Incorporating uncertainty of groundwater modeling in sea-level rise assessment: a case study in South Florida

Presentation for Greater Everglades Ecosystem Restoration (GEER)

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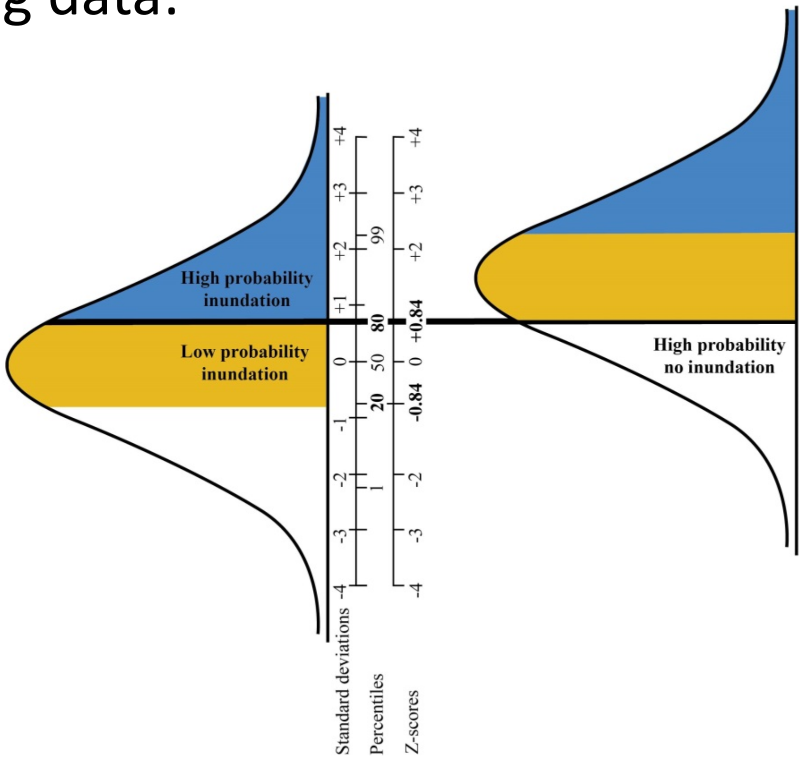
Introduction

- Considering uncertainties in Sea-Level Rise (**SLR**) assessments is important for managers & planners

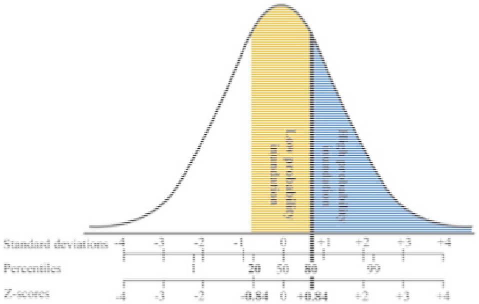
- Using statistical procedures, uncertainty is error in our measurement of the underlying data:
  - SLR estimates
  - LiDAR elevations
  - Water table elevations
  - Vertical datums
  - Vertical datum transformations



Introduction

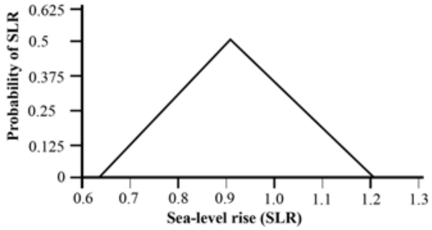
Errors limited to Normal distribution

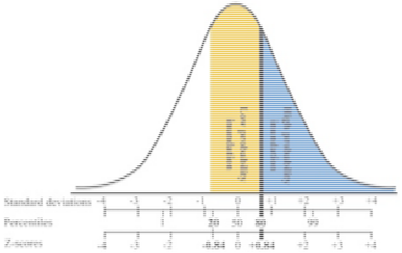
- USGS (Gesch, 2009; 2013)
  - Maps uncertainty zone centered on inundation boundary
- NOAA (Schmid et al., 2013)
  - Modifies z-score to generate probability surface



Errors NOT limited to Normal distribution

- Purvis et al. (2008)
  - Monte Carlo to propagate probability distributions through inundation model
- Cooper & Chen (2013)
  - Extends NOAA to Monte Carlo to include variables with different probabilities





