Introduction to Remote sensing of plant functional traits

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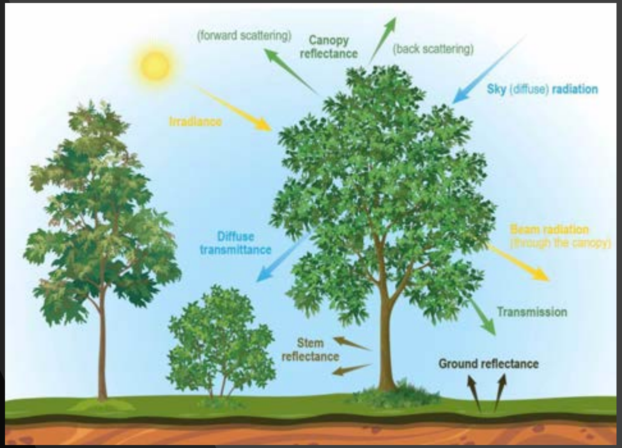
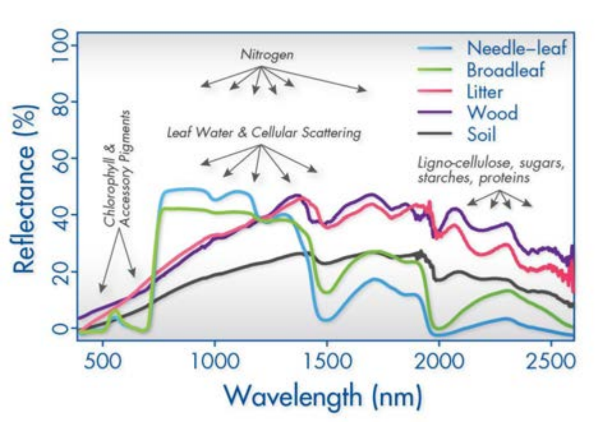
Introduction to Remote sensing of plant functional traits

- In Remote Sensing (*RS*), we normally focus on ***leaf level – canopy*** properties (*although with UAVs we can be more detailed*)
- <u>Overall aim</u>: to link leaf biochemical and structural properties with leaf optical properties
- Talk mostly based on *Optical RS*
- We assume that plant physiological properties, structure, and distribution of foliage are reflected as signatures in the canopy (*but for UAV not that necessary*)
- We can measure traits inked to health, status, stress of vegetation
- *RS* provides repeated, spatially continuous information over large scales - ideal for Earth System Science monitoring

What type of optical information can be linked to vegetation traits?

- When light from the sun interacts with plant leaves, a proportion of this is reflected and transmitted, and the remaining is absorbed.
- The reflected component is measured by optical remote sensing instruments.
- Reflectance curve: % or proportion of light reflected throughout the electromagnetic spectrum
  - VIS (~400nm-750 nm): at the leaf level, dominated by pigments' absorption
  - NIR (~800-1100 nm): scattering from leaf structures | leaf epidermal layer | leaf absorption of water (970-1100nm) – –> used to RS water content
  - SWIR (~1100-2500 nm): water absorption plus absorption of cellulose, lignin, structural carbon, nutrients, protein (required to retrieve many biochemicals and LMA)



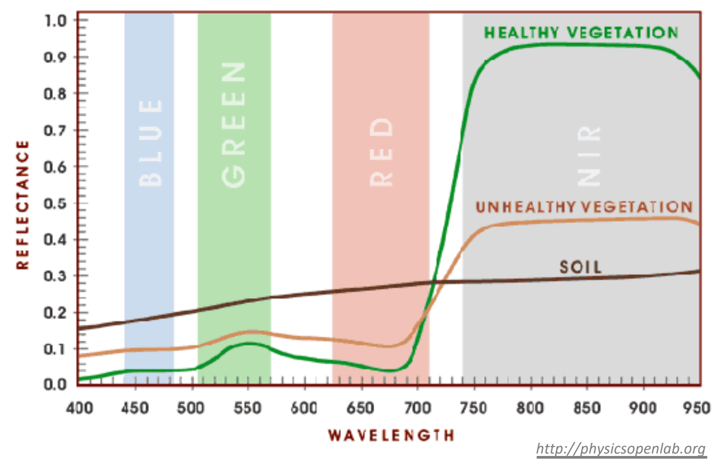


Serbin & Townsend Peterson (2019), Scaling Functional Traits From Leaves to Canopies, in Remote Sensing of Plant Biodiversity

How to convert reflectance information to vegetation traits?

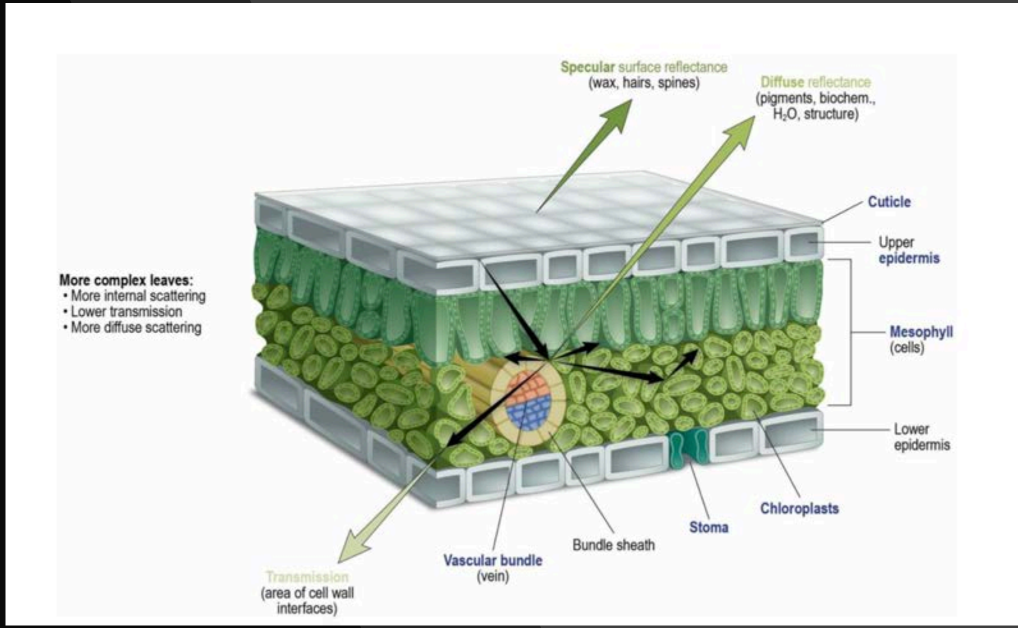
- This is normally done in an **Empirical / Statistical** way
- Spectral information is linked with measured traits on the ground, with the objective of making a map of traits eventually – we will be pursuing this in the field
  - *Option 1*: we understand the expected relationship between reflectance and the trait (e.g. NDVI) →
  - *Option 2*: we do NOT have such understanding – data mining – many statistical approaches: a very popular one is PLSR, but others also used (e.g. wavelet transform + regression), or machine learning algorithms (e.g. *spectranomics – Asner & Martin 2016, Global Ecology and Conservation*)

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red})}$$



How to convert reflectance information to vegetation traits?

