographic context and their statistical correlations among the eight categorical variables. To meet the target objectives, we then investigated deeper into the specific engineering applications and design methodologies, spanning CS, PS, and CPS. This section presents the results from these analyses. Table A1 of the Appendix contains a complete list of all literature include in the review. The review data is also accessible in a digital format in section *Data availability*.

4.1. Contextual analysis

Table 2 summarizes the top ten most frequent terms. Based on occurrences, "symbiotic organisms search" (SOS) and "case study" were frequently used terms. The term "SOS" also exhibited the steepest increase in usage between 2009 and 2022 across all other monogram and multi-word terms. Common terms also included environmental impacts ("climate change", "resource use"), scientific/design methods ("case study", "design principles", "design process"), and ecosystem properties ("ecosystem services", "biological ecosystems").

Table 2: Ten most frequently occurring terms across fields of title, keywords, and abstract.

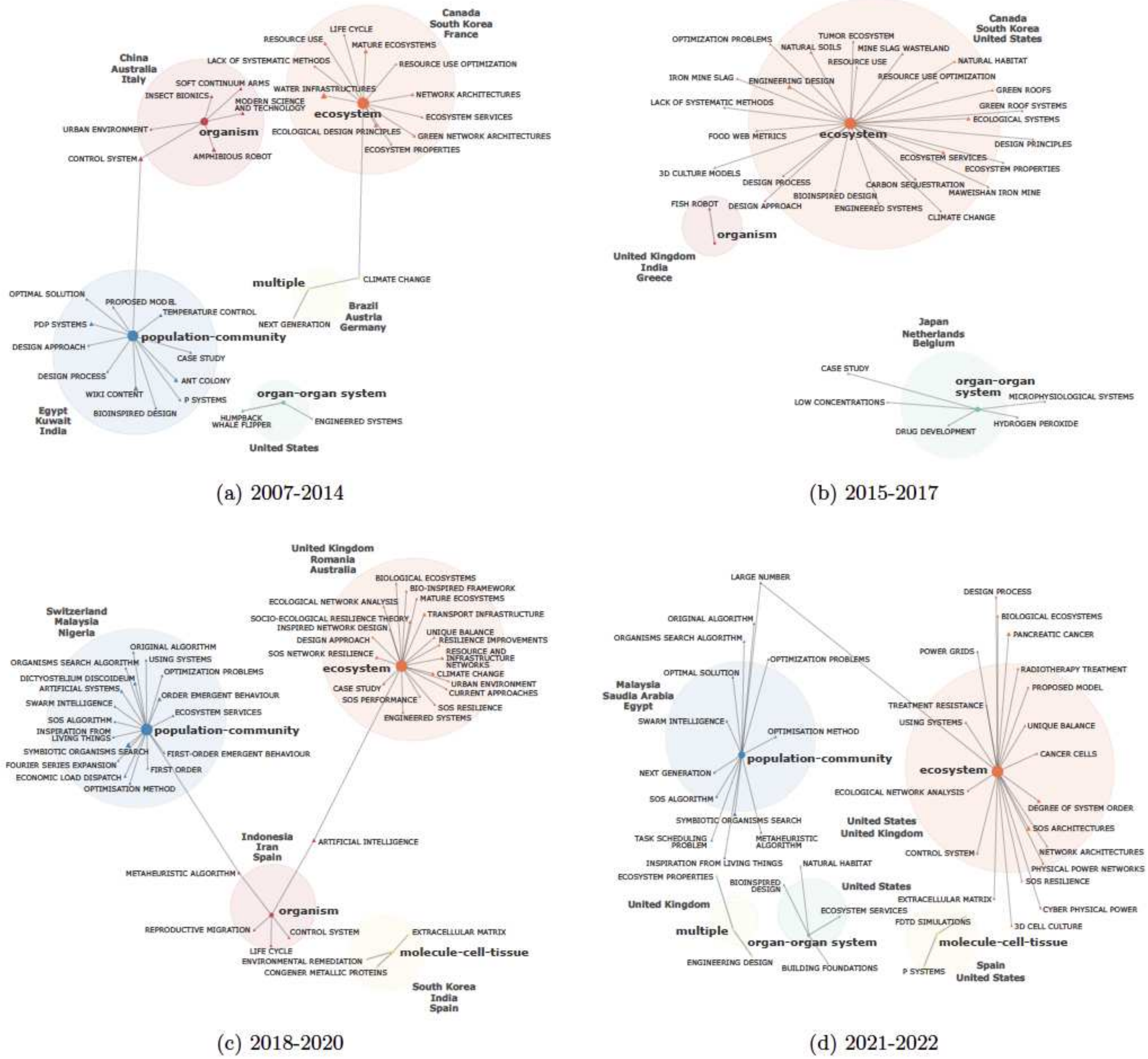
Term main form	*Occurrences*	*Cooccurrences*
symbiotic organisms search	7	25
case study	6	43
control system	5	17
climate change	5	20
design principles	4	5
resource use	4	14
organisms search algorithm	4	7
design process	4	18
ecosystem services	4	43
biological ecosystems	3	22

Over four time periods spanning 2007-2022, Figure 2 shows the network map of all publications with categories of terms (triangle nodes) and organizational level (circle nodes and shaded clusters). In this map, the edges represent the regularity in which various terms/levels co-occur across the set of publications. In addition, the top three countries corresponding to the authors' home institutions are listed with each cluster. Because the number of publications in early years were low compared to recent years (Figure 3), homogeneous time intervals produced more meaningful results compared to regular time intervals and were thus selected for the network map. The case study authors originated from 29 different countries and worked as both single-discipline and interdisciplinary teams. Across all case studies, 57% (n = 31) involved interdisciplinary teams, while all authors from the remaining 43% (n = 23) were from same or similar disciplines. Evaluating the correlation between authors' countries and terms, several countries produced high degrees of correlation. For example, authors from the United States highly correlated with "design", China with "soil", Malaysia with "symbiotic organisms search", Australia with "robot", and France with "architectures" ($p < 0.001$).

The textual network map (Figure 2) reveals common terms within each organizational level as well as similarities and differences between levels. Across all publications, terms were strongly clustered with respect to organizational level, as indicated by the lack of cluster-to-cluster connections. At the ecosystem level, publications frequently involved design, infrastructure systems, and cancer. Interestingly, the ecosystem level also contained "lack of systematic methods" as a common term across multiple documents from 2007 to 2017. Computing algorithms were predominant at the population-community level, while "extracellular matrix" occurred in both the lowest (molecule-cell-tissue) and highest (ecosystem) levels. The term "ecosystem services" commonly occurred at the ecosystem level from 2007-2017 (Figure 2a&b). However, after 2018, "ecosystem services" is not as common for ecosystem-level studies; instead, it appears as a common term for the population-community level from 2018-2020 (Figure 2c) and the organ/organ-system level from 2021-2022 (Figure 2d).

4.2. Statistical analysis

From the eight categorical variables in Table 1, a total of 28 pair-wise combinations is possible. Of these 28 pairs, 14 produced statistically significant correlations. This means that the differences we observe between the two categories are not due to chance, but real factors. Figure 4 presents the results for the 14 statistically significant pairs, including the correlation magnitude (highly significant, significant, or weakly significant) and the direction (which variables correspond to which within each of the two categories). Among these results, some statistical results followed expectations. For example, all piloting/implementation studies involved real case studies, while modeling/simulation had a mix of real and hypothetical cases, and theoretical/conceptual studies all had hypothetical cases (Figures 4 and 5, b4). Similarly, modeling/simulation studies were more likely to involve CS and CPS applications (Figures 4 and 5, a3). Numerical details regarding the statistical



(a) 2007-2014

(b) 2015-2017

(c) 2018-2020

(d) 2021-2022

Figure 2: Textual network map with two categories (organizational level and terms) divided over four homogeneous time periods. Triangle nodes represent commonly occurring terms; the clusters represent the organization levels (circle nodes and shaded regions); and the edge lengths describe the regularity in which the terms/organizational levels co-occur. The top three countries are also included at each level-based cluster.

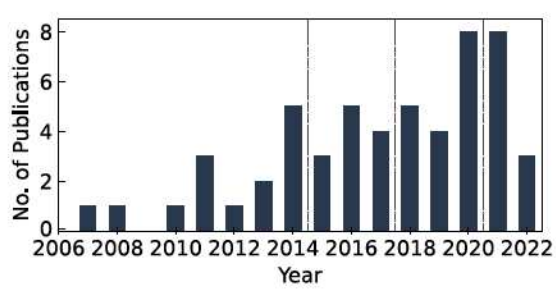
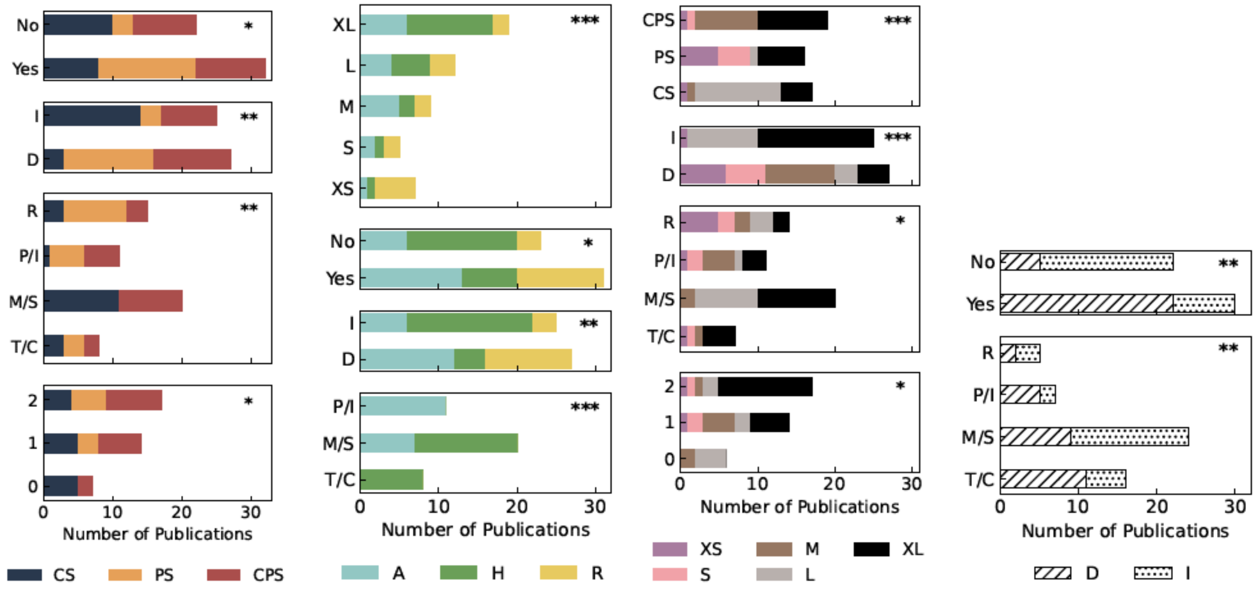


Figure 3: Number of publications over time. Vertical lines represent the time period divisions of Figure 2.

results across all pair-wise combinations are included in Table A2 of the Appendix.

