

1 Practical drone ecology: Data management to facilitate open, re- 2 producible science in drone-based terrestrial ecology applications

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11 Abstract

12 “Small science” ecology labs are increasingly collecting “big data” from drone-based instruments [1]. There is
13 currently a lack of a consensus framework on how to best manage these data from collection to publication.
14 Here, we propose a guide for established “data levels” for ecological applications akin to those developed for
15 NASA and USGS Earth observation data as well as practical suggestions for ensuring data privacy, data
16 redundancy, and reproducible workflows using drone-derived data.

17 Introduction

18 For drone technology to revolutionize spatial ecology [2], it must move beyond the “peak of inflated expectations”
19 on the Gartner Hype Cycle for Emerging Technologies [3].

20 Drones can be a means to democratize landscape and macroscale ecology due to their relative inexpensiveness,
21 their ease of use, and their ability to meet the demanding primary need of these disciplines: fine-enough
22 resolution data at a broad-enough spatial extent.

23 Thus, drone ecology is at a pivotal moment in its development wherein decisions made by current practitioners
24 can determine whether the field will add to or subtract from the “research debt” of future practitioners [4].

25 We advocate an open science model by which new, potential practitioners are welcomed into the field with a
26 clear-eyed view of how to best make use of the emerging technology in a practical sense.

27 In this brief *Communication*, we answer the call of [1] and propose a data organization and management scheme

28 that will help guide users to making intentional decisions about drone-derived data to foster collaboration,
29 data privacy, and reproducible science using data that may be many orders of magnitude larger than those
30 typically collected by ecologists.

31 **Data collection**

- 32 • Multiple SD cards
33 • Multiple hard drives in the field (to ensure redundancy)
34 • Network attached storage
35 • Cloud backup
36 • Separate hard drive for local processing

37 **Conceptual framework for varying levels of drone-derived data products**

38 NASA developed the concept of data levels (<https://earthdata.nasa.gov/collaborate/open-data-services-and-software/>
39 data-information-policy/data-levels) as a means of organizing the conceptual flow of a processing pipeline for
40 Earth observation data (e.g., from satellites).

41 There are some parallels with drone-derived data, but some important differences that limit the ability to
42 map the data typically collected for drone ecology onto these established levels [1].

43 We propose a scheme that fits the spirit of the NASA data levels but that more appropriately maps to typical
44 Structure from Motion workflows for terrestrial ecology missions. This example is a plant science example
45 (measuring and classifying trees), but we hope it has some capacity to generalize to other types of data
46 collection for ecological studies.

47 **Level 0**

48 Raw data from sensors. Often images representing reflectance or emission of objects on the ground.

49 **Level 1**

50 Basic outputs from photogrammetric software.

51 **Level 2**

52 Radiometrically or geometrically corrected outputs from photogrammetric software. Some of these corrections
53 can be done within the photogrammetry software itself. Some can be done outside the photogrammetry
54 software using other software (e.g., R [5]).

⁵⁵ **Level 3**

⁵⁶ Domain-specific information extracted from Level 2 products.

⁵⁷ **Level 3a**

⁵⁸ Information extracted using *just* spectral information or *just* geometric information.

⁵⁹ **Level 3b**

⁶⁰ Information extracted that uses *both* spectral and geometric information.

⁶¹ **Level 4**

⁶² Aggregations of Level 3 products to regular grids. For instance, to match to other sensors or to account for

⁶³ the scale at which calibration was performed.

⁶⁴ **Discussion**

⁶⁵ **Acknowledgements**

⁶⁶ We gratefully acknowledge funding from the USDA Forest Service Western Wildlands Environmental Threat

⁶⁷ Assessment Center (WWETAC) as well as the CU-Boulder Grand Challenge.

⁶⁸ **References**

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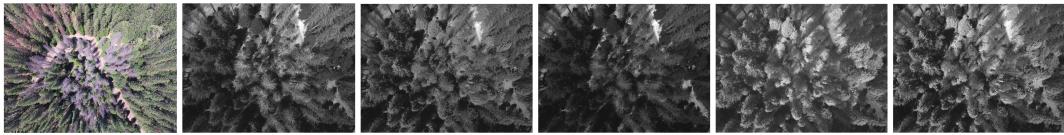
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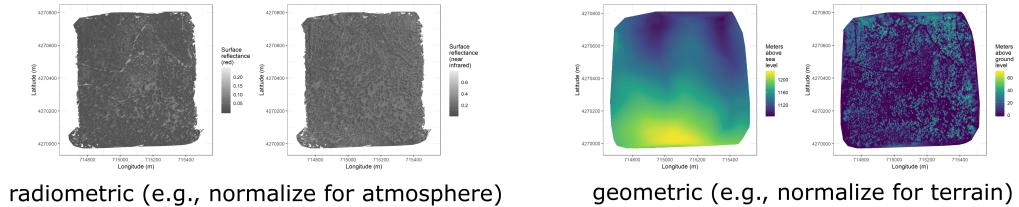
Level 0: raw data from sensors



Level 1: basic outputs from photogrammetric processing

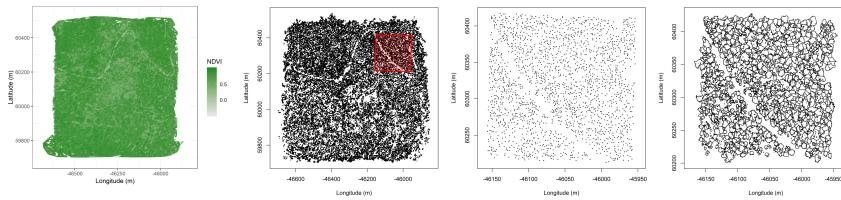


Level 2: corrected outputs from photogrammetric processing

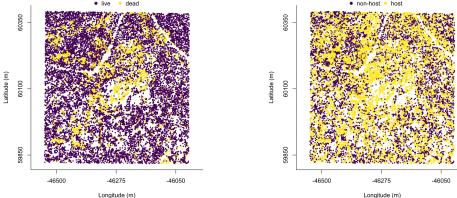


Level 3: domain-specific information extraction

L3a
spectral
OR
geometric



L3b
spectral
AND
geometric



Level 4: aggregations to regular grids

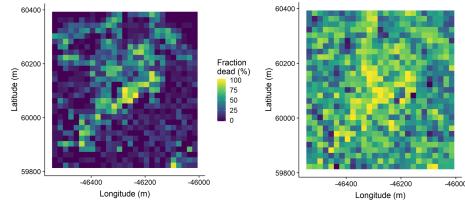


Figure 1: Proposed data levels for drone-derived data used in ecology applications.