

Darwin Core Guide

Standardizing Marine Biological Data Working Group

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Contents

Preface	5
1 Introduction	7
1.1 Data Structures	7
1.2 Ontologies	7
1.3 Controlled Vocabularies	8
1.4 Technologies	10
1.5 Notes on Integrating OBIS, Darwin Core as it relates to OOS's .	10
1.6 Metadata	10
1.7 Data QC	10
2 Applications	13
2.1 Salmon Ocean Ecology Data	13
2.2 Hakai Seagrass	17
2.3 Aligning Data to Darwin Core - Sampling Event with Measure- ment or Fact	28
3 Dealing with errors	37
3.1 Example using GitHub to resolve errors	37
4 Final Words	43
5 Tools	45
5.1 R	45
5.2 Python	48

5.3	Google Sheets	50
5.4	Validators	50
References		53

Preface

Biological data structures, definitions, measurements, and linkages are necessarily as diverse as the systems they represent. This presents a real challenge when integrating data across biological research domains such as ecology, oceanography, fisheries, and climate sciences.

Lots of standards exist for use with biological data but navigating them can be difficult for data managers who are new to them. The Earth Science Information Partners (ESIP) Biological Data Standards Cluster developed this primer for managers of biological data to provide a quick, easy resource for navigating a selection of the standards that exist. The goal of the primer is to spread awareness about existing standards and is intended to be shared online and at conferences to increase the adoption of standards for biological data and make them FAIR.

Benson, Abigail; LaScala-Gruenewald, Diana; McGuinn, Robert; Satterthwaite, Erin; Beaulieu, Stace; Biddle, Mathew; et al. (2021): Biological Observation Data Standardization - A Primer for Data Managers. ESIP. Online resource. <https://doi.org/10.6084/m9.figshare.16806712.v1>

Chapter 1

Introduction

The world of standardizing marine biological data can seem complex for the naive oceanographer, biologist, scientist, or programmer. Transforming and integrating data is about combining the right standards for your desired interoperability with other data types. For example, interoperating fish biology measurements with climate level variables. There are a few concepts necessary to make this possible such as standard data structures, controlled vocabularies and knowledge representations, along with metadata standards to facilitate data discovery. This will permit the inclusion of more data and broader access to better ecosystem based models. Many scientific domains data handling practices are currently being reshaped in light of recent advances in computing power, technology, and data science.

1.1 Data Structures

The OBIS-ENV Darwin Core Archive Data Structure.

OBIS manual

1.2 Ontologies

An ontology is a classification system for establishing a hierarchically related set of concepts. Concepts are often terms from controlled vocabularies.

From Marine Metadata: # TODO: add link

“Ontologies can include all of the following, but are not required to include them, depending on which perspective from above you adhere to:

Classes (general things, types of things) Instances (individual things) Relationships among things Properties of things Functions, processes, constraints, and rules relating to things”

TODO: Research Unified Modelling Language?

Environment Ontology (EnvO) EnvO is a community ontology for the concise, controlled description of environments.

1.3 Controlled Vocabularies

There are a number of controlled vocabularies that are used to describe parameters commonly used in specific research domains. This allows for greater interoperability of data sets within the domain, and ideally between domains. Here, we strive to document a number of relevant examples.

- Climate and Format (CF) Standard Names The purpose of the `standard_name` attribute is to provide a succinct and distinguishing description of a variable, in a way that encourages interoperability. These terms are typically for physical observations, however, there have been advancements in aligning biological taxa into the CF standard names (see here).
- NERC Vocabulary Server The NVS gives access to standardised and hierarchically-organized vocabularies.
 - Device categories using the SeaDataNet device categories
 - Device make/model using the SeaVoX Device Catalogue
 - Platform categories using SeaVoX Platform Categories
 - Platform instances using the ICES Platform Codes
 - Unit of measure
- GCMD Keywords (NASA)
- Geographic Domain/Features of Interest
- GeoLink base ontology was part of the EarthCube GeoLink Project

Note: To describe a measurement or fact of a biological specimen that conforms to Darwin Core standards, it’s necessary to use the ‘Biological entity described elsewhere’ method rather than taxon specific.

1.3.1 Taxonomy

- The World Registry of Marine Species (WoRMS) The aim of a World Register of Marine Species (WoRMS) is to provide an authoritative and comprehensive list of names of marine organisms, including information on synonymy. While the highest priority goes to valid names, other names in use are included so that this register can serve as a guide to interpret taxonomic literature.

1.3.2 Resources

1.3.3 Oceanography

Biological and Chemical Oceanography Data Management Office

Marine metadata interoperability vocab resources

1.3.4 Biology

BioPortal Ecosystem Ontology

1.3.5 NERC Search Interfaces

- SeaDataNet Common Vocab Search Interface:
- SeaDataNet Common Vocabularies:
- SeaDataNet Vocab Library
- Measurement Types in OBIS

1.3.6 Geosciences

UDUNITS are more common unit measurements in geosciences

1.3.7 Eco/EnvO

Environment Ontology including genomics.

1.3.8 Wild Cards

Question: Not sure use case for this.

P01 Biological Entity Parameter Code Builder

1.4 Technologies

1.4.1 ERDDAP

ERDDAP can be thought of as a data server. It provides ‘easier access to scientific data’ by providing a consistent interface that aggregates many disparate data sources. It does this by providing translation services between many common file types for gridded arrays (‘net CDF’ files) and tabular data (spreadsheets). Data access is also made easier because it unifies different types of data servers and access protocols. Here is a basic erddap installation that walks you through how to load a data set.

1.5 Notes on Integrating OBIS, Darwin Core as it relates to OOS’s

1.6 Metadata

OBIS uses the GBIF EML profile (version 1.1). In case data providers use ISO19115/ISO19139, there is a mapping available here: <http://rs.gbif.org/schema/eml-gbif-profile/1.1/eml2iso19139.xsl> This will be important for integrating OBIS datasets to other CIOOS and IOOS metadata profiles.

1.7 Data QC

There are a number of tools available to check the quality of data or check your data format against the expected standard.

OBIS Datatools shows some great R packages for this.

1.7.1 Compliance Checking

LifeWatch Belgium provides a number of tools to check your data against. Specifically you can test OBIS data format and see a map of your sample locations to check if they are on land. See <http://www.lifewatch.be/data-services/>

There’s also the GBIF data validator which allows anyone with a GBIF-relevant dataset to receive a report on the syntactical correctness and the validity of the content contained within the dataset.

1.7.2 Semantic Web and Darwin Core

Lessons learned from adapting the Darwin Core vocabulary standard for use in RDF

1.7.3 Resource Description Framework

Darwin Core Resource Description Framework Guide

Chapter 2

Applications

Some applications are demonstrated in this chapter.

2.1 Salmon Ocean Ecology Data

2.1.1 Intro

One of the goals of the Hakai Institute and the Canadian Integrated Ocean Observing System (CIOOS) is to facilitate Open Science and FAIR (findable, accessible, interoperable, reusable) ecological and oceanographic data. In a concerted effort to adopt or establish how best to do that, several Hakai and CIOOS staff attended an International Ocean Observing System (IOOS) Code Sprint in Ann Arbor, Michigan between October 7–11, 2019, to discuss how to implement FAIR data principles for biological data collected in the marine environment.

The Darwin Core is a highly structured data format that standardizes data table relations, vocabularies, and defines field names. The Darwin Core defines three table types: **event**, **occurrence**, and **measurementOrFact**. This intuitively captures the way most ecologists conduct their research. Typically, a survey (event) is conducted and measurements, counts, or observations (collectively measurementOrFacts) are made regarding a specific habitat or species (occurrence).

In the following script I demonstrate how I go about converting a subset of the data collected from the Hakai Institute Juvenile Salmon Program and discuss challenges, solutions, pros and cons, and when and what’s worthwhile to convert to Darwin Core.

The conversion of a dataset to Darwin Core is much easier if your data are already tidy (normalized) in which you represent your data in separate tables

that reflect the hierarchical and related nature of your observations. If your data are not already in a consistent and structured format, the conversion would likely be very arduous and not intuitive.

2.1.2 event

The first step is to consider what you will define as an event in your data set. I defined the capture of fish using a purse seine net as the **event**. Therefore, each row in the **event** table is one deployment of a seine net and is assigned a unique **eventID**.