The statistical analysis also revealed some surprising results. For example, CPS most frequently mimicked organisms and ecosystems, while CS and PS frequently mimicked populations-communities and molecules-tissues-organ systems, respectively (Figure 4, c1). In terms of system types, PS tend to have interdisciplinary teams (Figure 4, a1), employ a direct approach (Figure 4, a2), and contain more advanced research stages such as piloting/implementation and



(a) (b) (c) (d)

Figure 4: Distribution of publications across all statistically significant categorical pairs in groupings of (a) system type, (b) case study type, (c) organizational level, and (d) type of abstraction. The number ranks 0,1,2 in subplots a (bottom) and c (bottom) represent biomimetic process ranks. All categorical variable keys are summarized in Table 1. Asterisks within each subplot indicate statistical significance with *** for highly significant ($p \leq 0.001$), ** for significant ($0.001 < p \leq 0.01$), and * for weakly significant ($0.01 < p \leq 0.05$).

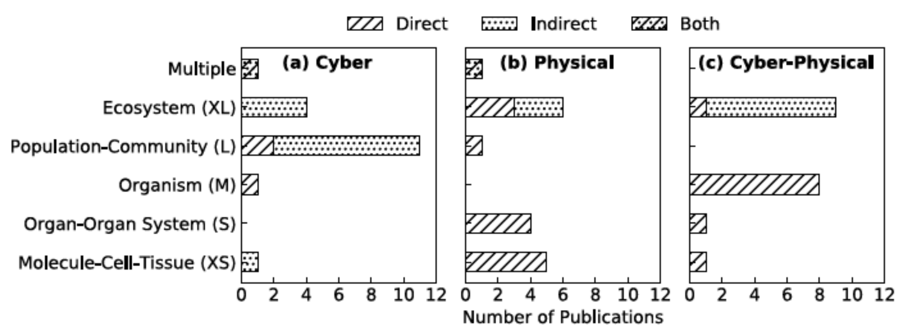


Figure 5: Distribution of biomimetic approaches for abstracting biological principles with respect to the organizational level for (a) cyber systems, (b) physical systems, and (c) cyber-physical systems.

review (Figure 4, a3). For abstraction type, interdisciplinary teams most often adopted a direct method (Figure 4, d1). An indirect method was most often used for mimicry at higher organizational levels (e.g., ecosystems), while a direct method was frequently used for lower organizational levels (e.g., cells, tissues) (Figure 4, c2).

Building upon the previous statistical analyses that evaluated two categories at a time, Figure 5 depicts the distribution of publications with respect to three categories: system type, organizational level, and type of abstraction. Within CS applications, indirect methods dominate, and these occur mostly at the population-community and ecosystem levels (Figure 5a). In contrast, direct methods dominate in PS applications, and these occur primarily at lower organizational levels from molecule to organ system (Figure 5b). At the ecosystem level in PS applications, both direct and direct methods are present. Lastly in CPS applications, indirect methods dominate at the ecosystem level, while direct methods dominate at the organism level (Figure 5c).

Table 3: Cyber system studies grouped by application category.

Application	*Details*	*Biology mimicked*	*Ref.*
Cloud computing	Standard & modified SOS	Heterogeneous swarms	[36]
	G_SOS	Heterogeneous swarms	[37]
Modeling/simulation	P-Lingua 5 (P systems)	Chemicals across cell membranes	[38]
	Survival of the fittest algorithm	Species evolution	[39]
	Modeling emergence	*Dictyostelium discoideum* (slime mold)	[40]
	Population Dynamics P systems	Population of active membranes	[41]
Generic optimization	Standard SOS	Heterogeneous swarms	[42]
	Bacterial foraging optimization	Bacteria	[43]
	Orthogonal SOS	Heterogeneous swarms	[44]
Physical networks	System of Systems (SoS) resilience	Decomposers; detritus †	[45]
	Standard SOS	Heterogeneous swarms	[46]
Sensing/control	Building temperature control	Ideal free distribution	[47]
	Ecogent; ERS platform	Ants; bees; evolution †	[48]
Web data	Ant colony optimization	Ants	[49]
	Global species database	Species biodiversity †	[50]
Other (concept model)	Cognitive regenerative design	Biological cycles †	[51]
Other (art)	Audio-visual experience	Swarm dynamics; hormones	[52]

† This study mimicked biology at an ecosystem organizational level (XL).

4.3. Engineering applications

Following the overarching contextual and statistical analyses, we dove deeper into the engineering applications. This included categorizing the general application, detailing the primary technical innovation, and identifying the biological system adopted for inspiration. Of the 54 studies, 31% ($n = 17$) were CS (e.g., optimization algorithms and controls); 31% ($n = 17$) were PS (e.g., mechanical equipment and materials); and 37% ($n = 20$) were CPS (e.g., robotic arms and buildings). In the following sections, the engineering applications are presented by system type.

4.3.1. Cyber systems Table 3 summarizes the engineering application studies involving CS. A reoccurring innovation across several CS studies is improvement upon the standard SOS algorithm. First introduced by Cheng and Prayogo [53], SOS is a stochastic, robust metaheuristic inspired by interactions among organisms in an ecosystem to survive and propagate. The symbiotic relationships represented in the algorithm include mutualism (positive-positive benefits for both organisms), commensalism (positive-neutral benefits), and parasitism (positive-negative benefits). By including these three relationship types, the search procedure can find diverse solutions in the domain space while avoiding local optima [42]. Modifications of the standard SOS abound, including both hybridization and algorithmic improvements. As some examples, G_SOS [37] simplifies the algorithm's mutualism phase to enable cloud task scheduling applications. With Orthogonal SOS [44], Panda and Pani incorporate orthogonal array strategies to enhance the exploration capacity. Further information on the standard SOS and the several modified versions are in Abdullahi et al. [42]. Beyond SOS, other nature-inspired algorithms include ant colony optimization [49], bacterial foraging optimization [43], and survival of the fittest [39].

For programming languages, P systems are a type of membrane computing that is highly paralyzed, non-deterministic, and inspired by the structure and function of living cells [38]. The structure involves various membrane systems (referred as P systems) that evolve, divide, separate, and are newly created throughout computations according to a set of rules. Pérez-Hurtado et al. [38] developed a new design of P-Lingua (a software ecosystem using P systems that also contains libraries and simulation tools), called P-Lingua 5 to allow for improved user customization and additional programming and simulation features. Modifying the standard P systems, Colomer-Cugat et al. [41] detail the modeling framework for Population Dynamics P systems and demonstrate a case study on pandemics. While membrane computing is highly promising for numerous research areas, it has yet to be applied for physical applications [38].

Additional nature-inspired CS applications involve the development of new control algorithms and networking platforms. For building applications, Pantoja et al. [47] developed a multizone temperature con-

Table 4: Physical system studies grouped by application category.

Application		*Details*	*Biology mimicked*	*Ref.*
Buildings/built environment		Marine structural foundations	Root systems	[54]
		Urban design	Ecosystem principles †	[55]
		Green roofs	Short-grass limestone prairies †	[56]
Chemical		Nature-inspired chemical engineering	Ecosystem mechanisms †	[57]
		Nanoparticle synthesis	Natural synthesis processes	[58]
		Fertilizer nano-formulations	Plant extracts; microorganisms	[59]
Environmental science		Mine slag land reclamation	Pre-development flora †	[60]
		Wastewater treatment	Microorganism proteins/peptides	[61]
Infrastructure	(transport)	Marine propulsion	Humpback whale flipper ‡	[62]
	(water)	Water infrastructure design	Ecosystem services †	[63]
Material science		Light interacting materials	Moon satyr butterfly & similar ‡	[64]
		Synthetic biology; hydrogels	Cell populations/interactions	[65]
		Mechanochromic devices	Marine organisms ‡	[66]
Medical	(oncology)	Hypoxic 3D platform	Tumor environments †	[67]
	(dentistry)	Surgery; drug delivery	Corals; seashells; sea urchins	[68]
	(oncology)	3D tumor platform	Ecosystem niche dynamics †	[69]
	(pharma)	Microfluidic biodevices	Human tissue/organ/circulation	[70]

† This study mimicked biology at an ecosystem organizational level (XL).
‡ This study falls in a gray space between form biomimicry and system biomimicry.

trol algorithm based on the concept of ideal free distribution, which specifies that all habitats are equally suitable under equilibrium conditions. Lastly, Moon and Nang [48] developed a multi-intelligent mobile agent (Ecogent) and application platform Ecogent Runtime Services (ERS) for large-scale network applications inspired by behaviors of ants and bees (agents) and evolution/stigmergy (platform controls).

