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Spectral biology across scales in changing environments

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1 **Abstract**

2

3 Understanding ecosystem processes on our rapidly changing planet requires integration across spatial,
4 temporal and biological scales. We propose that spectral biology, using tools that enable near- to far-
5 range sensing by capturing the interaction of energy with matter across domains of the electromagnetic
6 spectrum, will increasingly enable ecological insights across scales from cells to continents. Here, we
7 focus on advances using spectroscopy in the visible to short-wave infrared, chlorophyll fluorescence-
8 detecting systems, and optical laser scanning (light detection and ranging, LiDAR) to introduce the topic
9 and special feature. Remote sensing using these tools, in conjunction with *in situ* measurements, can
10 powerfully capture ecological and evolutionary processes in changing environments. These tools are
11 amenable to capturing variation in life processes across biological scales that span physiological,
12 evolutionary and macroecological hierarchies. We point out key areas of spectral biology with high
13 potential to advance understanding and monitoring of ecological processes across scales—particularly at
14 large spatial extents—in the face of rapid global change. These include: the detection of plant and
15 ecosystem composition, diversity, structure and function as well as their relationships; detection of the
16 causes and consequences of environmental stress, including disease and drought, for ecosystems; and
17 detection of change through time in ecosystems over large spatial extents to discern variation in and
18 mechanisms underlying their resistance, recovery and resilience in the face of disturbance. We discuss
19 opportunities for spectral biology to discover previously unseen variation and novel processes and to
20 prepare the field of ecology for novel computational tools on the horizon with vast new capabilities for
21 monitoring the ecology of our changing planet.

1 **Why spectral biology has high potential to advance knowledge of ecological processes across scales**

2 In this era of rapid global change, understanding how biological variation at one scale influences
3 emergent properties at other scales—including the functioning of organisms, ecosystems, and the
4 biosphere—is important to developing an integrative understanding that will allow us to actively support
5 a sustainable future for humanity. The approach we term ‘spectral biology’ encompasses integrative
6 measures of biological systems that harness the interaction of electromagnetic radiation in ways that are
7 scalable and support standardized, repeated measurements (Fig. 1). These spatio-temporally scalable tools
8 provide a means to measure biological variation and related emergent properties across levels of
9 organization. For example, the reflection of electromagnetic radiation by plants is influenced by their
10 phenotypic, chemical, structural, and functional properties, thereby providing a means to measure
11 biological variation and related emergent properties across levels of organization. Spectral information
12 thus provides a consistent data type to integrate aspects of the evolutionary and physiological variation
13 within and among plant species, the interactions of species within communities, and their consequences
14 for ecosystems responses to global change. The rapidly expanding use of the tools of spectral biology in
15 ecology (Fig. 2) provides the impetus to synthesize the capabilities and opportunities within the field and
16 consider the path forward.

17 The goal of this special feature is to explore how spectral biology enables integration across
18 spatial, temporal and biological scales to reveal novel insights in plant ecology, ecosystem dynamics and
19 global change biology. Focal areas represented in articles that are part of this special feature range from
20 quantitative genetics, phylogenetic ecology, ecophysiology, forest dynamics, global change biology, and
21 phenological variation in ecological systems, to biodiversity-ecosystem function relationships.

22

23 **What is spectral biology?**

24 We define spectral biology as the spectrally resolved observation of the interaction of electromagnetic
25 radiation with biological systems. We emphasize these interactions in the solar domain, specifically in the
26 visible-to-shortwave infrared (VSWIR, 400-2500 nm) but also include ultra-violet (UV, 100-400 nm) as

1 well as thermal emissions (3-14 μm) and active and passive microwave (0.1-1m) domains that enable the
2 discernment of biological properties. We focus on advances made in this new discipline through studying
3 plant life using reflectance, transmittance, and absorbance spectroscopy, as well as chlorophyll
4 fluorescence emission, including solar-induced fluorescence (SIF), which is coupled to photosynthetic
5 function (Fig. 3). We also include thermal emission, which provides observations of temperature and
6 water content/flux; microwave emission, which can be used to determine soil moisture; and LiDAR (light
7 detection and ranging)—an active sensing system, which provides detailed three-dimensional structural
8 information through the measurement of distance by pulsed lasers. These tools of spectral biology can
9 help decipher the causes and consequences of biological variation across scales. Spectral variation in
10 reflected, absorbed, transmitted or re-emitted electromagnetic radiation results from the variation of
11 chemical, anatomical, morphological, and architectural plant traits, as well as variations in viewing
12 geometry due to sun position, topography or sensor position. The biological variation may originate due
13 to selection, evolutionary history, community composition, diversity, plasticity and their varied responses
14 to environmental drivers.

15 Spectral biology encompasses a continuum of close- to far-range measurements, which are often
16 described as contact (e.g., using a leaf contact probe attached to a spectrometer), proximal (such as a
17 handheld measurement above a canopy, from a tower or low-flying drones [< 100 m]), or remote (higher
18 altitude aerial to space-based or orbital). Remote and proximal sensing of spectral variation most often
19 involve measuring reflectance. Full-range surface reflectance in the solar domain is calculated as a
20 fraction of incoming (atmosphere-penetrating) solar radiation across the electromagnetic spectrum, which
21 is highest in the visible to short wave infrared (400 - 2500 nm); or as a fraction of artificial, standardized
22 light sources providing a similar source spectrum for irradiating targets at close range. Surface reflectance
23 in this range—e.g., the surface of whole ecosystems or a plant leaf, depending on the scale of
24 measurement—is detected at each wavelength (or band of multiple wavelengths) by a sensor that can be
25 placed on a range of platforms (Fig. 1). Spectral signatures can distinguish among different kinds of
26 molecules in plants (Jacquemoud and Ustin 2019), are sensitive to differences in plant traits (Fig. 3c), and

1 reveal variation across a range of scales from leaves of individual plants, within and among species across
2 the tree of life, and within and among plant communities, ecosystems, and landscapes across the global
3 biosphere (Gamon et al. 2020). Beyond full-range, spectrally highly resolved (often termed
4 ‘hyperspectral’) reflectance data, we include in the set of tools multispectral sensors which capture
5 reflectance in many fewer bands that may each span a range of wavelengths of interest; fluorescence
6 sensors; associated technologies such as LiDAR; and new applications that emerge from the interpretation
7 of these signals in biological realms.

8 Chlorophyll fluorescence has long been used at the leaf level to assess photosynthetic light use
9 efficiency (Genty et al. 1989, Schreiber et al. 1994) and to scale from leaves to ecosystems (Gamon and
10 Qiu 1999, Cavender-Bares and Bazzaz 2004). Chlorophyll fluorescence associated with photosynthesis
11 can be captured proximally from UAVs, or remotely from aircraft and from space through measurements
12 of solar-induced fluorescence emission in specific wavelengths that overlap with “dark features” of the
13 Earth’s incoming or reflected light spectrum (Joiner et al. 2013) (Fig. 3b). Within these wavelengths,
14 sunlight is partially absorbed by oxygen (O₂-A or O₂-B bands, centered at 760 and 687 nm, respectively).
15 Dark features can also include wavelengths where gases in the Sun’s atmosphere absorb outgoing
16 radiation (Fraunhofer lines). Such absorption features where solar radiation is diminished are critical
17 because they allow distinction between the relatively weak signal emitted by plants as fluorescence and
18 the much stronger signal of solar radiation and reflectance (e.g., Köhler et al. 2018, Moya and Cerovic
19 2004, Sun et al. 2018, Mohammed et al. 2019). Like spectral data, solar-induced chlorophyll fluorescence
20 detection can involve a range of platforms from satellites (Köhler et al. 2018), aircraft (Frankenberg et al.
21 2018, Porcar-Castell et al. 2021), towers or movable carts (Kebabian et al. 1999, Flexas et al. 2000) to
22 leaf-level measurements (Magney et al. 2017) that vary in the specific detection approach and sensor
23 used.

24 LiDAR (Light Detection And Ranging) instruments uses pulsed laser light and detect the return
25 time of pulses. This provides distance information and is used to generate three-dimensional point clouds
26 with the level of detail depending on point density. The resulting three-dimensional models reveal

1 information that can be interpreted ecologically in terms of form and structure (e.g., Davies and Asner
2 2014). Long used in archeology and in the automotive industry, sensors can be hand-held, placed on
3 uncrewed aerial vehicles (UAVs) or on aircraft as well as on platforms orbiting the Earth (GEDI,
4 Dubayah et al. 2020). Many LiDAR instruments are also able to measure echo intensity, providing
5 additional information that can be used to classify targets (Wagner et al. 2006).

6 By harnessing these tools, spectral biology provides powerful and integrated means to capture
7 biological variation—or biodiversity—from leaves to landscapes and to determine the causal factors that
8 give rise to that variation. It is particularly powerful when spectral and remotely sensed information and
9 tools are coupled with deep biological knowledge across subdisciplines that span scales. The spectral
10 biology toolkit complements other tools, such as gas exchange systems, flux towers, and isotopic
11 measurements that can provide more precise, or different types, of information at specific biological
12 scales. The toolkit may enable biologists across disciplines to consider a greater breadth of relevant scales
13 when designing research to study focal processes, loosening constraints to focus on a specific scale
14 imposed by familiar tools and expertise.