My process for conversion was to make a new table called **event** and map the standard Darwin Core column names to pre-existing columns that serve the same purpose in my original **seine_data** table and populate the other required fields.

```
event <- tibble(eventID = survey_seines$seine_id,
               eventDate = date(survey_seines$survey_date),
               decimalLatitude = survey_seines$lat,
               decimalLongitude = survey_seines$long,
               geodeticDatum = "EPSG:4326 WGS84",
               minimumDepthInMeters = 0,
               maximumDepthInMeters = 9, # seine depth is 9 m
               samplingProtocol = "http://dx.doi.org/10.21966/1.566666" # This is the
            )

write_csv(event, here::here("datasets", "hakai_salmon_data", "event.csv"))
```

2.1.3 occurrence

Next you'll want to determine what constitutes an occurrence for your data set. Because each event captures fish, I consider each fish to be an occurrence. Therefore, the unit of observation (each row) in the occurrence table is a fish. To link each occurrence to an event you need to include the **eventID** column for every occurrence so that you know what seine (event) each fish (occurrence) came from. You must also provide a globally unique identifier for each occurrence. I already have a locally unique identifier for each fish in the original **fish_data** table called **ufn**. To make it globally unique I pre-pend the organization and research program metadata to the **ufn** column.

```
#TODO: Include bycatch data as well

## make table long first
seines_total_long <- survey_seines %>%
```

```

select(seine_id, so_total, pi_total, cu_total, co_total, he_total, ck_total) %>%
  pivot_longer(-seine_id, names_to = "scientificName", values_to = "n")

seines_total_long$scientificName <- recode(seines_total_long$scientificName, so_total = "Oncorhynchus nerka")

seines_taken_long <- survey_seines %>%
  select(seine_id, so_taken, pi_taken, cu_taken, co_taken, he_taken, ck_taken) %>%
  pivot_longer(-seine_id, names_to = "scientificName", values_to = "n_taken")

seines_taken_long$scientificName <- recode(seines_taken_long$scientificName, so_taken = "Oncorhynchus nerka")

## remove records that have already been assigned an ID
seines_long <- full_join(seines_total_long, seines_taken_long, by = c("seine_id", "scientificName"))
drop_na() %>%
  mutate(n_not_taken = n - n_taken) %>% #so_total includes the number taken so I subtract n_taken
  select(-n_taken, -n) %>%
  filter(n_not_taken > 0)

all_fish_caught <-
  seines_long[rep(seq.int(1, nrow(seines_long)), seines_long$n_not_taken), 1:3] %>%
  select(-n_not_taken) %>%
  mutate(prefix = "hakai-jsp-",
         suffix = 1:nrow(.),
         occurrenceID = paste0(prefix, suffix)
  ) %>%
  select(-prefix, -suffix)

#

# Change species names to full Scientific names
latin <- fct_recode(fish_data$species, "Oncorhynchus nerka" = "SO", "Oncorhynchus gorbuscha" = "P")
as.character()

fish_retained_data <- fish_data %>%
  mutate(scientificName = latin) %>%
  select(-species) %>%
  mutate(prefix = "hakai-jsp-",
         occurrenceID = paste0(prefix, ufn)) %>%
  select(-semsp_id, -prefix, -ufn, -fork_length_field, -fork_length, -weight, -weight_field)

occurrence <- bind_rows(all_fish_caught, fish_retained_data) %>%
  mutate(basisOfRecord = "HumanObservation",
         occurrenceStatus = "present") %>%
  rename(eventID = seine_id)

```

For each occurrence of the six different fish species that I caught I need to match the species name that I provide with the official `scientificName` that is part of the World Register of Marine Species database <http://www.marinespecies.org/>

```
# I went directly to the WoRMS website (http://www.marinespecies.org/) to download the
species_matched <- readxl::read_excel(here::here("datasets", "hakai_salmon_data", "raw",
occurrence <- left_join(occurrence, species_matched, by = c("scientificName" = "Scienti
  select(occurrenceID, basisOfRecord, scientificName, eventID, occurrenceStatus = occur
write_csv(occurrence, here::here("datasets", "hakai_salmon_data", "occurrence.csv"))
```

2.1.4 measurementOrFact

To convert all your measurements or facts from your normal format to Darwin Core you essentially need to put all your measurements into one column called `measurementType` and a corresponding column called `MeasurementValue`. This standardizes the column names are in the `measurementOrFact` table. There are a number of predefined `measurementTypes` listed on the NERC database that should be used where possible. I found it difficult to navigate this page to find the correct `measurementType`.

Here I convert length, and weight measurements that relate to an event and an occurrence and call those `measurementTypes` as `length` and `weight`.

```
fish_data$weight <- coalesce(fish_data$weight, fish_data$weight_field)
fish_data$fork_length <- coalesce(fish_data$fork_length, fish_data$fork_length_field)

fish_length <- fish_data %>%
  mutate(occurrenceID = paste0("hakai-jsp-", ufn)) %>%
  select(occurrenceID, eventID = seine_id, fork_length, weight) %>%
  mutate(measurementType = "fork length", measurementValue = fork_length) %>%
  select(eventID, occurrenceID, measurementType, measurementValue) %>%
  mutate(measurementUnit = "millimeters",
    measurementUnitID = "http://vocab.nerc.ac.uk/collection/P06/current/UXMM/")

fish_weight <- fish_data %>%
  mutate(occurrenceID = paste0("hakai-jsp-", ufn)) %>%
  select(occurrenceID, eventID = seine_id, fork_length, weight) %>%
  mutate(measurementType = "mass", measurementValue = weight) %>%
  select(eventID, occurrenceID, measurementType, measurementValue) %>%
  mutate(measurementUnit = "grams",
    measurementUnitID = "http://vocab.nerc.ac.uk/collection/P06/current/UGRM/")
```



```

measurementOrFact <- bind_rows(fish_length, fish_weight) %>%
  drop_na(measurementValue)

rm(fish_length, fish_weight)

write_csv(measurementOrFact, here::here("datasets", "hakai_salmon_data", "measurementOrFact.csv"))

```

2.2 Hakai Seagrass

2.2.1 Setup

This section clears the workspace, checks the working directory, and installs packages (if required) and loads packages, and loads necessary datasets

```

library("knitr")
# Knitr global chunk options
opts_chunk$set(message = FALSE,
                warning = FALSE,
                error   = FALSE)

```

2.2.1.1 Load Data

First load the seagrass density survey data, set variable classes, and have a quick look

```

# Load density data
seagrassDensity <-
  read.csv("raw_data/seagrass_density_survey.csv",
           colClass = "character") %>%
  mutate(date           = ymd(date),
         depth          = as.numeric(depth),
         transect_dist  = factor(transect_dist),
         collected_start = ymd_hms(collected_start),
         collected_end   = ymd_hms(collected_end),
         density         = as.numeric(density),
         density_msq     = as.numeric(density_msq),
         canopy_height_cm = as.numeric(canopy_height_cm),
         flowering_shoots = as.numeric(flowering_shoots)) %T>%
  glimpse()

```

```

## Rows: 3,031
## Columns: 22

```

```
## $ X <chr> "1", "2", "3", "4", "5", "6", "7", "8", "9", "10", "1~
## $ organization <chr> "HAKAI", "HAKAI", "HAKAI", "HAKAI", "HAKAI", "HAKAI",~
## $ work_area <chr> "CALVERT", "CALVERT", "CALVERT", "CALVERT", "CALVERT"~
## $ project <chr> "MARINEGEO", "MARINEGEO", "MARINEGEO", "MARINEGEO", "~
## $ survey <chr> "PRUTH_BAY", "PRUTH_BAY", "PRUTH_BAY", "PRUTH_BAY", "~
## $ site_id <chr> "PRUTH_BAY_INTERIOR4", "PRUTH_BAY_INTERIOR4", "PRUTH~
## $ date <date> 2016-05-13, 2016-05-13, 2016-05-13, 2016-05-13, 2016~
## $ sampling_bout <chr> "4", "4", "4", "4", "4", "4", "6", "6", "6", "6"~
## $ dive_supervisor <chr> "Zach", "Zach", "Zach", "Zach", "Zach", "Zach", "Zach~
## $ collector <chr> "Derek", "Derek", "Derek", "Derek", "Derek", "Derek",~
## $ hakai_id <chr> "2016-05-13_PRUTH_BAY_INTERIOR4_0", "2016-05-13_PRUTH~
## $ sample_type <chr> "seagrass_density", "seagrass_density", "seagrass_den~
## $ depth <dbl> 6.0, 6.0, 6.0, 6.0, 5.0, 6.0, 6.0, 9.1, 9.0, 8.9, 9.0~
## $ transect_dist <fct> 0, 5, 10, 15, 20, 25, 30, 10, 15, 20, 25, 30, 0, 5, 1~
## $ collected_start <dtm> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
## $ collected_end <dtm> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
## $ density <dbl> 13, 10, 18, 22, 16, 31, 9, 5, 6, 6, 6, 3, 13, 30, 23,~
## $ density_msq <dbl> 208, 160, 288, 352, 256, 496, 144, 80, 96, 96, 96, 48~
## $ canopy_height_cm <dbl> 60, 63, 80, 54, 55, 50, 63, 85, 80, 90, 95, 75, 60, 6~
## $ flowering_shoots <dbl> NA, NA, NA, NA, NA, NA, NA, 0, 0, 0, 0, 0, NA, NA, NA~
## $ comments <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
## $ quality_log <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
```