- Another way of addressing this question is using mechanistic approaches: Radiative Transfer models (RTMs)
  - At the leaf scale: they simulate leaf reflectance and transmittance based on leaf biochemical and structural properties (e.g. PROSPECT, LIBERTY, LEAFMOD models)
  - At the canopy scale: several models with a variety of assumptions and requirements



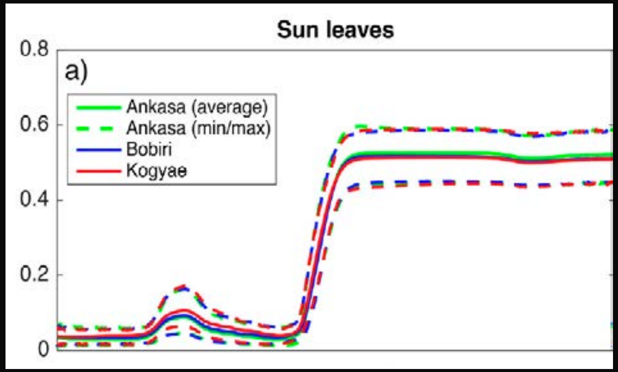
- These allow for inverse approaches: e.g. obtain traits (or more, e.g. landscape functional diversity) from reflectances, however challenge of equifinality

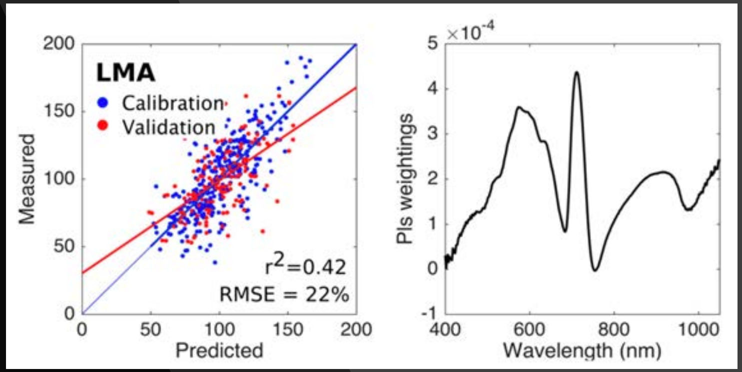
Serbin & Townsend Peterson (2019), Scaling Functional Traits From Leaves to Canopies, in Remote Sensing of Plant Biodiversity

What do we aim to produce?

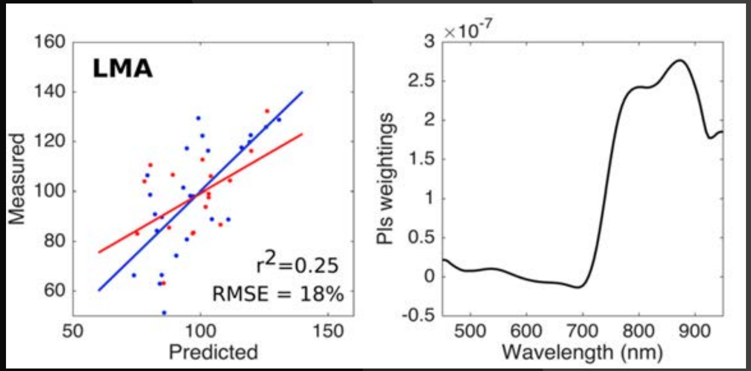
- A *primary* objective is to convert RS signatures to accurate trait maps

In the lab, on leaves, using a hand-held spectrometer



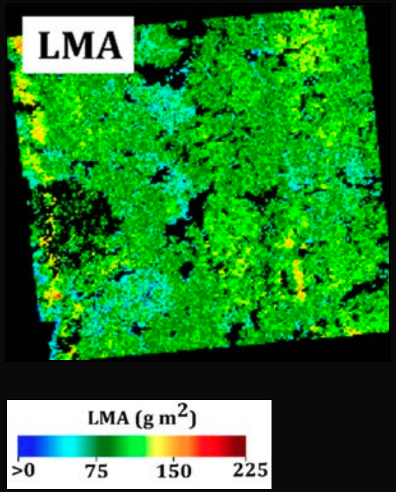


Lab-collected reflectance spectra to leaf



UAV-collected reflectance spectra to leaf

Map of *Leaf Mass per Area* (gm^{-2})



NOTE: This is our main exercise in the PFTC-5

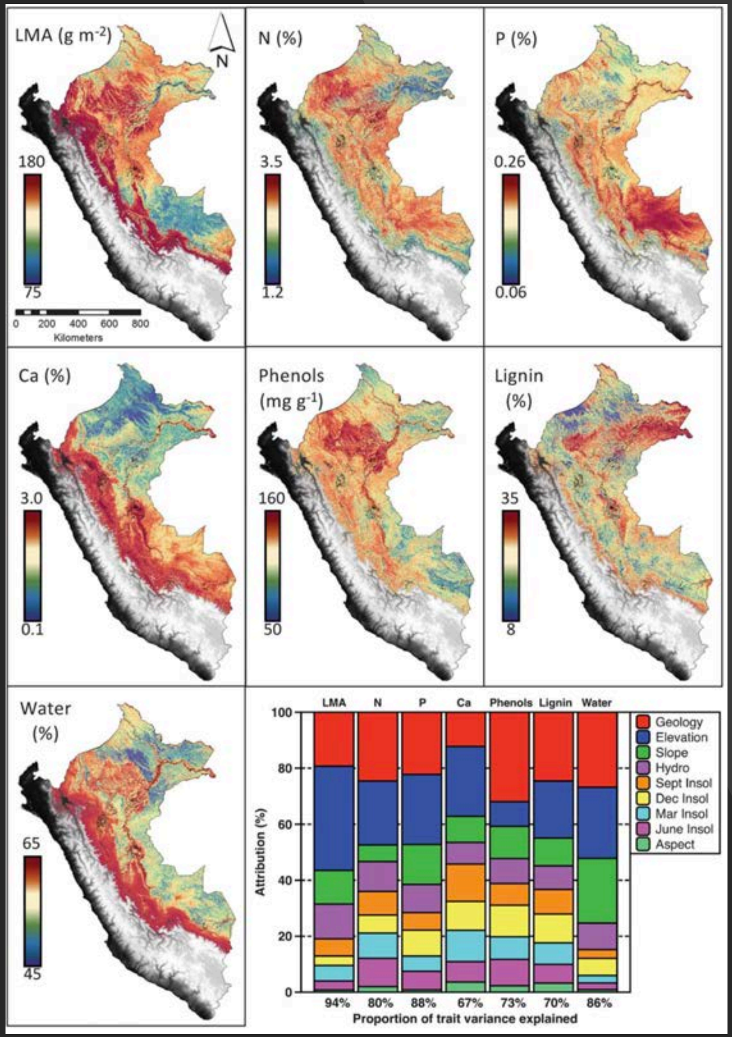
Thomson, E. R., et al. (2018), Remote Sensing 10(10)

What do we aim to produce?

