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2017 Coastal Master Plan

Attachment C3-27: Landscape Data

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Coastal Protection and Restoration Authority

This document was prepared in support of the 2017 Coastal Master Plan being prepared by the Coastal Protection and Restoration Authority (CPRA). CPRA was established by the Louisiana Legislature in response to Hurricanes Katrina and Rita through Act 8 of the First Extraordinary Session of 2005. Act 8 of the First Extraordinary Session of 2005 expanded the membership, duties and responsibilities of CPRA and charged the new authority to develop and implement a comprehensive coastal protection plan, consisting of a master plan (revised every five years) and annual plans. CPRA's mandate is to develop, implement and enforce a comprehensive coastal protection and restoration master plan.

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- Coastal Protection and Restoration Authority (CPRA) of Louisiana - Mandy Green, David Lindquist, and Angelina Freeman.

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Executive Summary

Input data is one of the most influential determinants of model output quality. As such, it is important to devote an appropriate amount of effort to identify newly available or improved input data to ensure the most up-to-date data are being used to drive the models. The objective of this task was to improve the input, calibration, and validation datasets upon which the models would be initiated and evaluated.

Critical datasets for model initialization were first identified. These included: a base period land and water delineation dataset, a base period integrated bathymetry and topography dataset, and a dataset delineating the extent of vegetation community types, upon which the vegetation model will be initiated. Each of these datasets constitutes a fundamental descriptor of the coastal landscape, upon which most processes the models are representing depend. Inaccuracy in these types of datasets manifest as inaccuracies in the models results.

One of the most influential datasets discussed here, land and water composition, is constantly changing in coastal Louisiana. As such, beginning with the most up-to-date data ensures that any land loss which has occurred since the last master plan is accurately reflected in the base conditions of this new modeling effort. Similarly, any land gain, including the benefits from coastal restoration projects that have been completed since the last iteration of the plan, need to be appropriately considered. For this reason, the latest available satellite imagery was compiled and analyzed to create a dataset, which delineates the latest possible land and water composition of the coast.

Although land and water is a fundamental landscape descriptor, elevation is an equally important dataset when it comes to coastal modeling. The landscape composition dataset previously discussed outlines the horizontal aspect of the landscape, and the elevation data provides information on the vertical dimension. Elevation data is possibly the most critical landscape descriptor, but it is also a dataset with tremendous collection, processing, and accuracy challenges.

Finally, while the previous two datasets describe the three-dimensional landscape, the land cover classes including the vegetation occupying that landscape must also be described. Many coastal processes vary depending upon the vegetation type occupying a site and as such, a dataset that describes the distribution of those classes is a necessary dataset for model initialization.

With these data priorities in mind, the 2017 Coastal Master Plan team undertook a rigorous effort to create datasets, which represent the best-available data describing the landscape in coastal Louisiana. While data collection dates vary, particularly with regard to elevation data, the datasets are intended to represent the fall of 2014 time period. This will serve as the initialization time period for the 2017 Coastal Master Plan modeling effort.

Hydrology and other input datasets prepared for use in the 2017 Coastal Master Plan are detailed in Attachment 6.1.

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List of Abbreviations

CoNED	Coastal National Elevation Database
CPRA	Coastal Protection and Restoration Authority
DEM	Digital Elevation Model
GIS	Geographic Information System
ICM	Integrated Compartment Model
LA CoNED	Louisiana Coastal National Elevation Dataset
LIDAR	Light Detection And Ranging
mNDWI	Modified Normalized Difference Water Index
NAVD 88	North American Vertical Datum of 1988
NED	National Elevation Dataset
NWI	National Wetlands Inventory
OLI	Operational Land Imagery
RMSE	Root Mean Square Error
SLR	Sea Level Rise
SONAR	Sound Navigation And Ranging
TBDEM	TopoBathy Digital Elevation Model
TOA	Time of Acquisition
TM	Thematic Mapper
USFWS	U.S. Fish and Wildlife Service

1.0 Introduction

The input data upon which models are initiated, calibrated and validated is of paramount importance to the quality and utility of the modeling results. The accuracy of those datasets has significant implications on the confidence that can be placed in the results. For these reasons, the Coastal Protection and Restoration Authority of Louisiana (CPRA), in cooperation with subject matter experts, undertook an effort to create input datasets from the best data available. These updated datasets were used to drive a set of refined and improved modeling tools for use in Louisiana's 2017 Coastal Master Plan. This attachment describes the 'landscape' datasets; boundary conditions needed for the hydrology and water quality subroutines of the Integrated Compartment Model (ICM) are documented in Attachment C3-26.

2.0 Spatial Data

When modeling spatially variable phenomena such as coastal hydrology, morphology, and vegetation change, the data representing those landscapes and processes must be considered in a spatial context. The datasets representing the landscape and processes must be spatially explicit, and as such, Geographic Information Systems (GIS), and remote sensing were utilized heavily in the creation of input datasets. Data are represented in spatial formats including shape files and raster images which have been created from a variety of sources including field data, aerial, and satellite imagery.

The domain (Figure 1) for these datasets is delineated by a 10 meter elevation contour landward and a seaward boundary that extends far enough into the Gulf of Mexico to alleviate boundary condition concerns in the hydrology subroutine of the Integrated Compartment Model (ICM). The domain extends beyond Sabine Lake to the west and just beyond Mobile Bay to the east (Figure 1). In total, the study area encompasses approximately 37,780 km². The land/water ratio of the study area is constantly changing, but has ranged from 46.27% land (17,482 km²) and 53.73% water (20,298 km²) in 1973 to 37.89% land (14,318 km²) and 62.10% water (23,462 km²) in 2014.

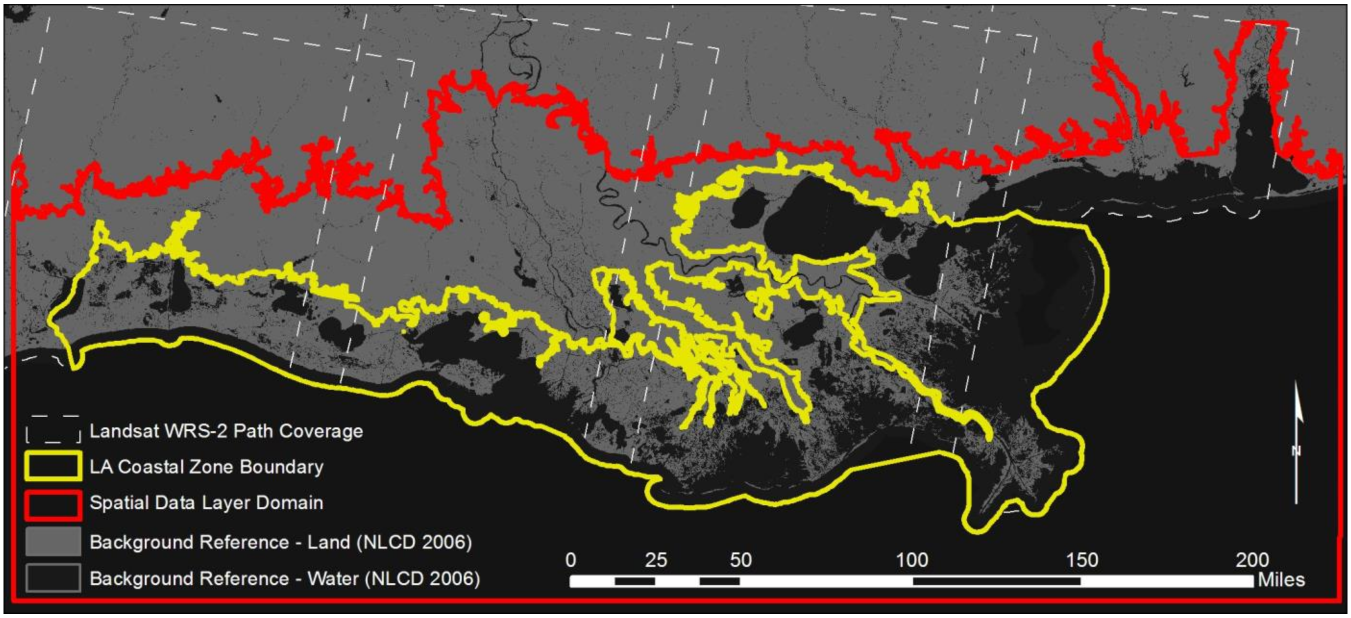


Figure 1: Study Domain.

2.1. Landscape Composition

One of the most fundamental measures of a coastal landscape is the composition of land and water in that landscape. While a concept such as the extent or amount of land may be a relatively stable measure in other regions, such a measure is not "stable" in coastal Louisiana. The composition of coastal Louisiana is constantly changing due to persistent factors such as wetland loss, but also transient effects of water levels due to tidal and wind driven variability. Because many functions in the ICM depend upon the classification of a particular area as "land" or water", the starting dataset which defines these two critical classes is of the utmost importance.

2.1.1. Imagery

While there are many sources of imagery from which landscape composition can be characterized, a few considerations pertinent to this particular effort were considered in the selection of an imagery source:

- Moderate spatial resolution was desired, as datasets at finer resolutions (1 m aerial photography for example) would increase processing times beyond the bounds of what is possible for this effort.
- Imagery had to cover the entire spatial domain within a relatively similar time period, and a recent acquisition must be readily available. As the landscape of coastal Louisiana is constantly changing, it is important to use a starting point that is as recent as is possible. The 2012 Coastal Master Plan used a 2010 initialization dataset, which described land/water composition. A more current dataset representing both land loss

or gains and restoration projects that have been constructed since 2010 was required to reduce potential error in model output.
- The image data must be capable of adequately distinguishing land and water classes.

These considerations led to the selection of Landsat 8 as the sensor of choice for this effort. Landsat OLI (Operational Land Imager) is a multi-spectral sensor onboard Landsat 8 which provides 11 bands of information at resolutions ranging from 15 m to 60 m (most bands are at 30 m resolution).

The specific imagery used to create the baseline datasets used in this modeling effort was determined within the consideration of several needs and constraints. The team needed to use the latest available data so as to include recently completed coastal restoration projects in the base landscape. The water levels during the dates of acquisition of the imagery must also be considered. Finally, one of the most restrictive constraints when it comes to remotely-sensed imagery is the availability of imagery acquired under cloud-free conditions. All of these considerations led the team to select one particular time period: fall 2014.

With these considerations in mind, the following images were used to develop the baseline dataset to define the composition and configuration of land/water conditions (Table 1). Although Table 1 lists two dates for each path, average land and water conditions were calculated and will be discussed in later sections of this document.

Table 1: List of Landsat Image Dates of Acquisition by Path (WRS-2). Refer to Figure 1 for boundaries of WRS-2.

