

# Hyperspectral Remote Sensing of Coastal Morphodynamics

**Nicolas Pucino**<sup>1</sup>, Rafael C. Carvalho<sup>1</sup>, Blake Allan<sup>1</sup>, David M. Kennedy<sup>2</sup>, Daniel Ierodiaconou<sup>1</sup>

<sup>1</sup> School of Life and Environmental Sciences, Deakin University, [npucino@deakin.edu.com](mailto:npucino@deakin.edu.com)

<sup>2</sup> School of Geography, Faculty of Science, The University of Melbourne



PhD Program



# Nicolas Pucino

PhD Candidate in Remote Sensing of Coastal Morphodynamics, Deakin University

- BA in Physical Geography  
@ University of Lausanne (Switzerland)
- MA in Coastal Management and Planning  
@ University of Wollongong (Australia)
- Geospatial sciences and Remote Sensing fanatic

## PhD Program

Chapter I	Sediment Facies Radiometrics	<ul style="list-style-type: none"><li>• <b>ASD Field Spectroscopy</b> of supra/intertidal sandy sediments + Lab analysis</li><li>• Endmembers extraction</li><li>• Open Source <b>Spectral Library</b> (Specchio)</li></ul>
Chapter II	UAS-based Sediment Facies Mapping	<ul style="list-style-type: none"><li>• Multitemporal <b>UAS SfM and Hyperspectral beach surveys</b></li><li>• Segmentation and supervised <b>classification</b> with spectral library</li><li>• Sand sampling for ground-truth</li><li>• SfM volumetrics + classification maps = <b>sediment transportation maps</b></li></ul>
Chapter III	Satellite-based hyper/multispectral monitoring	<ul style="list-style-type: none"><li>• Depending on <b>imagery availability</b> (Satellogic, Reaktor Space Lab)</li><li>• <b>Pixel unmixing</b> analysis to study the sand classes present in every pixel</li><li>• <b>Mineral abundance maps</b>, if UAS spectroscopy and lab radiometry is done prior to image acquisition</li></ul>
Chapter IV	Satellite-based shoreline monitoring	<ul style="list-style-type: none"><li>• Python scripting for <b>shoreline extraction</b> from Sentinel-2 and Planet imagery</li><li>• <b>DEA ARD data + NCI</b> cloud computing via Jupyter NB for Sentinel-2 imagery</li><li>• <b>Planet API + Google Earth Engine</b> and <b>Citizen Science UAS</b> data for Planet imagery</li></ul>
Ongoing	Citizen Science data analysis scripting	<ul style="list-style-type: none"><li>• Python scripting for <b>automatic analysis</b> (transects analysis)</li><li>• Creation of <b>Jupyter Notebook</b> for open source analysis tools</li><li>• Basic <b>spatial database</b> structure for storing profiles and volumetrics (future work)</li></ul>



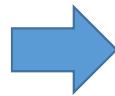
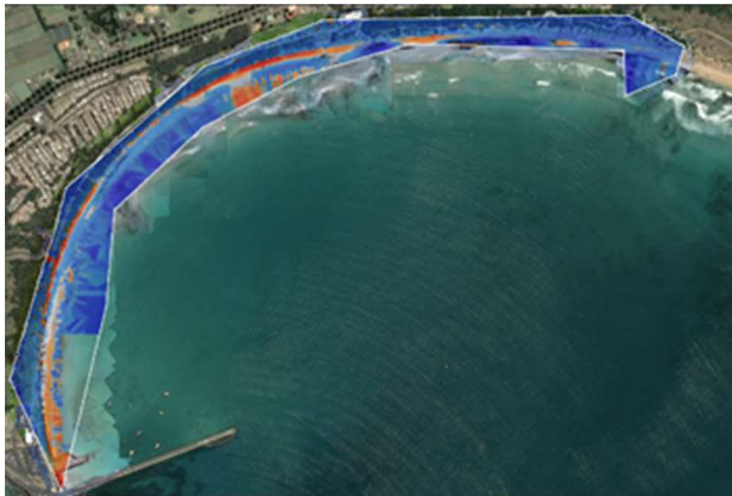
# Hyperspectral + Coasts

## From DoDs to Sediment Facies Maps

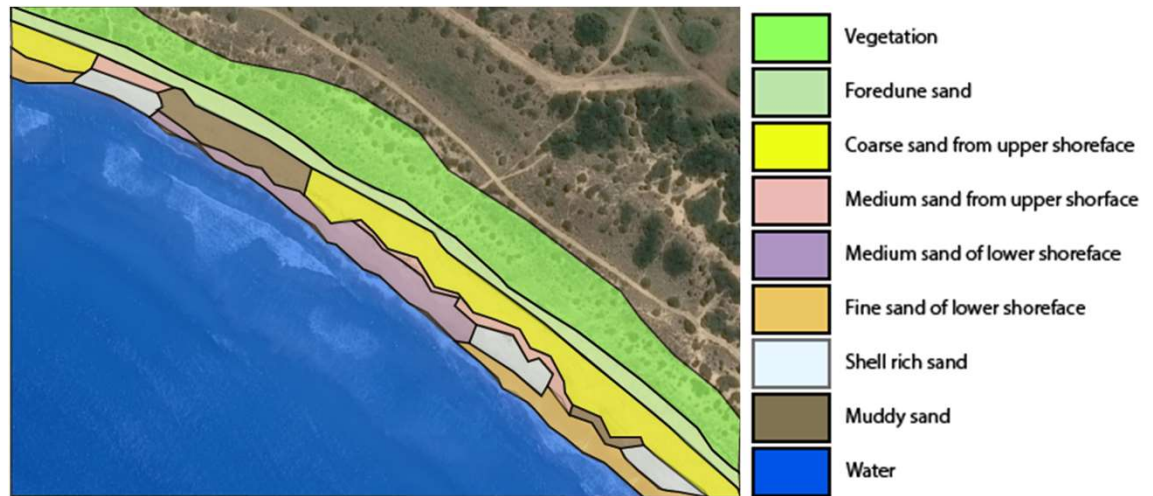
**SfM** allows to calculate volumes loss/fill in a spatially explicit way along sandy beaches, answering the question «**how much sediment has been cut/fill here?**». However, it doesn't provide a clear sediment directionality dimension and sediment exchanges between depositional environments or even coastal compartments can only be inferred by geomorphological observations or expensive and time consuming sediment tracking methods.