15

16 **What is the potential of spectral biology to advance ecological research?**

17 Advancing our understanding of Earth’s biodiversity and its response to global environmental
18 change at scales from molecules to ecosystems, revealing mechanisms that can be targeted for
19 management, is critical for societal capacity to adapt to, and mitigate, changes in biodiversity (Cavender-
20 Bares et al. 2022a). Here we define the term ‘biodiversity’ not simply in its most common usage as
21 species diversity at a community scale but to encompass the diversity of life on Earth including variation
22 in functional and evolutionary components within and among biological scales, ranging from cells to
23 organs, to individuals to ecosystems and regions. Decades of research on species diversity at the
24 community scale and its relationship to ecosystem functions have revealed its importance for how
25 ecosystems cycle elements (Weisser et al. 2017, Schuldt et al. 2023), produce biomass (Isbell et al. 2018,
26 Huang et al. 2018), and respond to environmental change (Reich et al. 2001, Loreau and de Mazancourt

1 2013). These functions are critical to providing ecosystem services that contribute to human well-being
2 (Mori et al. 2021, O'Connor et al. 2021). Integration across biological subdisciplines is required to
3 address fundamental questions that remain poorly understood, including how biodiversity varies across
4 scales—from genes and molecules within cells and tissues, to ecosystem variation. Our capacity to
5 understand and monitor changes in these biological processes at different scales is critical to sustainably
6 managing Earth's life support systems (Gonzalez et al. 2023). However, the scientific advances required
7 to tackle this set of problems have been hindered by the fragmentation of biology into specialized sub-
8 disciplines that are conceptually and methodologically divergent and do not meaningfully connect these
9 vastly different scales. The lack of a common data type to discern processes across scales has contributed
10 to these constraints.

11

12 *Critical scales in biology*

13 We focus on three kinds of biological hierarchies that form the basis of biological integration and scaling:
14 physiological, evolutionary, and macroecological (Fig. 4). The physiological hierarchy considers the
15 functional or metabolic units within a plant from genes and metabolites (molecular products of
16 metabolism) to organelles, cells, leaves, and other organs, to the whole plant. The evolutionary hierarchy
17 encompasses the nested and fractal organization of the tree of life from individuals nested within
18 populations, species and clades, or lineages of increasing size. Finally, the macroecological hierarchy
19 refers to the ecological processes at nested spatial and temporal scales that drive the distribution and
20 diversity of life—from density- and frequency-dependent neighborhood interactions, to sorting of species
21 across environmental gradients, and the dispersal, migration, and long-term biogeographic processes that
22 form the variation in ecosystems within and across biomes, and drive their function as well.

23

24 *How spectra help integrate across scales to address complex ecological problems*

25 As biological and ecological subdisciplines have become increasingly specialized, addressing complex
26 questions that span biological scales requires bridging subdisciplines. For example, resting within a single

1 subdiscipline, it is difficult to understand how climate change and landscape fragmentation influence the
2 genetic variation within species; or the complex ecological processes by which community composition
3 of ecosystems across biomes at broad geographic scales impacts changes in ecosystem function and
4 stability. Successful integration requires both conceptual and technical advances. Conceptually, we seek
5 to understand biological processes using a common data type across scales, including across evolutionary
6 hierarchies that capture the nature of phenotypic and functional variation within and among populations,
7 species and major lineages (Fig. 5a) and across temporal and spatial scales (Fig. 5b) to help elucidate how
8 processes at one scale affect processes at other scales and their combined influences on observed patterns,
9 properties, and dynamics.

10 The technological dimensions involved in generating common data types create a path forward
11 for the practical aspects of integrating across scales to address complex problems. An important point is
12 that monitoring methods should align with biological scales. For example, contact probes are appropriate
13 at the leaf scale, UAVs and low-flying piloted aircraft are often most appropriate at the community scale,
14 and satellites capture phenomena at landscape to global scales (Fig. 5b). Analysis and interpretation of
15 spectral measurements differ significantly based on measurement scale, due to the range of confounding
16 factors expressed at different scales. These factors may include atmospheric interference for high-altitude
17 and orbital imaging, or the influence of detector distance from the object of measurement (e.g., leaves or
18 canopies), or variation unrelated to biological factors due to source-sensor-object geometry. These issues
19 can be addressed through various data processing approaches (e.g., Queally et al. 2022). On the
20 conceptual side, advances emerge when we bridge subdisciplines across scales, fusing expertise from
21 different realms. For example, knowledge of genetic variation within species and how different genotypes
22 respond physiologically to environmental change emerges from the realms of quantitative genetics and
23 ecophysiology. These differences can be connected with typical functional differences among co-
24 occurring species that influence their interactions, and community dynamics that influence ecosystem
25 processes spanning community and ecosystem ecology. This integration may include linkages between
26 above- and belowground processes that drive long-term responses of nutrient cycling to community

1 change, integrating soil and microbial science (Cline et al. 2018, Cavender-Bares et al. 2022b). In another
2 important example, detecting changes in biodiversity in plants at the leaf level is advanced by our
3 understanding that spectra are coupled to genetic and phylogenetic information (Cavender-Bares et al.
4 2016, Meireles et al. 2020, Stasinski et al. 2021, Griffith et al. 2023, Li et al. 2023). Recent evidence finds
5 similar relationships at canopy scales (Czyż et al. 2020, 2023, Seeley et al. 2023, Griffith et al. 2023). The
6 physiological processes and stress responses that spectra reveal also appear to scale from leaf to canopy
7 levels (Sapes et al. 2024). These findings are important for understanding physiological processes that
8 underlie disease symptoms and can help monitor and map diseases to aid management (Sapes et al. 2022,
9 Guzmán et al. 2023). Spectral biology thus facilitates scaling from individual leaves to their aggregated
10 properties at the scale of landscapes and global observations, because it provides a common measure for
11 investigating how foliar tissue and photosynthetic processes interact with the environment, biological
12 phenomena that can be examined from microscopic to ecosystem scales. Spectral information can also be
13 combined with other measures, such as gas flux rates across scales, to gain insight into how processes at
14 one scale result in emergent properties at others. All of these advances in integration emerge from
15 conceptual and technological efforts.

16

17 *Avenues for major advances in spectral biology*

18 We address five dimensions of ecology in which spectral information will help to bridge scales and
19 subdisciplines to address complex ecological problems that affect humanity: 1) detecting the composition,
20 structure, function, and diversity of biological components, 2) measuring the consequences of
21 composition, structure, function and diversity for functions of plants and ecosystems, and 3) measuring
22 how those consequences will vary with global environmental change, enabling us 4) to characterize and
23 quantify how those consequences play out at differing temporal and spatial scales, including detecting the
24 resistance and recovery of vegetation in response to disturbance given the ecosystem composition and
25 diversity; and 5) discovery of novel biological phenomena through detection of emergent processes and
26 patterns enabled by cross-scale observation. These dimensions build on each other (Fig. 6). The

1 characterization of composition and diversity is key to understanding how they influence ecosystem
2 function. Deciphering linkages between biodiversity and ecosystem function at large spatial extents
3 provides a baseline for understanding how ecosystems and the components within them respond to stress
4 and global change. Determining the resilience of ecosystems depends on our ability to measure and
5 understand their response to perturbations over time. The fifth dimension highlights the importance of
6 detecting phenomena we are not yet aware of and preparing for new advances in other realms. We chose
7 these dimensions to highlight the potential of spectral biology to advance understanding and monitoring
8 of ecological processes across scales—particularly at large spatial extents—in the face of rapid global
9 change. All are relevant to managing our biosphere for sustainability. We recognize that properties and
10 processes in each dimension interact with those in all others, but we view this organization as enabling us
11 to discuss and investigate key elements in an unfolding or expanding fashion (Fig. 6).

12

13 **1. Composition and Diversity**

14 Spectral biology has made considerable advances in characterizing the identity and composition of organisms,
15 particularly plants, and in quantifying the diversity and composition of vegetation in ecosystems. These
16 developments also have potential to support evaluating the many organisms that depend on plants for their life
17 cycles and livelihoods. We first consider these capabilities and future potential before discussing how they
18 may be impacted by environmental change.

19

20 *Composition*

21 One of the most powerful attributes of spectral data is its ability to discern identity and composition by
22 coupling reflectance information across many wavelengths with pattern detection, including machine
23 learning approaches. While spectroscopy has been widely used to identify stars and the presence of
24 specific gases and elements in space, its application to differentiating genotypes, species and lineages of
25 plants on Earth has more recently expanded (Asner and Martin 2016). Species and functional group
26 identification from airborne spectra are well-established for temperate forest trees (Roberts et al. 1998,

1 Plourde et al. 2007, Williams et al. 2020, Sapes et al. 2022) and remain challenging in hyperdiverse
2 tropical systems (Baldeck et al. 2015), particularly from satellites, due to restrictions on spatial resolution
3 and signal-to-noise ratio for instruments in orbit (Papeş et al. 2010). The ability to classify plant species
4 depends crucially on spatial resolution and scale (Wang and Gamon 2019). Across biological scales from
5 genotypes within species (Stasinski et al. 2021, Li et al. 2023), species within lineages and lineages
6 within larger clades, classification appears to have high accuracy at the leaf level (Meireles et al. 2020)
7 and even across canopies (Torabzadeh et al. 2019, Seeley et al. 2023, Griffith et al. 2023). Classification
8 approaches may have greater accuracy or consistency at phylogenetic scales above the level of the species
9 (Cavender-Bares et al. 2016), in other words at the scale of lineages that roughly correspond to genera or
10 subgenera. Detecting lineages rather than species may be critical in highly diverse tropical regions where
11 species-level information is often impossible to obtain on the ground.