4.3.2. Physical systems Table 4 summarizes the engineering application studies involving PS. Compared to CS applications, the diversity of mimicked biological systems is greater with PS applications. Further, the PS applications contained studies that can be considered edge cases between *form* biomimicry and *system* biomimicry, as highlighted in the footnote of Table 4. The PS applications vary greatly, ranging from buildings and infrastructure systems to medical platforms and chemical products. Ecosystem-level processes inspired innovations across several application domains. For example, Coppens [57] details and provides diverse examples for the systematic nature-inspired chemical engineering methodology to achieve process intensification. Apul [63] re-conceptualized water infrastructure design process models and considerations based on ecosystem services. For medical applications, Kim and Tanner [69] reviewed 3D biomimetic platforms that have been re-engineered and reverse engineered from biological systems to mitigate tumor expansion and metastasis.

In addition, several PS application innovations have been made at low organizational levels. As some examples, Asuma Janeena et al. [61] developed a biological tool based on the design and function of microorganisms to remove toxic heavy metals from wastewater. Lastly, Stachew et al. [54] abstracted 25 function-focused design features of tree roots (spanning categories of soil erosion, structural support, soil penetration, conditions for living organisms, and other multi-functions) to design building foundations for coastal climates.

4.3.3. Cyber-physical systems Table 5 summarizes the engineering application studies involving CPS. For CPS applications, the organizational level of the mimiced biological system tended to match the scale of the technical application. For example, Onoda and Preethichandra [71] designed and fabricated a biosensor inspired by the information transfer-conversion processes of organ systems to measure hydrogen peroxide in low concentrations accurately. In robotics, mimicry of entire organisms is most common, such as with insects [72], tuna fish [73], and octopus [74]. Meanwhile, mimicry of ecosystem functions is popular for physically larger systems, such as building energy systems [75], communication networks [76], and transportation networks [10].

One emerging theme for ecosystem biomimicry

Table 5: Cyber-physical system studies grouped by application category.

Application	*Details*	*Biology mimicked*	*Ref.*
Bioengineering	Biophysical model	Fish swimming/jumping	[26]
	Hydrogen peroxide biosensor	Organ system cybernetics	[71]
	Neural stem cell bioreactor	Human body	[77]
Buildings/built environment	Ecomimetic method; Eastgate	Ecosystem processes †	[78]
	Building energy systems	Ecosystem processes †	[75]
	Techno-ecological synergy	Ecosystem services/properties †	[79]
Electrical systems/devices	Resilient power grids; ENA	Food webs †	[80]
	Building integrated PV	Trees	[81]
	Bioelectronics	Silk/cellulose/seaweed/etc.	[82]
Cyber-physical networks	SoS resilience/affordability; ENA	Ecosystem structure/functions †	[83]
	SoS resilience/affordability; ENA	Ecosystem structure/functions †	[84]
	Supply chain design; ENA	Resilient ecosystems †	[85]
	Industrial resource networks	Food webs †	[86]
	Communication network architecture	Mature ecosystem principles †	[76]
Robotics	Insect robots	Butterflies/flies/beetles/etc.	[72]
	Small underwater marine robots	Octopus	[74]
	Tuna fish robot	Tuna fish	[73]
	Amphibious robot (AmBot)	Centipede	[87]
	Soft continuum arm	Octopus arm	[88]
Transportation	Socio-ecological resilience theory	Climate adaptation †	[10]

† This study mimicked biology at an ecosystem organizational level (XL).

in CPS applications is ecological network analysis (ENA). This is a systems-oriented methodology to holistically analyze interactions among trophic networks (i.e., food webs) and understand whole-ecosystem dynamics [89, 90]. It leverages input-output analysis and can represent various flow types governed by the conservation law of nature (i.e., energy, mass, currency). A classic ENA example from ecology is the Cone Spring ecosystem [91] (Figure 6). This ecosystem involves five functional players (i.e., compartments) with internal flows of energy, input/output flows with the environment, and heat dissipations (shown as ground symbols). Using quantitative ENA metrics, ecologists have studied numerous natural ecosystems to understand optimal balances between resource efficiency and redundancy/resiliency (i.e., optimal fitness), among other network qualities [92]. Designers have translated these lessons from systems ecology to create and optimize technical system of systems (SoS), including electrical power grids [80], motor supply chains [85], carpet recycling networks [86], and other social-economic-technical SoS.

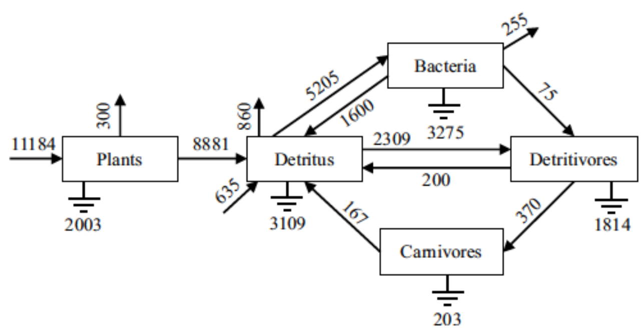


Figure 6: Trophic energy exchange (kcal/m^2/y) for Cone Spring ecosystem [91] represented as a directed graph in ENA, adopted from [92].

4.4. Design methodologies

The set of review publications employed a variety of research and biomimetic design methodologies. In terms of research methodologies, research stages included theoretical/conceptual ($n = 8$), modeling/simulation ($n = 20$), piloting/implementation ($n = 11$), and review studies ($n = 15$). Most publications involved hypothetical case studies ($n = 21$). This was followed closely by actual cases featuring real sites and examples ($n = 19$), while the remaining involved reviews ($n = 14$). In terms of biomimetic design methodologies, 87% ($n = 47$) used a technology pull approach, 9% ($n = 5$) used biology push, while the remaining two used both. Because the focus of this review was engi-

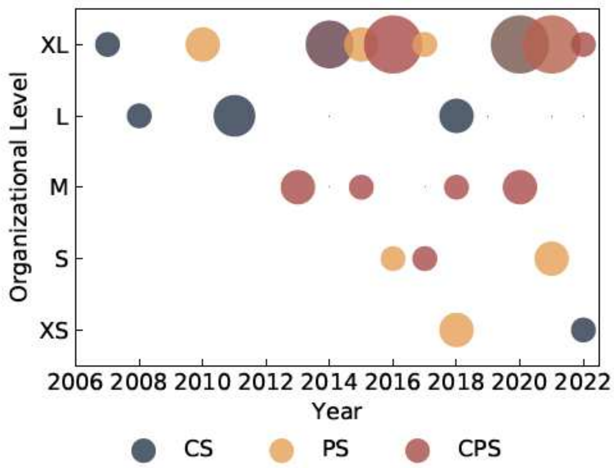


Figure 7: Sum of biomimetic process rankings with respect to time, organizational level, and system type. Mixed colors between different system types indicates the ratio of more than one type in the publication grouping. Bubble size indicates the sum of ranking points for the referenced biomimetic methodologies.

neering applications, this trend followed expectations and previous literature [21]. In terms of abstraction, 50% ($n = 27$) employed a direct method, 46% ($n = 25$) took an indirect method, and 4% ($n = 2$) used both.

With biomimetic processes ranked from 0 (no reference) to 2 (strong reference), the sum of the rankings across a group of publications can indicate the strength of the biomimetic design methods in that group. Figure 7 depicts the sum of biomimetic process ranks (indicated by the size of the bubble) with respect to time, organizational level, and system type. Even though the term "ecosystem" was required in the search parameters, only 31% ($n = 13$) of the studies involved ecosystem-level mimicry. The organizational levels of the mimicked biological systems also included molecule-cell-tissue ($n = 7$), organ-organ system ($n = 6$), organism ($n = 7$), and population-community ($n = 11$). Over time, publications shifted from population-community (L) and ecosystem (XL) to a wider spectrum of organizational levels (molecule through ecosystem), with molecule-cell-tissue (XS) becoming more common. Across the ecosystem level (XL), the strength of biomimetic process methodologies increased over time. Further, the ecosystem level (XL) contains more blending of CS, PS, and CPS applications, while lower organizational levels tended to be uniform in system type (i.e., bubbles are either CS, PS, or CPS, and not combinations of the three).

The reviewed literature contained 17 publications with strongly referenced biomimetic design processes (rank of 2), of which most adopted a procedural approach ($n = 15$) and the others a toolbox approach ($n = 2$). From these 17 publications, we identified eight unique biomimetic design process models, as well as two other application-specific models. The following sections (4.4.1–4.4.9) detail these ten methods and state the case study/studies that adopted the method.

4.4.1. ISO 18458 technology pull As could be expected, some studies [40, 47, 54] employed the internationally standardized methodology for biomimetics, ISO 18458 [20]. This method, previously presented in section 2, was adopted and mentioned explicitly in the study by Stachew et al. [54] for designign building foundations based on roots. In addition, Parhizkar and Di Marzo Serugendo [40] and Pantoja et al. [47] did not explicitly cite the standard, but the methodologies followed were consistent with this approach. The later two studies involved mimicking social amoeba for robotics control [40] and ideal free distribution in habitats for building temperature control [47].

4.4.2. Nature-inspired chemical engineering This method, developed by Coppens and referred in short as NICE [93], adopts a "predominantly physics-based approach...that abstracts and seeks universality in the fundamentals on which to base engineering design" [57]. Coppens defines four principle themes for NICE: (T1) hierarchical transport networks, (T2) force balancing; (T3) dynamic self-organization, and (T4) ecosystems, networks, and modularity [57]. The design framework contains six steps: (1) mechanism (i.e., select theme), (2) nature (i.e., identify inspiration source), (3) nature-inspired concept, (4) nature-inspired design, (5) prototype, and (6) application [57]. Several application examples are given in [57] for NICE, including a polymer electrolyte membrane fuel cell inspired by human lungs.