Landsat Image Dates of Acquisition (DOA)											
Path 24			Path 23			Path 22			Path 21		
Calendar Date	Julian Date	Decimal Date	Calendar Date	Julian Date	Decimal Date	Calendar Date	Julian Date	Decimal Date	Calendar Date	Julian Date	Decimal Date
10/16/2014	2014289	2014.792	10/25/2014	2014298	2014.816	11/3/2014	2014307	2014.841	11/28/2014	2014332	2014.910
11/1/2014	2014305	2014.836	11/10/2014	2014314	2014.860	11/19/2014	2014323	2014.885	12/14/2014	2014348	2014.953

2.1.2. Processing

Among the challenges that must be addressed in a satellite-based land-cover characterization are "consistent geometric correction, normalizing noise arising from atmospheric effect, adjusting for changing illumination geometry, and minimizing instrument errors inherent when using multiple frames of imagery" (Homer et al., 2001). Each of these issues can call into question the accuracy and utility of any dataset created if not properly dealt with before interpretations begin.

One of the greatest issues to be addressed in pre-processing is that of noise contained within or imposed on the spectral data by atmospheric, solar or instrument contaminants. Much of this noise can be normalized by accounting for instrument errors and illumination geometry. For this effort, all images utilized were processed to account for band bias, gain anomalies and solar-illumination angle. Next, the images were converted to at-satellite reflectance for the six reflective bands.

2.1.3. Indices and Fractional Water Estimation

The methodology used in this effort relied heavily on the use of a modified Normalized Difference Water Index (mNDWI), as suggested by Xu (2006). As the name suggest, the mNDWI is a modified version of McFeeters' original NDWI, first suggested in 1996. The mNDWI proposed by Xu modified McFeeters' original by changing the combination of bands in the index from a ratio of visible green and near infrared (NIR) to green and mid infrared (MIR). By doing so, it enhances water features while reducing noise from land, vegetation, and soil (Xu, 2006).

$$mNDWI = \frac{Green - MIR}{Green + MIR}$$

The resulting index is utilized to create fractional water estimates by thresholding the image at previously established values indicative of values in the index that represent changes in land/water composition.

Initial fractional water datasets were mosaicked and the average taken for each pixel. While two images from the fall of 2014 were used from each WRS-2 path, as much as 40% of the coastal zone is covered within the overlap of multiple paths. In these areas, the fractional water estimate for each pixel is the average of four pixels. The use of multiple images and utilization of average land/water conditions reduces the potential that noise or abnormality in any one image will contaminate the final coast wide dataset.

While the fractional water estimates are useful in providing information regarding mixels (pixel which contains a mix of targets, leading to a mixed spectral signature), the requirement for the modeling effort is a thematic or categorical (rather than quantitative) land/water classification. The final coast wide mosaic was therefore thresholded at a value of 50%, with values less than 50% water being coded as land, and greater than 50% coded as water.

2.1.4. Classification

While the methodology discussed above does a good job of separating most land/water areas, shadows, floating marsh, and burned areas require user interaction and recoding to classify those areas correctly. Therefore, unsupervised classification is then conducted on each class separately. The resulting isodata classes were then examined by an image analyst and potential error classes were identified on the basis of mean spectral characteristics.

2.1.5. Compilation

Fractional water datasets were first mosaicked and the average of all images was taken within the overlap regions (Figure 1). Although two images were used in each path, four images were averaged in these overlap regions. The average values of the fractional water estimates were then thresholded at a value of 50% as previously described.

2.2. Digital Elevation Model

The previously discussed dataset describes the landscape in terms of composition in the horizontal, (or X,Y dimensions); however, it is also important to describe the Z dimension (elevation). Accurate elevation data are of the utmost importance, particularly in micro-elevation, highly dynamic coastal regions. The primary and most expansive source of elevation data in the United States is the National Elevation Dataset (NED). A recently developed layer, the Coastal National Elevation Database (CoNED) TopoBathy Digital Elevation Model (TBDEM) has been incorporated into the National Elevation Dataset, which combines topography and bathymetry in the northern Gulf of Mexico. "The Coastal National Elevation Database (CoNED) Project - topobathymetric digital elevation models (TBDEMs) integrate hundreds of different data sources including topographic and bathymetric LIDAR point clouds, hydrographic surveys, side-scan sonar surveys, and multibeam surveys obtained from multiple agencies. The LIDAR and bathymetry surveys were sorted and prioritized based on survey date, accuracy, spatial distribution, and point density to develop a model based on the best available elevation data" (CoNED TBDEM, 2015). For the purposes of this effort, CPRA, in consultation with technical experts decided to utilize this nationally recognized dataset to maintain consistency with national programs.

When working with elevation data, clearly identifying the datum is of paramount importance. Although multiple datums exist, one of the most widely used in this region is the North American Vertical Datum of 1988 (NAVD 88). The CoNED/TBDEM uses the NAVD 88 datum, the geoid is 12A, and the units of the dataset are meters. "Because bathymetric data is typically referenced to tidal datums (such as Mean High Water or Mean Sea Level), all tidally-referenced heights were transformed into orthometric heights that are normally used for mapping elevation on land" (CoNED TBDEM, 2015).

While it may seem intuitive to think of positive elevation values as representing land area, and negative values as water, this is not necessarily the case. In a landscape that includes areas such as New Orleans, where land elevations are often below sea level, a negative elevation value can represent land. Conversely, features such as impoundments can lead to water bodies that have depth values greater than zero. On a related note, sea level is often mistakenly thought of as a constant, which occurs at zero. This is not the case. Sea level varies in both time and space, and as such, it must be treated as a spatially and temporally variable parameter. It is for this reason that elevation data relative to a datum were chosen, rather than warping the elevation relative to a water level at a particular point in time. Changes in water level through time are forecasted by the hydrology subroutine of the ICM relative to the same datum, and therefore inundation can be calculated at any given time in the modeling period.

While the CoNED TBDEM formed the primary data source for the digital elevation model created for and used in this effort, the dataset contains some areas of missing data and inaccuracies that had to be resolved before it could be used in the 2017 Coastal Master Plan modeling effort. In the following sections, alterations to the dataset will be discussed.

2.2.1. Topography

For the purposes of this report, the elevation dataset is divided into two components, 1) topography (the sub-aerial portion of the dataset) and 2) bathymetry (the sub-aqueous portion of the dataset). It is useful to discuss these two components separately, as they are usually created from different data sources. The topography elevation data used in this effort consisted of LIDAR data, described below.

Coastal Louisiana wetlands are generally considered to be a low-relief environment, meaning there is little variation in elevation values. The topographic variation that is present, however, has a substantial effect on many hydrologic parameters, including the distribution, duration, and frequency of inundation. The spatial and temporal variability in these parameters, even a relatively small change in the vertical dimension (e.g., water level) can have large effects on inundation patterns in the horizontal dimension. For this reason, understanding the accuracy of the elevation data utilized is paramount to the modeling, as well as interpreting and applying confidence levels to the results.

The LIDAR data used in this effort were collected on dates ranging from 2000–2012. The exact date of acquisition of the LIDAR data varies spatially. As previously mentioned, a "best-available" data criterion was utilized. While the most important consideration in that criterion is accuracy; generally, the most recent data were found to also be the most accurate. This is due to improvements that have occurred since the initial 2000 Statewide LIDAR acquisition (Cunningham, Gisclair, and Craig, 2002). These improvements include increased pulse frequency and decreased pulse spacing and strict guidelines on water levels appropriate for data collection. A major obstacle to the accuracy of LIDAR comes in the form obstructions, particularly vegetation. The increased pulse frequency and decreased pulse spacing increases the likelihood of some pulses reaching a bare earth surface, thereby reducing error associated with vegetative obstructions. The second main source of error prevalent in the 2000 Statewide LIDAR data was error associated with water levels. LIDAR data were flown with little or no consideration to water levels at the time of acquisition (TOA) and consequently, bare earth elevations could not be obtained in many locations where water level exceeded the marsh surface elevation. The newly available LIDAR used in this effort were collected with strict guidelines dictating that LIDAR data were only collected at low water levels further increasing the probability of obtaining bare earth elevations.

Root mean square error (RMSE) is often used to estimate vertical differences between LIDAR values and values from an independent, presumably higher accuracy source. In general, lower RMSE values represent higher accuracy of the dataset. The RMSE of the LIDAR data used varies spatially. Some of the oldest LIDAR that was used in this dataset possesses the highest RMSE of any topographic data used in this analysis and covers the western extent of the coast (the region known as the Chenier Plain). The RMSE in this region is listed as 15–30 cm, though this varies by land cover type (Cunningham, Gisclair, and Craig, 2002). To better understand the variable RMSE by land cover type, RMSE was calculated for each Land Use/Land Cover type in this region. In general, the RMSE of wetland areas was better (i.e., lower) than that of upland, forested, and shrub/scrub areas, and were typically observed at the lower end of the published range (Watershed Concepts, 2009). Refer to Cunningham, Gisclair, and Craig (2002) for a coverage map of the circa 2003 LIDAR.

For a majority of coastal Louisiana, newly available LIDAR (Woolpert, 2011) was acquired between 2010 and 2012, and the vertical accuracy RMSE of these LIDAR is listed as 7.0 cm. As these data represent an improvement in RMSE compared to that of the circa 2003 LIDAR, it was preferably chosen for areas in which both previously discussed LIDAR datasets were available.

To create a dataset which approximated a 2014 landscape, areas that had undergone a change in land cover between the date of acquisition of the LIDAR and the actual year 2014, as determined by Couvillion et al. (2011), the 2014 landscape composition dataset created for this effort used an estimated elevation value. To estimate elevation, this study applied a methodology that draws upon patterns observed in multiple dates of optical imagery. A regression tree classifier was used as these models can approximate complex, nonlinear relationships such as the relationships between inundation and elevation. For this effort, Cubist™ software, developed by RuleQuest Research (2012), was utilized to construct the regression trees, which were then used to obtain estimated elevations for sites at which no elevation data was available.

2.2.2. Bathymetry

The second elevation dataset is bathymetry. Opposite of topography, bathymetry refers to sub-aqueous elevation values. While it is intuitive to think of this as "depth", this is not always accurate, as depth varies with water level. Therefore, this dataset is intended to represent the elevation of a location relative to a datum at a particular point in time; in this case the starting period is 2014. Although the previous section described the utilization of LIDAR to assess elevation, with the exception of some bathymetric LIDARs, LIDAR is generally not used to assess bathymetry. This is due to the scattering of the laser pulse by particles within the water. In some cases in which the water is free of suspended particles and consequently very clear, bathymetric LIDARs have been used with some success in other regions; however, those water conditions are quite rare in coastal Louisiana. It is for this reason that SoNAR is generally used to assess bathymetry.

2.2.3. Error Masking

While the LA CoNED represents one of the best compilations of elevation data created to-date, as of the deadline for initialization of this effort, it still contained large areas of unknown elevation or values, which were undoubtedly errors. For example, Figure 2 below shows the LA CoNED for a portion of southwest Louisiana. The bathymetry values in Grand Lake and White Lake are obvious errors, probably resulting from an interpolation in the absence of better data. That is not to say, however, that there are not good bathymetry data in portions of Figure 2. The data offshore, for example, are quality bathymetric data.