12 Detection of ecosystem composition and identity of component lineages, species, or genotypes is
13 made challenging by shifts in spectral signatures through time (Chlus and Townsend 2022), by the
14 expression of both genetically and environmentally driven variation within taxa (Madritch et al. 2014,
15 Czyż et al. 2020), and by the many complications of different sensors and conditions across observations
16 (Li et al. 2023). The nature of these technical challenges shifts from handheld instruments to uncrewed
17 aerial vehicle (UAV) sensors to airborne sensors and the myriad satellite sensors (Schneider et al. 2017,
18 Helfenstein et al. 2022). Of the space agency-funded satellites, all have resolutions of 30 m or coarser,
19 requiring statistical approaches to discern identity at the scale of individual organisms that will be smaller
20 than the pixel size.

21 Using 30 m pixel satellite data (Landsat Thematic Mapper (L1TP) and Hyperion imaging
22 spectroscopy from NASA's EO-1 satellite, Visser et al. (2025, this feature) were able to differentiate
23 lianas, as a functional group, from trees. They used radiative transfer models that detect differences in leaf
24 angles and revealed larger apparent leaf areas and increased light scattering in the NIR and SWIR regions
25 in lianas, which they attributed to their less costly leaf construction compared to tree leaves.

26

1 *Diversity*

2 Various approaches have emerged for linking remotely sensed spectral diversity and *in situ* measures of
3 ecosystem diversity (Rocchini et al. 2010). Ecosystem diversity has sometimes been predicted by taking
4 advantage of identity detection using spectral libraries. For example, Williams et al. (2020) used airborne
5 spectroscopic imagery from AVIRIS NG at 1 m resolution to classify forest canopies in a young
6 experimental forest. By detecting species co-occurring within communities, they predicted forest diversity
7 with high accuracy (up to 12 species). They subsequently used remotely sensed predictions of forest
8 biomass to accurately predict tree diversity - ecosystem function relationships. Plant diversity has also
9 been directly predicted from spectra and from spectral diversity using methods that do not rely on identity
10 detection and range from simple measures of the coefficient of variation (CV) among spectra retrieved
11 from a vegetation plot to detection of spectral species (e.g., Frye et al. 2021). Wang et al. (2018) used the
12 coefficient of variation of spectra from experimental prairie systems at pixel sizes that ranged from 1 mm
13 to 1 m. Here the scale and resolution were critical, and spectral diversity was only predictive of plant
14 diversity at resolutions similar to that of whole plants, leaves, or stems. Gholizadeh et al. (2019, 2020)
15 used a similar approach in more diverse prairie systems and found that the CV of spectra predicted plant
16 diversity even at coarser resolutions up to ~ 4 m. Further studies (Schneider et al. 2017, Kamoske et al.
17 2022, Rossi et al. 2022) using additional spectral diversity metrics (e.g., convex hull volume [CHV],
18 spectral species [SS], total variance [TV]) found that accurate predictions will also depend on the metric
19 used to assess plant diversity from above. For example, some metrics are more susceptible to outliers than
20 others and thus did not capture the variability of local plant communities (Rossi et al. 2022). Despite
21 challenges, the variability of even a small number of spectral bands has enabled successful detection of
22 boreal forest diversity variation in time and space (Xi et al 2024).

23 The spectral species concept—pixels with similar signatures in the spectral space (sensu, Féret
24 and Asner 2014)—has gained traction as a conceptual and analytical means to predict plant species and
25 communities (Féret and de Boissieu 2020, Rocchini et al. 2022). Using spectral species, Pinto-Ledezma et
26 al. (in press) found consistent predictions across multiple dimensions of plant diversity across multiple

1 NEON sites and biomes in the United States. Guzman et al. (2025, this feature) used structural diversity
2 based on UAV LiDAR measurements across the season to predict forest diversity and consequences for
3 ecosystem function in an experimental forest. Forest communities that changed more in their structural
4 diversity across the season also had greater ecosystem productivity.

5

6 *Connecting spectra to the tree of life*

7 Species and lineages represent points along a continuum from genetic variation among cells and
8 individuals, to quantitatively increasing genetic differentiation defining clades across the tree of life (Fig.
9 5a). In this way, genetic diversity is not distinct from species or clade diversity, but a finer point to put on
10 our understanding of biological diversity. Genetic diversity concerns differences that are passed on
11 through generations, and therefore subject to evolutionary processes, such as gene flow, selection,
12 mutation, and genetic drift. These processes can result in genotypic diversity and differentiation between
13 populations that have phenotypic consequences. Spectra are information-rich measures of the phenotypes
14 that result from the interaction between genotypes and the environment and, consequently, can be used to
15 address genetic and evolutionary questions (Babar et al. 2006, Cavender-Bares et al. 2017, Kothari and
16 Schweiger 2022). The same kinds of features that allow the separation of species and clades by their
17 spectra (Meireles et al. 2020) can also help assess within-species genetic variation, including
18 differentiation among genotypes and populations (Cavender-Bares et al. 2016). Recent work has indicated
19 that, within specific environments, genetically more diverse populations of plants are also spectrally more
20 diverse (Hernandez-Leal, in review; Li *et al.* 2023) and that spectra can differentiate some genotypes and
21 their F1 crosses as intermediate between signatures of the parent genotypes (Seeley et al. 2023).
22 Similarly, in naturally occurring stands of hybrid poplars, Deacon et al. (2017) showed that spectral
23 phenotypes were intermediate between the parental species.

24 Studies in this area can draw on the rich toolkit of quantitative genetics, a discipline that has
25 dissected the quantitative relationship between phenotypic and genotypic variation since before the nature
26 of genetic material was known (Falconer and Mackay 1996). More recently, as whole-genome sequencing

1 techniques became increasingly affordable and available, genome-wide association studies (GWAS)
2 became a staple of quantitative genetics (Bazakos et al. 2017). In this issue, Li and co-authors test
3 approaches to apply GWAS to spectra, as well as to spectral features related to specific traits (aspects of
4 phenotypes). They quantify narrow-sense heritability that different parts of a spectrum represent, i.e., the
5 extent to which additive genetic variation contributes to additive variation in spectra; and associate
6 specific genetic and spectral variants. Spectra have also been shown to capture genomic variation in the
7 face of biological processes that blur the lines between populations, such as gene flow, and species, such
8 as hybridization. Stasinski et al. (2021) used leaf spectra to differentiate two species of *Dryas* that co-
9 occur and hybridize and to furthermore distinguish populations within each of those species and showed
10 that the degree of genetic ancestry of an individual plant can be predicted from spectra.

11

12 **2. Linking composition and diversity to ecosystem function**

13 Spectral biology further enables us to predict plant and ecosystem function—including structural,
14 chemical, photosynthetic and productivity dimensions—making possible large-scale assessments of the
15 relationships between ecosystem diversity, composition and function. Consistent, large-scale applications
16 of this potential remain untapped.

17

18 *Plant and ecosystem function*

19 The capacity of spectral information to predict a wide array of plant functional traits opens new doors for
20 mapping plant function across ecosystems (Wang et al. 2019, 2020b) and scaling up to the biosphere (Jetz
21 et al. 2016, Dechant et al. 2024). Spectral data and derived traits relate directly to photosynthesis, carbon
22 dynamics and resource allocation (Serbin et al. 2015, DuBois et al. 2018). These advances will ultimately
23 enable the inclusion of satellite-detected changes in plant function in Earth system models that predict
24 biosphere dynamics on our rapidly changing planet.

25 Pierrat et al. (2025, this feature) demonstrate the use of proximal remote sensing of solar induced
26 chlorophyll fluorescence (SIF) to discern seasonal changes in photosynthetic yields in *Pinus palustris* and

1 other evergreen needleleaf species at needle and canopy scales. This builds on long-standing efforts to use
2 SIF to measure ecosystem photosynthesis and productivity (Morales et al. 1999, Flexas and Medrano
3 2002, Freedman et al. 2002, Moya and Cerovic 2004, Sun et al. 2018) and to scale up from leaves to
4 ecosystems (Gamon and Qiu 1999, Cavender-Bares and Bazzaz 2004, Asner and Martin 2008). Detection
5 of ecosystem function has been a major global effort, with robust indices (NDVI) to detect GPP and the
6 development of Earth surface models e.g., (Sellers et al. 1996) and is at a highly advanced stage in terms
7 of predicting productivity and its change through time (Mohammed et al. 2019) in a range of diverse
8 ecosystems (Zhang et al. 2022, Dąbrowska-Zielińska et al. 2022). The coupling of space-borne LiDAR
9 and satellite data is rapidly enhancing global accuracy in monitoring of global ecosystem structure and
10 function (Saarela et al. 2018, Schneider et al. 2020, Di Tommaso et al. 2021, Liu et al. 2022).

11

12 *Biodiversity-Ecosystem Function relationships*

13 More recent developments have involved using detection of diversity and ecosystem function to decipher
14 how dimensions of biodiversity, including spectral diversity are associated with ecosystem function
15 (Madritch et al. 2014, Schweiger et al. 2018, Williams et al. 2020). While a large body of evidence has
16 shown relationships between species diversity and ecosystem function in experimental systems for a
17 quarter of a century (e.g., Tilman 1999, Reich et al. 2001, Isbell et al. 2015, Grossman et al. 2017, Huang
18 et al. 2018), similar relationships in natural systems have been demonstrated more recently (Liang et al.
19 2016, Oehri et al. 2017, Chen et al. 2023, Liu et al. 2024) albeit with some inconsistency across scales,
20 biomes and climates (Chisholm et al. 2013, Cheng et al. 2023). Spectral biology approaches are only
21 beginning to be applied at large spatial extents to detect these relationships (Oehri et al. 2020, Schuldt et
22 al. 2023, Liu et al. 2024). Williams et al. (2025, this feature) detect the influence of forest canopy
23 composition on the transmittance of light, showing how experimental forest communities of different
24 phylogenetic lineages change the light quality and quantity that reaches the understory. Guzmán et al
25 (2025, this feature) use remotely sensed lidar across the growing season to decipher changes in forest
26 structure that are associated with critical dimensions of forest diversity and predict ecosystem biomass.