- The *ultimate* objective is to provide:
  1) A baseline characterization of Earth’s functional diversity
  2) To test hypotheses for the drivers of such variation: that is, to contribute to ecological theory through the incorporation of **space** (and space-related aspects such as spatial organization and abundance) in an explicit way

1) A baseline characterization of Earth's functional diversity

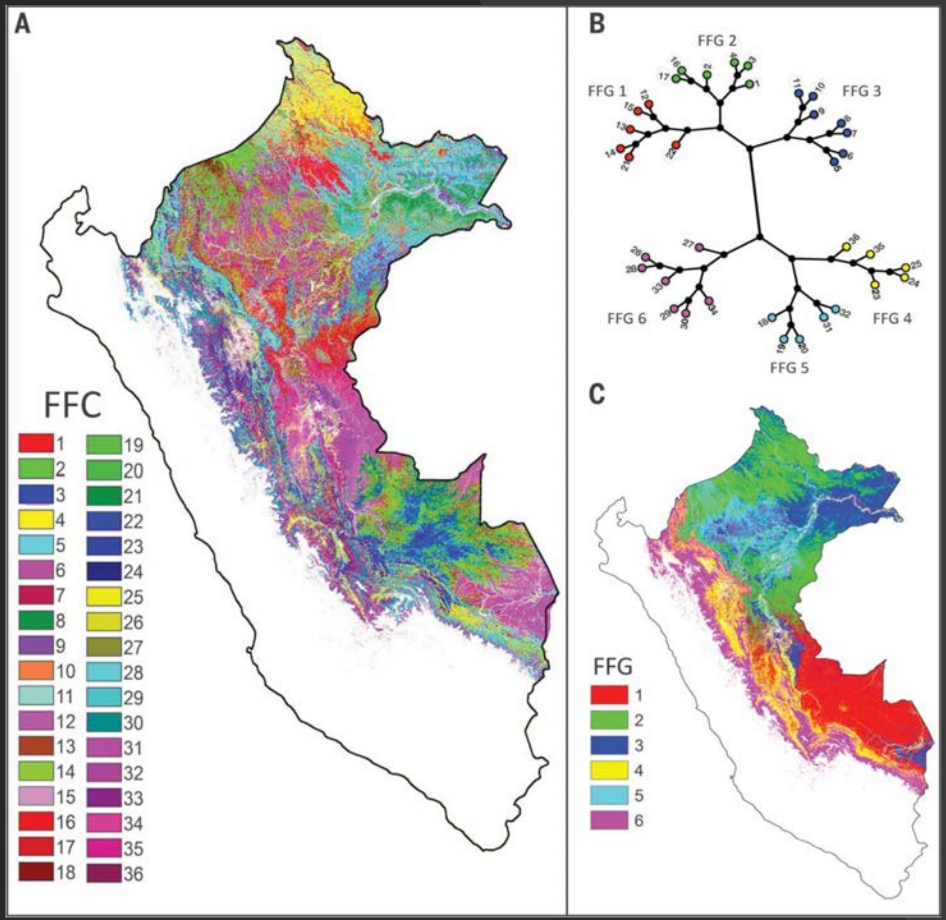
- Airborne laser-guided imaging spectroscopy + environmental modelling to derive large-scale, multivariate forest canopy functional trait maps of the Peruvian Andes-to-Amazon biodiversity hotspot
- Seven mapped canopy traits (largely uncorrelated) revealed functional variation in a geospatial pattern explained by geology, topography, hydrology, and climate
- Validated with functional traits measured in 301 field inventory plots



Asner et al. (2017) Science 355, 385–389

1) A baseline characterization of Earth's functional diversity

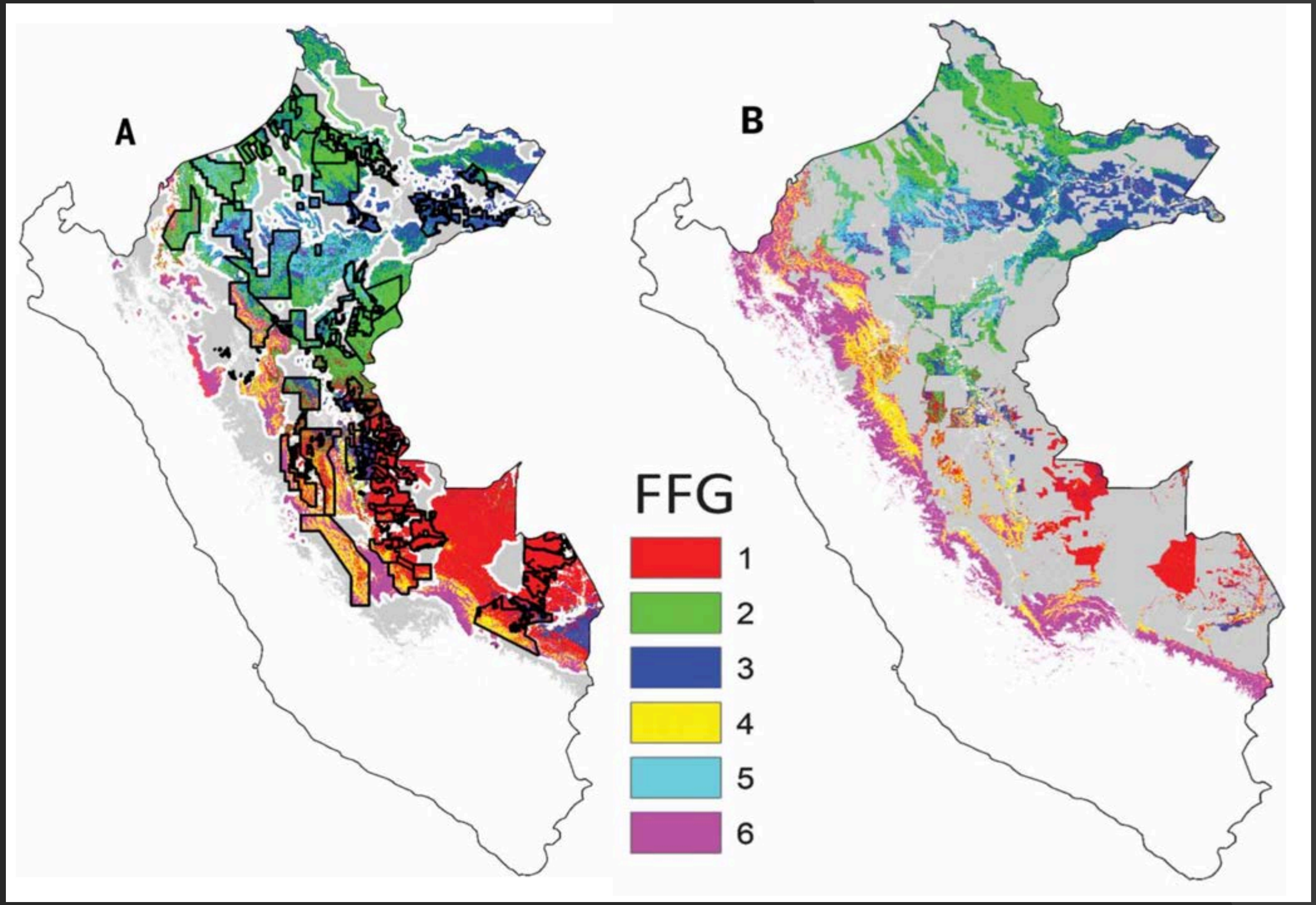
- Clustering of canopy traits yielded a map of forest *beta*-functional diversity:
  - ***FFG-1***: high canopy foliar N, low defense compound investment
  - ***FFG-2***: low foliar P & Ca, high phenol- and lignin-based defense investments
  - ***FFG-3***: lowland Amazonian floodplains in areas of high rock-derived cation deposition
  - ***FFG-4***: P-rich colluvial deposition zones at the base of the Andes
  - ***FFG-5***: anoxic swamp regions, low canopy foliar N & P, high defenses
  - ***FFG-6***: high LMA & leaf water content, low foliar N & Ca