4.4.3. Habitat template strategy This strategy develops green roofs and façades for buildings and involves four primary steps: (1) explore and describe the wild system; (2) create a model system; (3) compare performance of the model system with the wild prototype; and (4) progressively refine the model to optimize desired functions [56]. As stated by Lundholm, "[the] term 'habitat template' refers to a quantitative description of the physical and chemical parameters that define a particular habitat and separate it from other habitats" [94]. Best et al. [56] adopted the *habitat template strategy* to design a green roof for the Botanical Research Institute of Texas that was inspired by local prairie barrens and glades.

4.4.4. Ecomimetic method This method is modeled similarly to the *design spiral* from the Biomimicry Institute [19] but specifically targets architectural applications of biomimicry. The steps consist of (1) architectural design goal, (2) ecological solution searching, (3) abstraction, (4) correlation, (5) transference, and (6) modeling and benchmarking [78]. Garcia-Holguera et al. adopt this method for two publications: one that focuses on the methodology [75], and the other that demonstrates the approach for a case study with the Eastgate Center in Zimbabwe [78].

4.4.5. Techno-ecological synergy This framework, also referred as TES [95], "was developed to account for the carrying capacity of ecosystems by quantifying the demand and supply of ecosystem services" [79]. Figure 8 depicts the system and flows of TES. The analysis accounts for interexchanges of resources and wastes between ecological and technical systems based on the operating conditions and carrying capacities of both systems. The approach involves six procedural steps: (1) defining the system, (2) demand and supply of ecosystem services, (3) inventory and models, (4) allocation, (5) impact assessment and metrics, and (6) improvement and design [95]. Bakshi et al. [79] adopts TES for four case studies, which include a residential system with urban green spaces and a biofuel system with a wetland ecosystem.

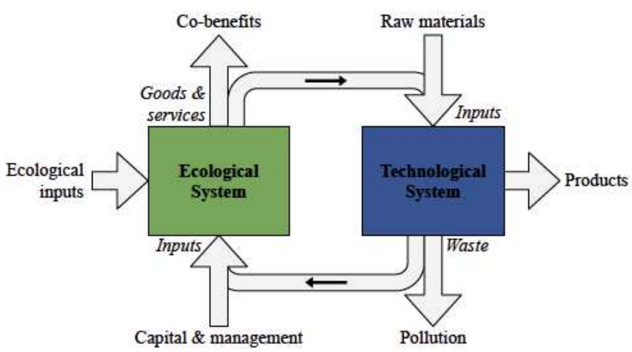


Figure 8: The techno-ecological synergy framework, adapted from Bakshi et al. [95].

4.4.6. Ecological network analysis Previously presented in section 4.3.3, ENA is a systems-oriented methodology to analyze interactions among trophic networks. Five strongly-documented case studies in this review employed ENA [45, 80, 84, 85, 86]. Comprehensive details on ENA methods and metrics are available in [89, 96].

4.4.7. Ten commandments These strategies were assembled and defined by Benyus [1] for mature ecosystems. The commandments include: (1) use waste as a resource, (2) diversify and cooperate to fully use the habitat, (3) gather and use energy efficiently, (4) optimize rather than maximize, (5) use materials sparingly, (6) don't fowl the nest, (7) don't draw down resources, (8) remain in balance with the biosphere, (9) run on information, and (10) shop locally [1]. Adopting this toolbox style method, Drouant et al. [76] developed a checklist guideline for green network architectures.

4.4.8. Natural step This approach emphasizes the *visioning* process to develop an absolute framework for sustainability, while the economic/technical steps needed to achieve the framework are retroactively determined [97]. The *Natural Step* defines four *system conditions* as rules for a sustainable society, which encompass substances in the atmosphere (both those in the lithosphere and those produced by society), the productivity/diversity of nature, and resource efficiency while meeting human needs [97]. Employing this method in a toolbox style, Apul [63] summarized indirect ecological design principles from numerous sources to create a new vision for sustainable water infrastructure.

4.4.9. Other application-specific methods Two case studies [61, 67] adopted application-specific methodologies that are untitled but well-documented. First, Asuma Janeena et al. [61] developed a methodology for biosynthesis of congener metallic proteins for heavy metal clean up inspired by microorganisms. Second, Wishart et al. [67] developed an *in vitro* tumor micro-environment for radiotherapy treatment screening that mimics the biological, physical, chemical, structural, and mechanical features of *in vivo* tissue niches. The methodology included scaffold fabrication, surface modification, and cell seeding [67].

5. Discussion

This paper reviewed engineering applications and design methodologies for the emerging field of ecosystem biomimicry across cyber, physical, and cyber-physical systems. While previous reviews indicated that ecosystem level studies are lacking [10, 12, 14], this paper took an interdisciplinary approach to address this shortcoming. After strategically sourcing papers across two major databases and preliminary filtering, the case studies were analyzed at a meta-level both contextually and statistically. Based on these results, we then discerned trends for ecosystem biomimicry across multiple engineering applications and thoroughly evaluated design methodologies. Through this process, future opportunities for biomimicry practitioners were identified.

The contextual and statistical analyses revealed unbiased trends across all publications. In Figure 2, the lack of inter-cluster connections indicate that organizational level is a strong conceptual delimiter among case studies. Future studies can use these results to understand the relation between their application space and common terms in ecosystem biomimicry literature. The statistical analysis revealed surprising trends among the eight categorical variables studied. For example, even though biomimicry is considered a highly interdisciplinary endeavor [1], only half of the publications involved authors from uniquely different disciplines. Statistically, interdisciplinary teams most often adopted a direct approach, work with PS, and be involved in actual or review case studies. Across all statistical tests, designers can use the results in Figure 4 to select best practices based on the literature or identify new design method variants that have yet to be evaluated. As an example, this review may encourage interdisciplinary teams to adopt an indirect abstraction approach, a combination that is statically lacking yet hypothetically can lead towards fruitful innovations.

Across the diverse range of engineering applications, ecosystem biomimicry principles were abstracted from biology at multiple levels in the organizational hierarchy. The fact that only 31% of the studies in this review involved ecosystem-level mimicry but all mention "ecosystem" in their title, keywords, or abstract indicates the possibility of emulating system-level biological functions at several biological scales. As mentioned in section 2, self-similarity is an indirect principle found in nature that at smaller scales, there exists a smaller piece of the object or feature that is similar to that which exists at a larger scale. Examples in nature that exhibit strong self-similarity include the fern leaf, Fibonacci spirals of nautilus shells, and distributions of species in landscape patches [98]. For ecosystem biomimetic practices in engineering applications, the results herein reinforce the self-similarity principle and expand the available biological space for divergent/convergent design ideation. Further, the evolution of ecosystem biomimicry methodologies over time reinforce this theme, as shown in Figure 7; while early ecosystem biomimicry papers focused only on high organizational levels (populations to ecosystems), the recent works span multiple organizational levels with frequency increasing in both the lowest (molecule-cell-tissue) and highest (ecosystem) scales. To proliferate ecosystem biomimicry, designers can keep an open mind to scale when seeking nature-inspired solutions to complex system problems.

While this work targeted engineering applications with system-level ecosystem biomimicry, the literature review process also reveled that the lines between form, process, and system levels can be at times obscure. As defined in section 1, a system is a set of elements or components working together towards a common purpose; but how many elements are needed to constitute a system? What are the functional requirements for the elements, if any? To our knowledge, there does not exist a universal threshold for how many elements or processes are required to be called a system, other than more than one. However, this may differ across disciplines. In this interdisciplinary review, we included the edge cases that fell between form and system levels (as noted in Table 4) so as to not overly compromise the analysis scope. However looking forward, it may be valuable for the biomimicry community to revisit the criteria for mimicking *biological systems* and adoption into *technological systems*, particularly as ecosystem biomimicry grows.

This paper focused on engineering applications of biomimicry; however, it is interesting to consider the parallel opportunities for *engineering-inspired biology.* There are many biological systems that are difficult to study directly, and functionally-equivalent engineering systems can offer valuable insights. For ENA applications as an example, the accessibility of data for engineering systems is much more readily available than natural ecosystems. Further, the data time resolution for most engineering systems (e.g., minutes to hours) is of much finer resolution compared to what is typically available for ecosystems (e.g, months to decades). By advancing ENA through engineering design, ecologists can gain insights into ecosystem-level dynamics across a much wider range of time scales.

With respect to design methodologies, a technology pull approach and structured procedural method were most common. This finding is in line with expectations. Within the scope of engineering, designers often begin the problem-solving process with a technological problem [21]. As such, they end up using a technology pull (i.e., problem driven) approach. Further, science and engineering encourage rigorous procedural methods as best practices to achieve reliable findings [99]. Indeed, well-structured design frameworks that allow for creative divergent-convergent ideation during the NPD process are most effective for engineering innovative technologies [22]. The results herein reinforce these findings for ecosystem biomimicry practices. However with that said, some papers with strongly referenced biomimetic methodologies employed an unstructured toolbox approach; this indicates that divergent ideation may have a heightened value in ecosystem biomimicry compared to typical NPD.

Lastly, this interdisciplinary review illuminated ten unique biomimetic process models in section 4.4 that build upon the well-established standards of biomimetics and NPD. This addresses the concern for a "lack of systematic methods" for ecosystem biomimicry, which was previously identified as a common term from 2007-2017 in Figure 2. However with that said, it cannot be understated how challenging complex system design and analysis remains, particularly when trying to address sustainability challenges. Among other reasons, one possible explanation for this challenge for engineering designers is that in engineering education, design is frequently only taught after a solid foundation in science and mathematics is established [22]. As a result, design is often treated as a capstone for senior students rather than an integral component throughout the degree process [22]. While many solutions to these challenges are available, this interdisciplinary review helps by synthesizing promising design methodologies across multiple engineering disciplines. Designers can leverage these findings to understand the diverse problem landscape more quickly, identify biological solutions with high impact potential, and select design methodologies that best suit their needs.