1 Marcilio-Silva et al. (2025, this feature) use GEDI LiDAR data from space in urban forest patches
2 coupled with ground-based measurements of forest diversity and structure to map urban forests. In doing
3 so, they uncover the importance of management legacies in urban forest structure. Understanding the
4 linkages between plant canopies that can be spectrally observed from above and the soils processes that
5 both influence and are influenced by them are critical spectral detection of belowground ecosystem
6 processes (Madritch et al. 2014, 2020, Cavender-Bares et al. 2022b).

7

8 **3. Environmental factors, stress, and global change**

9 In a world exposed to increasing threats from climate change, expansion of pests and pathogens,
10 disturbance and land-use change, and increasing pollution loads in the environment, spectral biology has
11 the potential to help detect and differentiate stressors of plants at large spatial extents. Doing so across
12 scales from leaves of individual plants to tree canopies and whole landscapes will require a range of
13 methodologies that may be combined for deeper understanding of mechanisms and interactions of
14 multiple stressors. We emphasize the importance of framing spectral biology in terms of careful
15 integration of spectroscopic and remote sensing methods with stress physiology and pathology, including
16 in-depth understanding of the life-cycle and natural history of biotic stress agents and disease progression,
17 as well as the physiological responses of plants to drought, pollution and their synergies with biotically-
18 induced disease. Stress leaves markers in spectral signatures of leaves, canopies and landscapes, some of
19 which can be generalized and scaled up using spectral regions that show changes in photosynthetic
20 biology, carotenoid and photoprotective pigments and changes in foliar water content across spatial
21 resolution and extent. Other stress markers are more idiosyncratic of specific stress factors and may
22 involve spatial or temporal patterns at the canopy or landscape scale that are diagnostic of a specific
23 pathogen. The degree to which more general stress signatures or system-specific responses are useful in
24 addressing questions regarding ecological processes depends on prior knowledge of organismal function
25 and species interactions as well as the scale of inquiry.

1 Using a unique open-air field experiment in Minnesota, USA, Stefanski et al (2025, this issue)
2 examined the spectral signature of experimental warming by collecting leaf spectral reflectance (400-
3 2400 nm) at the peak of the growing season for three years on juveniles (two to six years old) of five tree
4 species. They found that the imprint of environmental conditions, including those associated with
5 experimental warming, experienced by plants hours to weeks prior to spectral measurements was linked
6 to spectral regions associated with stress, in particular the water absorption regions of the near-infrared
7 and shortwave infrared. In contrast, the conditions plants experienced during leaf development, again
8 including those associated with climate manipulations, left lasting imprints on the spectral profiles of
9 leaves measured much later in the growing season; those imprints were related to structural and chemical
10 leaf attributes (e.g., pigment content and associated ratios). Moreover, after accounting for species
11 differences, spectral responses to warming did not differ among species, suggesting that developing a
12 general framework for quantifying forest responses to climate change through spectral biology may be
13 feasible.

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16 *Signatures of stress across scales*

17 Spectral and point cloud data are increasingly being used to detect trees that are dead or dying as a
18 consequence of drought, disease, and other global change-related stressors (Pontius et al. 2008, Hanavan
19 et al. 2015, Asner et al. 2016, 2018). Detecting mortality and discerning its causes is essential to
20 managing ecosystems in the face of multiple simultaneous stressors. Rapid detection of disease is critical
21 to management in stopping the spread of a pathogen. Less expensive containment measures can be used
22 when disease invasion is detected early, reducing cost.

23 Plants respond to environmental stress with a limited set of physiological symptoms that can
24 often be detected spectrally. At the level of physiological function in leaves, for example, reduced
25 photosynthetic function and water content are common responses to drought and wilting diseases as a
26 consequence of damage to the photosynthetic apparatus or reduced vascular function, which limits water

1 supply for gas exchange. Changes in chlorophyll concentration and in water content in leaves are readily
2 detectable signatures of stress from leaves to canopies to landscapes (Sapes et al. 2022, 2024, Guzmán et
3 al. 2023). Increases in expression of pigments used for photoprotection may be another general stress
4 response (Savage et al. 2009, Ramirez-Valiente et al. 2015, Encinas-Valero et al. 2021, Kothari et al.
5 2021). When photosynthetic rates are slowed due to stress (e.g., drought, cold, low nutrients, disease,
6 pollution), less absorbed light can be used for photochemistry. Consequently, plants often upregulate
7 photoprotective pigments (xanthophyll-cycle carotenoid pigments) that dissipate light energy as heat to
8 prevent oxidative damage to the protein components involved in photosynthesis (Demmig-Adams and
9 Adams 2000). Increased expression of carotenoids, detected by spectral regions in the visible—including
10 indices such as the photochemical reflectance index (PRI, (Gamon et al. 1997)) and the chlorophyll
11 carotenoid index (CCI, Gamon et al. 2016)—may be fairly generalizable responses to stress that can be
12 detected across spatial resolutions and extents. At the same time, each disease or disease syndrome may
13 have a distinct temporal and spatial progression pattern, enabling early and/or rapid detection of specific
14 pathogens and differentiating them from drought.

15 Across plant taxa, environmental stress alters not only the phytochemical composition of leaves,
16 but also the structure—and ultimately function—of canopies, impacting remote sensing signals. For
17 example, drought stress causes notable physiological and chemical shifts aimed at facilitating plant
18 survival through regulating key biological processes through hormonal signaling (McDowell et al. 2022,
19 Rai et al. 2024, Sato et al. 2024). Similarly, drought has also been shown to affect leaf chemical and
20 structural attributes—including changes in amino acids and pigment composition (Demmig-Adams and
21 Adams 2006, Yang et al. 2021), leaf size and density (i.e., leaf area index), orientation, and water content.
22 The extent of these changes are highly dependent on the severity and duration of stress, resulting in high
23 temporal and spatial variation. It can be challenging to disentangle the contribution of canopy structural
24 changes and leaf-level physiological changes, particularly when the spatial resolution of the sensor is
25 course relative to the size of leaves or canopies, making this a fertile area for investigation.

1 Understanding the biology of the disease can be critical to detecting it remotely. Pests and
2 pathogens tend to be lineage-specific, often requiring biological knowledge of the host, the pathogen and
3 the biotic vector. Within the oaks, the oak wilt fungal pathogen (*Bretziella fagacearum*) is considered the
4 most deadly threat to the genus, particularly the red oak lineage (*Quercus* section Lobatae). Its spores are
5 spread overland long distances by nitidulid sap beetles that can infect vulnerable trees if the cambium is
6 exposed from cracks or cuts (Juzwik et al. 2011). The spread to neighboring oak trees can be quite rapid
7 when roots from an infected tree graft with a neighbor, allowing the fungus to move from one tree to the
8 next (Koch et al. 2010). As trees succumb to the disease, there is a temporal progression of symptoms that
9 aid detection using time series data, as well as a characteristic spatial pattern.

10 Spectral signatures are capable of differentiating disease symptoms of the pathogen from drought
11 stress at leaf and canopy scales in both indoor (Fallon et al. 2020) and outdoor experiments (Sapes et al.
12 2024) due to differences in the spectral features that are affected and the rate of change. Heterogeneity in
13 pigment concentrations in foliage across the canopy, as a consequence of tylose formation in the xylem
14 that causes some branches to wilt, is characteristic of the disease and can be used to differentiate it from
15 drought using even inexpensive multispectral UAV sensors. At landscape scales, both spectral features
16 that can be characterized at the whole-plant level as well as temporal and spatial patterns can be detected
17 spectrally. Features in spectroscopic airborne imagery take advantage of host specificity in the disease to
18 help detect vulnerable hosts. Sapes et al. (2022) developed models to differentiate oaks from other tree
19 species, oak lineages vulnerable to oak wilt from less susceptible oaks and ultimately healthy from
20 diseased oaks, for accurate detection of the disease. At regional scales, land surface phenological metrics
21 used understanding of the temporal progression of disease to detect healthy, symptomatic and dead oak
22 trees of specific lineages using currently available satellite data (Sentinel2 and Landsat 8) in near-real
23 time with accuracies sufficient to aid management (Guzmán et al. 2023). Rapid and accurate detection
24 increases management options, from early options that may only involve girdling a single tree and
25 injecting herbicide, to more expensive options that involve the use of a vibratory plow and removal of

1 surrounding trees. If the disease is not treated early, it can spread to such extents that the cost of effective
2 treatment becomes prohibitive.

3 Spectral detection of stress responses are often not diagnostic of specific diseases (Pontius and
4 Hallett 2014, Pontius et al. 2020). The extent to which particular host-disease systems are discernable and
5 whether those diagnostic responses are idiosyncratic or themselves generalizable is an open question, but
6 one where rapid progress is being made. Drought predisposes many trees to infection by pests and
7 pathogens. Most tree lineages are threatened by multiple pests and pathogens, with similarities in
8 symptoms. Deciphering the cause of decline and mortality is likely to remain complicated. Spectral
9 biology has the potential to detect ecosystem-scale stress and connect it to whole-organism understanding
10 of biotic and abiotic stress responses as a means of understanding underlying mechanisms of forest
11 decline to aid management.