Asner et al. (2017) Science 355, 385–389

1) A baseline characterization of Earth's functional diversity

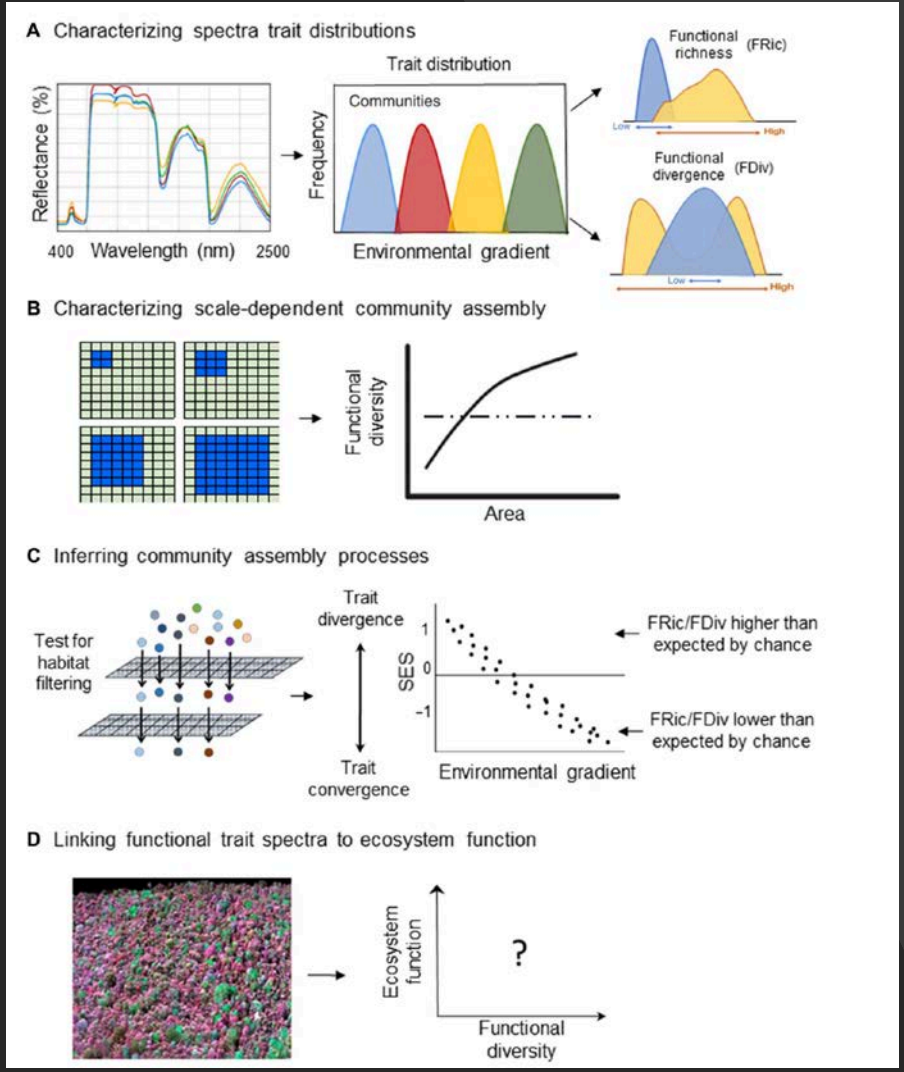
- Government land-use data + FFCs
- Assessment of conservation threats, protections, and opportunities
- Between 32 and 46% of each mapped FFG is currently protected.
- Up to 53% of each mapped, functionally distinct forest presents an opportunity for new conservation action