**This study** aims to deliver a method for answering the question «*how much of that specific type of sand accumulated/eroded from here?*», with **the type of sand being an indicator of the geographic and geomorphic sediment origin.**

Dems of Difference (DoDs)



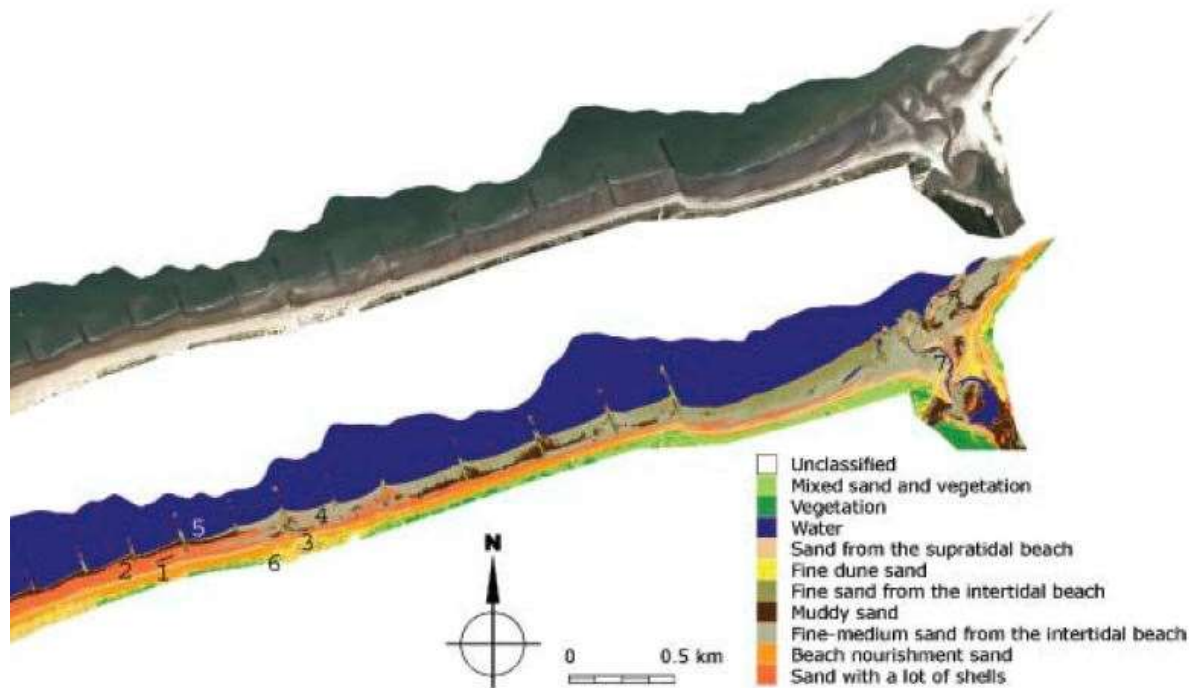
Site specific sediment facies maps



## Previous Study

### The Belgium Coastline (Deronde et al. 2008)

Sediment facies Map



#### PROs

- **Direction** of sediments can be qualitatively derived
- **Nourishment sand** is detected and monitored

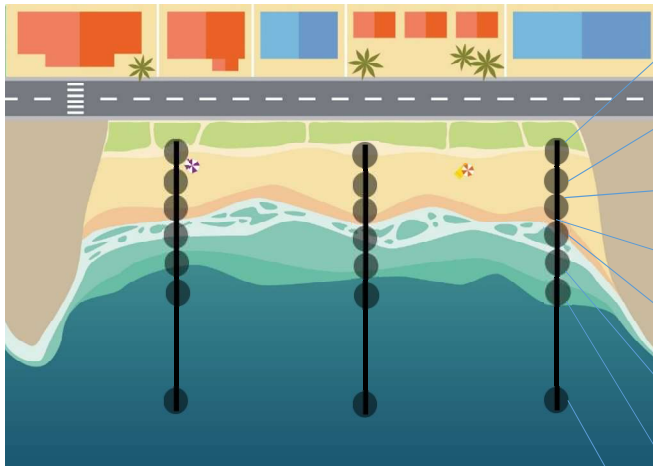
#### CONS

- High operational **costs** (aerial)
- Detect only **surficial sand**, not absolute classes volumetrics

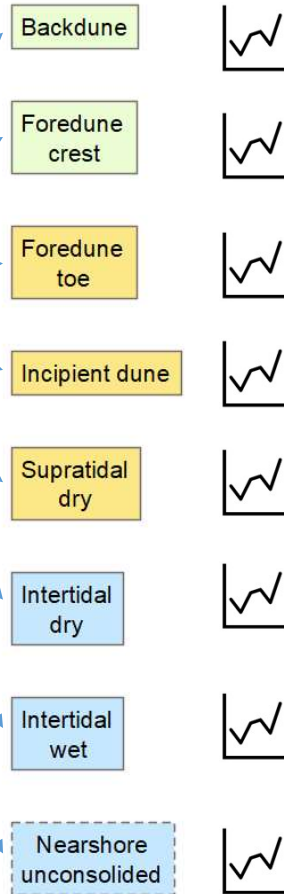


## My Approach

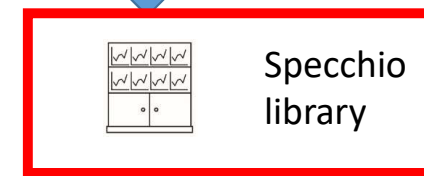
### Coastal compartment cross-shore transects



- Multiple Coastal Compartments Field Surveys
- Classes to be defined
- Biogenic stranded material



