



Control of linear and non-linear vertical land motion on modern sea-level change (with implications for projections) across the Indian Ocean

Introduction:

Vertical land motion (VLM) has key consequences for sea-level change¹ (SLC) at present and in the future, with a range of implications for the coast and coastal communities². The Indian Ocean (IO; Figure 1) coastline supports 2.6 billion inhabitants³ and its exposure is projected to increase⁴. VLM contributes to this increase by amplifying SLC through subsidence. VLM occurs across various spatio-temporal⁵ scales (e.g. seconds to millennia⁶, local to global⁷) and can be both linear (e.g. glacial-isostatic adjustment) and non-linear (e.g. seismicity and groundwater extraction)⁸. Recent syntheses of SL and VLM data address linear/non-linear effects but high uncertainty remains in the IO⁸, ⁹, ¹⁰, ¹¹.

Aim: to evaluate the role of VLM on SLC (1993 to 2024) by extracting linear and non-linear VLM signals from observations. We test the ability of SL data to record VLM by comparing an extraction method to colocated VLM sites.

Methodology: Data Strategy

- Tide Gauges (TG, monthly) records) from the Permanent Service for Mean Sea Level⁹ are selected based on adherence to a set of indicated criteria (Figure 1).
- GNSS stations colocated with TGs are selected from Nevada Geodetic Laboratory (NGL)¹⁰ with model offsets identified.
- Altimetry (A) data (Jet Propulsion Laboratory¹²) is extracted at nearest grid point (1° resolution) to TG (data sources depicted in Figure 2).
- For each colocated site and associated altimetry, the records were clipped to a common period with GNSS.

2. Annual Cycle Correction **4.** Non-linear analysis

An annual cycle correction is applied to A and TG time series at each location to reduce interannual variability (e.g., atmosphere-ocean loading).

3. Linear analysis

The VLM_{ATG} dataset is produced by calculating the residual:

 $V\dot{L}M_{ATG} = A\dot{S}L_A - R\dot{S}L_{TG}$

Where VLM_{ATG} , ASL_A and RSL_{TG} are the rates of VLM, altimetry, and tide-gauge time series.



Figure 2: Schematic of data strategy

We evaluate VLM_{ATG} at each time step to assess the capacity of the method to resolve non-linear VLM.

 $VLM_{ATG} = ASL_A - RSL_{TG}$

5. Testing Budget Closure

 VLM_{GNSS} (from NGL regression model¹⁰) and VLM_{GNSS} is used to test linear and non-linear budget of VLM_{ATG} and *VLM_{ATG}* respectively.

We assess misfit (linear) and RMS (nonlinear) of VLM_{ATG} and VLM_{GNSS} records.

6. Spatial extension across IO

We apply the linear VLM method to all TGs overlapping with A (5 yr < |t| < 31 yr) **Emmaline Martin¹**, Luke Jackson¹, Sophie Williams¹ (emmaline.a.martin@durham.ac.uk)

Results:

. Evaluation of linear rates

- ♦ Misfit (Figure 3) shows scatter (- Ξ⁵ 21 to +16 mm/yr) between VLM_{ATG} and VLM_{GNSS} rates, with $\frac{10}{5}$ mean misfit (-1.5 mm/yr) slightly underestimating true linear VLM.
- RMS (1.3±0.7 mm/yr) shows good agreement of misfits. Panwa Cape and Pulau Pinang (Figure 3) have largest uncertainties (±6 and ±5.6 respectively).
- Cocos Islands (COCO; Figure 4) shows a linear downward trend, indicative of VLM subsidence over time.
- Scatter across the VLM_{ATG} record indicates additional sources of VLM uncertainty (e.g. Cocos Islands as the VLM_{ATG} exceeds VLM_{GNSS} rate).



Islands.

2. Evaluation of non-linear rates



Figure 5: The corrected VLM record (ATG and GNSS) for Dzaoudzi.

3. Coexisting linear and non-linear signals

- Diego Garcia D (DGAR; Figure 6) exhibits evidence of both linear (VLM_{GNSS} record) and non-linear (VLM_{ATG} record) behaviour.
- The VLM_{ATG} contains a much lower signal to noise ratio compared with VLM_{GNSS}.
- Sites which are out of phase (e.g. Muscat; Figure 1) exhibit a ~2month lag between A and TG, creating an oscillatory residual and a systematic bias in the VLM_{ATG} .

The lag can be attributed to local oceanclimate dynamics (e.g. delayed ocean response to warming)¹³. Ref., 13 also identifies a 2-month delay at Rodrigues Island (Figure 1) and attributes it to westward advection and propagation (e.g. ENSO/IOD).



Figure 6: The corrected VLM record (ATG and GNSS) for Diego Garcia D.

- Dzaoudzi (MAYG; Figure 5) is a good example showing a clear non-linear signal. The record shows a shift in 2018 where a decrease in VLM is present in VLM_{ATG}
- confirmed by VLM_{GNSS}. Despite a low signal to noise ratio the VLM is observable unlike Coco Islands (Figure
- 4) suggesting local site-tosite factors are important.

Discussion: **Spatial extension across IO**

We apply the linear method to 105 TGs across the IO and find high variability in the rates with uncertainty mostly less than 1.0 mm/yr (Figure 7). The spread of uncertainty for noncolocated and colocated sites is consistent suggesting the approach is applicable for IO.



- uncertainties in the Bay of Bengal.

Implications

The implications of our findings suggest that the methodology is robust, therefore it is possible to apply it to locations outside the IO. However, sensitivity testing using alternative denoising strategies is needed (e.g., Common Modes¹⁴). For sites without a colocated station, we demonstrate that the methodology is still feasible with limited data. Comparison with VLM_{GNSS} data enhances linear rate estimates by assessing the similarity between observed rates.

Conclusions and Next Steps:

We conclude that the methodology outlined can be successfully used to determine linear and characterise non-linear VLM across the IO, even for sites without colocated stations. Evaluation of non-linear rates reveals that the methodology can also be applied to sites which experience large non-linear VLM events (e.g. Figure 5).

Next step: Time series modelling is required to further characterise nonlinear VLM, which could then be combined with linear contributions (in a stochastic forecasting model) to revise projections at individual locations (Figure 8). Uncertainty range

The outputs from this analysis will then be used to inform local and regional scaler policy adaptation frameworks around the IO.

References

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Figure 7: Linear rates and uncertainty for all sites across the IO.

Aden (Yemen) and Tanjung Keling (Malaysia) exhibit the largest uncertainties while Tuticorin (India) has the lowest uncertainty. ✤ Our findings are consistent with other research^{8,11} though with lower



2020 2030 2040 2050 2060 2070 2080 2090 2100 2110 2120 2130 2140 2150 Figure 8: NASA¹⁵ projection for Dzaoudzi (MAYG) to 2150 and with linear VLM based on modern rates (based on Figure 5).

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