Asner et al. (2017) Science 355, 385–389

2) Testing Ecological Hypotheses

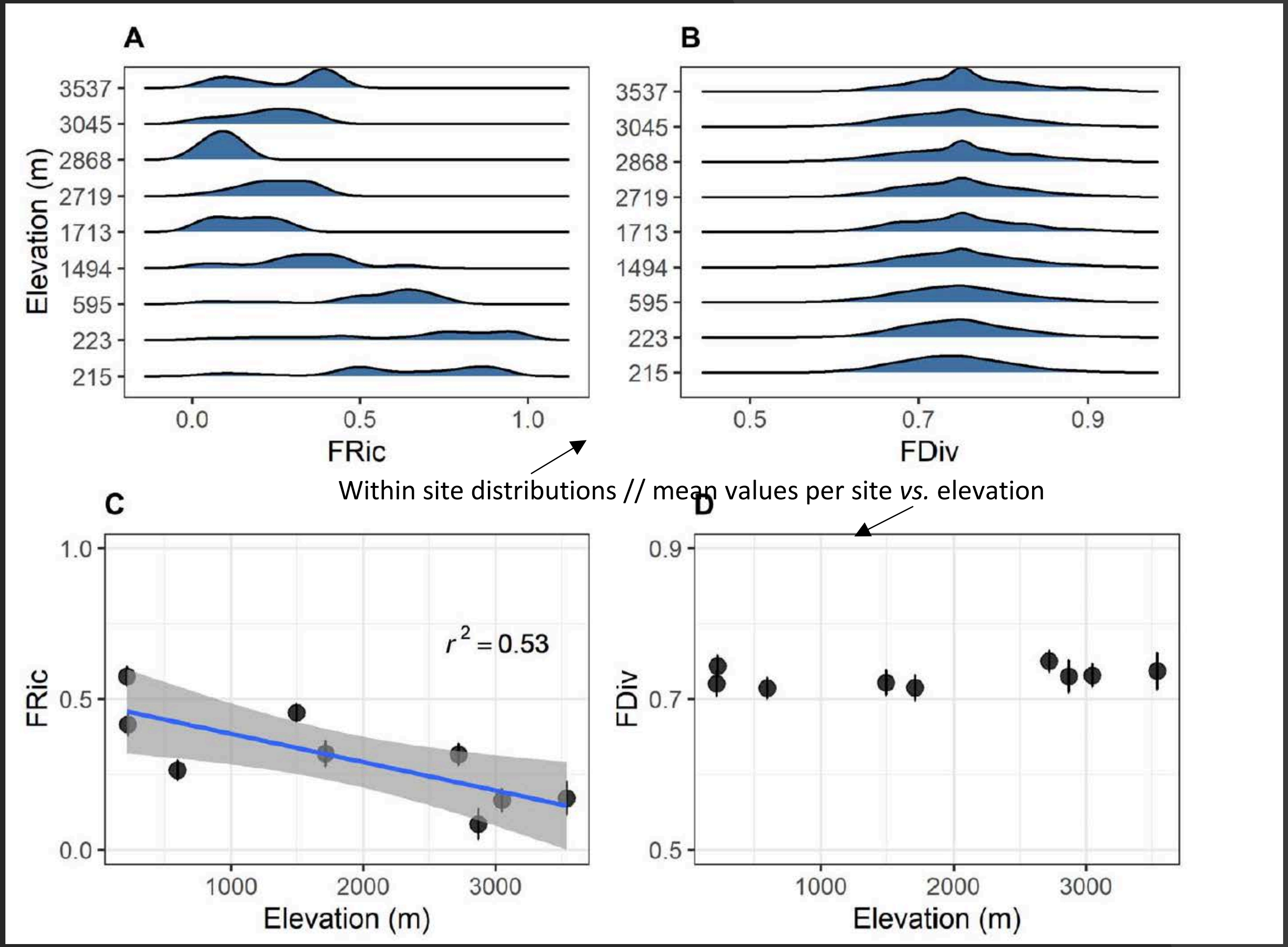
- *(A)* Trait distributions are derived from imaging spectroscopy
- *(A)* Functional diversity indices are quantified from trait distributions: functional richness (FRic) and functional divergence (FDiv)
- *(B)* Scale dependency of community assembly processes is evaluated by assessing variation in functional diversity across spatial scales
- *(C)* Community assembly processes are disentangled by testing for the relative importance of trait convergence (***environmental filtering***) and trait divergence (***biotic interactions***)
- *(D)* Functional diversity effects on ecosystem processes are tested by examining whether remotely sensed diversity indices are related to forest productivity.



Durán et al. (2019) Science Advances 5, eaaw8114

2) Testing Ecological Hypotheses

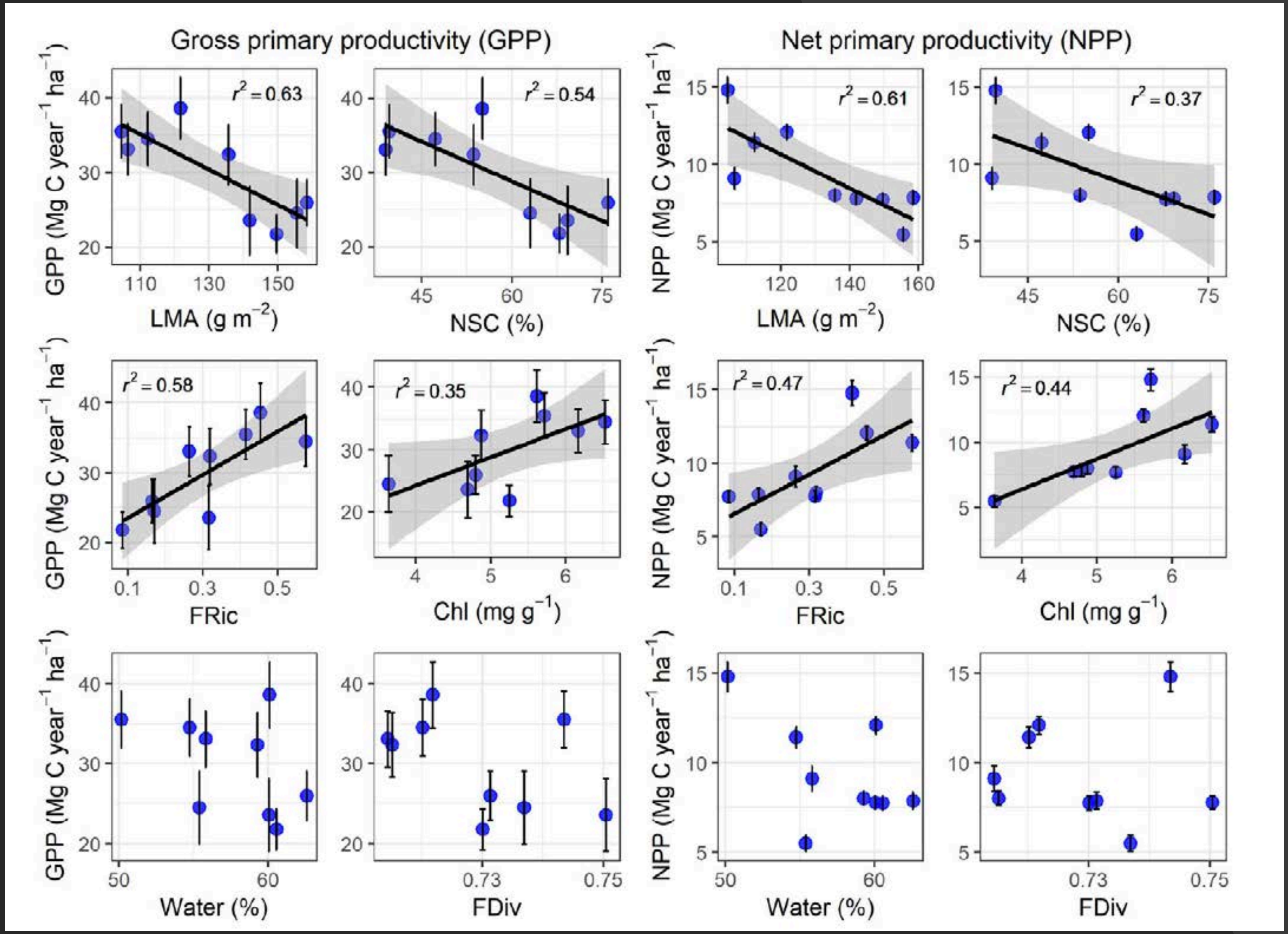
- Distribution of trait diversity indices within and among sites along elevation
- Multi-Trait Richness (***FRic***) increases with declining elevation *(increased T at lower elevations, more stable climate, more favorable conditions for tress with different leaf syndromes to thrive)*
- ***FRic*** distributions get narrower with elevation – more resource-limitation at higher elevations
- Trait Divergence does not change with elevation (perhaps due to high within-site variation)



Durán et al. (2019) Science Advances 5, eaaw8114

2) Testing Ecological Hypotheses

- *NPP* and *GPP* negatively associated with *LMA*, Non-structural carbohydrates (*NSC*)
- *NPP* and *GPP* positively associated with % Chlorophyll
- The above agree with the *Leaf Economic Spectrum*
- **Functional multi-trait richness** (*Fric*) best related (positively) to *GPP* (but also significantly to *NPP*)



Durán et al. (2019) Science Advances 5, eaaw8114

What about UAVs?