**Sand Facies Endmembers**  
*are site specific*



 Aerial/Satellite Spectroscopy

**Spectral Response**

function of

Grainsize

Mineralogy

Organic matter

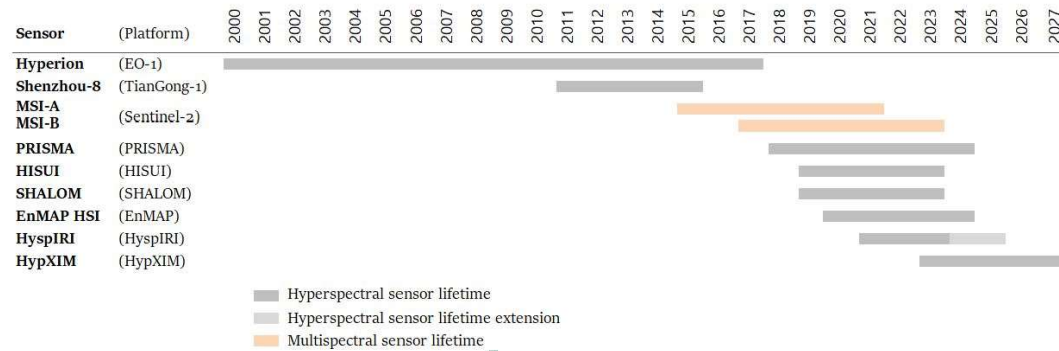
Water content

**Get ready for the future!**

## Future of EO

# Satellite Hyperspec is evolving rapidly ...

### Government



Instrument	MSI	EnMAP HSI	SHALOM	HypIRI	HypXIM
Platform name	Sentinel-2	EnMAP	Improved Multi-Purpose Satellite-II	HypIRI	HypXIM
Sensor type	Multispectral	Hyperspectral	Hyperspectral	Hyperspectral	Hyperspectral
Swath width (km)	290	30	30	145-600	15
Spectral range (nm)	443-2190	420-2450	400-2500	380-2510	400-2500
VNIR		420-1000	400-1010	380-1400	400-1100
SWIR		900-2450	920-2500	1400-2510	1100-2500
Spectral bands	13	244	275	214	210
Resolution					
Spatial (m)	10-20-60	30	10	30 (60)	8
Temporal (day)	5	27 (VZA ≥ 5°) 4 (VZA ≥ 30°)	4 (VZA ≥ 30°)	5-16	3-5
Spectral (nm)	15-180	6.5 (VNIR) 10 (SWIR)	10	10	10
SNR (30% albedo)					
VNIR	89:1 to 168:1	400:1	200:1	560:1 at 500 nm	≥200:1 to 250:1
SWIR	50:1 to 100:1	>400:1 at 495 nm 180:1 >180:1 at 2200 nm	600:1 at 650 nm 200:1 400:1 at 1550 nm 100:1 200:1 at 2100 nm	356 at 1500 nm 236 at 2200 nm	≥100:1
Objective	Earth observation	Earth observation	Land and ocean observation	Volcanic, vegetation, soil, exploration	Soil, urban, coastal, biodiversity
Country	Europe	Germany	Italy-Israel	USA	France
Organization	ESA	GFZ-DLR	ASI-ISA	JPL-NASA	CNES
Number of articles	41	41	2	35	1

Source: Tranon et al., 2018

### Commercial, nano and small satellites

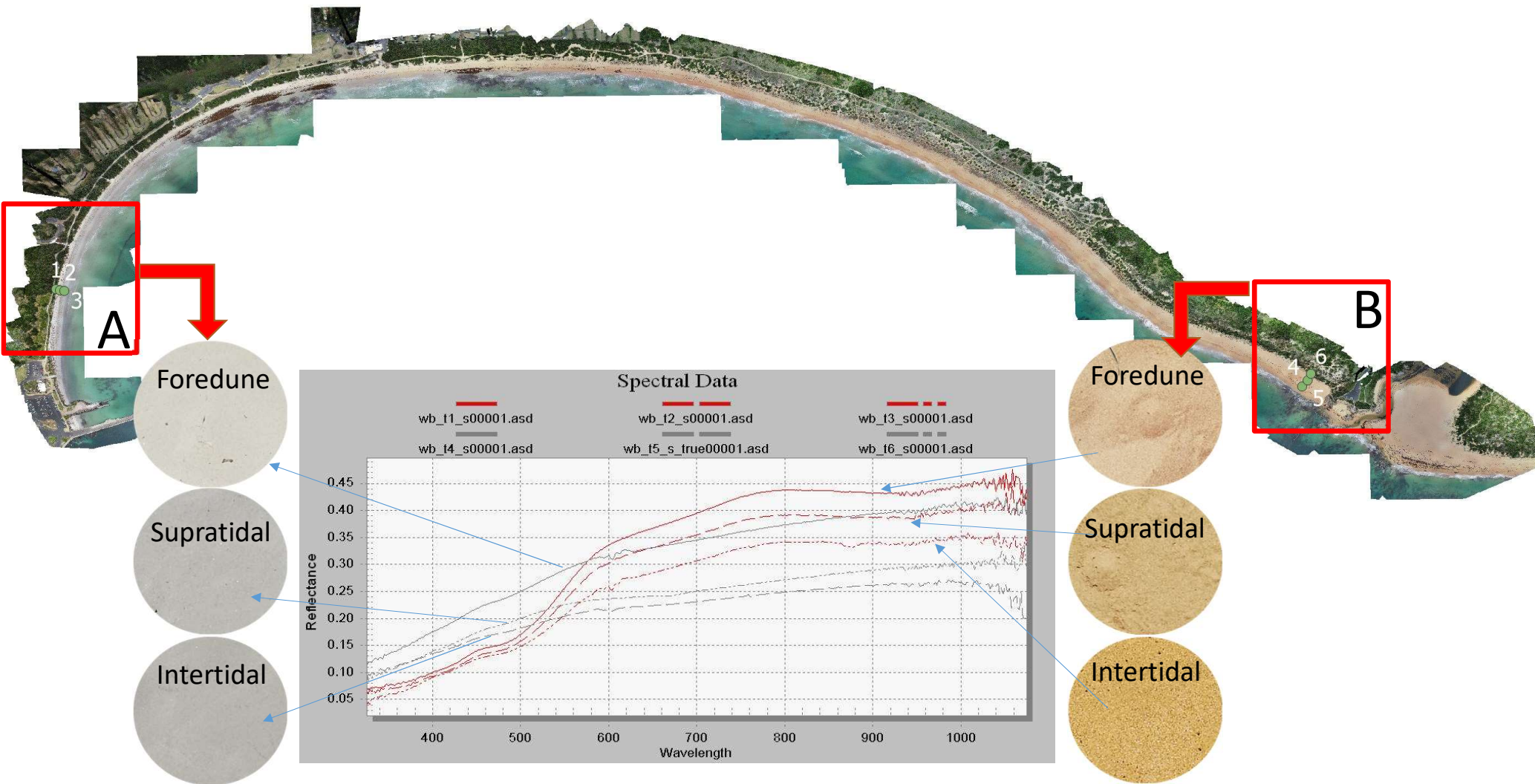
	Country	Status	Life span	n. bands	Spec. res	spectrum	Spatial Resolution
Satellogic	Argentina	2016	3y	600	5nm	VNIR-SWIR	30m
HyperSat	USA	2020		200	na	na	sub 10m
Reaktor	Finland	2019	na	na	na	SWIR	na
NorthStarCanada	Canada	2021	na	na	na	SWIR	na