Objectives

1. Determine which geospatial techniques produce Water Table Elevation Model (WTEM) with best vertical accuracy
2. In calculating vulnerable land area, evaluate effect when including uncertainty in:

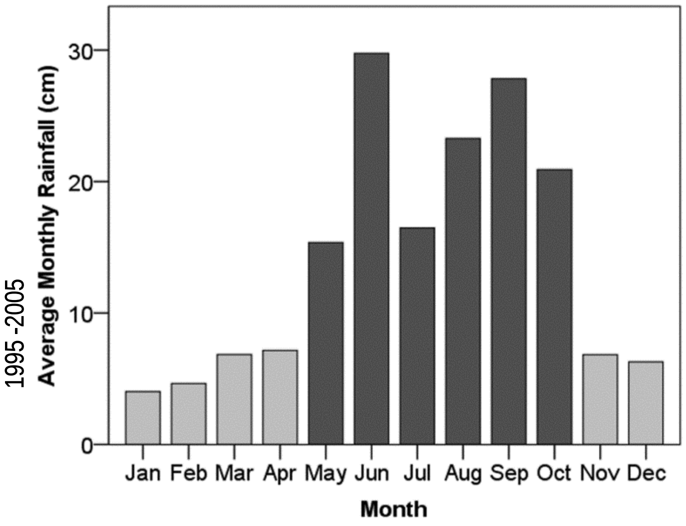
- SLR estimates
- LiDAR elevations
- Vertical datums
- Datum transformations

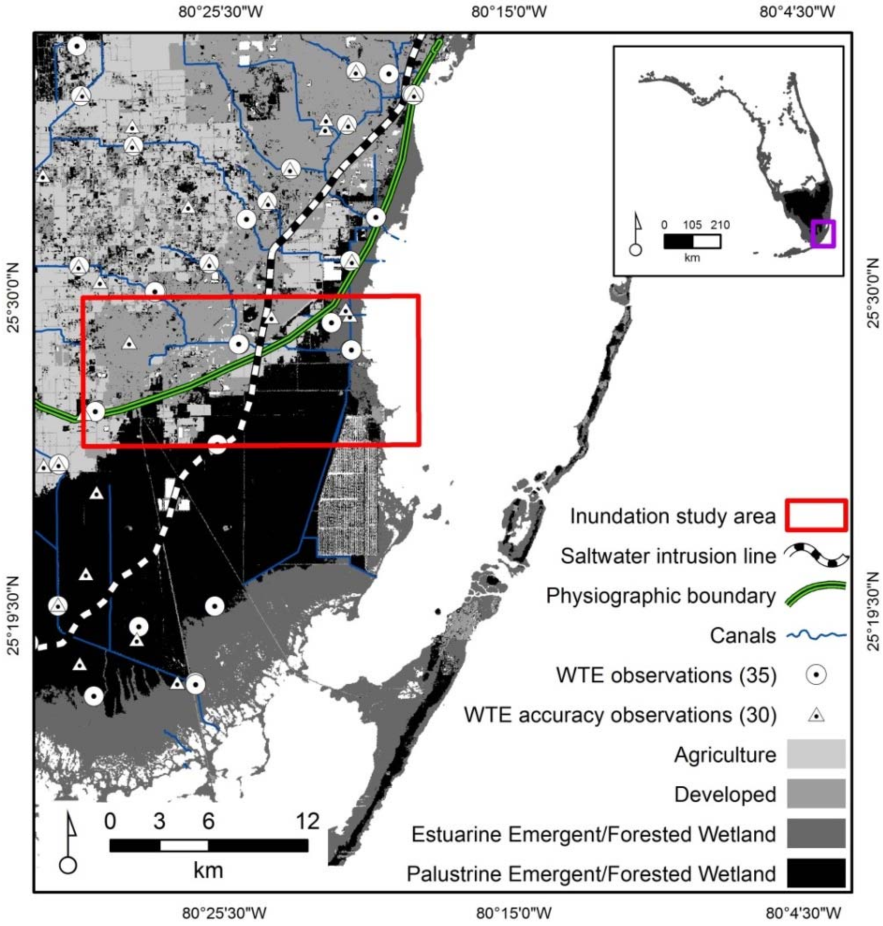
VS

- SLR estimates
- LiDAR elevations
- Vertical datums
- Datum transformations
- ***and* Water Table Elevation Model (WTEM)**