6. Conclusion

Ecosystem biomimicry is one promising approach for developing sustainable technologies by seeking natural solutions to complex system challenges. Beyond the form and process levels of biomimicry that are most common, ecosystem biomimicry is an emerging practice in engineering applications that integrate complex system functions from biology. This interdisciplinary review synthesized engineering applications and design methodologies for this emerging and promising field. Independent contextual and statistical analyses divulged bibliographic trends spanning cyber, physical, and cyber-physical systems; identified methodological variants for different application scenarios; and revealed focus areas receiving and in need of further attention. Despite an ecosystem focus, 61% of the case studies involved lower organizational levels (populations to molecules). This finding reinforces the self-similarity principle and indicates organizational level should not be an exclusionary category for biomimicry of complex systems. Although this review identified the "lack of systematic methods" as a common term among early studies, the presence of ten strongly-referenced methods addresses this concern. Furthermore, the analyses revealed a range of future opportunities, from statistically-uncommon design methods meriting exploration to well-established engineering concepts ready for technological advancement. In all, this review provides a comprehensive reference for ecosystem biomimetic design practices and application opportunities across multiple engineering domains.

Acknowledgments

This research was supported in part by an appointment with the IBUILD Graduate Student Research Program sponsored by the U.S. Department of Energy (DOE), Office of Energy Efficiency and Renewable Energy, and Building Technologies Office. This program is managed by Oak Ridge National Laboratory (ORNL). This program is administered by the Oak Ridge Institute for Science and Education (ORISE) for the DOE. ORISE is managed by ORAU under DOE contract number DESC0014664. All opinions expressed in this paper are the author's and do not necessarily reflect the policies and views of DOE, ORNL, ORAU, or ORISE. We would also like to acknowledge the generous support of the P.E.O. Scholar Award, the Pennsylvania State University (PSU) Harvey and Geraldine Brush Graduate Fellowship in Engineering, and the PSU Gordon D. Kissinger Graduate Research Fellowship. In addition, this material is based upon work supported by the National Science Foundation under Award No. 2025459.

Conflicts of interest

The authors declare no conflicts of interest.

Data availability

The data that support the findings of this study are openly available at the following URL: `https://doi.org/10.5281/zenodo.7420121`

Appendix A. Additional information

Table A1 presents identifying and general information for all publications included in the detailed review, in descending order by publication year. Table A2 summarizes the results of the statistical test results for all pair-wise combinations of categorical variables included in this study.

References

[1] Janine M Benyus. *Biomimicry: Innovation Inspired by Nature.* Harper Perennial, New York, NY, USA, 1997. ISBN 9780060533229.

[2] Maibritt Pedersen Zari and J. B. Storey. An ecosystem based biomimetic theory for a regenerative built environment. In *SB07 Portugal: Sustainable Construction, Materials and Practices: Challenge of the Industry for the New Millenium*, pages 620–627, Lisbon, Portugal, 2007.

Table A1: Identifying and classifying information for all publications.

Ref.	*Author (year)*	*System type*	*Case study type*	*Organizational level*	*Interdisciplinary team*	*Type of abstraction*	*Research stage*	*Biomimetic process rank*	*Engineering process rank*	*Document type*	*Cited by* *
[83]	Chatterjee et al. (2022)	CPS	H	XL	No	I	M/S	1	2	J	2
[38]	Pérez-Hurtado et al. (2022)	CS	H	XS	No	I	T/C	1	2	J	0
[37]	Zubair et al. (2022)	CS	H	L	No	I	M/S	0	2	J	0
[80]	Chatterjee et al. (2021)	CPS	H	XL	No	I	M/S	2	2	C	4
[84]	Chatterjee et al. (2021)	CPS	H	XL	No	I	M/S	2	2	J	7
[57]	Coppens (2021)	PS	A	†	No	†	R	‡	‡	R	6
[64]	McCoy et al. (2021)	PS	R	XS	Yes	D	R	‡	‡	R	1
[39]	Morozov et al. (2021)	CS	A	L	Yes	I	M/S	0	2	J	2
[54]	Stachew et al. (2021)	PS	H	S	Yes	D	T/C	2	2	R	1
[67]	Wishart et al. (2021)	PS	A	XL	Yes	D	P/I	2	2	J	1
[36]	Zubair et al. (2021)	CS	R	L	Yes	I	R	‡	‡	J	2
[42]	Abdullahi et al. (2020)	CS	R	L	Yes	I	R	‡	‡	R	23
[85]	Chatterjee and Layton (2020)	CPS	H	XL	No	I	M/S	2	2	J	21
[51]	Kadar and Kadar (2020)	CS	H	XL	Yes	I	T/C	1	0	C	7
[26]	Morán-López and Uceda Tolosa (2020)	CPS	H	M	Yes	D	M/S	2	2	J	3
[82]	Pradhan et al. (2020)	CPS	R	XS	No	D	R	‡	‡	R	46
[43]	Sajedi and Mohammadipanah (2020)	CS	R	M	Yes	D	R	‡	‡	R	0
[45]	Watson et al. (2020)	CS	A	XL	No	I	M/S	2	2	J	3
[55]	Wu and Zhang (2020)	PS	H	XL	No	I	T/C	1	0	C	0
[10]	Hayes et al. (2019)	CPS	R	XL	No	I	R	‡	‡	J	14
[68]	Lalzawmliana et al. (2019)	PS	R	XS	Yes	D	R	‡	‡	S	19
[65]	Millar-Haskell et al. (2019)	PS	R	L	Yes	D	R	‡	‡	J	7
[44]	Panda and Pani (2019)	CS	H	L	No	I	M/S	0	2	C	3
[46]	Gonidakis (2018)	CS	A	L	No	I	M/S	‡	‡	J	2
[61]	Asuma Janeena et al. (2018)	PS	A	XS	Yes	D	P/I	2	2	J	13
[40]	Parhizkar and Di Marzo Serugendo (2018)	CS	H	L	No	D	M/S	2	1	J	11
[77]	Sagita et al. (2018)	CPS	A	M	Yes	D	P/I	1	2	C	6
[58]	Singh et al. (2018)	PS	R	XS	Yes	D	R	‡	‡	R	900
[60]	Chen et al. (2017)	PS	A	XL	Yes	I	P/I	1	2	J	1
[59]	Gholami-Shabani et al. (2017)	PS	R	XS	Yes	D	R	‡	‡	S	10
[74]	Kazakidi et al. (2017)	CPS	A	M	Yes	D	M/S	0	1	C	3
[71]	Onoda and Preethichandra (2017)	CPS	A	S	No	D	P/I	1	2	C	0
[79]	Bakshi et al. (2016)	CPS	H	XL	No	I	M/S	2	1	C	0
[78]	Garcia-Holguera et al. (2016)	CPS	A	XL	Yes	D	M/S	2	1	J	35
[86]	Layton et al. (2016)	CPS	A	XL	Yes	I	M/S	2	2	J	53
[70]	Marx et al. (2016)	PS	R	S	Yes	D	R	‡	‡	J	278
[66]	Zeng et al. (2016)	PS	A	S	Yes	D	P/I	1	2	J	185
[73]	Ajith et al (2015)	CPS	A	M	Yes	D	P/I	1	2	C	2
[56]	Best et al. (2015)	PS	A	XL	Yes	D	P/I	2	2	S	26
[69]	Kim and Tanner (2015)	PS	R	XL	Yes	D	R	‡	‡	J	26

* Citation counts are per Google Scholar as of 8 September 2022.

† Multiple subcategories are included in this work.

‡ A cohesive ranking was not available for this publication.

Table A1: Identifying and classifying information for all publications (continued).

Ref.	*Author (year)*	*System type*	*Case study type*	*Organizational level*	*Interdisciplinary team*	*Type of abstraction*	*Research stage*	*Biomimetic process rank*	*Engineering process rank*	*Document type*	*Cited by* *
[41]	Colomer-Cugat et al. (2014)	CS	H	L	Yes	I	M/S	0	2	S	12
[87]	Cui et al. (2014)	CPS	A	M	No	D	P/I	0	2	J	14
[76]	Drouant et al. (2014)	CPS	H	XL	No	I	M/S	2	2	J	26
[75]	Garcia-Holguera et al. (2014)	CPS	H	XL	Yes	I	T/C	2	0	C	2
[72]	Liu et al. (2014)	CPS	R	M	No	D	R	‡	‡	J	4
[88]	Guglielmino et al. (2013)	CPS	A	M	Yes	D	P/I	1	1	C	8
[81]	Yin et al. (2013)	CPS	H	M	Yes	D	T/C	1	1	C	1
[50]	Wheeler et al. (2012)	CS	H	†	Yes	†	T/C	0	1	J	166
[49]	Banerjee et al. (2011)	CS	A	L	Yes	D	M/S	1	2	C	1
[62]	Fish et al. (2011)	PS	R	S	Yes	D	R	‡	‡	J	50
[47]	Pantoja et al. (2011)	CS	H	L	No	I	M/S	2	2	J	11
[63]	Apul (2010)	PS	H	XL	No	I	T/C	2	1	J	16
[52]	Jones (2008)	CS	A	L	No	I	P/I	1	2	C	30
[48]	Moon and Nang (2007)	CS	H	XL	No	I	M/S	1	2	C	2

* Citation counts are per Google Scholar as of 8 September 2022.
† Multiple subcategories are included in this work.
‡ A cohesive ranking was not available for this publication.

[3] Samantha Hayes, Cheryl Desha, and Dayna Baumeister. Learning from nature – Biomimicry innovation to support infrastructure sustainability and resilience. *Technological Forecasting & Social Change*, 161:120287, 2020. doi: 10.1016/j.techfore.2020.120287.

[4] Federico Sanchez and Shifan Zhu. Air to Air Heat Exchanger Mimicked from the Directional Passive Water Transport Featured by the Skin Morphology of Phrynosoma Cornutum. *IOP Conference Series: Materials Science and Engineering*, 649 (1):012014, 2019. doi: 10.1088/1757-899X/649/1/012014.