12 Rapid detection of stress physiology is now possible at scales and frequencies that would be
13 infeasible from the ground. Even if the mechanism of stress is not discernable, detecting the location of
14 stress in ecosystems aids management. Forests are expressing novel phenotypes due to rapid rates of
15 change and the emergence of novel environments (Housset et al. 2018). An important question is whether
16 ecosystem-level responses to stress are generalizable or whether each specific system is distinct, requiring
17 specific local knowledge to decipher stress responses. Is there convergence in system-level responses
18 across ecosystem types and host-disease systems, from lodgepole mountain pine beetle attack to oak wilt,
19 in terms of stress physiology? Or do we need more detailed information about life histories of pests and
20 pathogens to understand how each disease is expressed? Integration among subdisciplines is critical, with
21 remote sensing of spectral information providing one tool, but only partial answers. Unique combinations
22 of stress that do not have historical analogs may produce unique signatures of stress. Given the rate of
23 global change, it is more important than ever to detect these kinds of stress responses, and it is now
24 possible to examine interacting stress factors in ways we could not before. Rapid detection of stress is
25 critical to replanting and reforestation and will advance restoration and rehabilitation efforts mandated in
26 the Global Biodiversity Framework of the Convention on Biological Diversity.

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Genetic variation in stress response detectable from spectral phenotypes

Stress detection has received enormous attention in crops and with the goal of connecting spectrally derived functional information to genomic mechanisms (Mohd Asaari et al. 2018, Wang et al. 2020a, Calzone et al. 2021). Regulation of suites of genes in response to stress changes spectrally observable phenotypes (Tirado et al. 2020). In ecology and evolution, we often need to assess the performance of individual organisms or groups as indicators of their acclimation or fitness in the face of stress, but we do not have complete ways to measure performance. Traditionally, we measure one or a few traits as a proxy. In the worst case, one trait such as biomass accumulation is set as “equivalent” to performance, which is misleading and inhibits deeper thinking about organisms as agents, and mechanisms and facets of resilience. Having a more integrative measurement that lends itself to spatial and temporal scaling may help us to better consider how, when, and in what ways to assess different aspects of performance, and remind us that we are evaluating a multifaceted phenomenon.

4. Resistance, recovery, and resilience

Resistance, recovery, stability and resilience are concepts receiving increased attention in ecosystem and global change ecology, in relation to both strong event-type disturbances and chronic pressures. Despite inconsistent definitions (which harms progress), conceptual coherence and a variety of useful approaches make this an area of current and future focus and importance (Yi and Jackson 2021, Tai et al. 2023). Investigating these concepts over relevant time scales (decades to centuries) requires repeated observations that are challenging to acquire with direct observations. In contrast, remotely sensed data, which often is possible to acquire repeatedly over time, plays a special role in the development of both resilience theory and its testing (Pontius et al. 2020, Liu et al. 2021, Yi and Jackson 2021, Tai et al. 2023). Spectral biology enables us to observe ecosystems through time to test how diversity and composition influence resistance, recovery, and stability (Isbell et al. 2015): processes receiving increasing attention as important in a changing world (Wilcox et al. 2020, Avolio et al. 2021).

1 Frequent (e.g. every 1-2 weeks) or infrequent (e.g. seasonal to annual) satellite measurements
2 provide spectral information on ecosystems and how they change, which encompasses ecosystem
3 resistance and resilience (Fig. 6). Capturing transition states and predicting shifts in ecological function
4 under global change (Tai et al. 2023) will increasingly be critical to understanding how the Earth is
5 changing and provide important input for the sustainable management of ecosystems.
6 Diversity likely plays a key role in resilience. Linkages between diversity (e.g. species richness,
7 phylogenetic diversity, functional diversity) and stability are well established; for example, evidence is
8 increasing that forest diversity increases drought resistance in experimental systems (Blondeel et al.
9 2024). Such evidence has required long-term experiments, constraining analyses to small spatial extents, a
10 handful of biomes, and relatively few species. Time series data collected across the Earth's surface can be
11 used to feed or test models predicting relationships between diversity and function, and help decipher how
12 trends in ecosystem function are related to processes of resistance, compositional turnover, and recovery
13 after disturbance that influence resilience (Xu et al. 2022). Studies of tipping points and their signatures
14 indicate that increased variability can precede a regime shift to an alternative degraded state of an
15 ecosystem (Scheffer et al. 2001, Scheffer and Carpenter 2003, Steffen et al. 2015).

16 A mechanistic understanding of change will increase predictive capacity, even in non-linear
17 ecosystem dynamics – where detecting thresholds is critical. Changes in biome extent over time have long
18 been detected using NDVI (Simms and Ward 2013). Shifts in alpine ecotones in response to warming
19 climates have been detected in the Western US (Wei et al. 2020). Remotely sensed resilience data enabled
20 prediction of subsequent drought mortality across the continental US (Tai et al. 2023). An important
21 element is understanding the mechanisms underlying ecosystem transitions, which includes deciphering
22 causes of mortality, stress, and disturbance. High spectral resolution is important to understand
23 compositional changes and pinpoint changing physiological functions. Historically, scientists have
24 considered different stress factors in isolation. Complexities of interacting stress result in emergent
25 properties that can be detected using a holistic measurement approach such as that of spectral biology,

1 and untangled through a mechanistic approach by extracting specific information from spectral time
2 series in combination with other data types.

3 For example, Sturm et al. (2022) used changes in the canopy Normalized Differential Water
4 Index (NDWI) from a time series of multispectral satellite imagery from Sentinel-2 to calculate the
5 resistance, resilience, and recovery of forests across Switzerland to an unusually severe drought event in
6 2018. They explained differences among forests based on landscape characteristics and forest mixing
7 ratios (e.g. proportion of needle versus broadleaf trees). Helfenstein et al. (2024) used the same approach
8 to study the relationships of resistance, resilience, and recovery with functional diversity as calculated
9 from pigments and water content in the same forests (using different images for diversity metrics versus
10 the time series calculations) and found positive relationships of functional richness with both resistance
11 and resilience to drought. These kinds of patterns can also be detected in managed, urban, or naturally
12 assembled ecosystems through spectral and LiDAR information over time that is well-connected to
13 measured biological processes on the ground (Marcilio-Silva et al. 2025, this feature). Ultimately, these
14 approaches will enable mechanistically informed monitoring of forest stress responses and resilience.

15

16 **5. Discovery**

17 Finally, spectral biology will advance the realm of discovery by opening our capacity to observe Earth
18 and the living world around us. What new patterns can we quantify as a consequence of the ability to
19 “see” deep patterns and mechanisms across spatial and temporal scales? The new frontiers that will
20 emerge will encompass measurements of the linkages among the full range of biological organization,
21 and evolutionary and environmental drivers of plant distributions and functions, as well as their genetic
22 structure, competitive interactions and relationships to components of ecosystems such as microbes or
23 pathogens, detected by other methods. The capability of spectral biology to detect diversity, composition
24 and function of ecosystems, and how they change in response to stress through space and time, enables
25 new pathways for discovery at vastly divergent scales.

26

1 *The high dimensionality of spectra provides insurance against our ignorance*

2 Through the linkage of spectroscopy with biology, the potential of spectral biology goes beyond what our
3 frameworks and methods currently allow for (Townsend et al. 2013). For example, VSWIR spectroscopy
4 (400 – 2500 nm) captures coherent (i.e., non-noise) information beyond the variables we currently
5 estimate from the imagery (Schimel et al. 2020, Cawse-Nicholson et al. 2022) or use to model leaf
6 reflectance via physical models (e.g., Féret and De Boissieu 2024). The high dimensionality of spectral
7 data can enable future discoveries unlocked by advances in machine learning models, computational
8 power, technological advances in associated areas, and conceptual breakthroughs (Hong et al. 2024).

9 Stronger links between genetic diversity and spectra can be forged as the cost of genomics and
10 transcriptomics come down and spectral biology becomes more democratized. Spectral biology can help
11 guide genomic and transcriptomic analyses for scientists and ecosystem managers alike by identifying
12 promising relationships for deeper investigation: it may help to more efficiently search for the proverbial
13 needle in a haystack. Specifically, advances in scalable monitoring of biological diversity enable
14 measurement prioritization. In particular, the emerging Earth observation platforms that we envision will
15 lower barriers to entry to spectral biologists and provide the foundation for more effective monitoring of
16 biological diversity with tighter links of monitoring to mechanism and response.

17 Ultimately, the ability to detect patterns at broad spatial extents through time will facilitate the
18 discovery of phenomena relevant to understanding biological processes across scales. The broad spatial
19 perspective will allow us to test whether relationships we observe at fine scales or from experimental
20 studies are generalizable at regional-to-planetary scales, and, if not, why. Thus, we expect that advances
21 in technology will be followed by increases in the spatial extent of composition, functional, and stress
22 measurements that will facilitate either verification or falsification of hypothesized mechanisms, or,
23 alternatively, reveal patterns of variation not previously characterized. Already it is clear that more
24 functional variation emerges when functional traits are spatially mapped from above than is predicted
25 from functional trait measurements on the ground, largely due to the vastly increased sample size that
26 results from using image data (Wang et al. 2020b). In order to produce comparable measurements at the

1 pace of fieldwork, most functional ecologists adhere to specific protocols for how and when traits are
2 measured on plants, and focus on specific seasonal and ontogenetic life stages, prioritizing certain organs
3 over others. Remotely sensed and spectrally derived functional variation is agnostic to these protocols and
4 can pick up otherwise hidden functional variation. The “insurance against ignorance” is that we have only
5 scratched the surface of our understanding of the drivers of spectral variation, meaning that our archived
6 records provide a repository of data that can be re-mined into the future as we build out our knowledge in
7 spectral biology.