- *Satellogic*, microsat, 29MIO
- *Zhuhai Orbita Control*, smallsat, \$?
- *Orbital Sidekick*, 4.7MIO
- *Reaktor Space*, 6U, \$?
- *HyperSat*, smallsat, 85 MIO
- *NorStar NorthStar*, microsat
- *Hypercubes*
- *Cosine*
- *Siwei Star Co.Ltd.*

Source: www.newsspace.im



## Preliminary Tests





Citizens Science +  
UAV data

## Data Quality and Validation

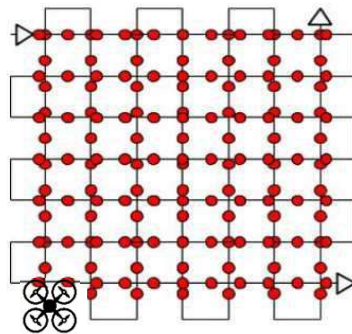
### Hardware



### Software



### Planning



### Professional Support



## Data Quality and Validation



	X variance (mm)	Y variance (mm)	Z variance (mm)
count	58.000000	58.000000	58.000000
mean	6.815517	4.103448	7.934483
std	4.764555	4.739900	8.424620
min	0.400000	0.400000	0.700000
25%	4.350000	1.225000	3.375000
50%	6.200000	2.450000	5.850000
75%	8.150000	5.725000	9.875000
max	24.400000	27.900000	53.400000

- **58** Smart GCPs
- **2-3** hours acquisition time
- **7,4 and 8 mm** XYZ variance during GCP acquisition time

Project	20181129_Warmambool_Harbour
Processed	2018-12-03 17:23:53
Camera Model Name(s)	FC6310_8.8_5472x3648 (RGB)(1), FC6310_8.8_5472x3648 (RGB)(2), FC6310_8.8_5472x3648 (RGB)(3)
Average Ground Sampling Distance (GSD)	2.56 cm / 1.01 in
Area Covered	1.616 km <sup>2</sup> / 161.5825 ha / 0.62 sq. mi. / 399.4857 acres
Time for Initial Processing (without report)	01h:52m:01s

### Quality Check

Images	median of 37454 keypoints per image	✓
Dataset	1073 out of 1109 images calibrated (96%), all images enabled	✓
Camera Optimization	0.49% relative difference between initial and optimized internal camera parameters	✓
Matching	median of 7556.25 matches per calibrated image	✓
Georeferencing	yes, 53 GCPs (53 3D), mean RMS error = 0.024 m	✓

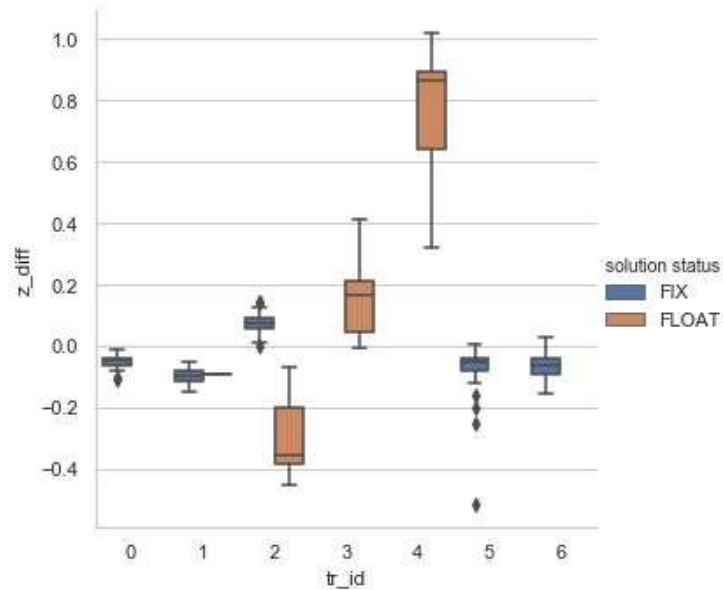
- Lady Bay, 1.6 km<sup>2</sup> (161.6 ha)
- **2.4 cm** RMSE 3D absolute accuracy
- **2.56 cm** GSD → 1 pixel of error