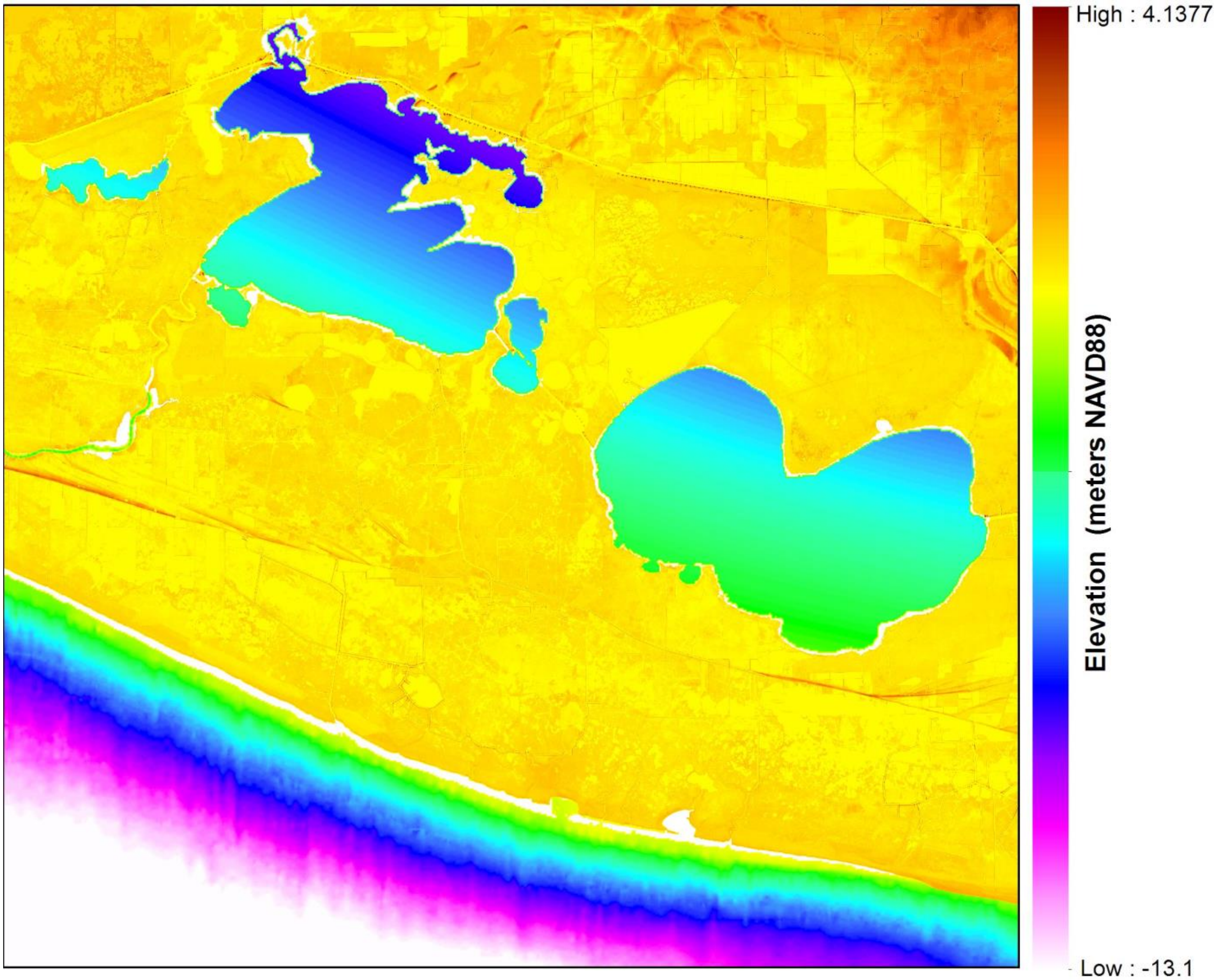


Figure 2: Example of Areas of Missing or Inaccurate Bathymetry Data in the CoNED TBDEM. Note the erroneous bathymetry values in Grand Lake and White Lake.

To identify areas of questionable bathymetry data in the CoNED TBDEM, no-data values were first identified and masked. In the original CoNED dataset, no-data could be represented by values of 0, -0.313 or -39350. Of course, some of these no-data values, particularly 0 and -0.313 are potentially real elevation values. Consequently, a blanket mask could not be applied throughout the entire dataset to exclude these values. Therefore, a user had to go through the dataset and isolate regions of suspected missing bathymetry data.

Similarly, detailed analysis of the dataset by a user was required for identifying areas of questionable quality bathymetric data. The user delineated polygons around regions of known data quality issues, and missing and no-data flags were then made from these user-identified regions. These flags are shown in Figure 3 below.

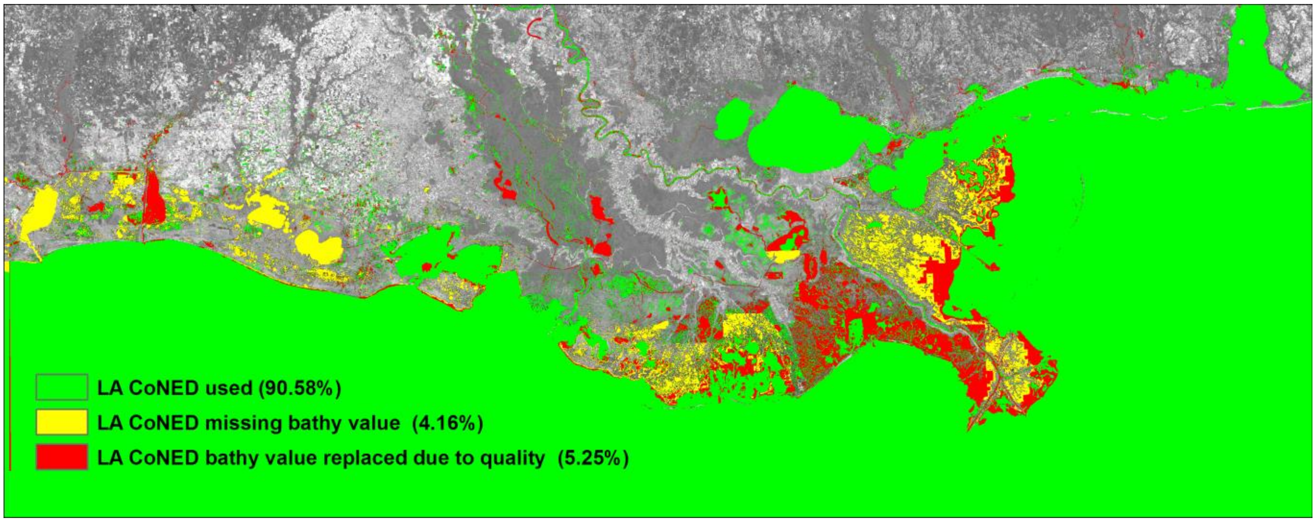


Figure 3: Visualization of Areas in which Bathymetry had to be Replaced due to Missing Data or Quality Issues.

2.2.4. Compilation

Datasets were compiled on the basis of the land/water composition datasets and the data quality/missing data flags outlined in Figure 3 above. A logical script was developed to composite the data based on which flags each particular pixel met. A pixel which was land and had not undergone a land gain since the TOA of the LIDAR for that particular pixel, took the CoNED TBDEM value in all cases. A pixel which was land but had recently become land since the TOA of the LIDAR for that particular pixel, took the estimated elevation value. A pixel which was water and was not flagged as missing or of insufficient quality for that particular pixel, took the CoNED TBDEM value in all cases. A pixel which was water and was flagged as missing or of insufficient quality for that particular pixel was given the multi-source replacement bathymetric data value.

The resulting coast wide elevation dataset is a seamless, integrated topographic and bathymetric dataset. It represents some improvements to the CoNED TBDEM in areas where bathymetric values would have caused problems for the ICM. This final dataset is shown in later sections of this document.

2.3. Vegetation Community Type Classification

This analysis used a 2013 wetlands land cover dataset. The vegetation cover dataset was created using coast wide vegetation survey data from 2013 (Sasser et al., 2014) as training data to classify marsh and shrub communities in the Louisiana coastal zone. This survey recorded species composition at marsh and shrub stations throughout coastal Louisiana, which were then assigned to vegetation types using common dominants as well as species assemblages known to occur in the area. These data points were then used as training data for a remotely sensed methodology using multiple Landsat OLI images acquired throughout the 2013 and 2014 time period, and a set of algorithms was created by training the model against existing wetland classes. The resulting 2013/14 layer was used both as the basis for the forecast model and also to help differentiate between the two fresh marsh types (tidal fresh marshes and inland fresh marshes), based primarily on the most recent U.S. Fish and Wildlife Service (USFWS) National Wetlands Inventory (NWI) Data (USFWS, 1988). This demarcation was required because the fresh marsh types are treated differently by the vegetation model, with tidal fresh marsh existing lower in the tidal frame and subject to accretion feedbacks as a function of frequency of inundation, as discussed below.

2.3.1. Community Types of Interest

The LAVegMod, the vegetation subroutine of the ICM, requires a base dataset delineating the coverages of vegetation types, upon which the model is initiated. Therefore, the vegetation community types of interest were decided upon by the vegetation modelers and other members of the modeling team.

The resulting list of vegetation types of interest is shown in Table 2 below. While each vegetation type is characterized by a particular dominant species, co-dominant species or common associates are also listed for many of the vegetation types.

Table 2: Land Use / Land Cover Community Types of Interest.