Study area

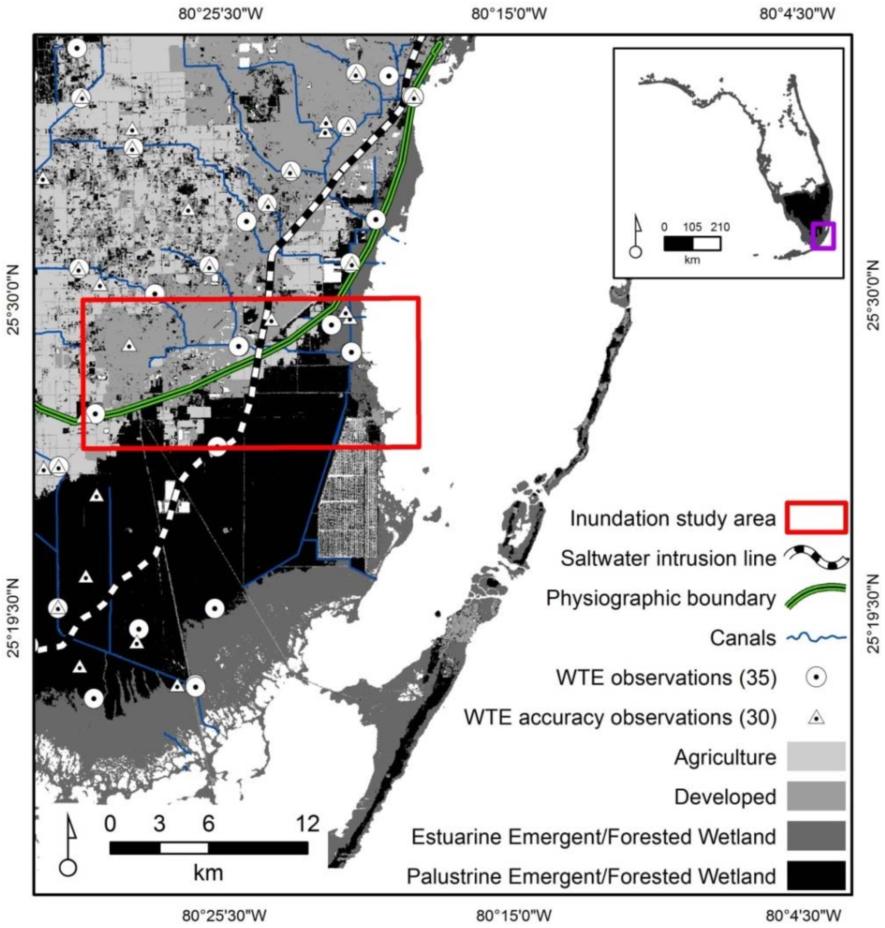
- Biscayne aquifer underlies study area
- Best indicator of peak groundwater levels at end of wet season is September:





Data

- 2007 FDEM LiDAR
  - 3 m DEM
  - Vertical accuracy 6.5cm
- Water table elevations (WTE)
  - 65 daily µ time-series averaged September 1995-2005
  - Transformed NGVD29 to NAVD88 (NGVD29 µ 47cm < NAVD88)
- Physiographic regions delineate hydrologic boundaries
  - GIS layers defined by White (1970)



Methods: WTEM

Geospatial approaches tested for each physiographic region

- Multiple Linear Regression (MLR)
- Geographic Weighted Regression (GWR)
- Global Polynomial Interpolation (GPI)
- Inverse Distance Weighted (IDW)
- Ordinary Kriging (OK)
- Empirical Bayesian Kriging (EBK)

Note: all parameters were chosen by trail and error for best results

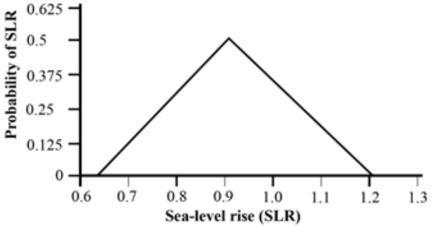
Vertical accuracy assessment identifying best approach

- 30 WTEs set aside for accuracy assessment used to calculate:

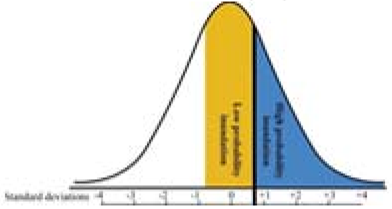
$$RMSE = \sqrt{\Sigma(Z_{data,i} - Z_{check,i})^2/n}$$

Methods: Errors

SLR estimates IPCC AR5 RCP 8.5 SLR estimates: 74 cm median & likely range 52 to 98 cm by year 2100 formalized as triangular distribution



LiDAR RMSE 6.5 cm corresponds to 1 σ & data Normally distributed since provider used NSSDA (FGDC, 1995)



WTEM

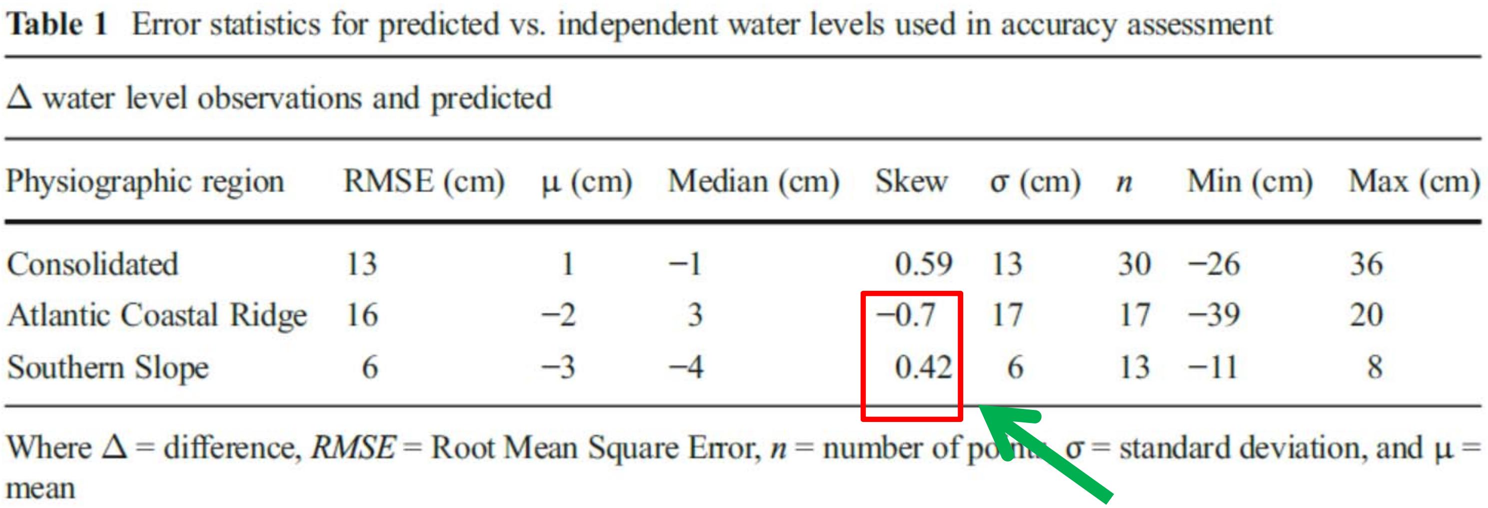


Table 1 Error statistics for predicted vs. independent water levels used in accuracy assessment

Δ water level observations and predicted								
Physiographic region	RMSE (cm)	μ (cm)	Median (cm)	Skew	σ (cm)	*n*	Min (cm)	Max (cm)
Consolidated	13	1	−1	0.59	13	30	−26	36
Atlantic Coastal Ridge	16	−2	3	−0.7	17	17	−39	20
Southern Slope	6	−3	−4	0.42	6	13	−11	8

Where Δ = difference, *RMSE* = Root Mean Square Error, *n* = number of points, σ = standard deviation, and μ = mean

Skewed to left (exceeds skew± 0.5)

Normally distributed (does not exceed skew± 0.5)