8 We will no doubt detect patterns that we could not see in other ways, and there is room for pattern
9 discovery in remote sensing across spatial and temporal scales, similar to the development of genomics.
10 Much of the focus of spectral biology to date has been on readily detected patterns, such as quantification
11 of traits that drive photosynthesis, like chlorophyll and nitrogen concentrations or leaf mass per area.
12 What is truly exciting is the potential to detect unanticipated anomalies or exceptions to expected
13 relationships—e.g., where predicted trait-trait or trait-environment relationships break down—or where
14 new relationships are observed that had not previously been identified as important. Advances in
15 modeling and computational tools may allow us to learn from the signals obtained across scales and study
16 planet Earth as a system, finally deciphering how processes at one scale influence and are influenced by
17 those at all other scales.

18 At the same time, it is important to acknowledge that many gaps remain in accurate interpretation
19 of signals, and excitement about advancing technology can result in overselling its potential. Signals can
20 only be interpreted to the extent that we can connect them to meaningful biological processes and patterns
21 that are carefully measured, understood, and verified in appropriate ways. There are technical issues with
22 signal detection from a distance based on geometry and atmospheric interference, as discussed earlier.
23 Near-surface remote sensing data are hard to acquire over time and require considerable training and
24 infrastructure investment; multiple interacting biological and environmental factors can be difficult to
25 disentangle. There is no shortcut to conducting the careful *in situ* work to decipher mechanisms

1 underlying biological phenomena that enables extension of our understanding across spatial and temporal
2 scales.

3

4 *Conclusions*

5 We close by emphasizing that spectral biology has enormous potential to expand the spatial extents and
6 timeframes at which we can decipher ecological processes relevant to managing our planet. Importantly,
7 ecologists have a critical role to play in conducting the research to enable accurate biological
8 interpretation of signals, whether from spectral measurements made at fine scales, or from the sky. The
9 theoretical frameworks and extensive field, experimental, and laboratory observations and analyses that
10 underpin the inferences made from spectral data are critical to the effective use of these measurements.
11 The tools of spectral biology, which still present challenges to accurate interpretation, also provide keys
12 to understanding and monitoring vegetation on Earth from the finest scale to our entire planet in ways that
13 have not been possible before. Moreover, by linking across components of the ecosystem, such as soil
14 biota, animals and microbes, we can further disentangle trophic and other complex or non-linear
15 dynamics operating across spatial and temporal scales. Spectral biology is one framework that will help
16 us to harness the information necessary for local to global efforts to manage ecosystems and sustain a
17 habitable planet. The framework and tools will increasingly play an important role in knowing how we
18 are doing in meeting the goals and targets of the Global Biodiversity Framework (Kissling et al. 2018,
19 Skidmore et al. 2021, Cavender-Bares et al. 2022a, Gonzalez et al. 2023).

20

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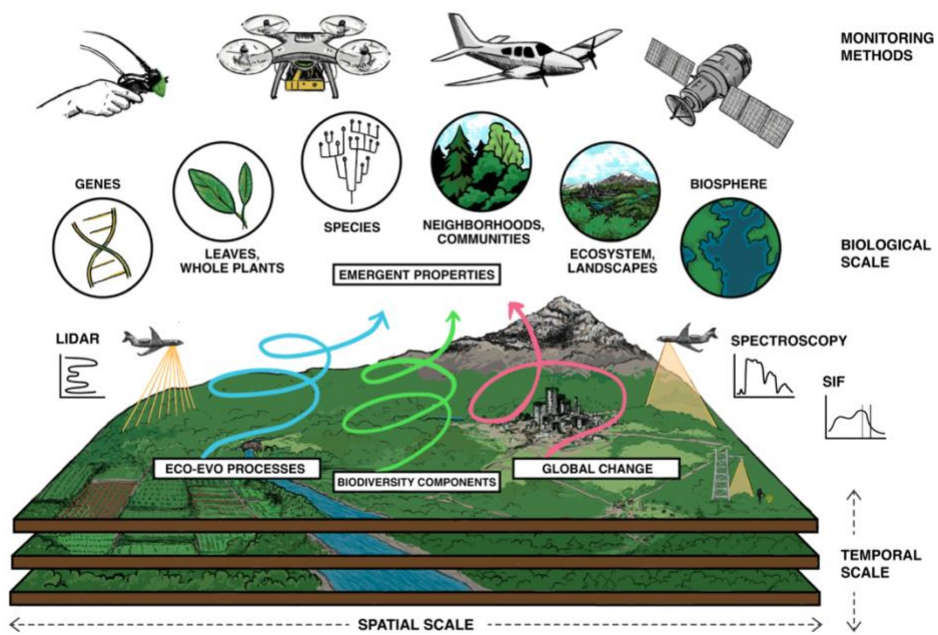
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1 **Figure Legends**

2

3 **Fig. 1.** Capturing biological variation across spatial and temporal scales to understand ecological and evolutionary
4 processes in changing environments. Shown are biological scales of measurement (circles) from genes and leaves to
5 the biosphere and some of the tools of spectral biology that capture optical information across these scales.
6 Spectroscopy, SIF and LiDAR from satellite, aircraft, UAVs, towers and hand-held instruments showing remote,
7 proximal and in-situ sensors that capture plant foliar chemistry, structure and function, photosynthesis and
8 productivity, and vegetation height and structure. The figure emphasizes the visual to the short-wave infrared
9 (VSWIR) solar domain (400-2500 nm), but the UV (100 - 400 nm), thermal emission (3 – 14 μm) as well as active
10 and passive microwave (0.1-1m) domains provide critical information, for example about light quality, ozone and
11 SO_2 ; land surface temperature, water content and flux; and soil water content or atmospheric water and ozone
12 content, respectively. Towers in a fixed location close to focal observation sites can support Phenocams, continuous
13 spectroscopic measurements, terrestrial laser scanning, and other sensor types. Combined with ground-based
14 measures and understanding of biological processes, spectral biology can contribute to measuring and understanding
15 life's variation (biodiversity components at any scale), ecological and evolutionary processes and their emergent
16 properties, and how they are changing with global environmental forces.

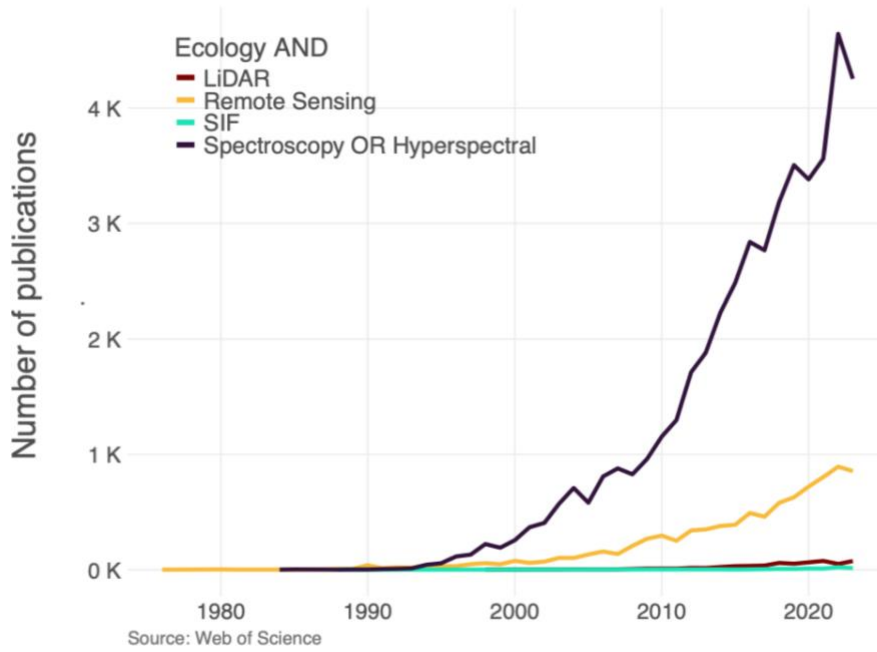
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1 **Fig. 2.** Number of publications listed within Web of Science over time from 1978 to 2024 with the
2 queries ‘ecology and spectroscopy or hyperpsectral’ (black), ‘ecology and remote sensing’ (orange),
3 ‘ecology and SIF’ (green), and ‘ecology and LiDAR’ (brown).