Symbol	Class Name	Community Type	Dominant Species
NOTMOD	Developed, High Intensity	Developed	NA
NOTMOD	Developed, Medium Intensity	Developed	NA
NOTMOD	Developed, Low Intensity	Developed	NA
NOTMOD	Developed, Open Space	Developed	Unknown
NOTMOD	Cultivated Crops	Agriculture	Unknown
NOTMOD	Pasture/Hay	Agriculture	Unknown
NOTMOD	Grassland/Herbaceous	Grassland	Unknown
NOTMOD	Upland - Mixed Deciduous Forest	Upland Forest	Unknown
NOTMOD	Upland - Mixed Evergreen Forest	Upland Forest	Unknown
NOTMOD	Upland Mixed Forest	Upland Forest	Unknown
NOTMOD	Upland Scrub/Shrub	Upland Forest	Unknown
NOTMOD	Longleaf/slash pine mix	Palustrine Forested Wetland	Pinus palustris/Pinus elliottii
NOTMOD	Loblolly pine	Palustrine Forested Wetland	Pinus taeda
NOTMOD	Mixed upland hardwoods	Palustrine Forested Wetland	Mixed upland hardwoods (e.g. Quercus alba/Quercus
NOTMOD	Bottomland hardwoods/longleaf/slash pine mix infrequent flooding	Palustrine Forested Wetland	Mixed bottomland hardwoods
NOTMOD	Bottomland hardwoods/loblolly pine mix infrequent flooding	Palustrine Forested Wetland	Mixed bottomland hardwoods
NOTMOD	Sycamore/pecan/american elm - infreq flooding	Palustrine Forested Wetland	Platanus occidentalis/Ulmus americana/Carya sp.
NOTMOD	Sweetgum/yellow poplar	Palustrine Forested Wetland	Liquidambar styraciflua/Liriodendron tulipifera
NOTMOD	Swamp chestnut oak/cherrybark oak - bottomland hardwoods - infreq. flooding	Palustrine Forested Wetland	Quercus michauxii/Quercus pagoda
QUTE	Sweetgum/nutall/willow oak - bottomland hardwoods seasonal flooding	Palustrine Forested Wetland	Liquidambar styraciflua/Quercus nutallii/Q. phellos/Q. nigra
QUVI	River birch / sycamore - bottomland hardwood sites - infrequent flooding	Palustrine Forested Wetland	Betula nigra/Platanus occidentalis
QULA3	Cottonwood - willow mixing - bottomland hardwood sites - occassional floodi	Palustrine Forested Wetland	Populus deltoides
ULAM	Higher site bottomland hardwoods such as sugarberry/elm/greenash	Palustrine Forested Wetland	Fraxinus pennsylvanica/Celtis laevigata/Ulmus sp
QUVI	Live oak / bottomland hardwoods mix	Palustrine Forested Wetland	Quercus virginiana
QULE	Lower site bottomland hardwoods such as overcup oak and water hickory	Palustrine Forested Wetland	Quercus lyrata / Carya aquatica
QUNI	Lower site bottomland hardwoods such as water oak - lower site ash	Palustrine Forested Wetland	Quercus nigra
NYAQ2	Sweetbay dominant - swamp tupelo mixing	Palustrine Forested Wetland	Magnolia virginiana
NYAQ2	Swamp tupelo dominant - Sweetbay mixing	Palustrine Forested Wetland	Nyssa biflora
TADI2	Red maple lowland	Palustrine Forested Wetland	Acer rubrum var. Drummondii
SANI	Willow - low sites - wax myrtle mixing	Palustrine Forested Wetland	Salix nigra/Salix interior
NYAQ2	Tupelo dominant - cypress co-dom - low sites - freq. flooded	Palustrine Forested Wetland	Nyssa aquatica/Taxodium distichum
TADI2	Cypress dominant - tupelo mixing - low sites - freq flooded	Palustrine Forested Wetland	Taxodium distichum/Nyssa aquatica
CLMA10	Sawgrass	Palustrine Herbaceous Wetland	Cladium mariscus
ELBA2	Spikerush	Palustrine Herbaceous Wetland	Eleocharis baldwinii
ELBA2_Flt	Spikerush - flotant	Palustrine Herbaceous Wetland	Eleocharis baldwinii
HYUM	Pennywort	Palustrine Herbaceous Wetland	Hydrocotyle umbellata
HYUM_Flt	Pennywort - flotatnt	Palustrine Herbaceous Wetland	Hydrocotyle umbellata
MOCE2	Wax myrtle	Palustrine Woody Wetland	Morella cerifera
PAHE2	Maidencane	Palustrine Herbaceous Wetland	Panicum hemitomon
PAHE2_Flt	Maidencane - flotant	Palustrine Herbaceous Wetland	Panicum hemitomon
SALA2	Arrowhead	Palustrine Herbaceous Wetland	Sagittaria latifolia
TYDO	Cattail	Palustrine Herbaceous Wetland	Typha domingensis
ZIMI	Cutgrass	Palustrine Herbaceous Wetland	Zizaniopsis miliacea
PHAU7	Roseaucane	Palustrine Herbaceous Wetland	Phragmites australis
SALA	Bulltongue	Palustrine Herbaceous Wetland	Sagittaria lancifolia
SCCA11	Bullwhip	Palustrine Herbaceous Wetland	Schoenoplectus californicus
BAHA	Baccharis	Palustrine Herbaceous Wetland	Baccharis halimifolia
IVFR	Iva	Palustrine Herbaceous Wetland	Iva frutescens
PAVA	Paspalum	Estuarine Herbaceous Wetland	Paspalum vaginatum
AVGE	Mangrove	Estuarine Woody Wetland	Avicennia germinans
SPPA	Wiregrass	Estuarine Herbaceous Wetland	Spartina patens
DISP	Saltgrass	Estuarine Herbaceous Wetland	Distichlis spicata
JURO	Needlegrass	Estuarine Herbaceous Wetland	Juncus roemerianus
SPAL	Oystergrass	Estuarine Herbaceous Wetland	Spartina alterniflora
STHE9	STHE9	Estuarine Herbaceous Wetland	Strophostyles helvola
SOSE	SOSE	Estuarine Herbaceous Wetland	Solidago sempervirens
DISPBI	DISPBI	Estuarine Herbaceous Wetland	Distichlis spicata
SPPABI	SPPABI	Estuarine Herbaceous Wetland	Spartina patens
SPVI3	SPVI3	Estuarine Herbaceous Wetland	Sporobolus virginicus
PAAM2	PAAM2	Estuarine Herbaceous Wetland	Panicum amarum
UNPA	UNPA	Estuarine Herbaceous Wetland	Uniola paniculata
BAHABI	BAHABI	Estuarine Herbaceous Wetland	Baccharis halimifolia
SAV	Submerged Aquatic Vegetation	Aquatic	Unknown
NOTMOD	Free Floating Aquatic Vegetation	Aquatic	Unknown
BAREGRND	Unconsolidated Shore	Bare Ground	NA
BAREGRND	Bare Land	Bare Ground	NA
WATER	Water	Aquatic	NA

2.3.2. Training Data

One of the most substantial requirements for supervised land-cover classification is the availability of adequate reference data. Training data must be representative, both spatially and spectrally, as well as accurate to adequately train the classifier. In this effort, training data primarily consisted of data from a vegetation survey known as the Chabreck and Linscombe Survey, which was collected on several dates in the summer of 2013.

This classification utilized specific training data with additional data specific to vegetation types in wetland environments. Upon compilation of these additional spatial datasets, a combination of random and user-specified training points were intersected with all data layers to create a master file needed to create a decision-tree.

2.3.3. Classification

There are numerous algorithms and methodologies for classifying satellite images. When considering the options for classification methodologies to be utilized in the National Land Cover Dataset (NLCD) and Coastal Change Analysis Program (C-CAP), developers desired "a method that optimally classifies many database layers in a single step, with the ability to document this relationship in a rule base" (Homer et al., 2001). Decision tree classifiers are "non-parametric, can accommodate both continuous and nominal data, generate interpretable classification rules, and are fast to train and often as accurate as, or even slightly more accurate than many other classifiers" (Homer et al., 2001). The use of decision tree algorithms for classification also allows for consideration of ancillary data in the classification process.

For these reasons, and to maintain consistency with nationally recognized programs, land-cover classification for this effort was performed using the C5© decision tree program. This software focuses initial efforts on recognizing patterns in each class, as delineated by the training data, among all spectral and ancillary datasets and employs an information gain ratio method in tree development and pruning (Quinlan, 1993). This software has advanced features including boosting and cross-validation, but multiple iterations of this workflow are typically required to finalize land cover.

2.3.4. Neighborhood Functions

The resulting land cover dataset was processed by using a neighborhood filter to remove changes smaller than 1.4 ha. The filtering removed some of the "noise" caused by environmental variance and classification error and increased the interpretability of the dataset. Rules were employed to govern which classes were filtered.

2.3.5. Accuracy Assessment

The resulting classifications were then subjected to accuracy assessments. Accuracy assessments utilized ground data (not used as initiation data) at randomly selected points. These data provide a high-quality reference dataset, enabling the creation and assessment of more consistent and more-specific wetland classifications. The majority of herbaceous wetland reference data were provided by Chabreck/Linscombe vegetative transect surveys.

3.0 Results

3.1. Landscape Composition

The final landscape composition dataset constitutes the starting point for modeling efforts (Figure 4). Land and water categories represent one of the most fundamental divisions of the landscape that drives processes and ecosystem services. This is an improvement over what was used in the 2012 Coastal Master Plan.

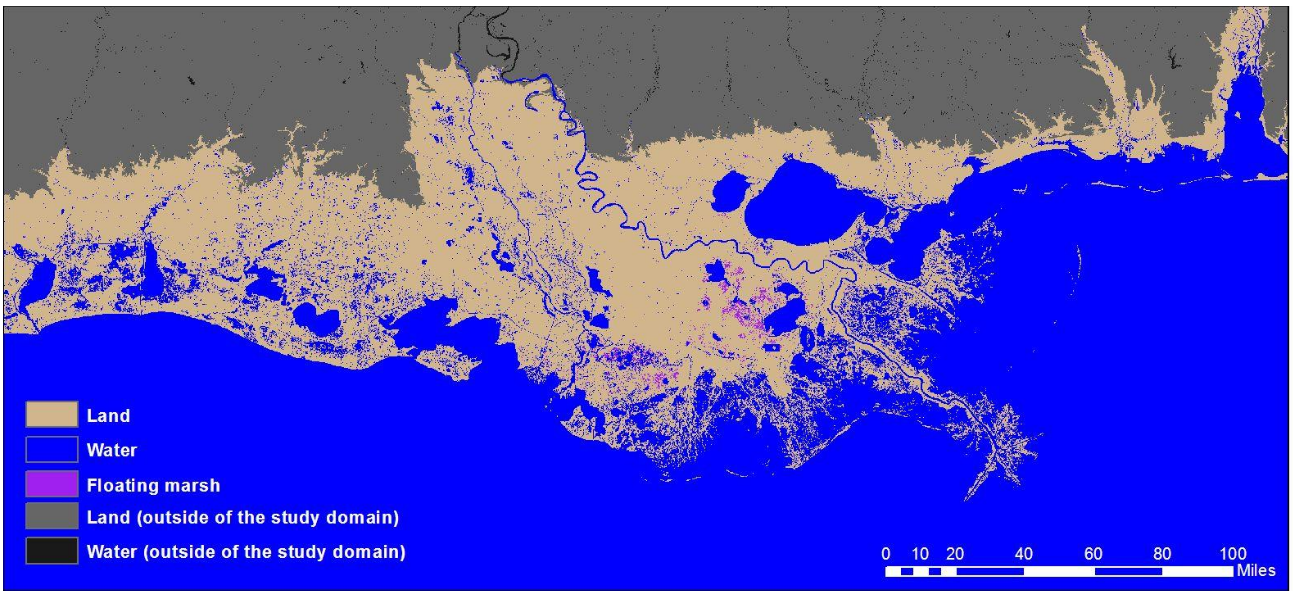


Figure 4: Final 2014 Initial conditions Land/Water Composition Dataset.