Next, load the habitat survey data, and same as above, set variable classes as necessary, and have a quick look.

```
# load habitat data, set variable classes, have a quick look
seagrassHabitat <-
  read.csv("raw_data/seagrass_habitat_survey.csv",
           colClasses = "character") %>%
  mutate(date = ymd(date),
         depth = as.numeric(depth),
         hakai_id = str_pad(hakai_id, 5, pad = "0"),
         transect_dist = factor(transect_dist),
         collected_start = ymd_hms(collected_start),
         collected_end = ymd_hms(collected_end)) %T>%
  glimpse()
```

```
## Rows: 2,052
## Columns: 28
## $ X <chr> "1", "2", "3", "4", "5", "6", "7", "8", "9", "10", "1~
## $ organization <chr> "HAKAI", "HAKAI", "HAKAI", "HAKAI", "HAKAI", "HAKAI",~
## $ work_area <chr> "CALVERT", "CALVERT", "CALVERT", "CALVERT", "CALVERT"~
## $ project <chr> "MARINEGEO", "MARINEGEO", "MARINEGEO", "MARINEGEO", "~
## $ survey <chr> "CHOKED_PASS", "CHOKED_PASS", "CHOKED_PASS", "CHOKED_~
```

```
## $ site_id      <chr> "CHOKED_PASS_INTERIOR6", "CHOKED_PASS_INTERIOR6", "CH~
## $ date         <date> 2017-11-22, 2017-11-22, 2017-11-22, 2017-11-22, 2017~
## $ sampling_bout <chr> "6", "6", "6", "6", "6", "6", "1", "1", "1", "1", "1"~
## $ dive_supervisor <chr> "gillian", "gillian", "gillian", "gillian", "gillian"~
## $ collector     <chr> "zach", "zach", "zach", "zach", "zach", "zach", "kyle~
## $ hakai_id      <chr> "10883", "2017-11-22_CHOKED_PASS_INTERIOR6_5 - 10", "~
## $ sample_type   <chr> "seagrass_habitat", "seagrass_habitat", "seagrass_hab~
## $ depth         <dbl> 9.2, 9.4, 9.3, 9.0, 9.2, 9.2, 3.4, 3.4, 3.4, 3.4, 3.4~
## $ transect_dist <fct> 0 - 5, 10-May, 15-Oct, 15 - 20, 20 - 25, 25 - 30, 0 --
## $ collected_start <dtm> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
## $ collected_end   <dtm> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
## $ bag_uid        <chr> "10883", NA, NA, "11094", NA, "11182", "7119", "7~
## $ bag_number     <chr> "3557", NA, NA, "3520", NA, "903", "800", NA, "318", ~
## $ density_range   <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
## $ substrate       <chr> "sand,shell hash", "sand,shell hash", "sand,shell has~
## $ patchiness      <chr> "< 1", "< 1", "02-Jan", "< 1", "< 1", "< 1", "< 1", "~
## $ adj_habitat_1    <chr> "seagrass", "seagrass", "seagrass", "seagrass", "seag~
## $ adj_habitat_2    <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
## $ sample_collected <chr> "TRUE", "FALSE", "FALSE", "TRUE", "FALSE", "TRUE", "T~
## $ vegetation_1     <chr> NA, NA, NA, NA, NA, NA, "des", NA, "des", NA, NA, NA, ~
## $ vegetation_2     <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
## $ comments         <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
## $ quality_log      <chr> "1: Flowering shoots 0 for entire transects", NA, NA,~
```

Finally, load coordinate data for surveys, and subset necessary variables

```
coordinates <-
  read.csv("raw_data/seagrassCoordinates.csv",
           colClass = c("Point.Name" = "character")) %>%
  select(Point.Name, Decimal.Lat, Decimal.Long) %T>%
  glimpse()
```

```
## Rows: 70
## Columns: 3
## $ Point.Name   <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
## $ Decimal.Lat  <dbl> 52.06200, 52.05200, 51.92270, 51.92500, 51.80900, 51.8090~
## $ Decimal.Long <dbl> -128.4120, -128.4030, -128.4648, -128.4540, -128.2360, -1~
```

2.2.1.2 Merge Datasets

Now all the datasets have been loaded, and briefly formatted, we'll join together the habitat and density surveys, and the coordinates for these.

The seagrass density surveys collect data at discrete points (ie. 5 metres) along the transects, while the habitat surveys collect data over sections (ie. 0 - 5

metres) along the transects. In order to fit these two surveys together, we'll narrow the habitat surveys from a range to a point so the locations will match. Based on how the habitat data is collected, the point the habitat survey is applied to will be the distance at the end of the swath (ie. 10-15m will become 15m). To account for no preceeding distance, the 0m distance will use the 0-5m section of the survey.

First, we'll make the necessary transformations to the habitat dataset.

```
# Reformat seagrassHabitat to merge with seagrassDensity
## replicate 0 - 5m transect dist to match with 0m in density survey;
## rest of habitat bins can map one to one with density (ie. 5 - 10m -> 10m)
seagrass0tmp <-
  seagrassHabitat %>%
  filter(transect_dist %in% c("0 - 5", "0 - 2.5")) %>%
  mutate(transect_dist = factor(0))

## collapse various levels to match with seagrassDensity transect_dist
seagrassHabitat$transect_dist <-
  fct_collapse(seagrassHabitat$transect_dist,
    "5" = c("0 - 5", "2.5 - 7.5"),
    "10" = c("5 - 10", "7.5 - 12.5"),
    "15" = c("10 - 15", "12.5 - 17.5"),
    "20" = c("15 - 20", "17.5 - 22.5"),
    "25" = c("20 - 25", "22.5 - 27.5"),
    "30" = c("25 - 30", "27.5 - 30"))

## merge seagrass0tmp into seagrassHabitat to account for 0m samples,
## set class for date, datetime variables
seagrassHabitatFull <-
  rbind(seagrass0tmp, seagrassHabitat) %>%
  filter(transect_dist != "0 - 2.5") %>% # already captured in seagrass0tmp
  droplevels(.) # remove now unused factor levels
```

With the distances of habitat and density surveys now corresponding, we can now merge these two datasets plus there coordinates together, combine redundant fields, and remove unnecessary fields.

```
# Merge seagrassHabitatFull with seagrassDensity, then coordinates
seagrass <-
  full_join(seagrassHabitatFull, seagrassDensity,
    by = c("organization",
           "work_area",
           "project",
           "survey",
           "site_id",
```

```

      "date",
      "transect_dist")) %>%
# merge hakai_id.x and hakai_id.y into single variable field;
# use combination of date, site_id, transect_dist, and field uid (hakai_id
# when present)
mutate(field_uid = ifelse(sample_collected == TRUE, hakai_id.x, "NA"),
      hakai_id = paste(date, "HAKAI:CALVERT", site_id, transect_dist, sep = ":"),
      # below, aggregate metadata that didn't merge naturally (ie. due to minor
      # differences in watch time or depth gauges)
      dive_supervisor = dive_supervisor.x,
      collected_start = ymd_hms(ifelse(is.na(collected_start.x),
                                      collected_start.y,
                                      collected_start.x)),
      collected_end   = ymd_hms(ifelse(is.na(collected_start.x),
                                      collected_start.y,
                                      collected_start.x)),
      depth_m         = ifelse(is.na(depth.x), depth.y, depth.x),
      sampling_bout    = sampling_bout.x) %>%
left_join(., coordinates, # add coordinates
      by = c("site_id" = "Point.Name")) %>%
select( - c(X.x, X.y, hakai_id.x, hakai_id.y, # remove unnecessary variables
            dive_supervisor.x, dive_supervisor.y,
            collected_start.x, collected_start.y,
            collected_end.x, collected_end.y,
            depth.x, depth.y,
            sampling_bout.x, sampling_bout.y)) %>%
mutate(density_msq = as.character(density_msq),
      canopy_height_cm = as.character(canopy_height_cm),
      flowering_shoots = as.character(flowering_shoots),
      depth_m = as.character(depth_m)) %T>%
glimpse()

```

```

## Rows: 3,743
## Columns: 38
## $ organization    <chr> "HAKAI", "HAKAI", "HAKAI", "HAKAI", "HAKAI", "HAKAI", ~
## $ work_area       <chr> "CALVERT", "CALVERT", "CALVERT", "CALVERT", "CALVERT"~
## $ project         <chr> "MARINEGEO", "MARINEGEO", "MARINEGEO", "MARINEGEO", "~
## $ survey          <chr> "CHOKED_PASS", "CHOKED_PASS", "CHOKED_PASS", "PRUTH_B~
## $ site_id         <chr> "CHOKED_PASS_INTERIOR6", "CHOKED_PASS_EDGE1", "CHOKED~
## $ date            <date> 2017-11-22, 2017-05-19, 2017-05-19, 2017-07-03, 2017~
## $ collector.x     <chr> "zach", "kyle", NA, "tanya", "zach", "zach", "zach", ~
## $ sample_type.x   <chr> "seagrass_habitat", "seagrass_habitat", "seagrass_hab~
## $ transect_dist    <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, ~
## $ bag_uid         <chr> "10883", "7119", "7031", "2352", "10255", "10023", "1~
## $ bag_number      <chr> "3557", "800", "301", "324", "3506", "3555", "3534", ~

```

2.2.2 Convert Data to Darwin Core - Extended Measurement or Fact format

2.2.2.1 Add Event ID and Occurrence ID variables to dataset

As this dataset will be annually updated, rather than using natural keys (i.e. using `package::uuid` to autogenerate) for event and occurrence IDs, here we will use surrogate keys made up of a concatenation of date survey, transect location, observation distance, and sample ID (for `occurrenceID`, when a sample is present).

```

# create and populate eventID variable
## currently only event is used, but additional surveys and abiotic data
## are associated with parent events that may be included at a later date
seagrass$eventID <- seagrass$hakai_id

# create and populate occurrenceID; combine eventID with transect_dist
# and field_uid
## in the event of <NA> field_uid, no sample was collected, but
## measurements and occurrence are still taken; no further subsamples
## are associated with <NA> field_uids
seagrass$occurrenceID <-
  with(seagrass,
    paste(eventID, transect_dist, field_uid, sep = ":"))