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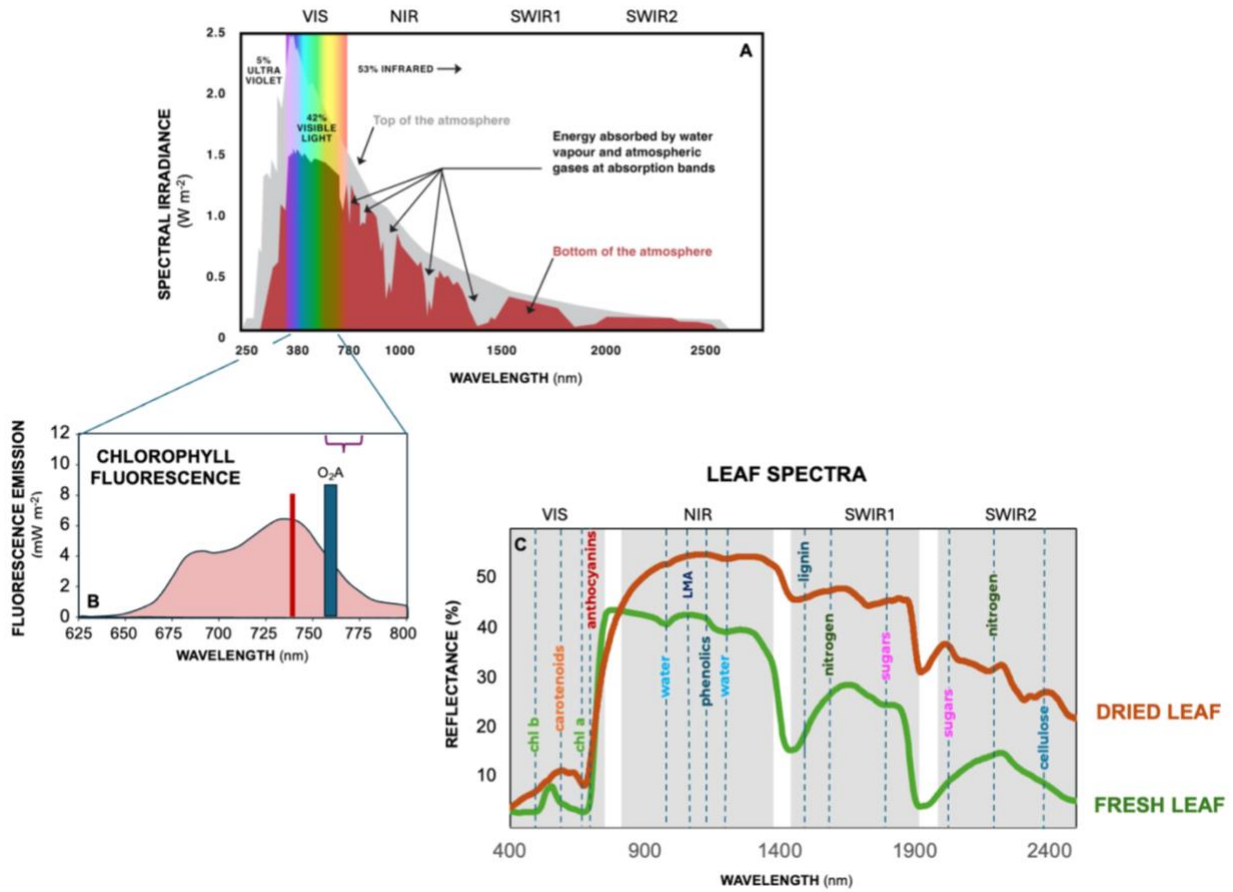


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1 **Fig. 3.** Spectral biology is defined as the interaction of electromagnetic energy, shown for (A), with
2 biological systems to reveal patterns and processes, such as (B) chlorophyll fluorescence emission
3 (middle) and (C) reflectance from plant tissues (bottom). A) Solar irradiance at the top of the atmosphere
4 (gray) and the sun's energy that penetrates the atmosphere to reach the Earth's surface (red) falls mostly
5 within the range of 250-2500 nm, spanning the ultraviolet (UV), visible range (VIS), near-infrared (NIR),
6 and two short-wave infrared regions (SWIR1, SWIR2). Plants absorb energy primarily in the red and blue
7 wavelengths for photosynthesis and re-emit a small fraction of the energy as chlorophyll fluorescence (B)
8 within the range of 625 to 800 nm, with peak emission shown at 737 (red vertical line). Solar-induced
9 fluorescence (SIF) can be differentiated from solar irradiance within features such as the O₂A band, where
10 oxygen absorbs (vertical blue band), providing a means to detect photosynthesis. Satellite sensors
11 designed to retrieve SIF capture emission within the range of 758–771 nm, indicated by the curly bracket,
12 taking advantage of the O₂A band. Different parts of the chlorophyll emission spectrum are used by
13 different sensors, depending on distance from the vegetation and depth of the atmosphere. C) Spectral
14 reflectance of fresh (green) and dried (brown) leaf tissue include features from the visible to the short-
15 wave infrared that are informative for predicting plant functional traits (e.g., leaf mass per area, LMA),
16 indicated as dotted lines. Reflectance spectra (solid curves) show the percent of incoming light reflected
17 at each wavelength within the VIS, NIR and SWIR1 and SWIR2.

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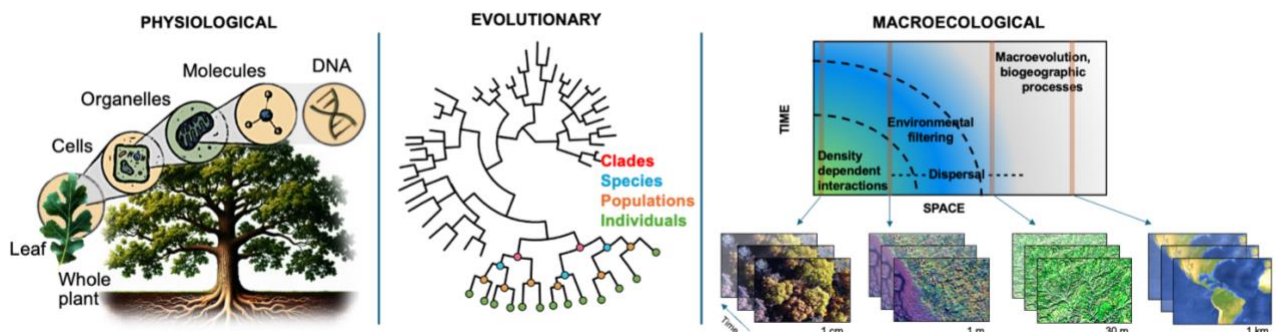
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1 **Fig. 4.** Three critical scaling hierarchies in spectral biology. Left: the physiological hierarchy encompasses how
 2 functions are expressed within nested levels of organization from genes, to molecules, organelles, cells, tissues
 3 (leaves) and the whole organism. Middle: the evolutionary hierarchy captures the fractal nature of the tree of life
 4 based on shared ancestry, where variation among individuals is nested within populations, which are in turn nested
 5 within species, and within clades of larger and larger size. Right: the macroecological hierarchy traverses the
 6 ecological processes that shift with spatial and temporal scales, shown here spanning the density-dependent
 7 interactions of individual trees, environmental filtering that sorts species based on niche preferences operating at the
 8 scale of critical environmental gradients, dispersal processes driven by migration and propagule movement, and the
 9 biogeographic and macroevolutionary processes that operate at deeper temporal and larger spatial scales.

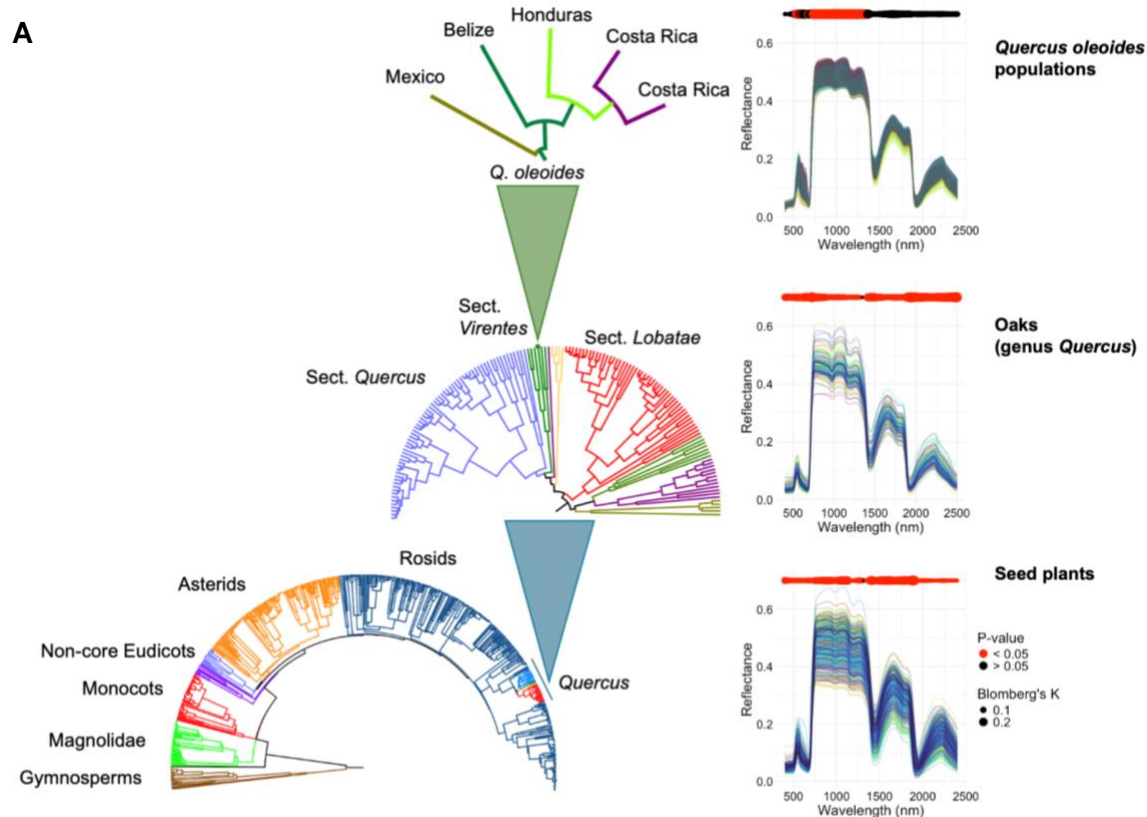
10 Three critical hierarchies in biology: 1) the physiological hierarchy with nested biological components from DNA to
 11 the whole organism, 2) the evolutionary hierarchy where variation among individuals is nested within populations,
 12 which are in turn nested within species and increasingly larger clades across the tree of life, and 3) a
 13 macroecological hierarchy in which ecological processes shift with spatial and temporal scale from density-
 14 dependent processes that involve organismal and species interactions in local environments, to environmental
 15 sorting and dispersal and migration processes at landscape scales, to long-term biogeographic and evolutionary
 16 processes at continental scales that extend deep in time. A typical spatial resolution (grain size) is shown below each
 17 spectral image associated with the different spatial scales. This figure is adapted with permission from Cavender-
 18 Bares et al. (2021).