[5] David O. Olawale, William Sullivan, Tarik Dickens, Okenwa Okoli, and Ben Wang. Mimicking the human nervous system with a triboluminescence sensory receptor for the structural health monitoring of composite structures. In *SPIE 7981, Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2011*, volume 7981, page 798125, 2011. doi: 10.1117/12.880574.

[6] Maibritt Pedersen Zari. Biomimetic Approaches to Architectural Design for Increased Sustainability. In *SB07 New Zealand Sustainable Building Conference*, number November, page 003, New Zealand, 2007.

[7] Maibritt Pedersen Zari. *Regenerative Urban Design and Ecosystem Biomimicry*. Routledge, London, 1st edition, 2018. doi: 10.4324/9781315114330.

[8] Ingrid C. De Pauw, Elvin Karana, Prabhu Kandachar, and Flora Poppelaars. Comparing Biomimicry and Cradle to Cradle with Ecodesign: A case study of student design projects. *Journal of Cleaner Production*, 78:174–183, 2014. doi: 10.1016/j.jclepro.2014.04.077.

[9] U Tischner and M Hora. Sustainable electronic product design. In Vannessa Goodship, Ab Stevels, and Jaco Huisman, editors, *Waste Electrical and Electronic Equipment (WEEE) Handbook*, Woodhead Publishing Series in Electronic and Optical Materials, chapter 17, pages 443–482. Woodhead Publishing, 2nd edition, 2019. doi: 10.1016/B978-0-08-102158-3.00017-3.

[10] Samantha Hayes, Cheryl Desha, and Mark Gibbs. Findings of Case-Study Analysis: System-Level Biomimicry in Built-Environment Design.

Table A2: Statistical results from chi-square tests of independence. Asterisks indicate statistical significance with *** for highly significant ($p \leq 0.001$), ** for significant ($0.001 < p \leq 0.01$), and * for weakly significant ($0.01 < p \leq 0.05$).

Category 1	*Category 2*	N	*df*	χ^2	$p-value$	
System type	Case study type	54	4	7.619	0.107	
	Organizational level	52	8	44.636	< 0.001	***
	Interdisciplinary team	54	2	6.330	0.042	*
	Type of abstraction	52	2	12.642	0.002	**
	Research stage	54	6	18.203	0.006	**
	Biomimetic process rank	43	4	10.098	0.039	*
	Engineering process rank	43	4	1.419	0.841	
Case study type	Organizational level	52	8	382.079	< 0.001	***
	Interdisciplinary team	54	2	8.485	0.014	*
	Type of abstraction	52	2	13.715	0.001	**
	Research stage	39	2	20.692	< 0.001	***
	Biomimetic process rank	38	2	1.495	0.479	
	Engineering process rank	38	2	†	†	
Organizational level	Interdisciplinary team	52	4	5.863	0.210	
	Type of abstraction	52	4	26.903	< 0.001	***
	Research stage	52	12	23.284	0.0254	*
	Biomimetic process rank	37	8	18.247	0.019	*
	Engineering process rank	37	8	†	†	
Interdisciplinary team	Type of abstraction	52	1	10.373	0.001	**
	Research stage	54	3	6.804	0.078	
	Biomimetic process rank	43	2	0.048	0.976	
	Engineering process rank	43	2	0.137	0.934	
Type of abstraction	Research stage	52	3	15.257	0.002	**
	Biomimetic process rank	43	2	0.048	0.976	
	Engineering process rank	43	2	0.137	0.934	
Research stage	Biomimetic process rank	37	4	7.053	0.133	
	Engineering process rank	37	4	†	†	
Biomimetic process rank	Engineering process rank	40	4	3.473	0.482	

† Minimum required frequency of 5 not met.

Biomimetics, 4(4):1–18, 2019. doi: 10.3390/biomimetics4040073.

[11] Miguel Chen Austin, Dagmar Garzola, Nicole Delgado, José Ulises Jiménez, and Dafni Mora. Inspection of Biomimicry Approaches as an Alternative to Address Climate-Related Energy Building Challenges: A Framework for Application in Panama. *Biomimetics*, 5(3), 2020. doi: 10.3390/biomimetics5030040.

[12] I. D. Wijegunawardana and W. R. de Mel. Biomimetic Designs for Automobile Engineering: A Review. *International Journal of Automotive and Mechanical Engineering*, 18(3):9029–9041, 2021. doi: 10.15282/ijame.18.3.2021.15.0692.

[13] Md Hassanul Karim Roni, M. S. Rana, H. R. Pota, Md Mahmudul Hasan, and Md Shajid Hussain. Recent trends in bio-inspired meta-heuristic optimization techniques in control applications for electrical systems: a review. *International Journal of Dynamics and Control*, 2022. doi: 10.1007/s40435-021-00892-3.

[14] Devesh Bhasin and Daniel A. McAdams. The characterization of biological organization, abstraction, and novelty in biomimetic design. *Designs*, 2(54), 2018. doi: 10.3390/designs2040054.

[15] The Biomimicry Institute. Biomimicry Toolbox: Your guide to applying nature's lessons to design challenges, 2022. URL `https://toolbox.biomimicry.org/`.

[16] Karl T Ulrich and Steven D Eppinger. *Product Design and Development*. McGraw-Hill Education, 5th edition, 2011. ISBN 978-0073404776.

[17] Lidia Badarnah and Usama Kadri. A methodology for the generation of biomimetic design concepts. *Architectural Science Review*, 58(2):120–133, 2015. doi: 10.1080/00038628.2014.922458.

[18] The Biomimicry Institute. Energy in Nature, 2020. URL `https://asknature.org/collections/`.

[19] The Biomimicry Institute. Methods, 2015. URL `https://toolbox.biomimicry.org/methods`.

[20] ISO/TC 266. *Biomimetics — Terminology, concepts and methodology*, volume 18458. ISO, 1st edition, 2015.

[21] P. E. Fayemi, K. Wanieck, C. Zollfrank, N. Maranzana, and A. Aoussat. Biomimetics: Process, tools and practice. *Bioinspiration and Biomimetics*, 12 (1), 2017. doi: 10.1088/1748-3190/12/1/011002.

[22] Clive L. Dym, Alice M. Agogino, Ozgur Eris, Daniel D. Frey, and Larry J. Leifer. Engineering design thinking, teaching, and learning. *Engineering Education*, 94(1):103–120, 2005. doi: 10.1002/j.2168-9830.2005.tb00832.x.

[23] Michael Helms, Swaroop S. Vattam, and Ashok K. Goel. Biologically inspired design: process and products. *Design Studies*, 30(5):606–622, 2009. doi: 10.1016/j.destud.2009.04.003.

[24] Dayna Baumeister. *Biomimicry Resource Handbook: A Seed Bank of Best Practices.* CreateSpace Independent Publishing Platform, Missoula, MT, 2014. ISBN 1505634644.

[25] T. Speck and O. Speck. Process sequences in biomimetic research. *WIT Transactions on Ecology and the Environment*, 114:3–11, 2008. doi: 10.2495/DN080011.

[26] R Morán-López and O Uceda Tolosa. Biomechanics of fish swimming and leaping under waterfalls: a realistic field, image-based biophysical model with bioengineering implications. *Bioinspiration and Biomimetics*, 15:056011, 2020. doi: 10.1088/1748-3190/ab9b64.

[27] Markus Milwich, Thomas Speck, Olga Speck, Thomas Stegmaier, and Heinrich Planck. Biomimetics and technical textiles: Solving engineering problems with the help of nature's wisdom. *American Journal of Botany*, 93(10): 1455–1465, 2006. doi: 10.3732/ajb.93.10.1455.

[28] Mariana Almeida, Rui L. Reis, and Tiago H. Silva. Marine invertebrates are a source of bioadhesives with biomimetic interest. *Materials Science and Engineering C*, 108:110467, 2020. doi: 10.1016/j.msec.2019.110467.

[29] Marlén López, Ramón Rubio, Santiago Martín, and Ben Croxford. How plants inspire façades. From plants to architecture: Biomimetic principles for the development of adaptive architectural envelopes. *Renewable and Sustainable Energy Reviews*, 67:692–703, 2017. doi: 10.1016/j.rser.2016.09.018.

[30] Benoit B Mandelbrot. *The Fractal Geometry of Nature.* Freeman, 1983.

[31] Biomimicry 3.8. DesignLens: Life's Principles, 2013. URL `https://biomimicry.net/the-buzz/resources/designlens-lifes-principles/`.

[32] A. Gleich, C. Pade, U. Petschow, and E. Pissarskoi. *Potentials and Trends in Biomimetics.* Springer Berlin Heidelberg, 2010. ISBN 9783642052460.

[33] Ken Yeang. *Designing with Nature: The Ecological Basis for Architectural Design.* McGraw-Hill, 1st edition, 1995. ISBN 9780070723177.

[34] IFRIS and INRAE. CorTexT platform, 2022. URL `https://www.cortext.net/`.

[35] Karl Pearson F.R.S. X. on the criterion that a given system of deviations from the probable in the case of a correlated system of variables is such that it can be reasonably supposed to have arisen from random sampling. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, 50(302):157–175, 1900. doi: 10.1080/14786440009463897.

[36] Ajoze Abdulraheem Zubair, Shukor Bin Abd Razak, Asri Bin Ngadi, and Aliyu Ahmed. Current Perspective of Symbiotic Organisms Search Technique in Cloud Computing Environment: A Review. *International Journal of Advanced Computer Science and Applications*, 12(6):446–453, 2021. doi: 10.14569/IJACSA.2021.0120650.

[37] Ajoze Abdulraheem Zubair, Shukor Abd Razak, Asri Ngadi, Arafat Al-dhaqm, Wael M. S. Yafooz, Abdel-Hamid M. Emara, Aldosary Saad, and Hussain Al-Aqrabi. A Cloud Computing-Based Modified Symbiotic Organisms Search Algorithm (AI) for Optimal Task Scheduling. *Sensors*, 22(4): 1674, 2022. doi: 10.3390/s22041674.