```

2.2.2.2 Create Event, Occurrence, and eMoF tables

Now that we've created eventIDs and occurrenceIDs to connect all the variables together, we can begin to create the Event, Occurrence, and extended Measurement or Fact table necessary for DarwinCore compliant datasets

```

# subset seagrass to create event table
seagrassEvent <-
  seagrass %>%
  distinct %>% # some duplicates in data stemming from database conflicts
  select(date,
    Decimal.Lat, Decimal.Long, transect_dist,
    depth_m, eventID) %>%
  rename(eventDate = date,
    decimalLatitude = Decimal.Lat,
    decimalLongitude = Decimal.Long,
    coordinateUncertaintyInMeters = transect_dist,
    minimumDepthInMeters = depth_m,
    maximumDepthInMeters = depth_m) %>%
  mutate(geodeticDatum = "WGS84",
    samplingEffort = "30 metre transect") %T>% glimpse

```

2.2.2.2.1 Event Table

```

## Rows: 3,659
## Columns: 8
## $ eventDate      <date> 2017-11-22, 2017-05-19, 2017-05-19, 201~

```

```
## $ decimalLatitude      <dbl> 51.67482, 51.67882, 51.67493, 51.64532, ~
## $ decimalLongitude     <dbl> -128.1195, -128.1148, -128.1237, -128.11~
## $ coordinateUncertaintyInMeters <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0~
## $ maximumDepthInMeters <chr> "9.2", "3.4", "4.8", "2.4", "5.3", "5.6"~
## $ eventID              <chr> "2017-11-22:HAKAI:CALVERT:CHOKED_PASS_IN~
## $ geodeticDatum        <chr> "WGS84", "WGS84", "WGS84", "WGS84", "WGS~
## $ samplingEffort        <chr> "30 metre transect", "30 metre transect"~
```

```
# save event table to csv
write.csv(seagrassEvent, "processed_data/hakaiSeagrassDwcEvent.csv")
```

```
# subset seagrass to create occurrence table
seagrassOccurrence <-
  seagrass %>%
  distinct %>% # some duplicates in data stemming from database conflicts
  select(eventID, occurrenceID) %>%
  mutate(basisOfRecord = "HumanObservation",
         scientificName = "Zostera subg. Zostera marina",
         occurrenceStatus = "present")

# Taxonomic name matching
# in addition to the above metadata, DarwinCore format requires further
# taxonomic data that can be acquired through the WoRMS register.
## Load taxonomic info, downloaded via WoRMS tool
# zmWorms <-
#   read.delim("raw_data/zmworms_matched.txt",
#             header = TRUE,
#             nrow = 1)

zmWorms <- wm_record(id = 145795)

# join WoRMS name with seagrassOccurrence create above
seagrassOccurrence <-
  full_join(seagrassOccurrence, zmWorms,
            by = c("scientificName" = "scientificname")) %>%
  select(eventID, occurrenceID, basisOfRecord, scientificName, occurrenceStatus, AphiaID,
         url, authority, status, unacceptreason, taxonRankID, rank,
         valid_AphiaID, valid_name, valid_authority, parentNameUsageID,
         kingdom, phylum, class, order, family, genus, citation, lsid,
         isMarine, match_type, modified) %T>%
  glimpse
```

2.2.2.2.2 Occurrence Table


```
## Rows: 3,659
## Columns: 27
## $ eventID <chr> "2017-11-22:HAKAI:CALVERT:CHOKED_PASS_INTERIOR6:0", ~
## $ occurrenceID <chr> "2017-11-22:HAKAI:CALVERT:CHOKED_PASS_INTERIOR6:0:0:~
## $ basisOfRecord <chr> "HumanObservation", "HumanObservation", "HumanObserv~
## $ scientificName <chr> "Zostera subg. Zostera marina", "Zostera subg. Zoste~
## $ occurrenceStatus <chr> "present", "present", "present", "present", "present~
## $ AphiaID <int> 145795, 145795, 145795, 145795, 145795, 145795, 1457~
## $ url <chr> "https://www.marinespecies.org/aphia.php?p=taxdetail~
## $ authority <chr> "Linnaeus, 1753", "Linnaeus, 1753", "Linnaeus, 1753"~
## $ status <chr> "accepted", "accepted", "accepted", "accepted", "acc~
## $ unacceptreason <lg1> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, ~
## $ taxonRankID <int> 220, 220, 220, 220, 220, 220, 220, 220, 220, 22~
## $ rank <chr> "Species", "Species", "Species", "Species", "Species", "Species~
## $ valid_AphiaID <int> 145795, 145795, 145795, 145795, 145795, 145795, 1457~
## $ valid_name <chr> "Zostera subg. Zostera marina", "Zostera subg. Zoste~
## $ valid_authority <chr> "Linnaeus, 1753", "Linnaeus, 1753", "Linnaeus, 1753"~
## $ parentNameUsageID <int> 370435, 370435, 370435, 370435, 370435, 370435, 3704~
## $ kingdom <chr> "Plantae", "Plantae", "Plantae", "Plantae", "Plantae~
## $ phylum <chr> "Tracheophyta", "Tracheophyta", "Tracheophyta", "Tra~
## $ class <chr> "Magnoliopsida", "Magnoliopsida", "Magnoliopsida", "~
## $ order <chr> "Alismatales", "Alismatales", "Alismatales", "Alisma~
## $ family <chr> "Zosteraceae", "Zosteraceae", "Zosteraceae", "Zoster~
## $ genus <chr> "Zostera", "Zostera", "Zostera", "Zostera", "Zostera~
## $ citation <chr> "WoRMS (2022). Zostera subg. Zostera marina Linnaeus~
## $ lsid <chr> "urn:lsid:marinespecies.org:taxname:145795", "urn:ls~
## $ isMarine <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
## $ match_type <chr> "exact", "exact", "exact", "exact", "exact", "exact"~
## $ modified <chr> "2008-12-09T10:03:16.140Z", "2008-12-09T10:03:16.140~
```

```
# save occurrence table to csv
write.csv(seagrassOccurrence, "processed_data/hakaiSeagrassDwcOccurrence.csv")
```

```
seagrassMof <-
  seagrass %>%
    # select variables for eMoF table
    select(date,
           eventID, survey, site_id, transect_dist,
           substrate, patchiness, adj_habitat_1, adj_habitat_2,
           vegetation_1, vegetation_2,
           density_msq, canopy_height_cm, flowering_shoots) %>%
    # split substrate into two variables (currently holds two substrate type in same variable)
    separate(substrate, sep = ",", into = c("substrate_1", "substrate_2")) %>%
```

```

# change variables names to match NERC database (or to be more descriptive where non
rename(measurementDeterminedDate = date,
       SubstrateTypeA            = substrate_1,
       SubstrateTypeB            = substrate_2,
       BarePatchLengthWithinSeagrass = patchiness,
       PrimaryAdjacentHabitat      = adj_habitat_1,
       SecondaryAdjacentHabitat    = adj_habitat_2,
       PrimaryAlgaeSp             = vegetation_1,
       SecondaryAlgaeSp           = vegetation_2,
       BedAbund                   = density_msq,
       CanopyHeight               = canopy_height_cm,
       FloweringBedAbund          = flowering_shoots) %>%
# reformat variables into DwC MeasurementOrFact format
# (single values variable, with measurement type, unit, etc. variables)
pivot_longer( - c(measurementDeterminedDate, eventID, survey, site_id, transect_dist,
                  names_to = "measurementType",
                  values_to = "measurementValue",
                  values_ptypes = list(measurementValue = "character"))) %>%
# use measurement type to fill in remainder of variables relating to
# NERC vocabulary and metadata fields
mutate(
  measurementTypeID = case_when(
    measurementType == "BedAbund" ~ "http://vocab.nerc.ac.uk/collection/P01/current/",
    measurementType == "CanopyHeight" ~ "http://vocab.nerc.ac.uk/collection/P01/current/",
    # measurementType == "BarePatchWithinSeagrass" ~ "",
    measurementType == "FloweringBedAbund" ~ "http://vocab.nerc.ac.uk/collection/P01/current/"),
  measurementUnit = case_when(
    measurementType == "BedAbund" ~ "Number per square metre",
    measurementType == "CanopyHeight" ~ "Centimetres",
    measurementType == "BarePatchhhLengthWithinSeagrass" ~ "Metres",
    measurementType == "FloweringBedAbund" ~ "Number per square metre"),
  measurementUnitID = case_when(
    measurementType == "BedAbund" ~ "http://vocab.nerc.ac.uk/collection/P06/current/",
    measurementType == "CanopyHeight" ~ "http://vocab.nerc.ac.uk/collection/P06/current/",
    measurementType == "BarePatchhhLengthWithinSeagrass" ~ "http://vocab.nerc.ac.uk/collection/P06/current/",
    measurementType == "FloweringBedAbund" ~ "http://vocab.nerc.ac.uk/collection/P06/current/"),
  measurementAccuracy = case_when(
    measurementType == "CanopyHeight" ~ 5),
  measurementMethod = case_when(
    measurementType == "BedAbund" ~ "25cmx25cm quadrat count",
    measurementType == "CanopyHeight" ~ "in situ with ruler",
    measurementType == "BarePatchhhLengthWithinSeagrass" ~ "estimated along transect",
    measurementType == "FloweringBedAbund" ~ "25cmx25cm quadrat count"))) %>%
select(eventID, measurementDeterminedDate, measurementType, measurementValue,
       measurementTypeID, measurementUnit, measurementUnitID, measurementAccuracy,