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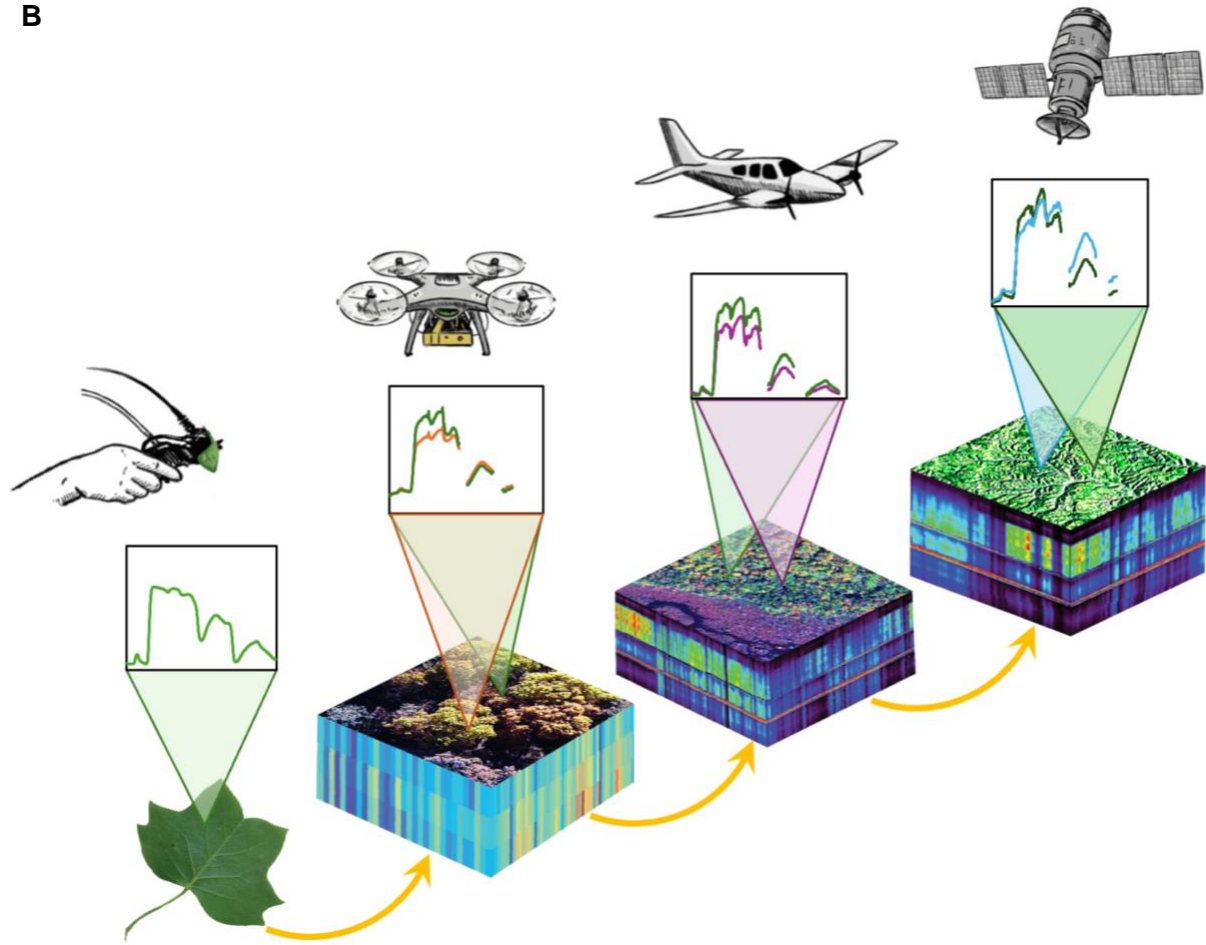
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1 **Fig. 5.** Using a common data type (spectral reflectance) across evolutionary (A) and macroecological
 2 scaling hierarchies (B). A) Phylogenetic signal across wavelengths and phylogenetic scales from seed
 3 plants to an adaptive radiation within a single genus (*Quercus*, the oaks) to populations within a single
 4 species. Phylogenetic relationships and spectra from fresh leaves are shown for species across the seed
 5 plants (bottom), for species of the oak genus *Quercus* (middle), and for the variation among individuals
 6 within populations of a single species (top). A filled red circle for a given wavelength indicates that close
 7 relatives have a more similar normalized spectral reflectance value than expected at random. Data are
 8 redrawn from Meireles et al. 2020 and Cavender-Bares et al. 2016. B) A range of instruments from
 9 handheld devices, uncrewed aerial vehicles (UAV), aircraft and satellites capture reflectance spectra and
 10 image cubes of vegetation reflectance at every biological scale. Spectral reflectance from different
 11 platforms has the potential to advance ecological integration across spatial and temporal scales.
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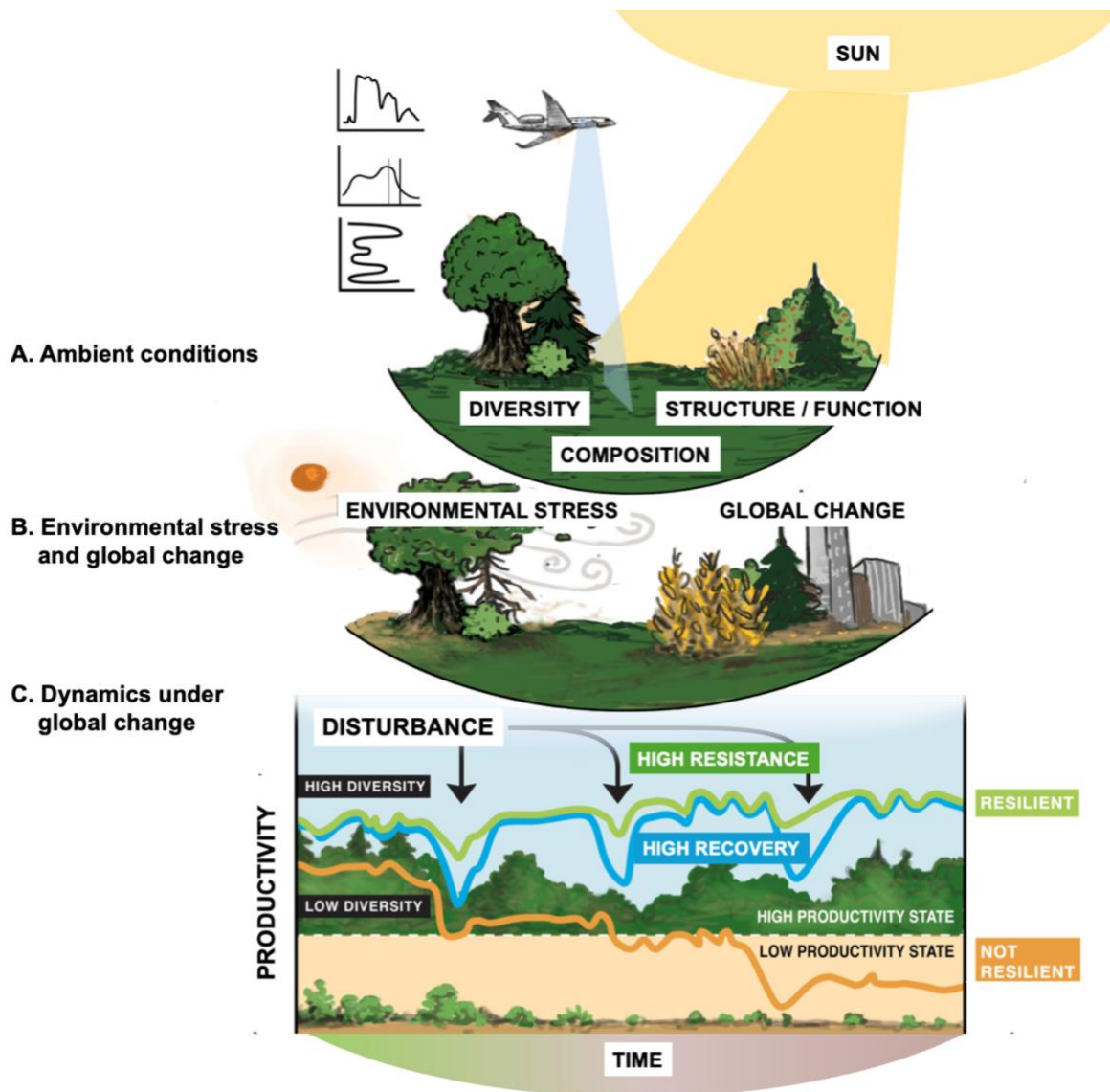
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1 **Fig. 6.** Key realms for advancement in spectral biology. The realms are conceptual and nested. A) Plant
 2 identity, diversity, and composition as well as plant and ecosystem structure and function can be
 3 spectrally detected in ambient steady state conditions using vegetation spectra, SIF and/or LiDAR. B) The
 4 average responses of ecosystems to global change and environmental stress can also be detected
 5 spectrally, across space, time or experimental treatments. C) Differences over time can further be used to
 6 understand the dynamics of ecosystem responses to change, including their resistance and capacity to
 7 recover from disturbance, both of which help capture the nature and underlying mechanisms of resilience
 8 of ecosystems.



9