A special category, floating marsh, is delineated in Figure 4 above. Floating marshes were defined by Sasser (1995) as "wetlands of emergent vegetation with a mat of live roots and associated and decomposing organic material and mineral sediments that move vertically as ambient water levels rise and fall." These vegetation types are distinguished from free-floating aquatic vegetation species such as *Eichhornia crassipes* (water hyacinth) by the formation of a mat. Floating marshes exhibit differing tolerances to stressors, such as water level changes (inundation does not occur in these habitats), and the consequences of vegetation loss differ from those of attached marshes (Sasser et al., 1995) and as such, should be modeled as a distinct group. In terms of remotely sensed classifications, floating marshes often exhibit spectral characteristics more similar to those of land than those of water. They are often vegetated with vigorous vegetation, and this vegetation signal would lead most spectral algorithms to mistakenly identify these areas as land. Therefore, floating marshes must be carefully classified to account for these areas appropriately.

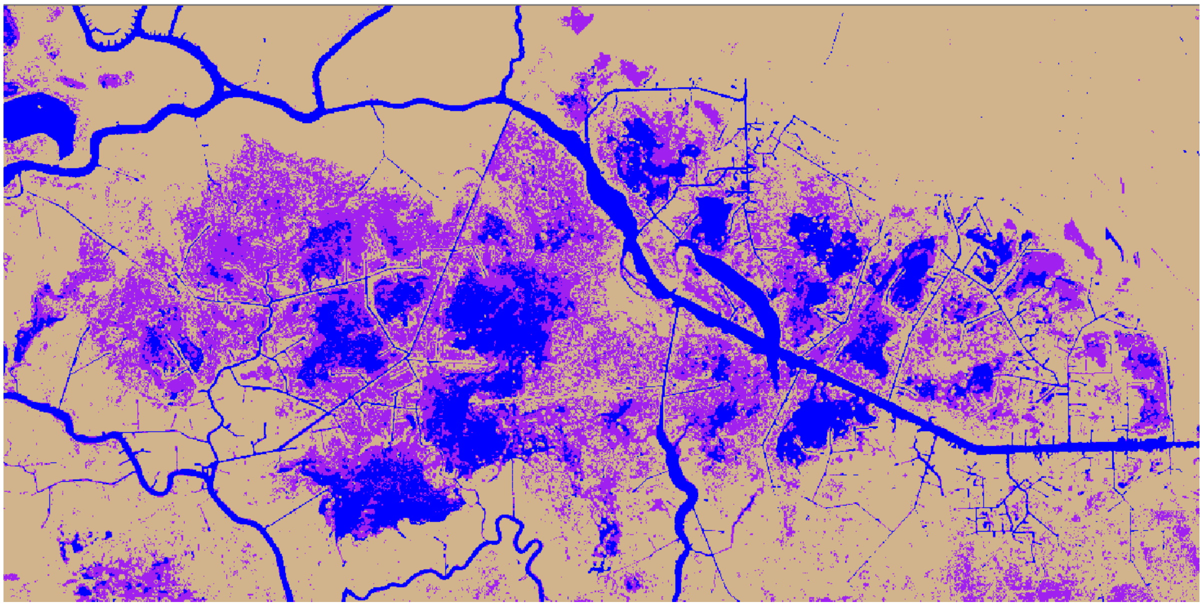


Figure 5: View of the Floating Marsh in Terrebonne Basin.

Following the recoding of floating marsh to a water category, the overall coastal area in 2014 within the LA Coastal Zone Boundary was 14,318 km^2 which constitutes a slight net land loss from the 2010 dataset used in the 2012 Coastal Master Plan effort which estimated land area at 14,666 km^2 (Couvillion et al., 2011). It is important to keep in mind that 2010 estimated land area represented a land area data point which was above the longer term trend due in part to water levels at the TOA, and as such, it may have contained some error. The net 348 km^2 of wetland loss implied by comparison of these two datasets may not be entirely accurate. It is also important to note that this net reduction does not imply that there are not areas on the coast, which gained new land during the 2010-2014 time period. Several restoration projects for example are clearly visible when the 2010 and 2014 datasets are compared.

3.2. Digital Elevation Model

The final coast wide composite Digital Elevation Model represents a composite of the best available elevation data for the northern Gulf of Mexico region. It is not free of inaccuracy, which is an artifact of dealing with elevation data in a very complex and dynamic environment. It is however the most complete and accurate dataset ever compiled for this large-scale region. Its use should proceed only with knowledge of its accuracies and inaccuracies, and the potential implications of those errors on model output. For this reason, a sensitivity analysis will be run in the ICM to quantify the changes that may occur as a result of uncertainty in the elevation data. In general, known accuracy issues with the dataset include:

- Bathymetry values are often taken from data sources acquired several decades ago, and the assumption is that bathymetric elevations have not changed between the TOA and the initialization period (2014). While this is in many cases an unrealistic assumption, it is necessitated by the lack of more recent bathymetry data in many areas.

- LIDAR elevations vary in TOA as well, but all data was collected between 1999 and present. Again, an assumption of no change between the TOA and 2014 was used.
- LIDAR-derived bare earth elevations are often contaminated by obstructions including structures and dense vegetation.

This dataset is an improvement over what was used in the 2012 Coastal Master Plan as it used newly available LIDAR with improved accuracy and reduced influence of water levels on the dataset.

The final coast wide composite Digital Elevation Model is provided in Figure 6. While very little detail can be seen at this scale, detailed maps of each grid cell are provided in Figure 7 through Figure 48.

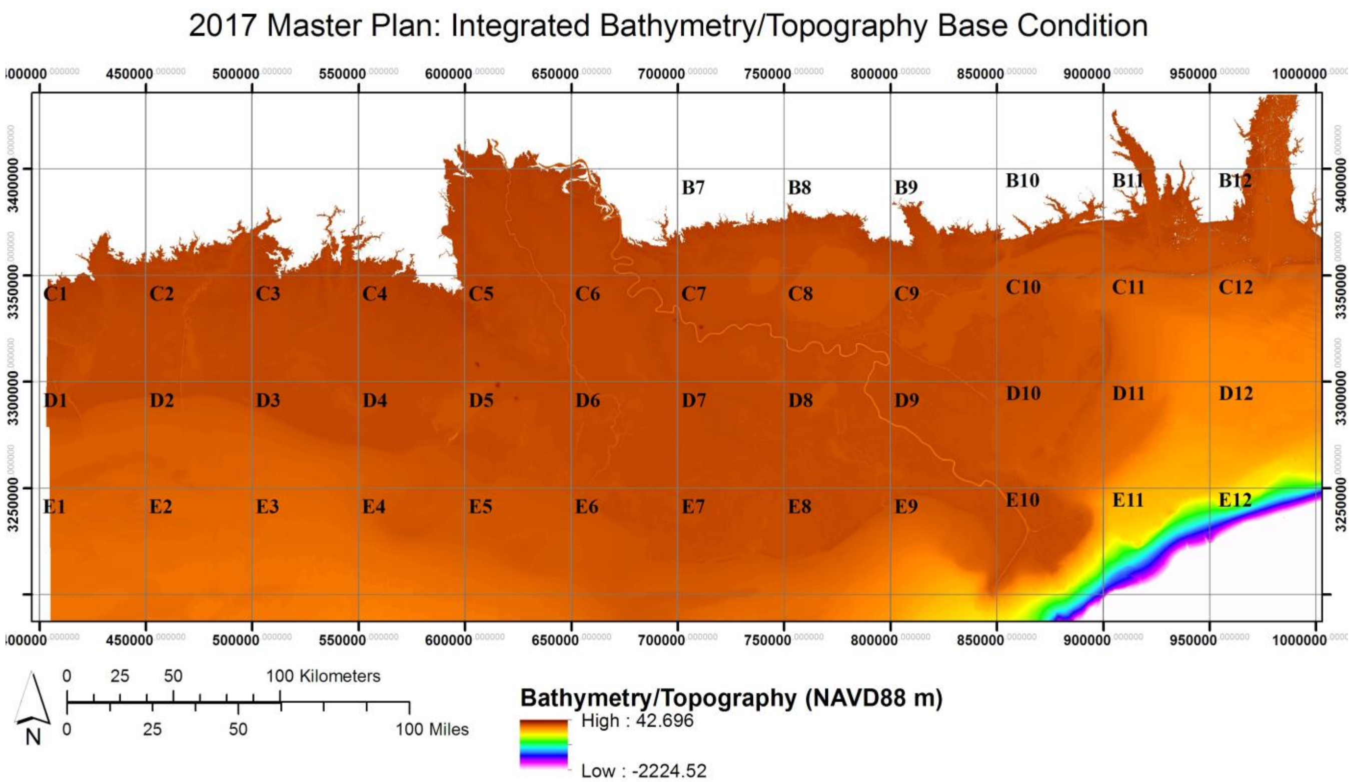


Figure 6: Landscape scale view of the final 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

The legends vary for each grid cell map below (Figures 7-48), which complicates cross-grid comparison; however, elevation values vary so much across the coastal Louisiana landscape this is the only way to visualize even a portion of the detail available in this dataset. In all of these figures, elevation values are mapped along a color ramp, which varies from light pink for low elevation values to red for high elevation areas. Data are represented based upon standard deviations of the values in each grid cell.