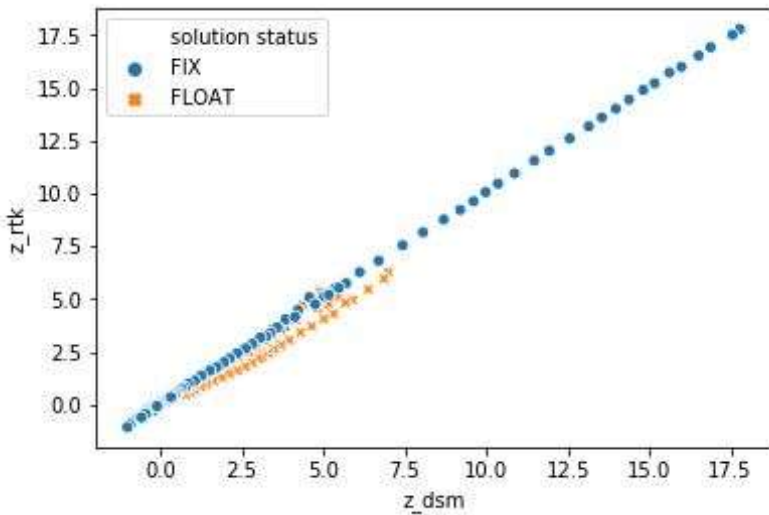
## Data Quality and Validation



## Data Quality and Validation



	fid	x	y	z_dsm	lateral rms	tr_id	z_rtk	new_field	z_diff
count	150.000000	150.000000	1.500000e+02	150.000000	150.000000	150.000000	150.000000	150.000000	150.000000
mean	109.673333	630516.725701	5.748889e+06	2.893818	0.004704	3.613333	2.937904	107.233333	-0.044086
std	68.745567	1139.485686	3.414026e+02	4.739371	0.001037	2.382224	4.750810	67.005300	0.077730
min	1.000000	628838.900500	5.748539e+06	-1.013198	0.002600	0.000000	-1.075440	1.000000	-0.514993
25%	39.250000	629083.574250	5.748563e+06	-0.138148	0.003925	1.000000	-0.095515	39.250000	-0.081568
50%	133.500000	631189.392150	5.748789e+06	0.770039	0.004700	5.000000	0.790380	129.500000	-0.047882
75%	170.750000	631634.218100	5.749270e+06	3.828357	0.005400	6.000000	3.946635	166.750000	-0.023891
max	208.000000	631679.697000	5.749501e+06	17.777303	0.008000	6.000000	17.797445	204.000000	0.141925



**Mean Error (ME) = -0.04m (4cm)**

→ DSM values are slightly overestimated, but accurate.

**Root Mean Squared Error (RMSE) = 0.09m (9cm)**

→ RMSE over PR method are known to overestimate the error estimations (Carrivick et.al, 2016).

→ 9 cm RMSE in Z is a common value in the **scientific** UAV literature and also aerial LiDAR surveys.



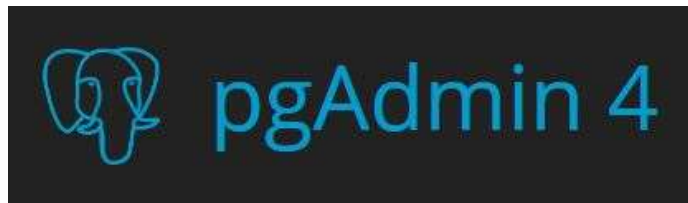
## Analysis and Communication

By the end of the **3 years** time Citizen Scientists will have produced more than **200 datasets** ...

... there will be **1 Tb of DSM and orthophotos** to analyse ...

... **14 locations** with differences in wind, wave and sediment regimes. **Good research** possibilities!

How to analyse such an amount of geospatial data in an efficient way?