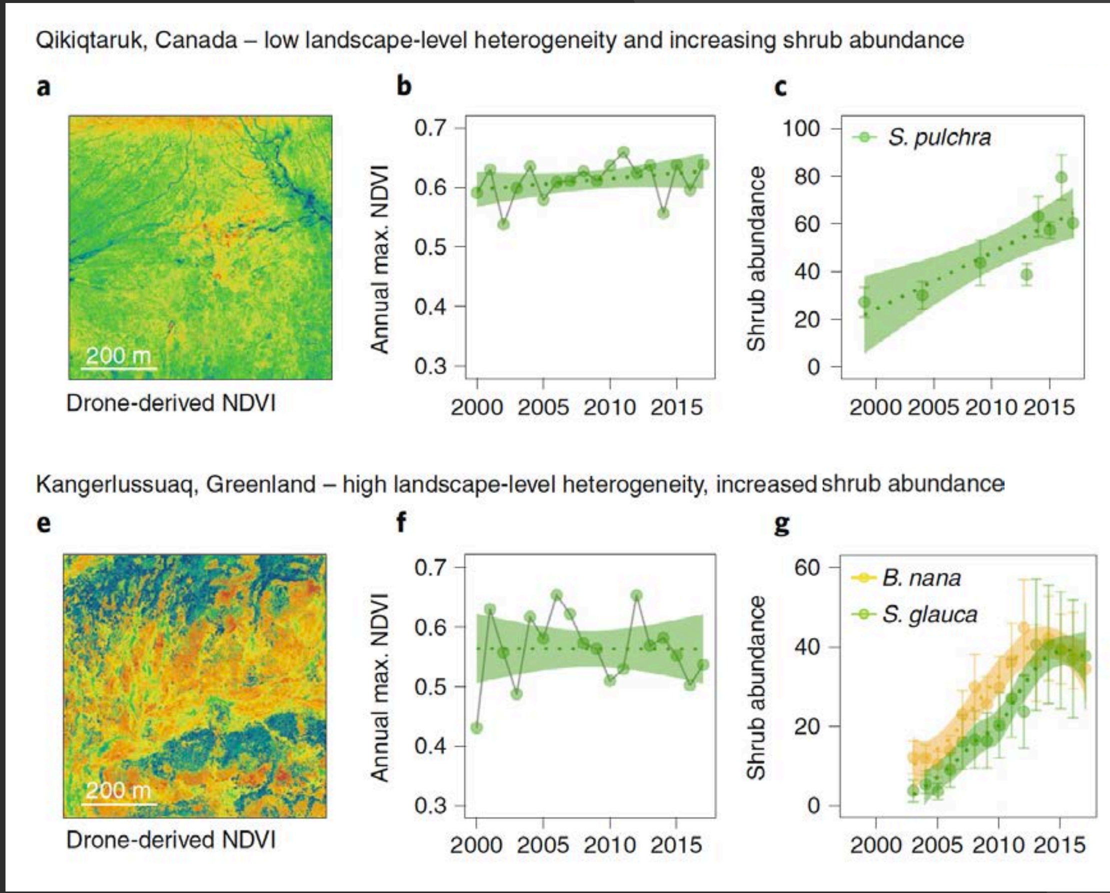
Unmanned Aerial Vehicles (UAVs, a.k.a. drones): lightweight aircraft platforms operated from the ground that can carry imaging or non-imaging payloads

- *"Low and slow"* – image acquisition at cm resolution || Efficient, affordable
- Developed to be useful in ecology due to the miniaturization of measurement technologies (LiDAR, reflectance & other sensors)

- Enable scale-appropriate measurement of ecological phenomena (e.g. individual organisms)
- Expand plot-level observations to landscape scales
- Produce data at fine spatial & temporal resolutions over prolonged periods of time (*repeatable, e.g.* phenology, longer term responses to experimental treatment)
- Have the potential to bridge critical information gaps and to advance our understanding of key Earth System processes
- Produce detailed structural canopy variables – *Structure from Motion – SfM*: *estimation of 3D structures from overlapping 2D image sequences that may be coupled with local motion signals*

Mismatch between pixel and temporal resolution and ecological process in space-borne imagery

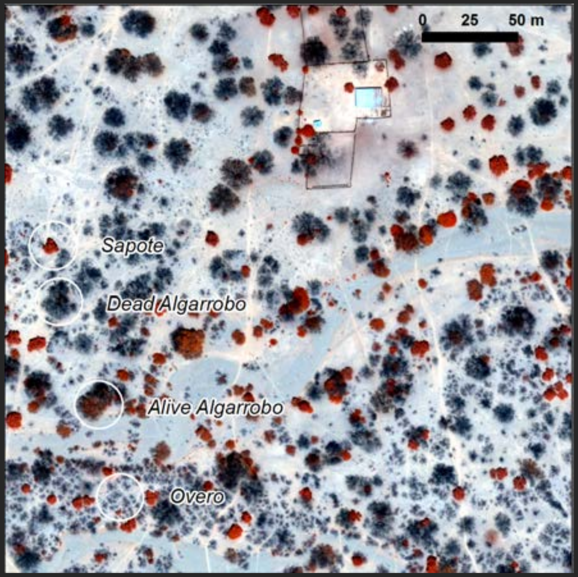
- An example form the Arctic tundra:
  - Spatial heterogeneity in landcover can influence NDVI–vegetation relationships
  - Sub-pixel spatial heterogeneity in vegetative greening and browning cannot be accurately captured at coarser grains
  - In both cases shrub cover has increased, but NDVI at a coarse scale is unable to detect it
  - UAV data provides information at the adequate spatial scale

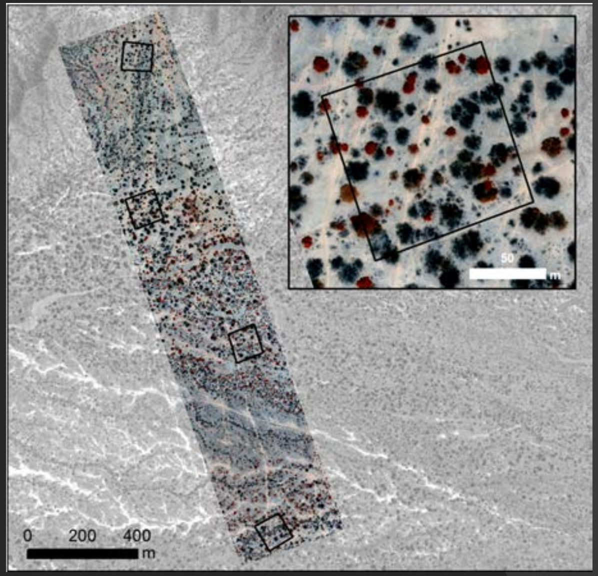


Myers-Smith & Kerby (2020) Nature Climate Change 10, 106–117

Some UAV-based studies: Individual plant recognition & assessment of health

- UAV with red edge band + *Structure from Motion* canopy height
- Plant species and plant health can be retrieved
- Species:
  - Algarrobo (*Prosopis pallida*)
  - Overo (*Cordia lute*a)
  - Sapote (*Capparis scrabrida*)