[38] Ignacio Pérez-Hurtado, David Orellana-Martín, Miguel A Martínez-del Amor, Luis Valencia-Cabrera, and Agustín Riscos-Núñez. A new P-Lingua toolkit for agile development in membrane computing. *Information Sciences*, 587:1–22, 2022. doi: 10.1016/j.ins.2021.12.003.

[39] Andrew Yu Morozov, Oleg A Kuzenkov, and Simran K Sandhu. Global optimisation in Hilbert spaces using the survival of the fittest algorithm. *Communications in Nonlinear Science and Numerical Simulation*, 103:106007, 2021. doi: 10.1016/j.cnsns.2021.106007.

[40] Mohammad Parhizkar and Giovanna Di Marzo Serugendo. Agent-based models for first- and second-order emergent collective behaviours of social amoeba Dictyostelium discoideum aggregation and migration phases. *Artificial Life and Robotics*, 23(4):498–507, 2018. doi: 10.1007/s10015-018-0477-3.

[41] M A Colomer-Cugat, M García-Quismondo, L F Macías-Ramos, M A Martínez-del Amor, I Pérez-Hurtado, M J Pérez–Jiménez, A Riscos-Núñez, and L Valencia-Cabrera. Membrane System-Based Models for Specifying Dynamical Population Systems. In P Frisco, M Gheorghe, and M J Pérez–Jiménez, editors, *Applications of Membrane Computing in Systems and Synthetic Biology*, volume 7 of *Emergence Complexity and Computation*, pages 97–132. Springer-Verlag, Berlin, Germany, 2014. ISBN 978-3-319-03191-0; 978-3-319-03190-3. doi: 10.1007/978-3-319-03191-0_4.

[42] Mohammed Abdullahi, Asri Ngadi, Salihu Idi, and Muhammad Abdulhamid. A survey of symbiotic organisms search algorithms and applications. *Neural Computing and Applications*, 32(2):547–566, 2020. doi: 10.1007/s00521-019-04170-4.

[43] Hedieh Sajedi and Fatemeh Mohammadipanah. Developed Optimization Algorithms Based on Natural Taxis Behavior of Bacteria. *Cognitive Computation*, 12:1187–1204, 2020. doi: 10.1007/s12559-020-09760-2.

[44] Arnapurna Panda and Sabyasachi Pani. An Orthogonal Symbiotic Organisms Search Algorithm to Determine Approximate Solution of Systems. *Advances in Intelligent Systems and Computing*, 816:507–519, 2019. doi: 10.1007/978-981-13-1592-3_40.

[45] Bryan C Watson, Stephen Malone, Marc Weissburg, and Bert Bras. Adding a Detrital Actor to Increase System of System Resilience: A Case Study Test of a Biologically Inspired Design Heuristic to Guide Sociotechnical Network Evolution. *Journal of Mechanical Design*, 142:121705, 2020. doi: 10.1115/1.4048579.

[46] D Gonidakis. Symbiotic organisms search algorithm for different economic load dispatch problems. *International Journal of Bio-Inspired Computation*, 12(3):139–151, 2018. doi: 10.1504/IJBIC.2018.094623.

[47] A Pantoja, N Quijano, and S Leirens. A bioinspired approach for a multizone temperature control system. *Bioinspiration and Biomimetics*, 6:13, 2011. doi: 10.1088/1748-3182/6/1/016007.

[48] Joosun Moon and Jongho Nang. Design and Implementation of a Bio-Inspired System Platform. In *IEEE Region 10 Annual International Conference, Proceedings/TENCON*, page 4428874. IEEE, 2007. doi: 10.1109/TENCON.2007.4428874.

[49] Soumya Banerjee, Nashwa El-Bendary, and Hameed Al-Qaheri. Exploring Wiki: Measuring the Quality of Social Media Using Ant Colony Metaphor. In *The International Conference on Management of Emergent Digital EcoSystems (MEDES)*, pages 305–312, San Francisco, USA, 2011. ACM. doi: 10.1145/2077489.2077545.

[50] Q D Wheeler, S Knapp, D W Stevenson, J Stevenson, S D Blum, B M Boom, G G Borisy, J L Buizer, M R De Carvalho, A Cibrian, M J Donoghue, V Doyle, E M Gerson, C H Graham, P Graves, S J Graves, R P Guralnick, A L Hamilton, J Hanken, W Law, D L Lipscomb, T E Lovejoy, H Miller, J S Miller, S Naeem, M J Novacek, L M Page, N I Platnick, H Porter-Morgan, P H Raven, M A Solis, A G Valdecasas, S Van Der Leeuw, A Vasco, N Vermeulen, J Vogel, R L Walls, E O Wilson, and J B Woolley. Mapping the biosphere: exploring species to understand the origin, organization and sustainability of biodiversity. *Systematics and Biodiversity*, 10(1):1–20, 2012. doi: 10.1080/14772000.2012.665095.

[51] Timea Kadar and Manuella Kadar. Sustainability Is Not Enough: Towards AI Supported Regenerative Design. In *IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, page 9198554. IEEE, 2020. doi: 10.1109/ICE/ITMC49519.2020.9198554.

[52] Daniel Jones. AtomSwarm: A Framework for Swarm Improvisation. In M Giacobini, editor, *EvoWorkshops, Lecture Notes in Computer Science*, volume 4974 LNCS, pages 423–432, 2008. doi: 10.1007/978-3-540-78761-7_45.

[53] Min Yuan Cheng and Doddy Prayogo. Symbiotic Organisms Search: A new metaheuristic optimization algorithm. *Computers and Structures*, 139:98–112, 2014. doi: 10.1016/j.compstruc.2014.03.007.

[54] Elena Stachew, Thibaut Houette, and Petra Gruber. Root Systems Research for Bioinspired Resilient Design: A Concept Framework for Foundation and Coastal Engineering. *Frontiers in Robotics and AI*, 8:548444, 2021. doi: 10.3389/frobt.2021.548444.

[55] Fan Wu and Jun Zhang. Explore Urban Sustainable Ecology Construction from Bio-design Perspective. In J Charytonowicz, editor, *Advances in Intelligent Systems and Computing*, volume AISC, pages 71–77. Springer, 2020. doi: 10.1007/978-3-030-51566-9.

[56] Brooke Byerley Best, Rebecca K Swadek, and Tony L Burgess. Soil-Based Green Roofs. In Richard K Sutton, editor, *Green Roof Ecosystems*, volume 223 of *Ecological Studies-Analysis and Synthesis*, chapter 6, pages 139–174. Springer International Publishing, Cham, Switzerland, 2015. doi: 10.1007/978-3-319-14983-7_6.

[57] Marc-Olivier Coppens. Nature-Inspired Chemical Engineering for Process Intensification. *Annual Review of Chemical and Biomolecular Engineering*, 12:187–215, 2021. doi: 10.1146/annurev-chembioeng-060718-030249.

[58] Jagpreet Singh, Tanushree Dutta, Ki Hyun Kim, Mohit Rawat, Pallabi Samddar, and Pawan Kumar. 'Green' synthesis of metals and their oxide nanoparticles: applications for environmental remediation. *Journal of Nanobiotechnology*, 16 (84), 2018. doi: 10.1186/s12951-018-0408-4.

[59] Mohammadhassan Gholami-Shabani, Zeynab Gholami-Shabani, Masoomeh Shams-Ghahfarokhi, Fatemehsadat Jamzivar, and Mehdi Razzaghi-Abyaneh. Green Nanotechnology: Biomimetic Synthesis of Metal Nanoparticles Using Plants and Their Application in Agriculture and Forestry. In R. Prasad, editor, *Nanotechnology*, pages 133–175. Springer, 2017. doi: 10.1007/978-981-10-4573-8_8.

[60] L Chen, B Chai, M Liang, and F Wang. Engineering study on reclamation of Maweishan iron mine slag wasteland in Huangmei, Hubei, China. *Chinese Journal of Environmental Engineering*, 11(3):1966–1974, 2017. doi: 10.12030/j.cjee.201511205. language: Chinese.

[61] J Asuma Janeena, M Ilamaran, A George, S A George, S Sriram Raghavan, P Surya Lakshmi, M Aarthy, N R Kamini, K Gunasekaran, and N Ayyadurai. Biomimetic strategies to design metallic proteins for detoxification of hazardous heavy metal. *Journal of Hazardous Materials*, 358: 92–100, 2018. doi: 10.1016/j.jhazmat.2018.06.057.

[62] Frank E Fish, Paul W Weber, Mark M Murray, and Laurens E Howle. Marine Applications of the Biomimetic Humpback Whale Flipper. *Marine Technology Society Journal*, 45(4):198–207, 2011. doi: 10.4031/MTSJ.45.4.1.

[63] Defne Apul. Ecological design principles and their implications on water infrastructure engineering. *Journal of Green Building*, 5(3):147–164, 2009. doi: 10.3992/jgb.5.3.147.

[64] Dakota E Mccoy, Anna V Shneidman, Alexander L Davis, and Joanna Aizenberg. Finite-difference Time-domain (FDTD) Optical Simulations: A Primer for the Life Sciences and Bio-Inspired Engineering. *Micron*, 151:103160, 2021. doi: 10.1016/j.micron.2021.103160.

[65] Catherine S Millar-Haskell, Allyson M Dang, and Jason P Gleghorn. Coupling synthetic biology and programmable materials to construct complex tissue ecosystems. *MRS Communications*, 9(2): 421–432, 2019. doi: 10.1557/mrc.2019.69.

[66] Songshan Zeng, Dianyun Zhang, Wenhan Huang, Zhaofeng Wang, Stephan G Freire, Xiaoyuan Yu, Andrew T Smith, Emily Y Huang, Helen Nguon, and Luyi Sun. Bio-inspired sensitive and reversible mechanochromisms via strain-dependent cracks and folds. *Nature Communications*, 7:11802, 2016. doi: 10.1038/ncomms11802.

