Identifying Population Tipping Points Through Imagery Super-resolution Christian Che-Castaldo¹, Mathew Schwaller² & Heather Lynch²









Adélies as <u>sentinel</u> species

Dependent on both terrestrial and marine habitat Sensitive to multiple stressors, especially climate change Respond to changes occurring in marine food chain Indicator for Southern Ocean ecosystem health From individuals to population-level...



(Bestley et al., Frontiers in Ecology and Evolution, 2020)

"living observatory"

DAVID G. AINLEY The Adélie Penguin

BELLWETHER OF CLIMATE CHANGE

with Illustrations by Lucia deLeiris



Antarctic Danger Islands penguin breeding colony









Heather J. Lynch¹, Christian Che-Castaldo¹, Dimitris Samaras¹ Stony Brook University

Goal 1: Landsat images over penguin colonies are georegistered and stacked for assessing super-resolution methodologies.



Identifying population tipping points through imagery

Matt Schwaller NASA



Goal 2: Computational geometry is used to reconstruct the most likely shape given the Landsat estimates. (2) Computational geometry Goal 3: Photographs of the Antarctic landscape taken by tourists can be (3) Phototourism aligned to digital elevation models and the colony boundaries extracted as a





Penguin Guano Data Pipleline

PURPOSE: Build a reproducible ecological data pipeline for penguin guano so <u>our research team</u> can:

• Acquire and cloud clear ~68,000 Landsat scenes



- **Co-register** cleared scenes \rightarrow stackable pixels **Improve** existing DEM and feature data
- Machine learning \rightarrow classify guano







HPC Cluster (Stony Brook)

Landsat satellite imagery



R Shiny App cloud-clearing

68k images

SQL Cloud Database (read/write user choices)



R Shiny App co-registration

20k images



Scene alignment: Use sunlit rock as a ground control point to geo-register Landsat scenes to one another to study per-pixel change over time



easting

easting



R SHINY GEOREGISTRATION APP



OUT OF POSITION BY OVER 1 KM



R SHINY GEOREGISTRATION APP





Landsat to improve topographical features: Use mosaics of Landsat images to produce highly accurate water masks to ground DEMs and identify all rock pixels

...yet penguins nest here on rock

BAS water

mask

Cape Hallet penguin colony

water mask derived from Landsat 4578 mosaic

An automated methodology for differentiating rock from snow, clouds and sea in Antarctica from Landsat 8 imagery: a new rock outcrop map and area estimation for the





Landsat to improve topographical features: Use mosaics of Landsat images to

LT05_L1GS_062111_19910128_20200915_02_T2

Cape Hallet penguin colony

produce highly accurate water masks to ground DEMs and identify all rock pixels







<u>16,115 Adélie colony Landsat images each containing 18 channels</u>



- Spectral data (7 channels) red, green, blue, NIR, SWIR1, SWIR2
- Spectral indices (3 channels) NDWI, NDSI, NDMI
- Topographical data (5 channels) elevation, slope, roughness, aspect
- Masks (3 channels) ocean, rock, shade, bad pixel data



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Lindsay Islands (1989-2017)

Franklin Island West (1984-2017)

Matt Schwaller NASA

Eden Rocks (1987-2017)

Hope Bay (1987-2016)

Duke of York Island (1989 – 2017)



Cockburn Island (1999-2017)



Annotate VHR imagery for guano and pair with Landsat



Clare Flynn, Stony Brook University



Heather Lynch, Stony Brook University

annotate

guano



(a) vhr



(b) annotated vhr





(c) Landsat 8

(d) Landsat 8 annotations added

Landsat labeled with percent guano per pixel



pink dots are annotated from vhr and transferred



Percent guano transferred from VHR

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Split data to test guano classification across colonies and seasons

		LANDSAT 7							LANDSAT 8				
		2003	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2018
AP	BEAG										4		
	DEVI					1					3		
	RHYO					1							
	VORT										1		
	ADAM										2		
Eastern Antarctica (EA)	AKAR					4					4		
	ALAS									7	4		
	AUST								1				
	BALA										1		
	BATT					-					2		
	BERK_SHLY_WHIY					1				· · · ·	0		
											2		
	CLIBZ					1				· · · · ·	3		
	DAVI					1							
	DENI MACK										3		
	FRAM		3		1								
	HASW		1			· · · · · · · · · · · · · · · · · · ·					5		
	HINO				2								
	HOLL										3		
	JULE					1					2		
	KIDS										6		
	MALL										3		
	MAME_ONGU										1		
	MCDO							4			2		
	MIDG					1					2		
	ODBE					2			-				
	PGEO								2		4		
	PISL		-								3		
	SCOL										2		
	SVIS								1		1		
	TENM										4		
	TBYN						1				1		
	WATT										2		
	YTRE					1							
Ross Sea	ADAR					1					1		
	ARTH			1									
	BEAN	1											
	BRDM_BRDN_BRDS		2										
	BSON						3			4			
	BURK					2							
	CHAL										5		
	CHAR					1					0		
										0. 2. 9	2		
	CRUZ					1				4			-
										4	2		1
						9					3		
	JONE					3					1		
	LOVI										1	1	
	LSAY										2		
	MAHE											1	
	NELL									2			
	NORF										7		
	POSS										4		
	SIMS										5		
	SVEN										4		
	UNGE										7		



to be predicted

annotated scenes





T-matrix: Binary Guano Classifier



Tau is calculated as follows, with $\tau = 1$ for a perfect classification.

(10)
$$\tau = \frac{(ab-cd)}{\sqrt{(b+c)(d+a)(b+d)(c+a)}}$$





Landsat 7 training-test set...

band order: swir1, swir2, red, nir, green, blue



<u>Test set omission using repeat visits: 3.4%</u>

For non-shaded dry pixels containing >= 5% guano, which contain 83% of all guano in the





Odbert Island (-66.3742, 110.5421) January 2011



actual guano

estimated guano

"commission"

Odbert Island (-66.3742, 110.5421) January 2011

Super-resolution: Moving beyond the T-matrix

- machine learning methods such as random forest, SVM etc.

<u>U-Net CNN: Semantic seqmentation with PyTorch</u>

https://github.com/milesial/Pytorch-UNet

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science + energy + sustainability

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