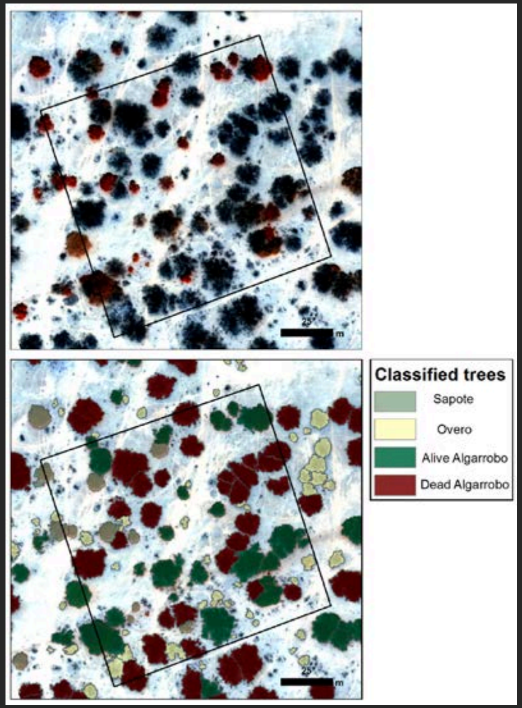




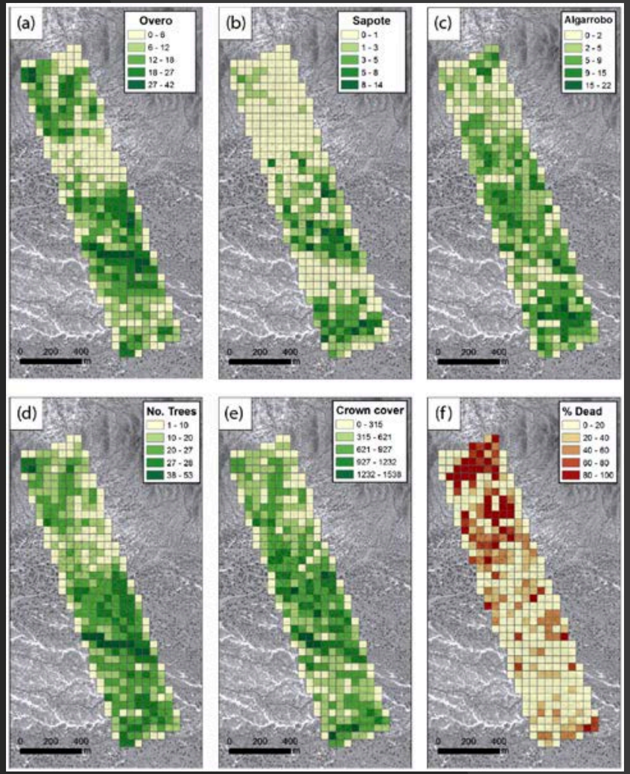
Baena et al. (2017) PLOS ONE 12(11), e0188714

Some UAV-based studies: Individual plant recognition & assessment of health

- Distribution of species composition and state can be modelled using
  - Crown delineation with object image algorithm
  - Vegetation indices
  - SFM tree height



Summarized in 50x50m pixel statistics in the study area

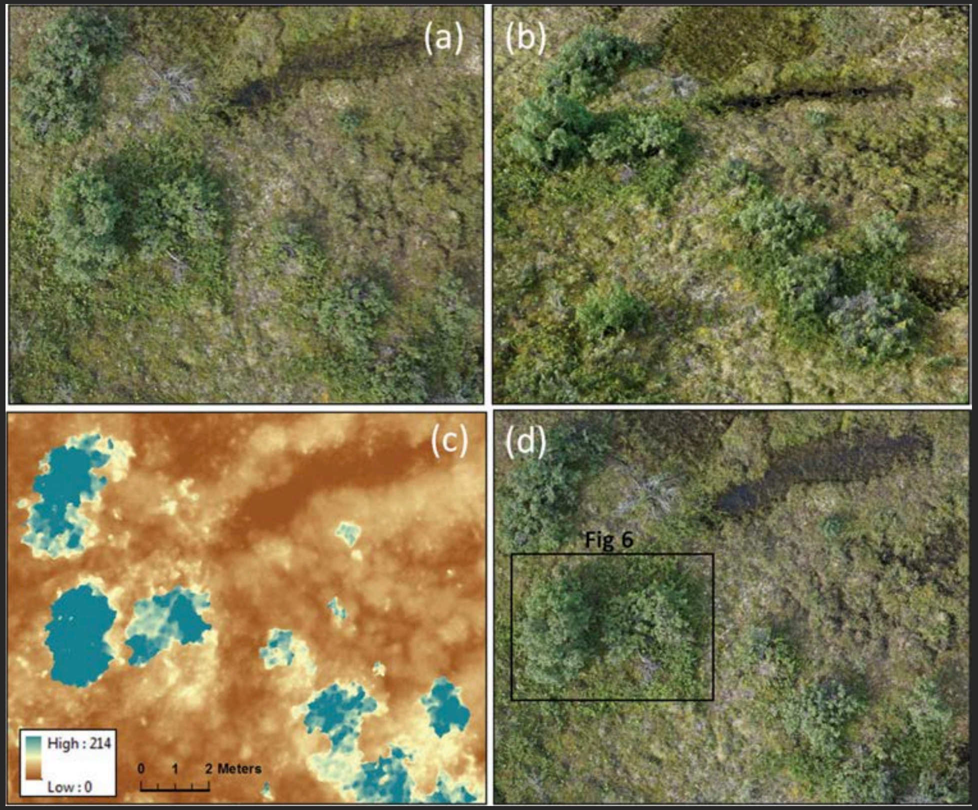


Baena et al. (2017) PLOS ONE 12(11), e0188714

Some UAV-based studies: more on *Structure from Motion* – plant height from cloud points

- Using a simple RGB camera onboard a small UAV
- Overlapping images were used to create ultra-dense 3D cloud points (on average 30,000 points per m^2)
- Final product is a 1cm resolution surface elevation raster able to identify the elevation of individual tundra shrubs