```

```

        measurementMethod) %T>%
# select(!c(survey, site_id, transect_dist)) %T>%
glimpse()

```

2.2.2.2.3 Extended MeasurementOrFact table

```

## Rows: 37,430
## Columns: 9
## $ eventID <chr> "2017-11-22:HAKAI:CALVERT:CHOKED_PASS_INTERI~
## $ measurementDeterminedDate <date> 2017-11-22, 2017-11-22, 2017-11-22, 2017-11-~
## $ measurementType <chr> "SubstrateTypeA", "SubstrateTypeB", "BarePat~
## $ measurementValue <chr> "sand", "shell hash", "< 1", "seagrass", NA,~
## $ measurementTypeID <chr> NA, NA, NA, NA, NA, NA, NA, "http://vocab.ne~
## $ measurementUnit <chr> NA, NA, NA, NA, NA, NA, NA, "Number per squa~
## $ measurementUnitID <chr> NA, NA, NA, NA, NA, NA, NA, "http://vocab.ne~
## $ measurementAccuracy <dbl> NA, NA, NA, NA, NA, NA, NA, 5, NA, NA, N~
## $ measurementMethod <chr> NA, NA, NA, NA, NA, NA, NA, "25cmx25cm quadr~

# save eMoF table to csv
write.csv(seagrassMof, "processed_data/hakaiSeagrassDwcEmof.csv")

```

2.2.3 Session Info

Print session information below in case necessary for future reference

```

# Print Session Info for future reference
sessionInfo()

## R version 4.1.1 (2021-08-10)
## Platform: x86_64-apple-darwin17.0 (64-bit)
## Running under: macOS Big Sur 10.16
##
## Matrix products: default
## BLAS: /Library/Frameworks/R.framework/Versions/4.1/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/4.1/Resources/lib/libRlapack.dylib
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## attached base packages:
## [1] stats graphics grDevices utils datasets methods base
##
## other attached packages:

```

```
## [1] worrms_0.4.2      magrittr_2.0.2    knitr_1.37        lubridate_1.8.0
## [5] here_1.0.1        forcats_0.5.1     stringr_1.4.0     dplyr_1.0.7
## [9] purrr_0.3.4       readr_2.1.2       tidyr_1.2.0       tibble_3.1.6
## [13] ggplot2_3.3.5     tidyverse_1.3.1
##
## loaded via a namespace (and not attached):
## [1] Rcpp_1.0.8         assertthat_0.2.1  rprojroot_2.0.2   digest_0.6.29
## [5] utf8_1.2.2         R6_2.5.1          cellranger_1.1.0  backports_1.4.1
## [9] reprex_2.0.1       evaluate_0.14     httr_1.4.2        pillar_1.7.0
## [13] rlang_1.0.0        curl_4.3.2        readxl_1.3.1      rstudioapi_0.13
## [17] jquerylib_0.1.4    rmarkdown_2.11    urltools_1.7.3     triebeard_0.3.0
## [21] bit_4.0.4          munsell_0.5.0     broom_0.7.12      compiler_4.1.1
## [25] modelr_0.1.8       xfun_0.29         pkgconfig_2.0.3   htmltools_0.5.2
## [29] tidyselect_1.1.1   httpcode_0.3.0    bookdown_0.24     fansi_1.0.2
## [33] crayon_1.4.2       tzdb_0.2.0        dbplyr_2.1.1      withr_2.4.3
## [37] crul_1.2.0         grid_4.1.1        jsonlite_1.7.3    gtable_0.3.0
## [41] lifecycle_1.0.1    DBI_1.1.2         scales_1.1.1      cli_3.1.1
## [45] stringi_1.7.6      vroom_1.5.7       fs_1.5.2           xml2_1.3.3
## [49] ellipsis_0.3.2     generics_0.1.2    vctrs_0.3.8       tools_4.1.1
## [53] bit64_4.0.5        glue_1.6.1        hms_1.1.1          parallel_4.1.1
## [57] fastmap_1.1.0      yaml_2.2.2        colorspace_2.0-2  rvest_1.0.2
## [61] haven_2.4.3
```

2.3 Aligning Data to Darwin Core - Sampling Event with Measurement or Fact

Abby Benson
October 8, 2019

2.3.1 General information about this notebook

This notebook was created for the IOOS DMAC Code Sprint Biological Data Session. The data in this notebook were created specifically as an example and meant solely to be illustrative of the process for aligning data to the biological data standard - Darwin Core. These data should not be considered actual occurrences of species and any measurements are also contrived. This notebook is meant to provide a step by step process for taking original data and aligning it to Darwin Core.

```
library(readr)
library(uuid)
library(dplyr)
```

2.3. ALIGNING DATA TO DARWIN CORE - SAMPLING EVENT WITH MEASUREMENT OR FACT²⁹

```
MadeUpDataForBiologicalDataTraining <- read_csv("~/OBIS/Reference Documentation/Presentations/IOU

## Parsed with column specification:
## cols(
##   date = col_character(),
##   lat = col_double(),
##   lon = col_double(),
##   region = col_character(),
##   station = col_double(),
##   transect = col_double(),
##   `scientific name` = col_character(),
##   `percent cover` = col_double(),
##   depth = col_double(),
##   `bottom type` = col_character(),
##   rugosity = col_double(),
##   temperature = col_double()
## )
```

First we need to decide if we will provide an occurrence only version of the data or a sampling event with measurement or facts version of the data. Occurrence only is easier to create. It's only one file to produce. However, several pieces of information will be left out if we choose that option. If we choose to do sampling event with measurement or fact we'll be able to capture all of the data in the file creating a lossless version. Here we decide to use the sampling event option to include as much information as we can. First let's create the eventID and occurrenceID in the original file so that information can be reused for all necessary files down the line.

```
MadeUpDataForBiologicalDataTraining$eventID <- paste(MadeUpDataForBiologicalDataTraining$region,
                                                    MadeUpDataForBiologicalDataTraining$station,
                                                    MadeUpDataForBiologicalDataTraining$transect)
MadeUpDataForBiologicalDataTraining$occurrenceID <- ""
MadeUpDataForBiologicalDataTraining$occurrenceID <- sapply(MadeUpDataForBiologicalDataTraining$occurrenceID,
                                                           function(x) UUIDgenerate(use.time = TRUE))
```

We will need to create three separate files to comply with the sampling event format. We'll start with the event file but we only need to include the columns that are relevant to the event file.

```
event <- MadeUpDataForBiologicalDataTraining[c("date", "lat", "lon", "region", "station",
                                              "transect", "depth", "bottom type", "eventID")]
```

Next we need to rename any columns of data that match directly to Darwin Core. We know this based on our crosswalk spreadsheet CrosswalkToDarwin-Core.csv

```

event$decimalLatitude <- event$lat
event$decimalLongitude <- event$lon
event$minimumDepthInMeters <- event$depth
event$maximumDepthInMeters <- event$depth
event$habitat <- event$`bottom type`
event$island <- event$region

```

Let's see how it looks:

```
head(event, n = 10)
```

```

## # A tibble: 10 x 15
##   date    lat  lon region station transect depth `bottom type` eventID
##   <chr> <dbl> <dbl> <chr>    <dbl>    <dbl> <dbl> <chr>         <chr>
## 1 7/16~ 18.3 -64.8 St. J~    250      1    25 shallow reef~ St. Jo~
## 2 7/16~ 18.3 -64.8 St. J~    250      1    25 shallow reef~ St. Jo~
## 3 7/16~ 18.3 -64.8 St. J~    250      1    25 shallow reef~ St. Jo~
## 4 7/16~ 18.3 -64.8 St. J~    250      1    25 shallow reef~ St. Jo~
## 5 7/16~ 18.3 -64.8 St. J~    250      2    35 complex back~ St. Jo~
## 6 7/16~ 18.3 -64.8 St. J~    250      2    35 complex back~ St. Jo~
## 7 7/16~ 18.3 -64.8 St. J~    250      2    35 complex back~ St. Jo~
## 8 7/16~ 18.3 -64.8 St. J~    250      2    35 complex back~ St. Jo~
## 9 7/16~ 18.3 -64.8 St. J~    250      3    85 deep reef   St. Jo~
## 10 7/16~ 18.3 -64.8 St. J~    250      3    85 deep reef   St. Jo~
## # ... with 6 more variables: decimalLatitude <dbl>,
## #   decimalLongitude <dbl>, minimumDepthInMeters <dbl>,
## #   maximumDepthInMeters <dbl>, habitat <chr>, island <chr>

```

We need to convert the date to ISO format

```
event$eventDate <- as.Date(event$date, format = "%m/%d/%Y")
```

We will also have to add any missing required fields

```

event$basisOfRecord <- "HumanObservation"
event$geodeticDatum <- "EPSG:4326 WGS84"

```

Then we'll remove any columns that we no longer need to clean things up a bit.

```

event$date <- NULL
event$lat <- NULL
event$lon <- NULL
event$region <- NULL

```

2.3. ALIGNING DATA TO DARWIN CORE - SAMPLING EVENT WITH MEASUREMENT OR FACT31

```
event$station <- NULL
event$transect <- NULL
event$depth <- NULL
event$`bottom type` <- NULL
```