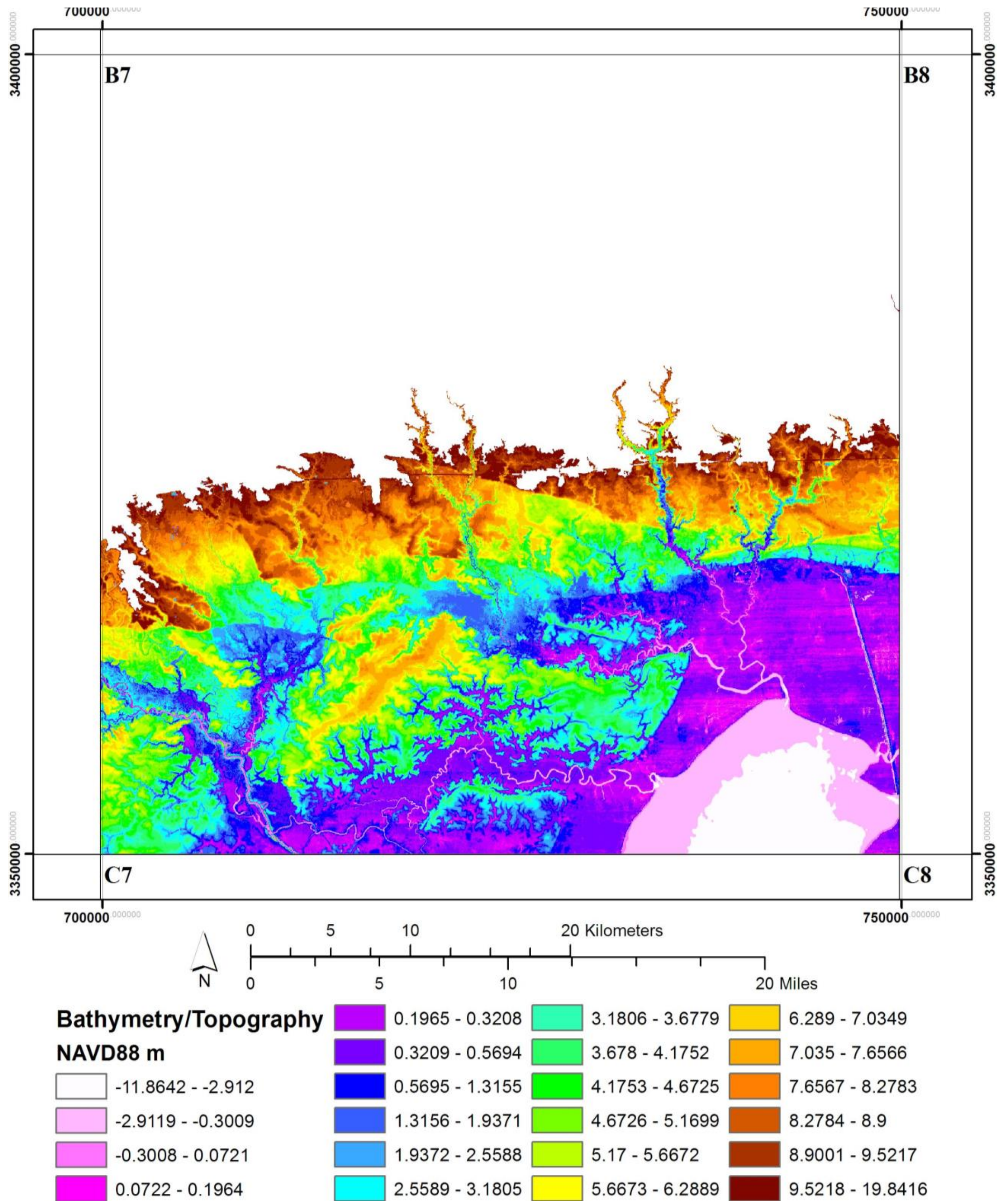


Figure 7: Grid B7 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

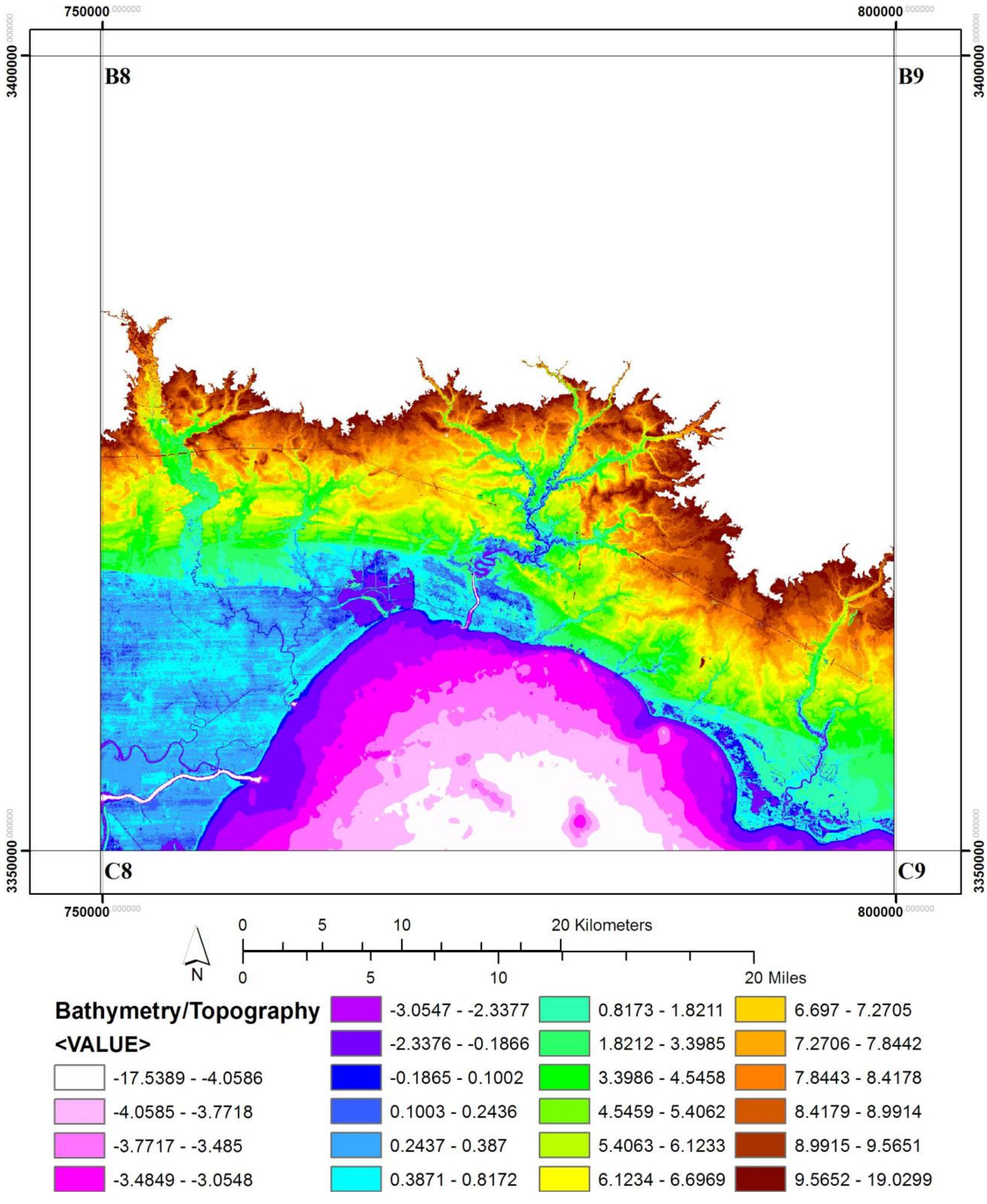


Figure 8: Grid B8 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

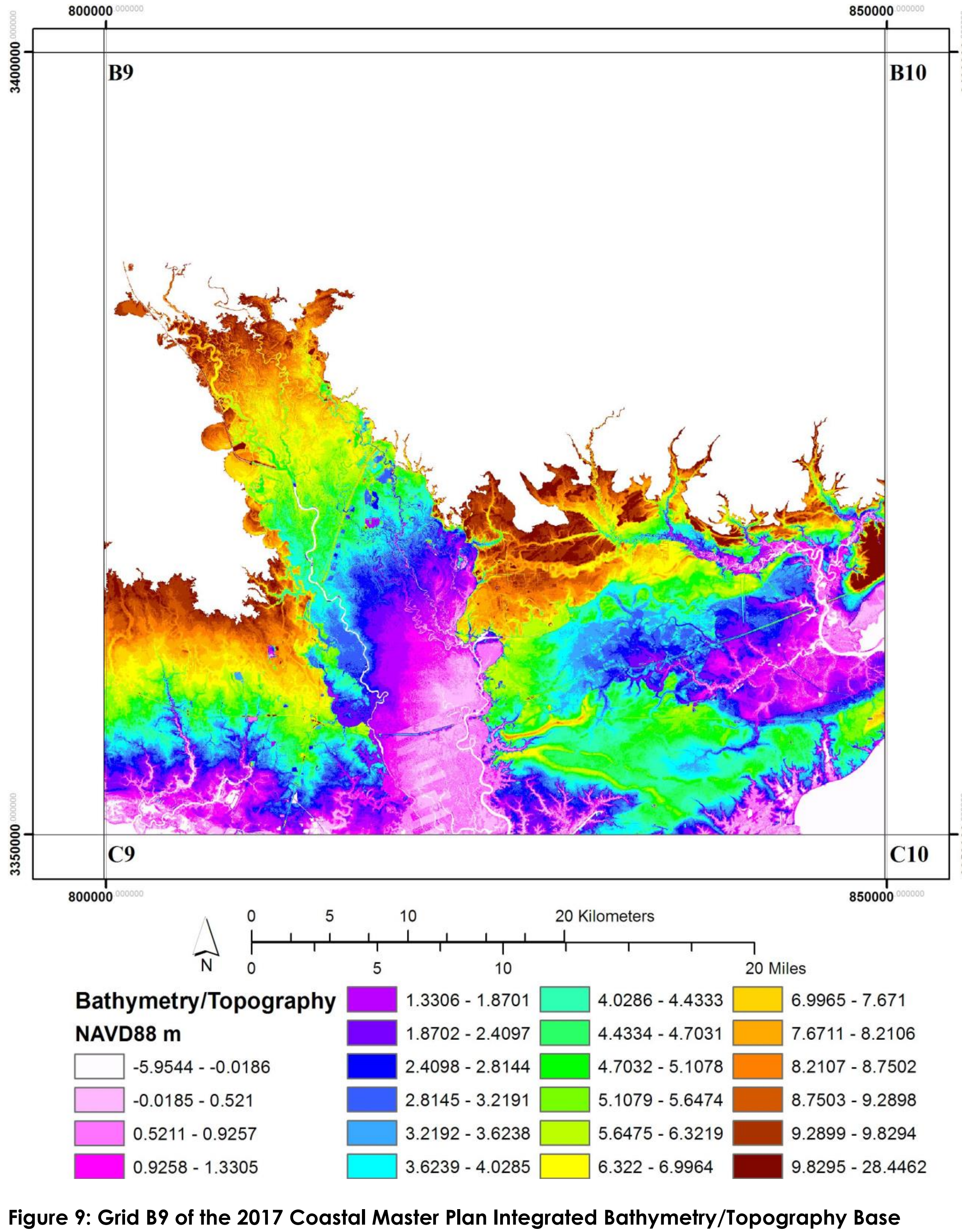


Figure 9: Grid B9 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