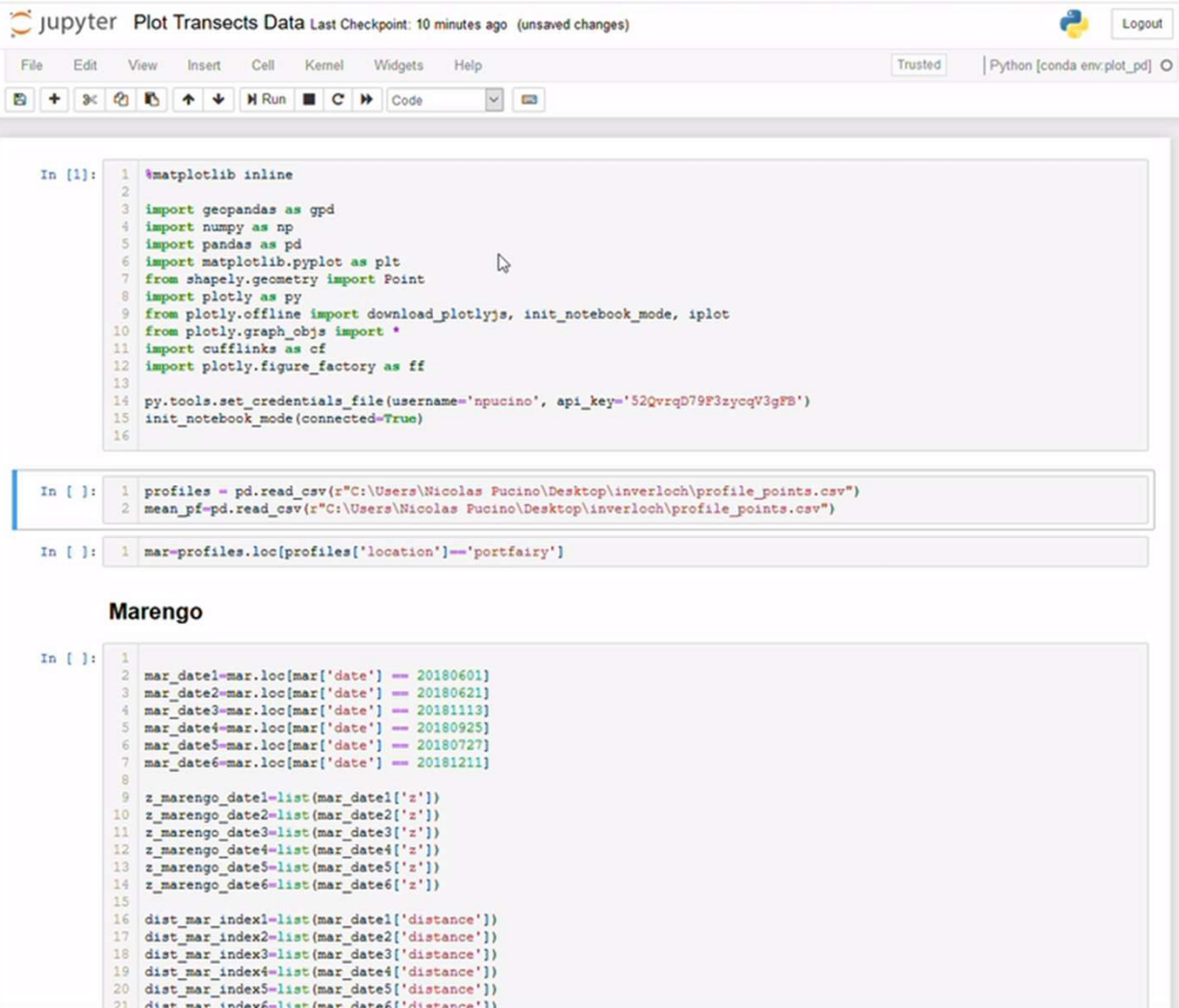


PostgreSQL + PostGIS



Python Geospatial Scripting

## Analysis and Communication



The screenshot shows a Jupyter Notebook titled "Plot Transects Data" with a last checkpoint 10 minutes ago. The interface includes a menu bar (File, Edit, View, Insert, Cell, Kernel, Widgets, Help), a toolbar with icons for file operations and execution, and a code editor. The code is written in Python and is organized into three input cells. The first cell imports necessary libraries like geopandas, numpy, pandas, matplotlib, and plotly. The second cell reads CSV files for profiles and mean profiles. The third cell filters the data for a specific location and then processes it for the Marengo area, creating lists for dates and distances.

```
In [1]: 1 %matplotlib inline
2
3 import geopandas as gpd
4 import numpy as np
5 import pandas as pd
6 import matplotlib.pyplot as plt
7 from shapely.geometry import Point
8 import plotly as py
9 from plotly.offline import download_plotlyjs, init_notebook_mode, iplot
10 from plotly.graph_objs import *
11 import cufflinks as cf
12 import plotly.figure_factory as ff
13
14 py.tools.set_credentials_file(username='npucino', api_key='52QvrgD79F3zycqV3gFB')
15 init_notebook_mode(connected=True)
16

In [ ]: 1 profiles = pd.read_csv(r"C:\Users\Nicolas Pucino\Desktop\inverloch\profile_points.csv")
2 mean_pf=pd.read_csv(r"C:\Users\Nicolas Pucino\Desktop\inverloch\profile_points.csv")

In [ ]: 1 mar=profiles.loc[profiles['location']=='portfairy']

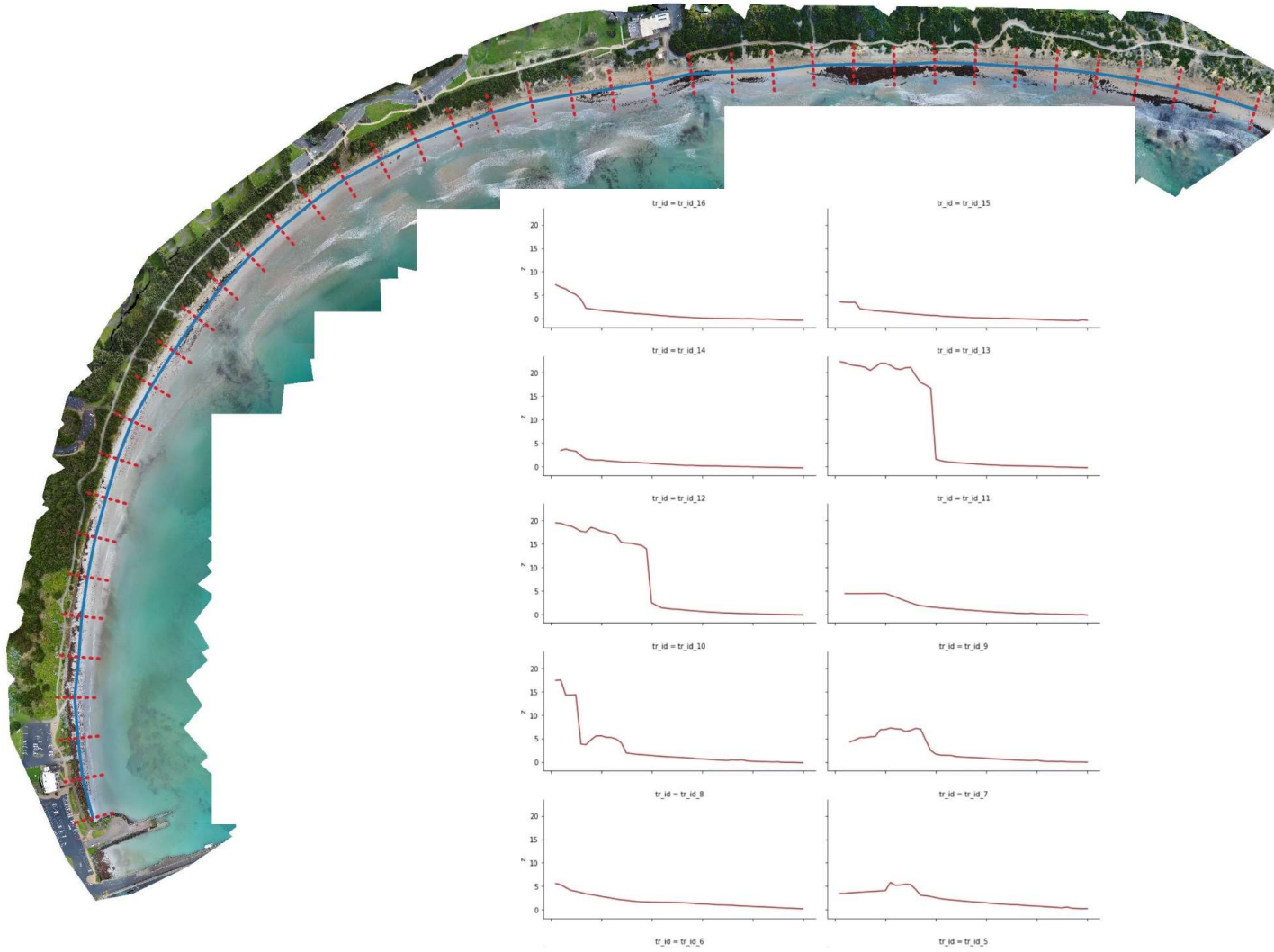
Marengo

In [ ]: 1
2 mar_date1=mar.loc[mar['date'] == 20180601]
3 mar_date2=mar.loc[mar['date'] == 20180621]
4 mar_date3=mar.loc[mar['date'] == 20181113]
5 mar_date4=mar.loc[mar['date'] == 20180925]
6 mar_date5=mar.loc[mar['date'] == 20180727]
7 mar_date6=mar.loc[mar['date'] == 20181211]
8
9 z_marengo_date1=list(mar_date1['z'])
10 z_marengo_date2=list(mar_date2['z'])
11 z_marengo_date3=list(mar_date3['z'])
12 z_marengo_date4=list(mar_date4['z'])
13 z_marengo_date5=list(mar_date5['z'])
14 z_marengo_date6=list(mar_date6['z'])
15
16 dist_mar_index1=list(mar_date1['distance'])
17 dist_mar_index2=list(mar_date2['distance'])
18 dist_mar_index3=list(mar_date3['distance'])
19 dist_mar_index4=list(mar_date4['distance'])
20 dist_mar_index5=list(mar_date5['distance'])
21 dist_mar_index6=list(mar_date6['distance'])
```