We have too many repeating rows of information. We can pare this down using eventID which is a unique identifier for each sampling event in the data- which is six, three transects per site.

```
event <- event[which(!duplicated(event$eventID)),]

head(event, n = 6)
```

```
## # A tibble: 6 x 10
##   eventID decimalLatitude decimalLongitude minimumDepthInM~
##   <chr>          <dbl>          <dbl>          <dbl>
## 1 St. Jo~        18.3          -64.8           25
## 2 St. Jo~        18.3          -64.8           35
## 3 St. Jo~        18.3          -64.8           85
## 4 St. Jo~        18.3          -64.8           28
## 5 St. Jo~        18.3          -64.8           16
## 6 St. Jo~        18.3          -64.8           90
## # ... with 6 more variables: maximumDepthInMeters <dbl>, habitat <chr>,
## #   island <chr>, eventDate <date>, basisOfRecord <chr>,
## #   geodeticDatum <chr>
```

Finally we write out the event file

```
write.csv(event, file="MadeUpData_event.csv", row.names=FALSE, fileEncoding="UTF-8", quote=TRUE)
```

Next we need to create the occurrence file. We start by creating the dataframe.

```
occurrence <- MadeUpDataForBiologicalDataTraining[c("scientific name", "eventID", "occurrenceID",
```

Then we'll rename the columns that align directly with Darwin Core.

```
occurrence$scientificName <- occurrence$`scientific name`
```

Finally we'll add required information that's missing.

```
occurrence$occurrenceStatus <- ifelse (occurrence$`percent cover` == 0, "absent", "present")
```

2.3.2 Taxonomic Name Matching

A requirement for OBIS is that all scientific names match to the World Register of Marine Species (WoRMS) and a scientificNameID is included. A scientificNameID looks like this “urn:lsid:marinespecies.org:taxname:275730” with the last digits after the colon being the WoRMS aphia ID. We’ll need to go out to WoRMS to grab this information. Create a lookup table of unique scientific names

```
lut_worms <- as.data.frame(unique(occurrence_only$scientificName))
lut_worms$scientificName <- as.character(lut_worms$`unique(occurrence_only$scientificName)`)
lut_worms$`unique(occurrence_only$scientificName)` <- NULL
lut_worms$scientificName <- as.character(lut_worms$scientificName)
```

Add the columns that we can grab information from WoRMS including the required scientificNameID.

```
lut_worms$acceptedname <- ""
lut_worms$acceptedID <- ""
lut_worms$scientificNameID <- ""
lut_worms$kingdom <- ""
lut_worms$phylum <- ""
lut_worms$class <- ""
lut_worms$order <- ""
lut_worms$family <- ""
lut_worms$genus <- ""
lut_worms$scientificNameAuthorship <- ""
lut_worms$taxonRank <- ""
```

Taxonomic lookup using the library taxizesoap

```
for (i in 1:nrow(lut_worms)){
  df <- worms_records(scientific = lut_worms$scientificName[i])
  lut_worms[i,]$scientificNameID <- df$lsid[1]
  lut_worms[i,]$acceptedname <- df$valid_name[1]
  lut_worms[i,]$acceptedID <- df$valid_AphiaID[1]
  lut_worms[i,]$kingdom <- df$kingdom[1]
  lut_worms[i,]$phylum <- df$phylum[1]
  lut_worms[i,]$class <- df$class[1]
  lut_worms[i,]$order <- df$order[1]
  lut_worms[i,]$family <- df$family[1]
  lut_worms[i,]$genus <- df$genus[1]
  lut_worms[i,]$scientificNameAuthorship <- df$authority[1]
  lut_worms[i,]$taxonRank <- df$rank[1]
  message(paste("Looking up information for species:", lut_worms[i,]$scientificName))
}
```


2.3. ALIGNING DATA TO DARWIN CORE - SAMPLING EVENT WITH MEASUREMENT OR FACT33

```
## Looking up information for species: Acropora cervicornis
```

```
## Looking up information for species: Madracis auretenra
```

```
## Looking up information for species: Mussa angulosa
```

```
## Looking up information for species: Siderastrea radians
```

Merge the lookup table of unique scientific names back with the occurrence data.

```
occurrence <- merge(occurrence, lut_worms, by = "scientificName")
```

We're going to remove any unnecessary columns to clean up the file

```
occurrence$`scientific name` <- NULL
occurrence$`percent cover` <- NULL
```

Quick look at what we have before we write out the file

```
head(occurrence, n = 10)
```

```
##           scientificName           eventID
## 1  Acropora cervicornis St. John_250_1
## 2  Acropora cervicornis St. John_250_2
## 3  Acropora cervicornis St. John_250_3
## 4  Acropora cervicornis St. John_356_1
## 5  Acropora cervicornis St. John_356_2
## 6  Acropora cervicornis St. John_356_3
## 7   Madracis auretenra St. John_250_1
## 8   Madracis auretenra St. John_250_2
## 9   Madracis auretenra St. John_250_3
## 10  Madracis auretenra St. John_356_1
##           occurrenceID occurrenceStatus
## 1  63be8f7e-ea9a-11e9-8649-49c6324f3a06      absent
## 2  63beb687-ea9a-11e9-8649-49c6324f3a06      absent
## 3  63beb68b-ea9a-11e9-8649-49c6324f3a06      present
## 4  63bedd76-ea9a-11e9-8649-49c6324f3a06      present
## 5  63bedd7a-ea9a-11e9-8649-49c6324f3a06      present
## 6  63bedd7e-ea9a-11e9-8649-49c6324f3a06      present
## 7  63beb684-ea9a-11e9-8649-49c6324f3a06      present
## 8  63beb688-ea9a-11e9-8649-49c6324f3a06      present
## 9  63beb68c-ea9a-11e9-8649-49c6324f3a06      absent
```

```

## 10 63bedd77-ea9a-11e9-8649-49c6324f3a06      present
##          acceptedname acceptedID
## 1  Acropora cervicornis      206989
## 2  Acropora cervicornis      206989
## 3  Acropora cervicornis      206989
## 4  Acropora cervicornis      206989
## 5  Acropora cervicornis      206989
## 6  Acropora cervicornis      206989
## 7   Madracis auretenra      430664
## 8   Madracis auretenra      430664
## 9   Madracis auretenra      430664
## 10  Madracis auretenra      430664
##          scientificNameID kingdom  phylum  class
## 1  urn:lsid:marinespecies.org:taxname:206989 Animalia Cnidaria Anthozoa
## 2  urn:lsid:marinespecies.org:taxname:206989 Animalia Cnidaria Anthozoa
## 3  urn:lsid:marinespecies.org:taxname:206989 Animalia Cnidaria Anthozoa
## 4  urn:lsid:marinespecies.org:taxname:206989 Animalia Cnidaria Anthozoa
## 5  urn:lsid:marinespecies.org:taxname:206989 Animalia Cnidaria Anthozoa
## 6  urn:lsid:marinespecies.org:taxname:206989 Animalia Cnidaria Anthozoa
## 7  urn:lsid:marinespecies.org:taxname:430664 Animalia Cnidaria Anthozoa
## 8  urn:lsid:marinespecies.org:taxname:430664 Animalia Cnidaria Anthozoa
## 9  urn:lsid:marinespecies.org:taxname:430664 Animalia Cnidaria Anthozoa
## 10 urn:lsid:marinespecies.org:taxname:430664 Animalia Cnidaria Anthozoa
##          order          family    genus  scientificNameAuthorship
## 1  Scleractinia    Acroporidae Acropora      (Lamarck, 1816)
## 2  Scleractinia    Acroporidae Acropora      (Lamarck, 1816)
## 3  Scleractinia    Acroporidae Acropora      (Lamarck, 1816)
## 4  Scleractinia    Acroporidae Acropora      (Lamarck, 1816)
## 5  Scleractinia    Acroporidae Acropora      (Lamarck, 1816)
## 6  Scleractinia    Acroporidae Acropora      (Lamarck, 1816)
## 7  Scleractinia Pocilloporidae Madracis Locke, Weil & Coates, 2007
## 8  Scleractinia Pocilloporidae Madracis Locke, Weil & Coates, 2007
## 9  Scleractinia Pocilloporidae Madracis Locke, Weil & Coates, 2007
## 10 Scleractinia Pocilloporidae Madracis Locke, Weil & Coates, 2007
##          taxonRank
## 1  Species
## 2  Species
## 3  Species
## 4  Species
## 5  Species
## 6  Species
## 7  Species
## 8  Species
## 9  Species
## 10 Species

```

2.3. ALIGNING DATA TO DARWIN CORE - SAMPLING EVENT WITH MEASUREMENT OR FACT 35

Write out the file. All done with occurrence!

```
write.csv(occurrence, file="MadeUpData_Occurrence.csv", row.names=FALSE, fileEncoding="UTF-8", qu
```