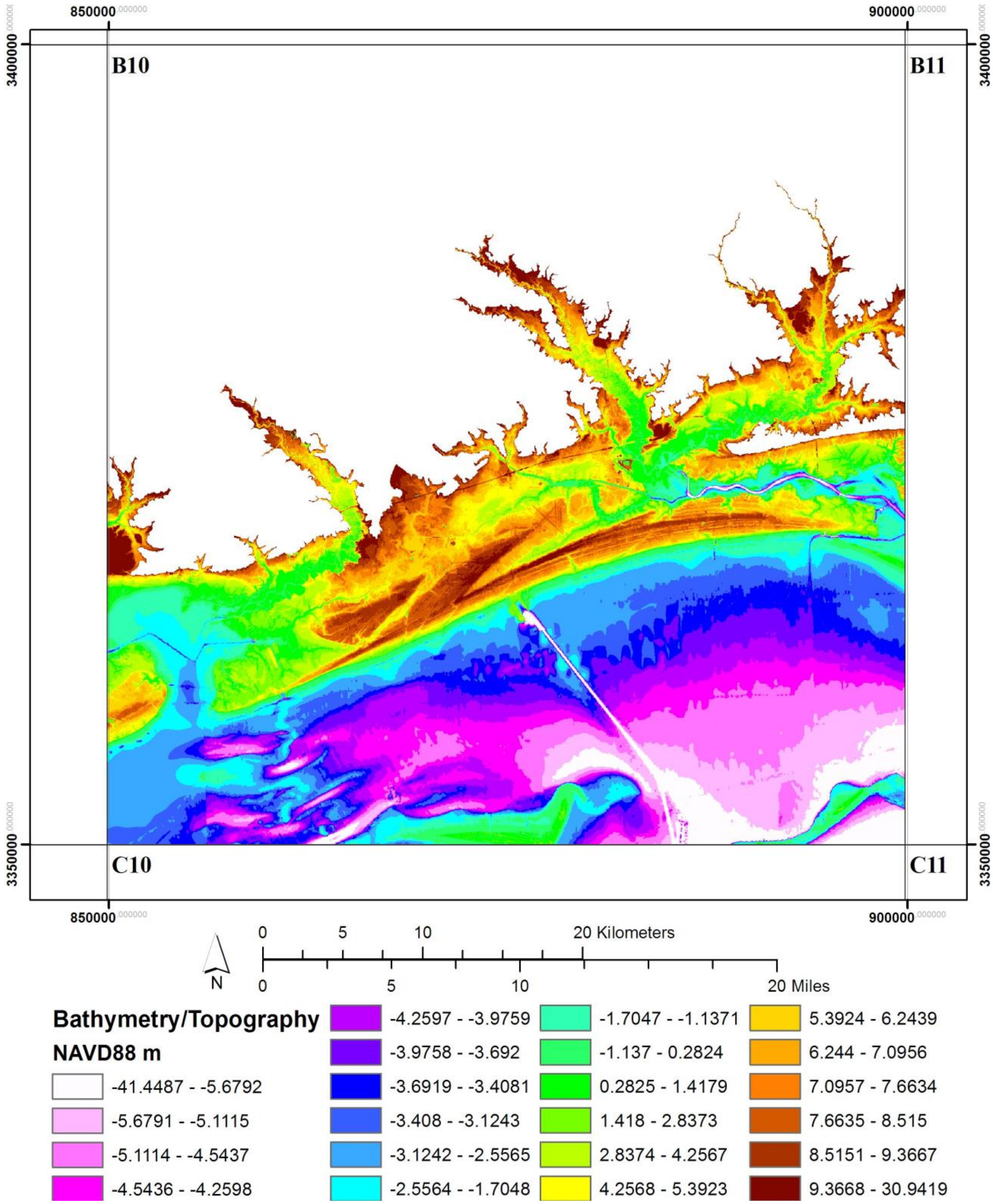


Figure 10: Grid B10 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

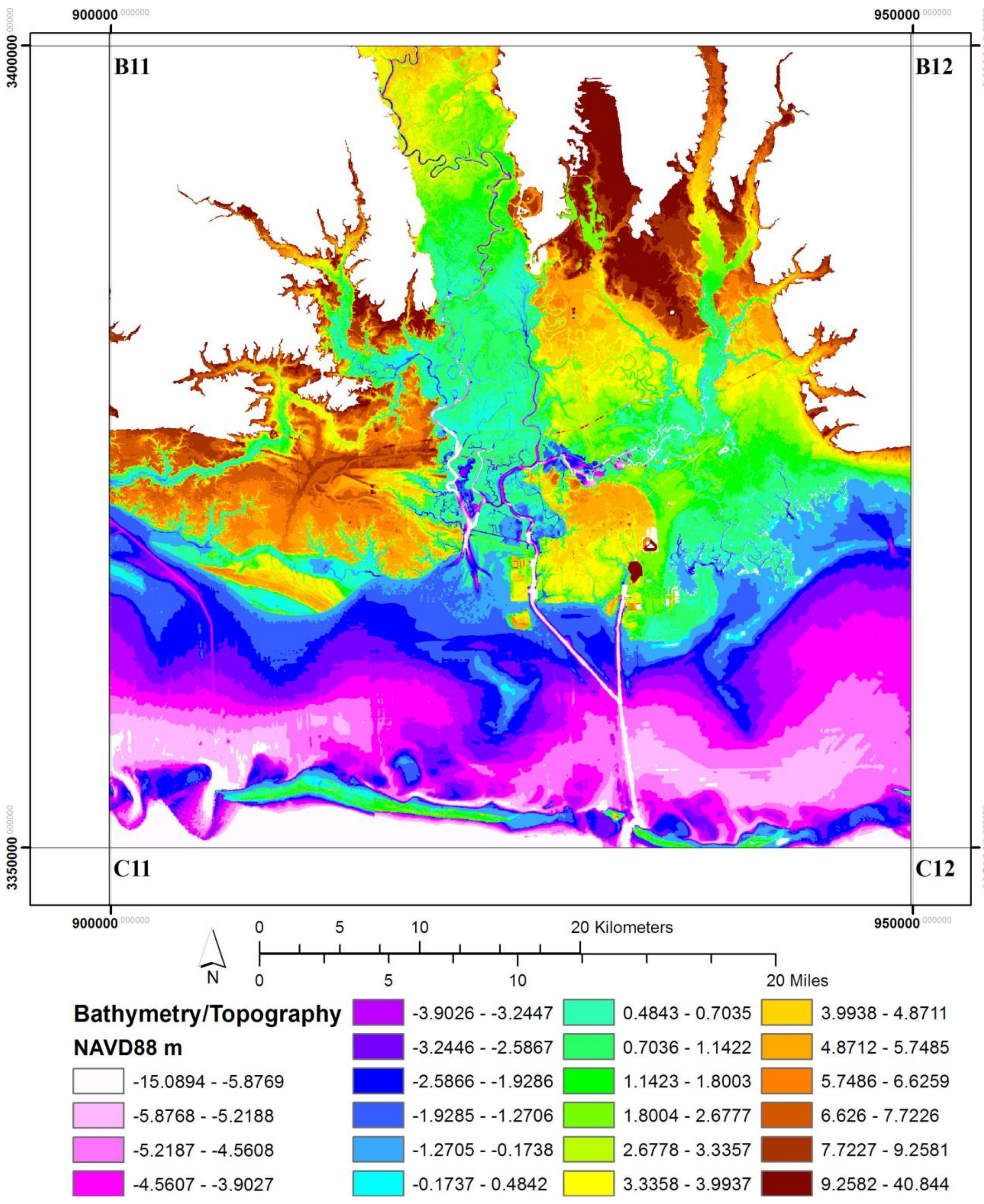


Figure 11: Grid B11 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

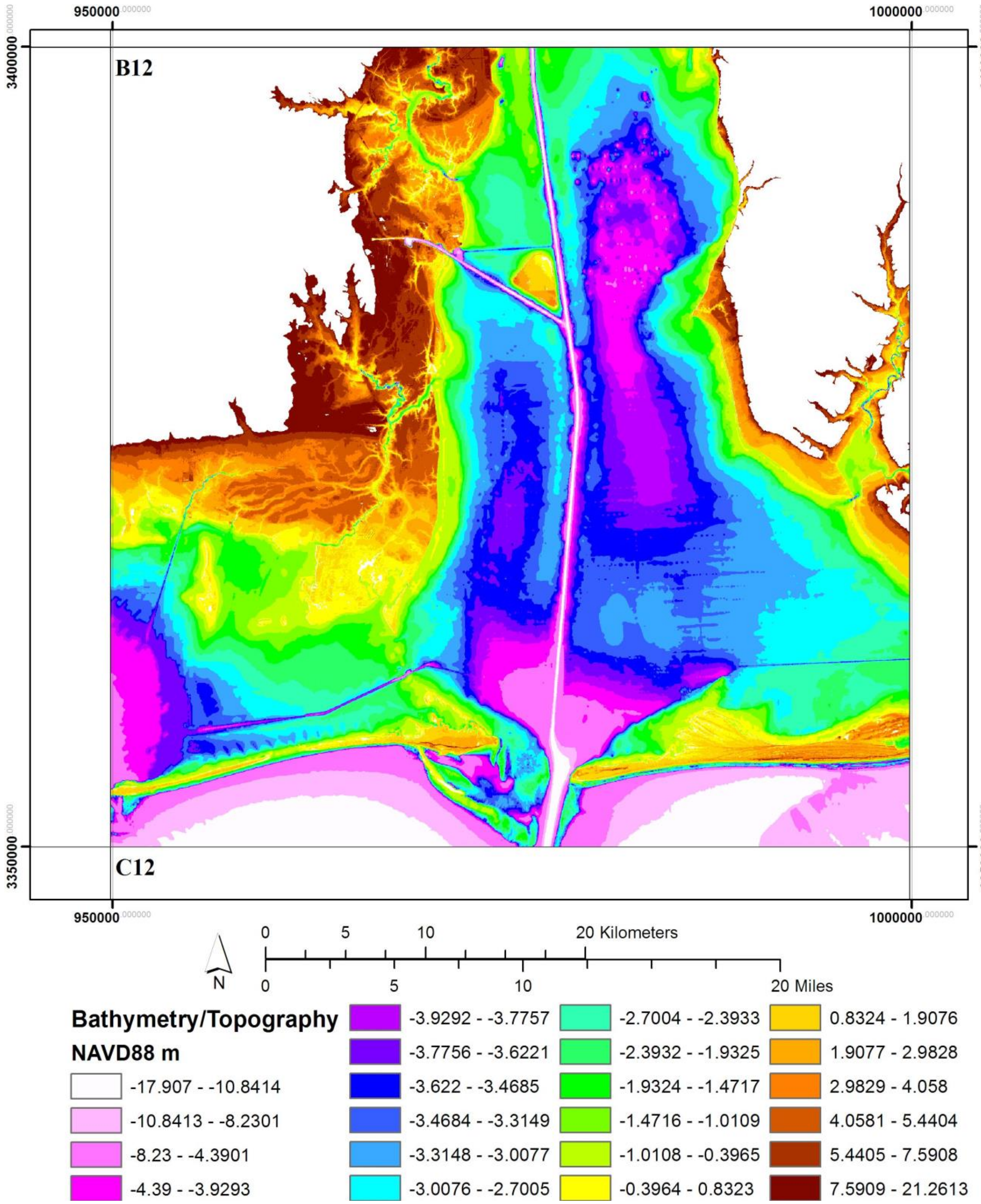