Methods: Errors

Vertical datums and transformations

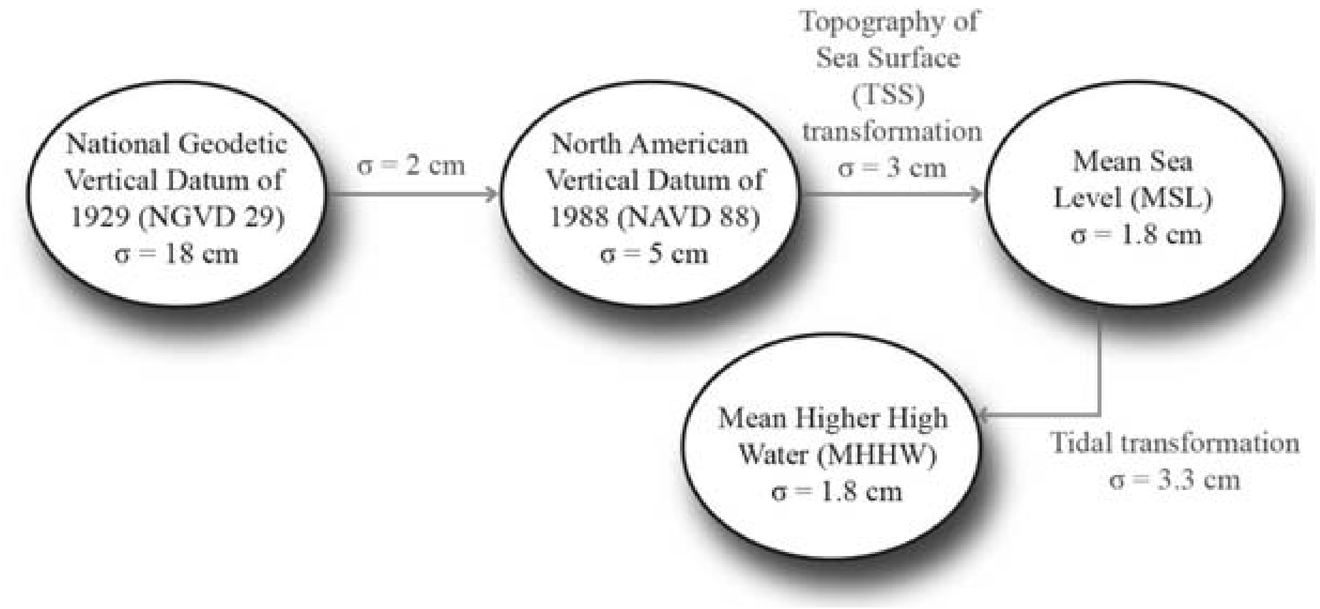


Fig. 2 VDatum vertical errors calculated as standard deviation values for South Florida modified from NOAA (2013). Arrows denote transformation processes, and ovals denote source data.

Cumulative Vertical Uncertainty (CVU) standard deviation: $CVU_\sigma = \sqrt{\sigma_1^2 + \sigma_2^2 + \ldots \sigma_N^2}$

Methods: Inundation modeling

Inundation models:

Excluding WTEM:

$$P_{x,y} = \Sigma(SLR_{\varepsilon} > LiDAR_{CVU_{\sigma}} + LiDAR_{x,y})$$

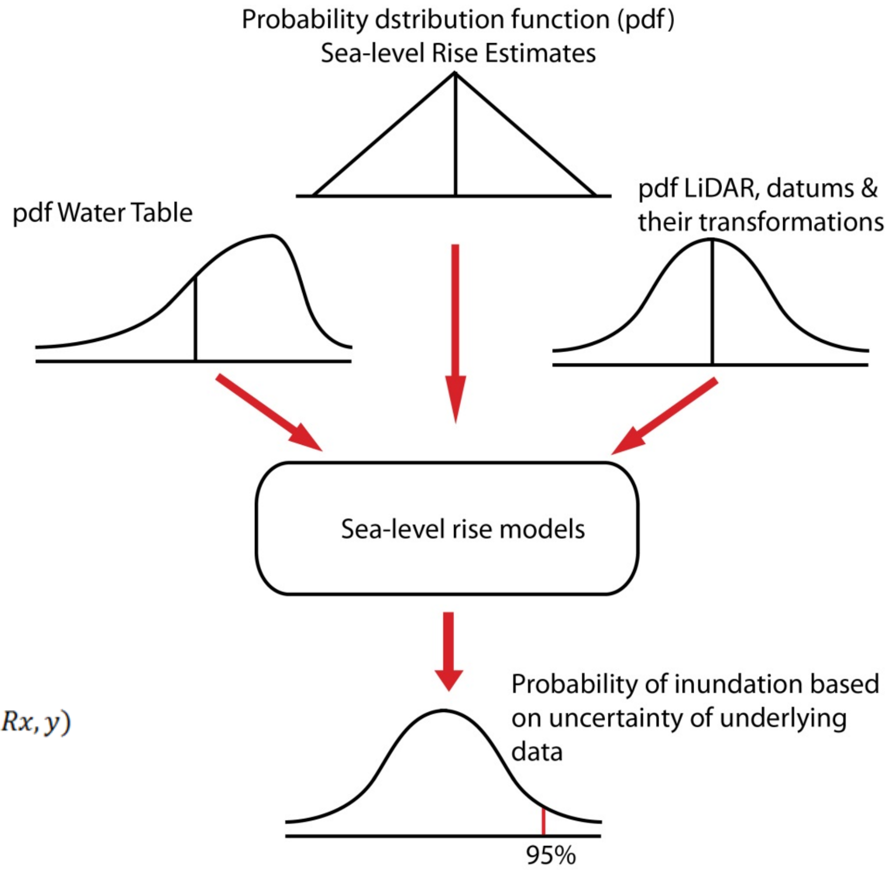
Including WTEM Southern Slope (errors normal):