UAV picture *Ultra-dense cloud point*

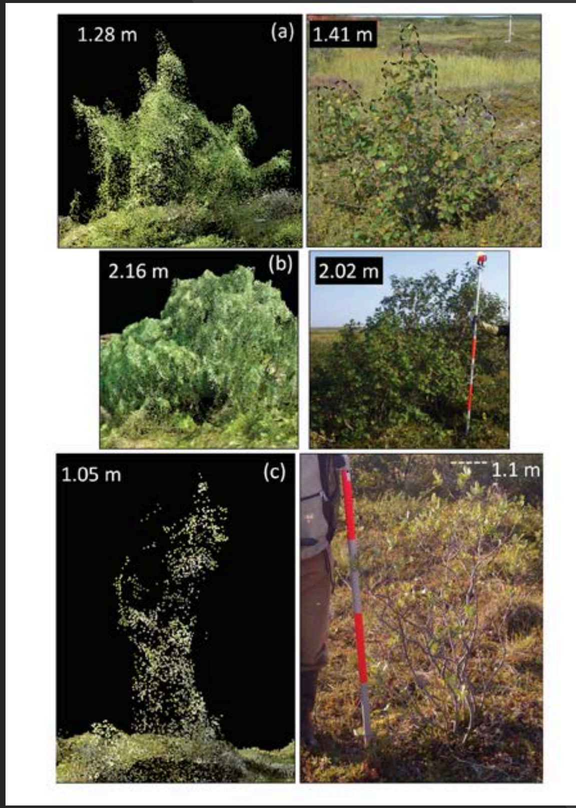


Vegetation height model *Orthophoto*

Comparison between SfM-modelled and ground-measured individual shrubs

Alder

Willow

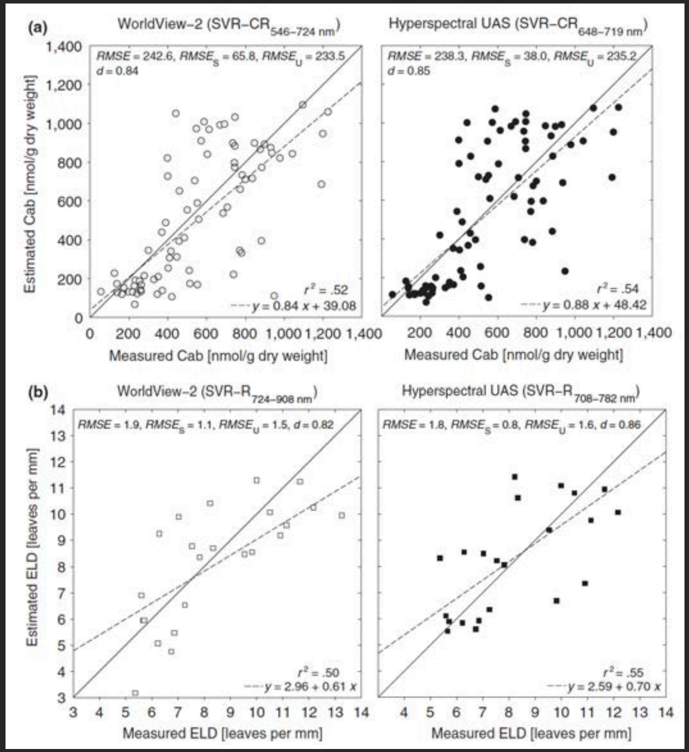


Fraser et al. (2016) Arctic Science 2(3), 79-102

Some UAV-based studies: Individual plant recognition and assessment of health

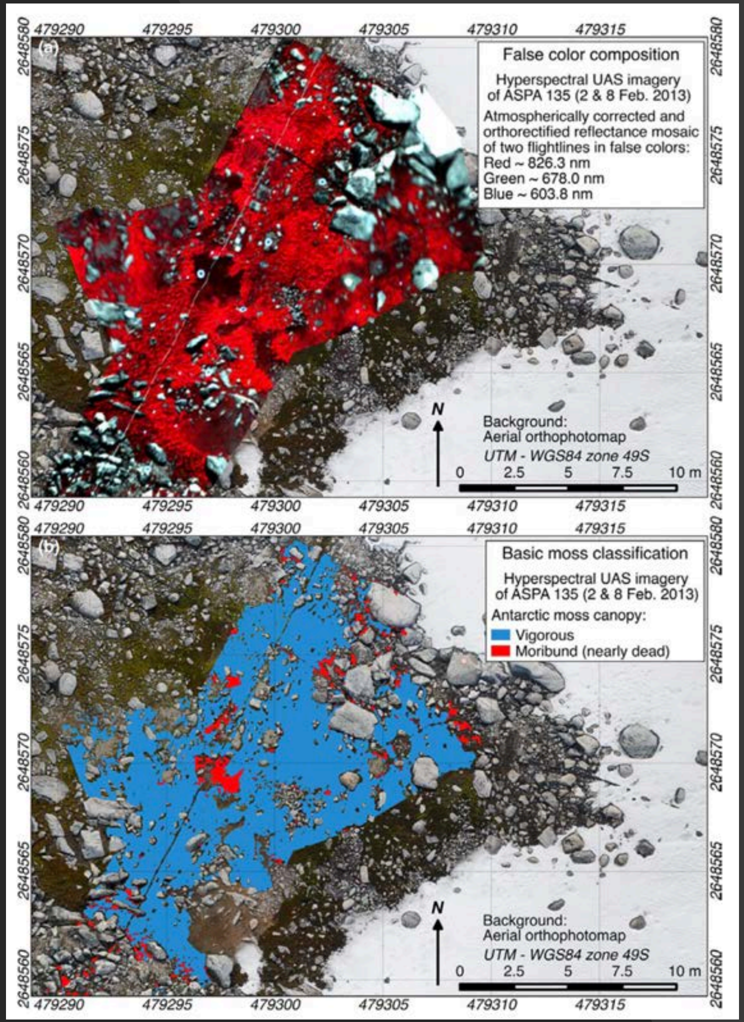
- 162 spectral bands between 361 and 961 nm (hyperspectral VNIR camera)
- Machine learning algorithm to link field-based vegetation health and spectral signature (*Support Vector Regressions, SVR*)
- Remote detection of health status on mosses

Total chlorophyll *a* and *b* content (**Cab**: nmol chlorophyll a and b molecules per g dry weight)



Effective leaf density (**ELD**): number of leaflets per mm of gametophyte stem

Map of moss health



Malenovský (2017), Methods in Ecology and Evolution 8(12), 1842-1857

Concluding Remarks

- Retrieval of leaf traits from *RS* reflectance is normally achieved through the establishment of empirical statistical relationships between reflectance and measured traits – but can also be done mechanistically through *Radiative Transfer Models*
- Although producing a map is a primary objective of *RS* vegetation trait research, ultimately this aims to produce baseline information of functional diversity and to test ecological hypotheses with spatially continuous information
- UAVs offer very high resolution and repeatability at ecologically relevant spatial and temporal scales
- UAV ecology is in its infancy and in constant revolution in part driven by technological advances largely related with miniaturization of sensors and batteries