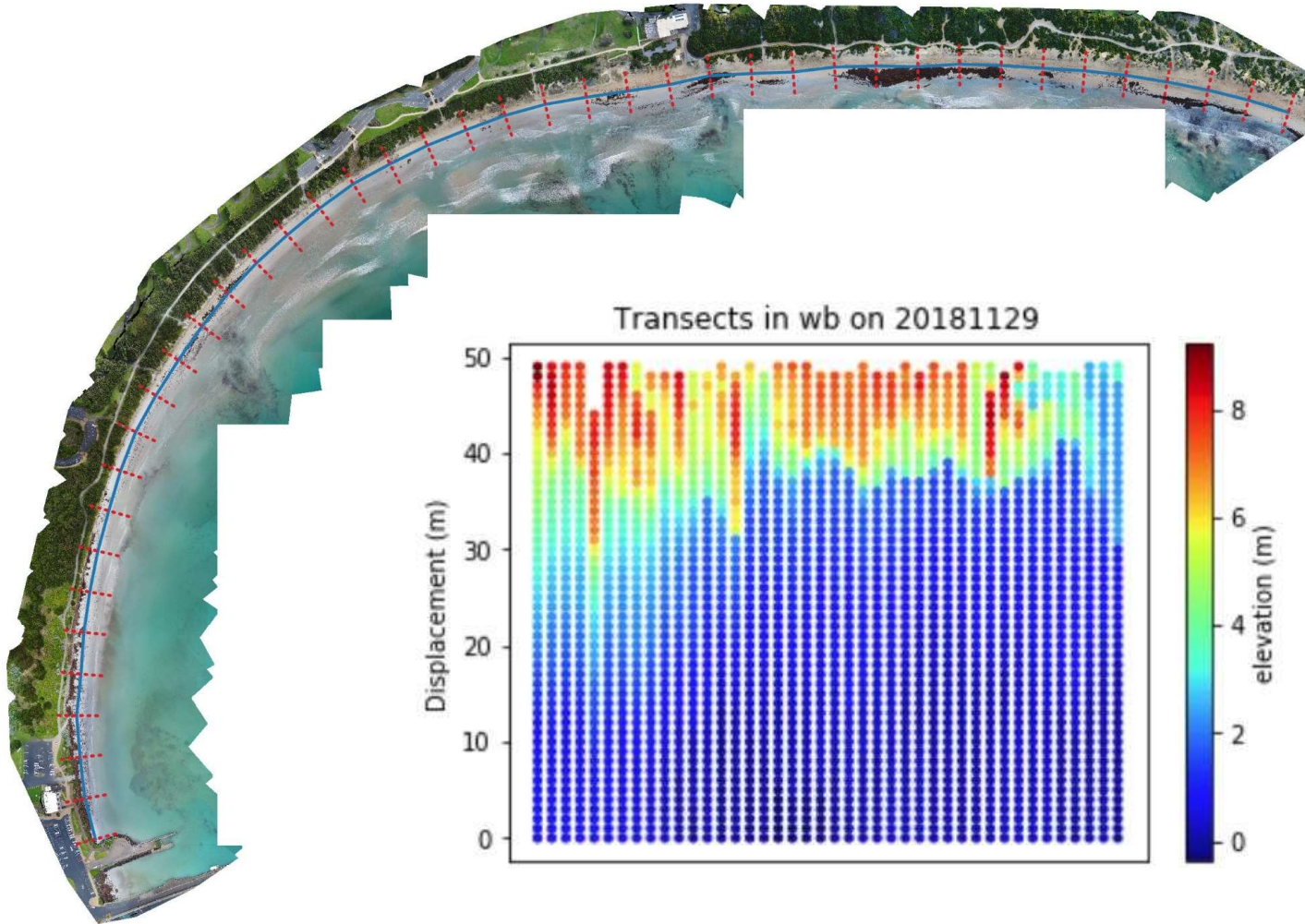


- **Automatic** extraction of all elevation profiles along the multitemporal DSMs
- **2 main inputs:** the DSM and the transects (vector lines)
- **1 big data table**, text format, full of information
- **Python** geospatial processing is fast and efficient
- **Interactive plotting** inside Jupyter Notebooks
- **Powerful** geostatistical analysis with Geopandas
- **Big Data** table feeds directly into PostgreSQL to be manipulated and queried with PostGIS
- Fits perfectly with **Qgis** and ArcGIS