$$P_{x,y} = \Sigma(WTEM_{CVU_{\sigma}} + WTEMx,y + SLR_{\varepsilon} > LiDAR_{CVU_{\sigma}} + LiDARx,y)$$

Including WTEM Atlantic Coastal Ridge (errors skewed):

$$P_{x,y} = \Sigma(WTEM_{\varepsilon} + WTEM_{CVU_{\sigma}} + WTEMx,y + SLR_{\varepsilon} > LiDAR_{CVU_{\sigma}} + LiDARx,y)$$

Monte Carlo simulation



Probability dstribution function (pdf)
Sea-level Rise Estimates

pdf Water Table

pdf LiDAR, datums & their transformations

Sea-level rise models

Probability of inundation based on uncertainty of underlying data

95%

Results: WTEM accuracy

Table 3 The Root Mean Square Errors (RMSEs) of six tested approaches for generating Water Table Elevation Model (WTEM) in two physiographic regions. Two identified approaches are in bold.

Approach	Atlantic Coastal Ridge		Southern Slope	
	RMSE (cm)	R^2	RMSE (cm)	R^2
Global Polynomial Interpolation (GPI)	**16**		10	
Empirical Bayesian Kriging (EBK)	18		**6**	
Ordinary Kriging (OK)	18		7	
Inverse Distance Weighting (IDW)	19		8	
Geographic Weighted Regression (GWR)	18	0.93	8	0.72
Multiple Linear Regression (MLR)	20	0.90	11	0.66

Results: Effect of WTEM on land area

Table 4 Vulnerable area to sea-level rise (SLR) when we do and do not consider uncertainty. Where WTEM = Water Table Elevation Model, and Σ = sum.

			No uncertainty: LiDAR, SLR estimates		No uncertainty: LiDAR, SLR estimates, WTEM		Uncertainty: LiDAR, SLR estimates, datums & their transformations		Uncertainty: LiDAR, SLR estimates, datums & their transformations, WTEM	
							High confidence (P>95%)			
Physiographic region	Area (km^2)	% study area	Area (km^2)	% study area	Area (km^2)	% study area	Area (km^2)	% study area	Area (km^2)	% study area
Atlantic Coastal Ridge$_{NAVD88}$	61.12	37.70	7.04	4.34	12.73	7.85	5.18	3.19	4.77	2.94
Atlantic Coastal Ridge$_{MHHW}$	8.88	5.48	4.52	2.79	4.75	2.93	3.65	2.25	0.97	0.60
Southern Slope$_{NAVD88}$	35.18	21.70	19.75	12.18	24.89	15.35	16.24	10.02	11.36	7.01
Southern Slope$_{MHHW}$	56.96	35.13	51.94	32.03	53.13	32.77	48.27	29.77	45.39	27.99
Σ	162.14	100.00	83.25	51.34	95.50	58.90	73.34	45.23	62.49	38.54

*Excluding uncertainty in WTEM at 95% threshold consistently **overestimates** land area regardless region, vertical reference, & probability density function*