The last file we need to create is the measurement or fact file. For this we need to combine all of the measurements or facts that we want to include making sure to include IDs from the BODC NERC vocabulary where possible.

```
temperature <- MadeUpDataForBiologicalDataTraining[c("eventID", "temperature", "date")]
temperature$occurrenceID <- ""
temperature$measurementType <- "temperature"
temperature$measurementTypeID <- "http://vocab.nerc.ac.uk/collection/P25/current/WTEMP/"
temperature$measurementValue <- temperature$temperature
temperature$measurementUnit <- "Celsius"
temperature$measurementUnitID <- "http://vocab.nerc.ac.uk/collection/P06/current/UPAA/"
temperature$measurementAccuracy <- 3
temperature$measurementDeterminedDate <- as.Date(temperature$date, format = "%m/%d/%Y")
temperature$measurementMethod <- ""
temperature$temperature <- NULL
temperature$date <- NULL
rugosity <- MadeUpDataForBiologicalDataTraining[c("eventID", "rugosity", "date")]
rugosity$occurrenceID <- ""
rugosity$measurementType <- "rugosity"
rugosity$measurementTypeID <- ""
rugosity$measurementValue <- rugosity$rugosity
rugosity$measurementUnit <- ""
rugosity$measurementUnitID <- ""
rugosity$measurementAccuracy <- ""
rugosity$measurementDeterminedDate <- as.Date(rugosity$date, format = "%m/%d/%Y")
rugosity$measurementMethod <- ""
rugosity$rugosity <- NULL
rugosity$date <- NULL
percentcover <- MadeUpDataForBiologicalDataTraining[c("eventID", "occurrenceID", "percent cover",
percentcover$measurementType <- "Percent Cover"
percentcover$measurementTypeID <- "http://vocab.nerc.ac.uk/collection/P01/current/SDBIOL10/"
percentcover$measurementValue <- percentcover$`percent cover`
percentcover$measurementUnit <- "Percent/100m^2"
percentcover$measurementUnitID <- ""
percentcover$measurementAccuracy <- 5
percentcover$measurementDeterminedDate <- as.Date(percentcover$date, format = "%m/%d/%Y")
percentcover$measurementMethod <- ""
percentcover$`percent cover` <- NULL
percentcover$date <- NULL
measurementOrFact <- rbind(temperature, rugosity, percentcover)
```

```
## Error in match.names(clabs, names(xi)): names do not match previous names
```

Let's check to see what it looks like

```
head(measurementOrFact, n = 50)
```

```
## # A tibble: 50 x 9
##   eventID occurrenceID measurementType measurementType~ measurementValue
##   <chr>    <chr>          <chr>          <chr>                <dbl>
## 1 St. Jo~ ""            temperature    ""                25.2
## 2 St. Jo~ ""            temperature    ""                25.2
## 3 St. Jo~ ""            temperature    ""                25.2
## 4 St. Jo~ ""            temperature    ""                25.2
## 5 St. Jo~ ""            temperature    ""                24.8
## 6 St. Jo~ ""            temperature    ""                24.8
## 7 St. Jo~ ""            temperature    ""                24.8
## 8 St. Jo~ ""            temperature    ""                24.8
## 9 St. Jo~ ""            temperature    ""                23.1
## 10 St. Jo~ ""           temperature    ""                23.1
## # ... with 40 more rows, and 4 more variables: measurementUnit <chr>,
## #   measurementUnitID <chr>, measurementDeterminedDate <date>,
## #   measurementMethod <chr>

write.csv(measurementOrFact, file="MadeUpData_mof.csv", row.names=FALSE, fileEncoding=
```

Chapter 3

Dealing with errors

Datasets can have a wide variety of errors that pop up during the darwin core alignment process. This chapter details ways in which a data manager can identify, discuss, and resolve potential errors in the data.

It should be noted that, in most cases, the data manager/scientist aligning the data to darwin core should reach out to the data originator to ensure the actions taken are not incorrectly representing the observations.

3.1 Example using GitHub to resolve errors

1. Dataset sent to OBIS-USA via email.
2. OBIS-USA uploaded to IPT.
3. Once the data were uploaded, the IPT identified there was an issue with the `occurrenceID` field. The issue was then presented and discussed in a

ioos/bio_data_guide Public

<> Code Issues 11 Pull requests Discussions Actions Projects Wiki

managing duplicate occurrenceIDs #78

Closed MathewBiddle opened this issue 12 days ago · 5 comments

MathewBiddle commented 12 days ago

Making unique occurrenceID for the rows. Unfortunately, the best I could do was to concatenate the station, organism, life stage, and type. This still left me w/ 205 duplicates (410 rows). Looking a little more closely at the duplicates (see screenshot below) it seems that there are duplicate observations (same methods, place, time, and species - stage is missing). Not sure what to do in this case, most likely need to reach back to the PI and get their 2 cents.

	27	28
Cruise	AMBON2017	AMBON2017
Station	ML1.1	ML1.1
Type	TWINRING_150UM_MICROSCOPY	TWINRING_150UM_MICROSCOPY
Date_Time	2017-08-17 15:24:00	2017-08-17 15:24:00
Longitude [decimal_degrees_east]	-162.766	-162.766

GitHub ticket:

- The data manager uploaded the raw data and code to GitHub through the pull request below. This included a fix for the `occurrenceID` issue.

Ambon zooplankton #77

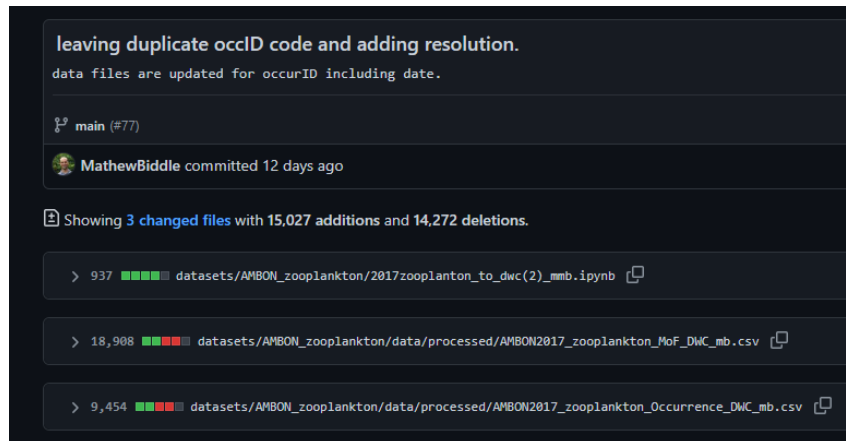
Merged MathewBiddle merged 3 commits into ioos:main from MathewBiddle:ambon_zooplankton 12 days ago

Conversation 1 Commits 3 Checks 0 Files changed 6

Changes from all commits File filter X Clear filters Conversations Jump to

- > 6,610 datasets/AMBON_zooplankton/2017zooplankton_to_dw(2)_mmb.ipynb
- > 155 datasets/AMBON_zooplankton/data/processed/AMBON2017_zooplankton_Event_DWC_mb.csv
- > 9,455 datasets/AMBON_zooplankton/data/processed/AMBON2017_zooplankton_MoF_DWC_mb.csv
- > 4,728 datasets/AMBON_zooplankton/data/processed/AMBON2017_zooplankton_Occurrence_DWC_mb.csv
- > 2,937 datasets/AMBON_zooplankton/data/raw/AMBON2017150.csv
- > 1,794 datasets/AMBON_zooplankton/data/raw/AMBON2017505.csv

- The OBIS node manager was notified of the availability of a revised dataset by pointing directly to the appropriate commit in GitHub:



6. The OBIS node manager downloaded the data from the commit above and uploaded them to the IPT.
7. The IPT returned a summary of the dataset including that 434 records had invalid `scientificNameID` records in the occurrence file.
8. After some data sleuthing, the data manager noticed that the code accidentally removed trailing zeros from `scientificNameID` that ended in 0:

```
#taxonid needs to not have trailing .0
taxons = df[['taxonID']].astype('string', errors='ignore')
t=taxons['taxonID'].convert_dtypes()
t=t.str.strip('.0')
t
df['taxonID']=t
df.head()
```

9. So, the data manager updated the code to resolve the issue and generate a



new occurrence file.

```

1 #OK, rename and then add new columns
2 #Rename columns as necessary
3
4 df.rename(columns={'Depth_m': 'minimumDepthMeters',
5                  'life_stage': 'lifeStage',
6                  'type': 'samplingProtocol',
7                  'Longitude_decimal_degrees_east': 'decimalLongitude',
8                  'Latitude_decimal_degrees_north': 'decimalLatitude',
9                  'Accepted_Organism_Identification': 'scientificName',
10                 'dwcID' + ' ' + 'taxonID' + ' ' + 'aphidID' + ' ' + 'specimenID', inplace=True)
11
12 # add new parameters
13
14 df['scientificNameID'] = 'urn:lsid:marinespecies.org:taxname:' + df['taxonID'].astype(str)
15
16 df['identificationReferences'] = 'MBG'
17 df['basisOfRecord'] = 'HumanObservation' #haspace!
18 df['occurrenceStatus'] = 'present'
19
20 df.head()

```

1. Here is fixing the scientificNameID generation:

```

1 #finally!
2 #nope it's scientificNameID that needs this
3 sciids = df[['scientificNameID']].astype('string', errors='ignore')
4 s = sciids['scientificNameID'].convert_dtypes()
5 s = s.str.strip('.0')
6 df['scientificNameID'] = s
7
8 df.head()

```

2. Here is removing the problematic code:

```

1 #finally!
2 #nope it's scientificNameID that needs this
3
4 # mmb - Think this was not necessary.
5 # sciids = df[['scientificNameID']].astype('string', errors='ignore')
6 # s = sciids['scientificNameID'].convert_dtypes()
7 # s = s.str.strip('.0')
8 # df['scientificNameID'] = s
9 df.head()