## Analysis and Communication



## Analysis and Communication



### Virtual Network of Elevation Profiles

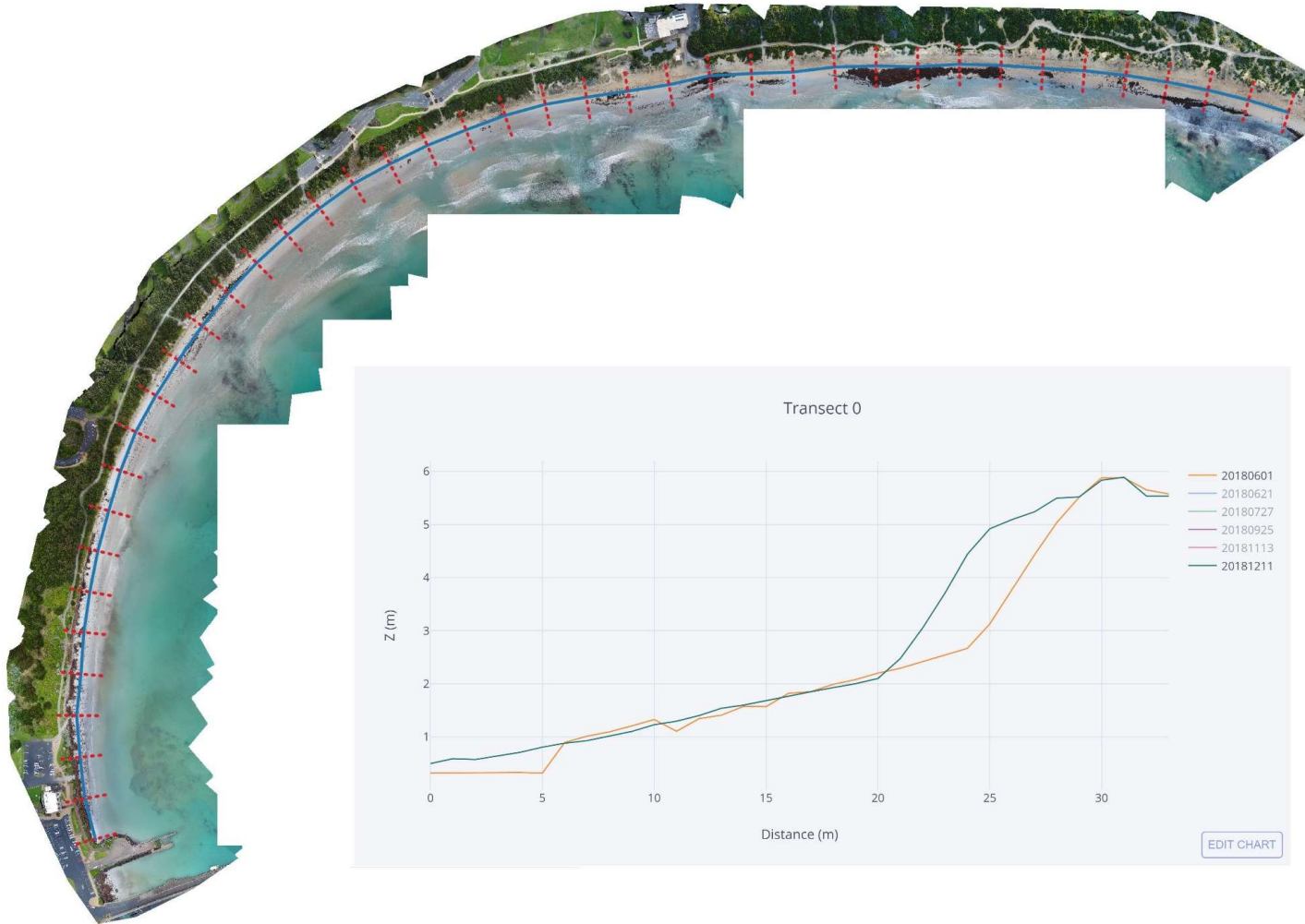
Several hundreds virtual profiles will be monitoring the UAV sites at unprecedented accuracy.

### Why elevation profiles?

- **Convenience** (data format and size)
- **Cut/Fill** observations → seasonal? Storm-dependent?
- **Dynamic equilibrium?**
- Lack of wave data → wind+profiles= wave conditions?



## Analysis and Communication



### Virtual Network of Elevation Profiles

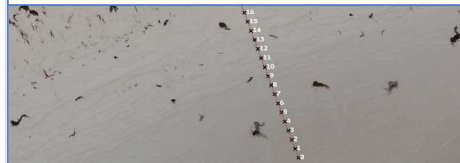
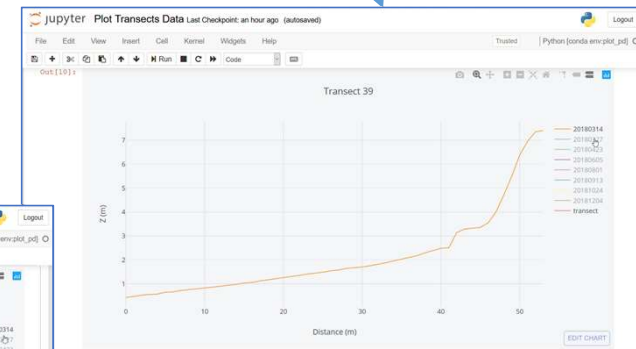
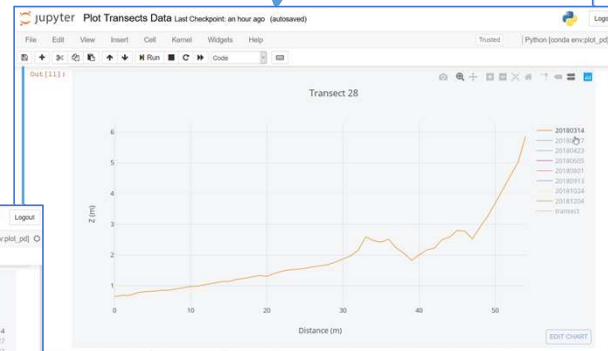
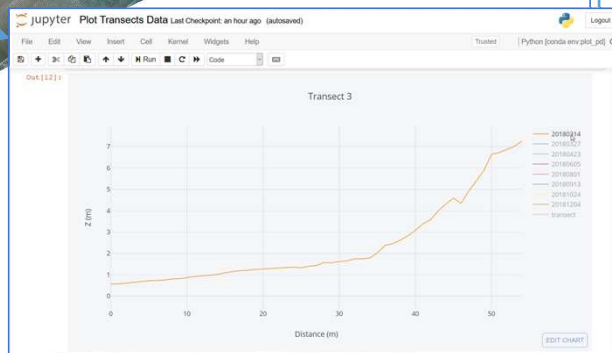
Several hundreds virtual profiles will be monitoring the UAV sites at unprecedented accuracy.

### Why elevation profiles?

- **Convenience** (data format and size)
- **Cut/Fill** observations → seasonal? Storm-dependent?
- **Dynamic equilibrium?**
- Lack of wave data → wind+profiles= wave conditions?

## Port Fairy Beach

Beach length: 5800 m  
Surveyed section: 2200m  
Orientation: SE  
Waves: avg 1.5m







# Thanks ! Questions ?

CONTACTS → [NPUCINO@DEAKIN.EDU.AU](mailto:NPUCINO@DEAKIN.EDU.AU)  
0423690189