[67] Gabrielle Wishart, Priyanka Gupta, Andrew Nisbet, Giuseppe Schettino, and Eirini Velliou. On the Evaluation of a Novel Hypoxic 3D Pancreatic Cancer Model as a Tool for Radiotherapy Treatment Screening. *Cancers*, 13:6080, 2021. doi: 10.3390/cancers13236080.

[68] V Lalzawmliana, Prasenjit Mukherjee, Biswanath Kundu, and Samit Kumar Nandi. Clinical Application of Biomimetic Marine-Derived Materials for Tissue Engineering. In A.H. Choi and B. Ben-Nissan, editors, *Springer Series in Biomaterials Science and Engineering*, chapter 15, pages 329–356. Springer, 14 edition, 2019. doi: 10.1007/978-981-13-8855-2.

[69] Jiyun Kim and Kandice Tanner. Recapitulating the tumor ecosystem along the metastatic cascade using 3D culture models. *Frontiers in Oncology*, 5 (170), 2015. doi: 10.3389/fonc.2015.00170.

[70] Uwe Marx, Tommy B. Andersson, Anthony Bahinski, Mario Beilmann, Sonja Beken, Flemming R. Cassee, Murat Cirit, Mardas Daneshian, Susan Fitzpatrick, Olivier Frey, Claudia Gaertner, Christoph Giese, Linda Griffith, Thomas Hartung, Minne B. Heringa, Julia Hoeng, Wim H. de Jong, Hajime Kojima, Jochen Kuehnl, Marcel Leist, Andreas Luch, Ilka Maschmeyer, Dmitry Sakharov, Adrienne J. A. M. Sips, Thomas Steger-Hartmann, Danilo A. Tagle, Alexander Tonevitsky, Tewes Tralau, Sergej Tsyb, Anja van de Stolpe, Rob Vandebriel, Paul Vulto, Jufeng Wang, Joachim Wiest, Marleen Rodenburg, and Adrian Roth. Biology-Inspired Microphysiological System Approaches to Solve the Prediction Dilemma of Substance Testing. *Altex*, 33(3):272–321, 2016. doi: 10.14573/altex.1603161.

[71] Mitsuyoshi Onoda and Daluwathu M G Preethichandra. Detection of Environmental Pollutants with Oxidoreductases. In *The International Symposium on Electrical Insulating*

Materials (ISEIM), pages 449–452, 2017. doi: 10.23919/ISEIM.2017.8166527.

[72] Chao Liu, Jing Liu, Li Xu, and Wei Xiang. Recent achievements in bionic implementations of insect structure and functions. *Kybernetes*, 43(2):307–324, 2014. doi: 10.1108/K-09-2013-0192.

[73] A M Ajith, K S Sachin, and A P Sudheer. Design, Fabrication and Analysis of a bio-inspired Tuna Fish Robot. In *ACM International Conference Proceeding Series*, Goa, India, 2015. doi: 10.1145/2783449.2783503.

[74] Asimina Kazakidi, Dimitris Tsakiris, and John A. Ekaterinaris. Impact of Arm Morphology on the Hydrodynamic Behavior of a Two-arm Robotic Marine Vehicle. *IFAC-PapersOnLine*, 50(1):2304–2309, 2017. doi: 10.1016/j.ifacol.2017.08.231.

[75] Mercedes Garcia-Holguera, Grant Clark, Aaron Sprecher, and Susan Gaskin. Ecomimetics: Ecological engineering tools for resource use optimization in buildings. In *ASABE and CSBE/SCGAB Annual International Meeting*, page 1904876, Montreal, Quebec Canada, 2014. ASABE.

[76] Nicolas Drouant, Éric Rondeau, Jean-Philippe Georges, and Francis Lepage. Designing green network architectures using the ten commandments for a mature ecosystem. *Computer Communications*, 42:38–46, 2014. doi: 10.1016/j.comcom.2014.01.005.

[77] Ignasius Dwi Sagita, Yudan Whulanza, Radon Dhelika, and Ibrahim Nurhadi. Designing electrical stimulated bioreactors for nerve tissue engineering. In *AIP Conference Proceedings*, volume 1933, page 040019. AIP Publishing, 2018. doi: 10.1063/1.5023989.

[78] Mercedes Garcia-Holguera, O Grant Clark, Aaron Sprecher, and Susan Gaskin. Ecosystem biomimetics for resource use optimization in buildings. *Building Research and Information*, 44 (3):263–278, 2016. doi: 10.1080/09613218.2015.1052315.

[79] Bhavik R Bakshi, Varsha Gopalakrishnan, Xinyu Liu, Rebecca Hanes, and Geoffrey F Grubb. Nature in engineering: Expanding the engineering design space by including ecosystem goods and services. In *AIChE Annual Meeting*, pages 468–470, 2016.

[80] Abheek Chatterjee, Hao Huang, Katherine R Davis, and Astrid Layton. A Multigraph Modeling Approach to Enable Ecological Network Analysis of Cyber Physical Power Networks. In *IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, pages 239–244, 2021. doi: 10.1109/SmartGridComm51999.2021.9631989.

[81] Baoquan Yin, Yiping Wang, Li Zhu, and Yong Cui. Photosynthesis of plant and photovoltaic integrated application of buildings. *Applied Mechanics and Materials*, 357-360:467–473, 2013. doi: 10.4028/www.scientific.net/AMM.357-360.467.

[82] S Pradhan, A K Brooks, and V K Yadavalli. Nature-derived materials for the fabrication of functional biodevices. *Materials Today Bio*, 7: 100065, 2020. doi: 10.1016/j.mtbio.2020.100065.

[83] Abheek Chatterjee, Richard Malak, and Astrid Layton. Ecology-inspired resilient and affordable system of systems using degree of system order. *Systems Engineering*, 25(1):3–18, 2022. doi: 10.1002/sys.21598.

[84] Abheek Chatterjee, Richard Malak, and Astrid Layton. Exploring System of Systems Resilience Versus Affordability Trade-Space Using a Bio-Inspired Metric. *Journal of Computing and Information Science in Engineering*, 21:050905, 2021. doi: 10.1115/1.4050288.

[85] Abheek Chatterjee and Astrid Layton. Mimicking nature for resilient resource and infrastructure network design. *Reliability Engineering and System Safety*, 204:107142 Contents, 2020. doi: 10.1016/j.ress.2020.107142.

[86] Astrid Layton, Bert Bras, and Marc Weissburg. Designing Industrial Networks Using Ecological Food Web Metrics. *Environmental Science and Technology*, 50(20):11243–11252, 2016. doi: 10.1021/acs.est.6b03066.

[87] Lei Cui, Paul Cheong, Ridge Adams, and Thomas Johnson. AmBot: A Bio-Inspired Amphibious Robot for Monitoring the Swan-Canning Estuary System. *Journal of Mechanical Design*, 136(11): 115001, 2014. doi: 10.1115/1.4028094.

[88] Emanuele Guglielmino, Isuru Godage, Letizia Zullo, and Darwin G Caldwell. A pragmatic bio-inspired approach to the design of octopus-inspired arms. In *IEEE International Conference on Intelligent Robots and Systems*, pages 4577–4582, Tokyo, Japan, 2013. IEEE. doi: 10.1109/IROS.2013.6697014.

[89] Robert E. Ulanowicz. Quantitative methods for ecological network analysis. *Computational Biology and Chemistry*, 28:321–339, 2004. doi: 10.1016/j.compbiolchem.2004.09.001.

[90] Brian D. Fath, Ursula M. Scharler, Robert E. Ulanowicz, and Bruce Hannon. Ecological network analysis: network construction. *Ecological Modelling*, 208(1):49–55, 2007. doi: 10.1016/j.ecolmodel.2007.04.029.

[91] Laurence J Tilly. The Structure and Dynamics of Cone Spring. *Ecological Monographs*, 38(2):169–197, 1968. doi: 10.2307/1942291.

[92] Robert E. Ulanowicz. The dual nature of ecosystem dynamics. *Ecological Modelling*, 220 (16):1886–1892, 2009. doi: 10.1016/j.ecolmodel.2009.04.015.

[93] Marc-Olivier Coppens. *Nature-Inspired Chemical Engineering*. Delft University Press, Delft, Netherlands, oct. edition, 2003. ISBN 90-407-2405-9.

[94] Jeremy T Lundholm. Green Roofs and Facades: A Habitat Template Approach. *Urban Habitats*, 4 (1):87–101, 2006. ISSN 15417115.

[95] Bhavik R. Bakshi, Guy Ziv, and Michael D. Lepech. Techno-ecological synergy: A framework for sustainable engineering. *Environmental Science and Technology*, 49(3):1752–1760, 2015. doi: 10.1021/es5041442.

[96] Robert E. Ulanowicz, Sally J. Goerner, Bernard Lietaer, and Rocio Gomez. Quantifying sustainability: Resilience, efficiency and the return of information theory. *Ecological Complexity*, 6(1):27–36, 2009. doi: 10.1016/j.ecocom.2008.10.005.

[97] Karl Hennk Robèrt, Herman Daly, Paul Hawken, and John Holmberg. A compass for sustainable development. *International Journal of Sustainable Development and World Ecology*, 4(2):79–92, 1997. doi: 10.1080/13504509709469945.

[98] John Harte, Ann Kinzig, and Jessica Green. Self-Similarity in the Distribution and Abundance of Species. *Science*, 284(5412):334–336, 1999. doi: 10.1126/science.284.5412.334.

[99] Kieran Conboy, Rob Gleasure, and Eoin Cullina. Agile Design Science Research. In Brian Donnellan, Markus Helfert, Jim Kenneally, Debra VanderMeer, Marcus Rothenberger, and Robert Winter, editors, *10th International Conference on Design Science Research in Information Systems and Technology*, volume LNCS 9073, pages 168–180, Dublin, Ireland, 2015. Springer. doi: 10.1007/978-3-319-18714-3_11.