```

10. The revised occurrence file was then resubmitted to the OBIS node manager by pointing them at the appropriate commit record:

fixing taxonID and aphidID columns

we lopped of trailing zeros making invalid ids

 main (#82)

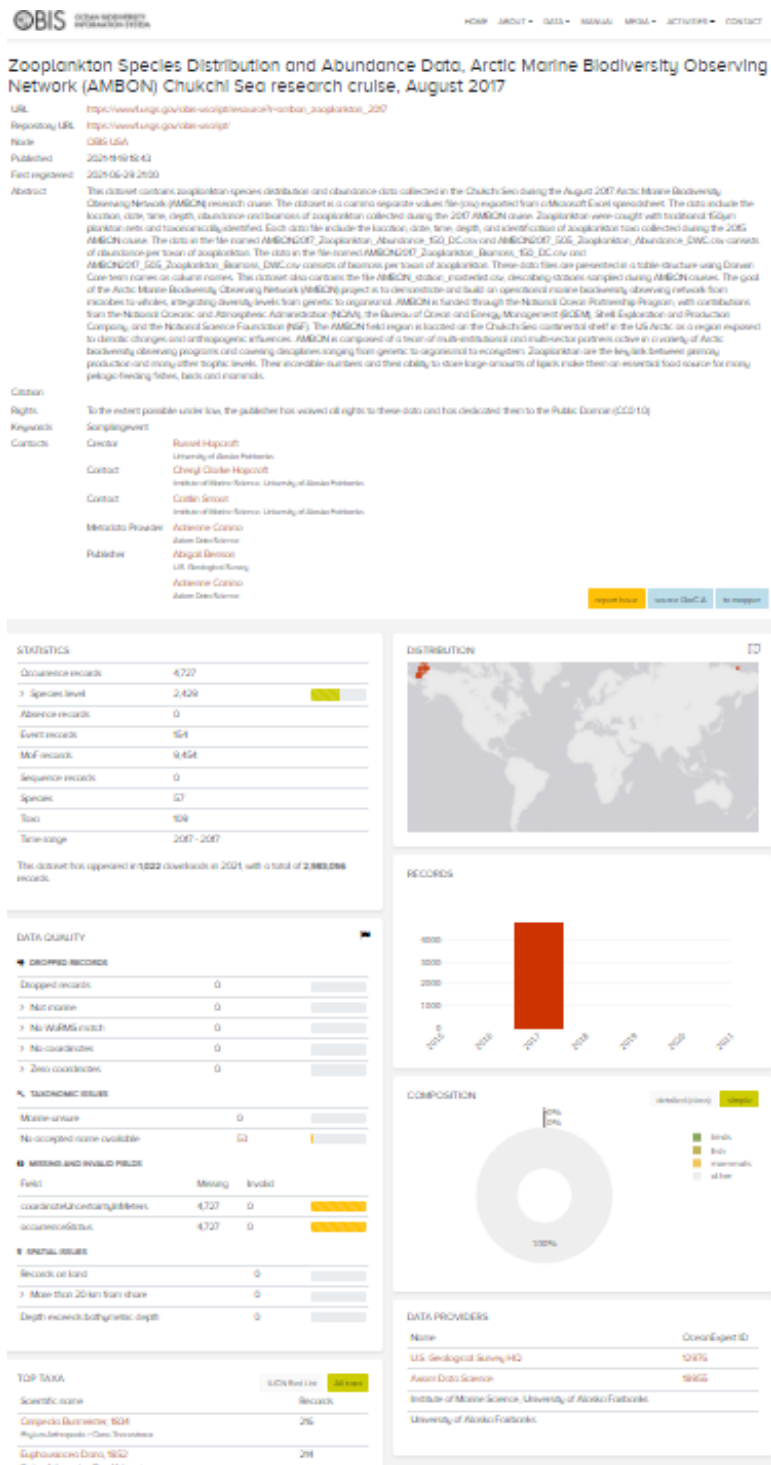
 MathewBiddle committed 3 days ago

Showing 2 changed files with 989 additions and 1,230 deletions.

> 915 datasets/AMBON_zooplankton/2017zooplankton_to_dwc(2)_mmb.ipynb

> 1,304 datasets/AMBON_zooplankton/data/processed/AMBON2017_zooplankton_Occurrence_DWC_mb.csv

11. The OBIS node manager downloaded the data from the commit above and uploaded them to the IPT.
12. The IPT and OBIS landing page now indicated that no more issues with



these data are present:

Chapter 4

Final Words

We have finished a nice book.

Chapter 5

Tools

Below are some of the tools and packages used in workflows. R and Python package “Type” is BIO for packages specifically for biological applications, and GEN for generic packages.

5.1 R

Package	Type	Description
bdveRse	BIO	A family of R packages for biodiversity data.
ecocomDP	BIO	Work with the Ecological Community Data Design Pattern. ‘ecocomDP’ is a flexible data model for harmonizing ecological community surveys, in a research question agnostic format, from source data published across repositories, and with methods that keep the derived data up-to-date as the underlying sources change.

Package	Type	Description
EDIorg/EMLassemblelylin	BIO	For scientists and data managers to create high quality EML metadata for dataset publication.
finch	BIO	Parse Darwin Core Files
iobis/obistools	BIO	Tools for data enhancement and quality control.
robis	BIO	R client for the OBIS API
ropensci/EML	BIO	Provides support for the serializing and parsing of all low-level EML concepts
taxize	BIO	Interacts with a suite of web ‘APIs’ for taxonomic tasks, such as getting database specific taxonomic identifiers, verifying species names, getting taxonomic hierarchies, fetching downstream and upstream taxonomic names, getting taxonomic synonyms, converting scientific to common names and vice versa, and more.
worms	BIO	Client for World Register of Marine Species. Includes functions for each of the API methods, including searching for names by name, date and common names, searching using external identifiers, fetching synonyms, as well as fetching taxonomic children and taxonomic classification.

Package	Type	Description
Hmisc	GEN	Contains many functions useful for data analysis, high-level graphics, utility operations, functions for computing sample size and power, simulation, importing and annotating datasets, imputing missing values, advanced table making, variable clustering, character string manipulation, conversion of R objects to LaTeX and html code, and recoding variables. Particularly check out the describe() function.
lubridate	GEN	Functions to work with date-times and time-spans: fast and user friendly parsing of date-time data, extraction and updating of components of a date-time (years, months, days, hours, minutes, and seconds), algebraic manipulation on date-time and time-span objects.
stringr	GEN	Simple, Consistent Wrappers for Common String Operations

Package	Type	Description
tidyverse	GEN	The ‘tidyverse’ is a set of packages that work in harmony because they share common data representations and ‘API’ design. This package is designed to make it easy to install and load multiple ‘tidyverse’ packages in a single step.
uuid	GEN	Tools for generating and handling of UUIDs (Universally Unique Identifiers).

5.2 Python

Package	Type	Description
metatype	BIO	A lightweight Python 3 library for generating EML metadata
python-dwca-reader	BIO	A simple Python package to read and parse Darwin Core Archive (DwC-A) files, as produced by the GBIF website, the IPT and many other biodiversity informatics tools.
pyworms	BIO	Python client for the World Register of Marine Species (WoRMS) REST service.

Package	Type	Description
numpy	GEN	NumPy (Numerical Python) is an open source Python library that's used in almost every field of science and engineering. It's the universal standard for working with numerical data in Python, and it's at the core of the scientific Python and PyData ecosystems.
pandas	GEN	pandas is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool, built on top of the Python programming language. Super helpful when manipulating tabular data!
uuid	GEN	This module provides immutable UUID objects (class UUID) and the functions <code>uuid1()</code> , <code>uuid3()</code> , <code>uuid4()</code> , <code>uuid5()</code> for generating version 1, 3, 4, and 5 UUIDs as specified in RFC 4122. Built in – part of the Python standard library.

Package	Type	Description
obis-qc	BIO	Quality checks on occurrence records. Checks <code>occurrenceStatus</code> , <code>individualCount</code> , <code>eventDate</code> , <code>decimalLatitude</code> , <code>decimalLongitude</code> , <code>coordinateUncertaintyInMeters</code> , <code>minimumDepthInMeters</code> , <code>maximumDepthInMeters</code> , <code>scientificName</code> , <code>scientificNameID</code> . Checks from Vandepitte et al. flags not implemented: 3, 9, 14, 15, 16, 10, 17, 21-30.

5.3 Google Sheets

Package	Description
Google Sheet DarwinCore Archive Assistant add-on	Google Sheet add-on which assists the creation of Darwin Core Archives (DwCA) and publishing to Zenodo. DwCA's are stored into user's Google Drive and can be downloaded for upload into IPT installations or other software which is able to read DwC-archives.

5.4 Validators

Name	Description
Darwin Core Archive Validator	This validator verifies the structural integrity of a Darwin Core Archive. It does not check the data values, such as coordinates, dates or scientific names.

Name	Description
GBIF DATA VALIDATOR	The GBIF data validator is a service that allows anyone with a GBIF-relevant dataset to receive a report on the syntactical correctness and the validity of the content contained within the dataset.
LifeWatch Belgium	Through this interactive section of the LifeWatch.be portal users can upload their own data using a standard data format, and choose from several web services, models and applications to process the data.

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