Results: Sea-level rise map

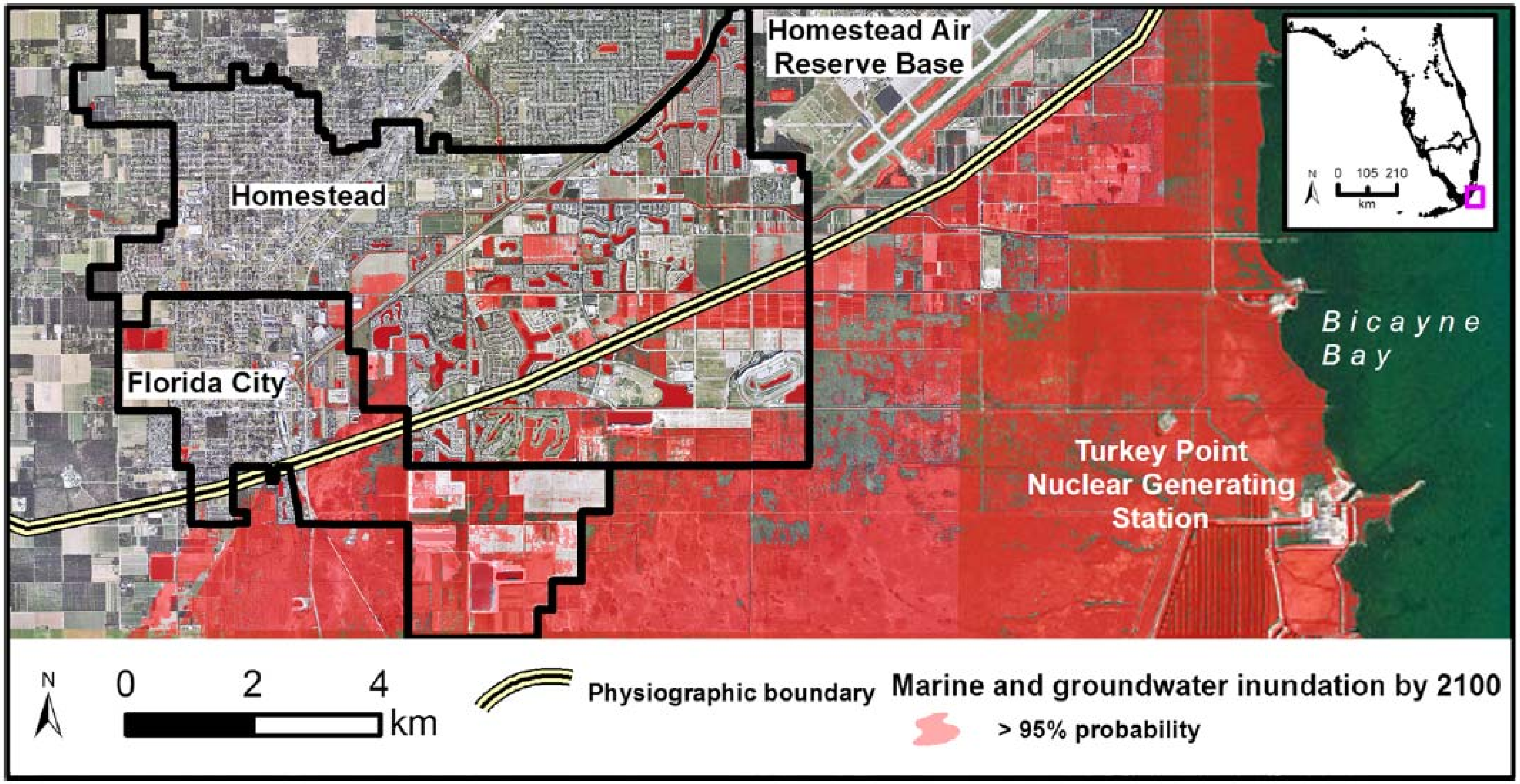


Fig. 3 SLR vulnerability map including uncertainty in SLR estimates, LiDAR, vertical datums, transformations, and groundwater modeling highlighting lands vulnerable under SLR of 74 cm with range between 52 and 98 by year 2100 for the two most southern cities in mainland Florida

Conclusions

- It is important to test different approaches for each physiographic region in order to reduce uncertainty in WTEM.
- Excluding uncertainty in WTEM at >95% threshold overestimates total land area for South FL
- **Including WTEM uncertainty adds to the integrity of the SLR mapping tools** & should be considered so that more effective adaptation decisions can be made.

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