Figure 12: Grid B12 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

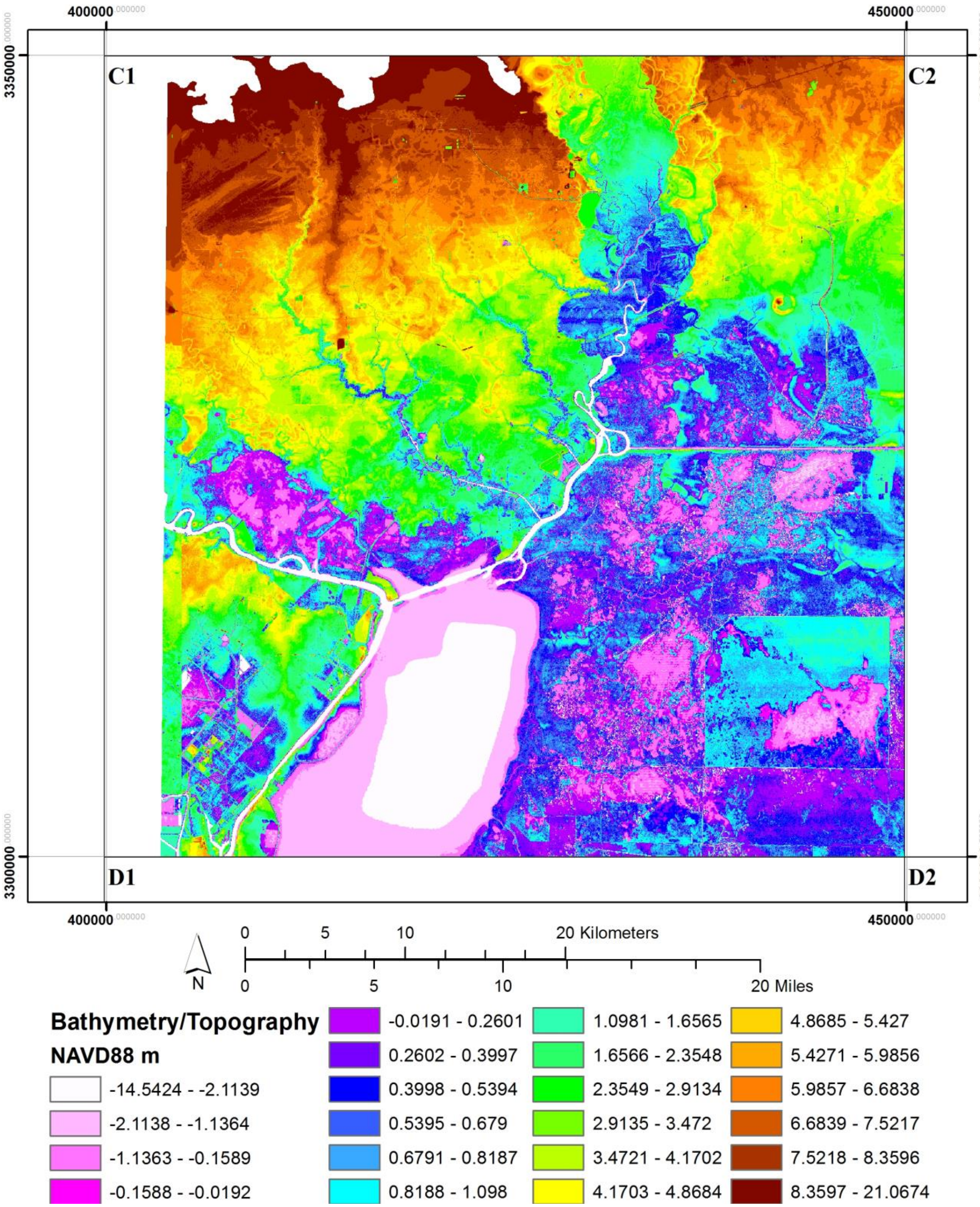


Figure 13: Grid C1 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

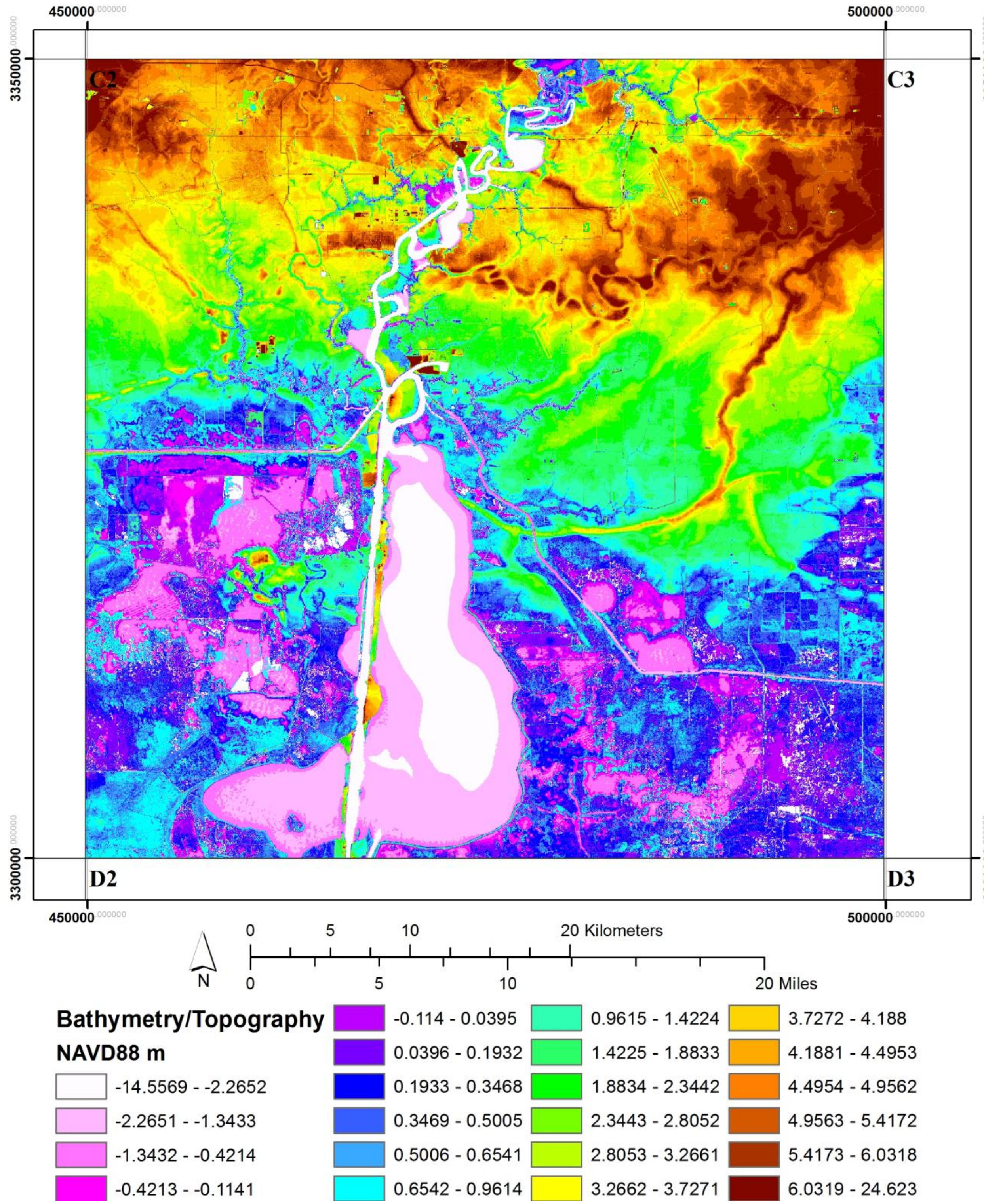


Figure 14: Grid C2 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

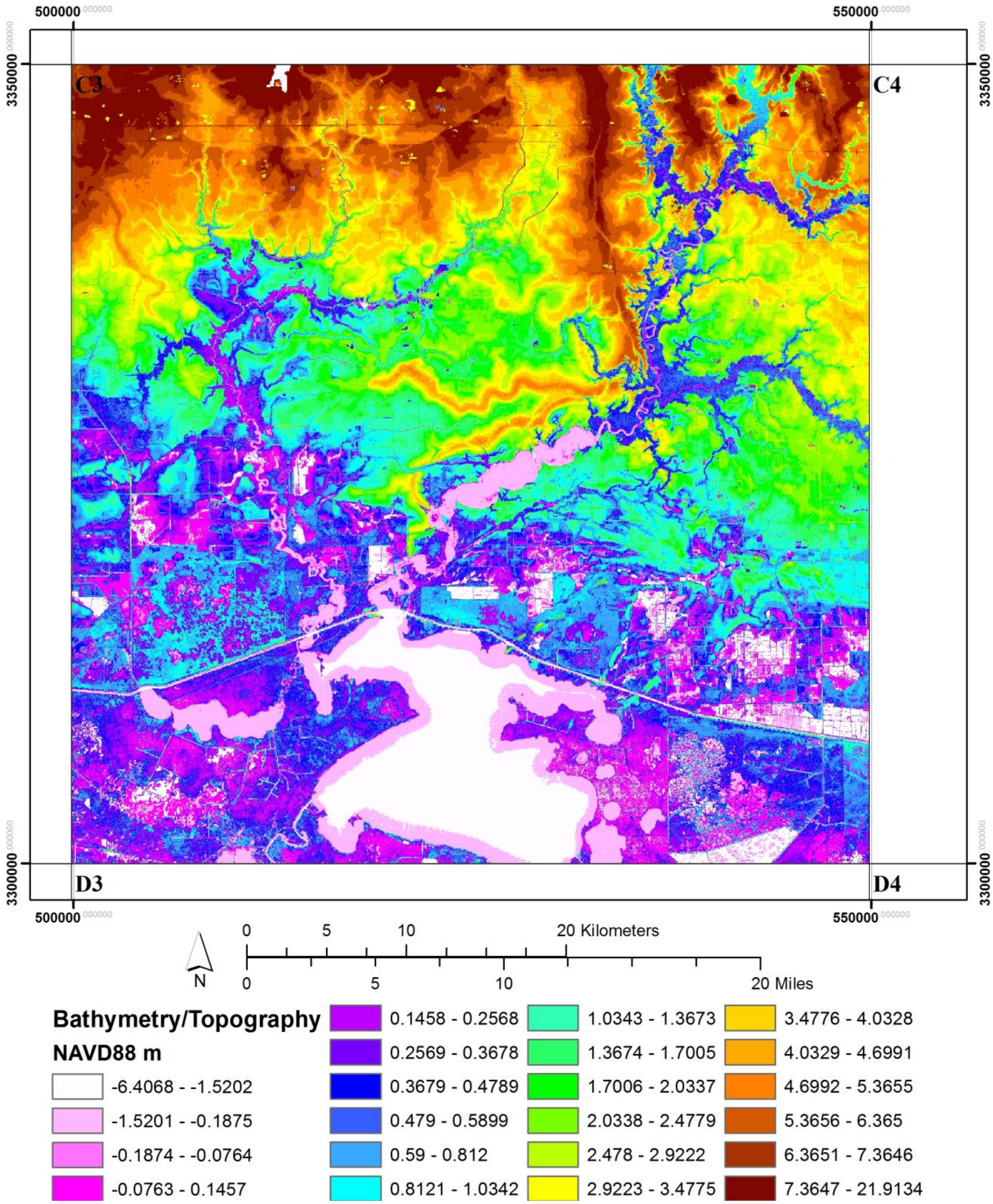


Figure 15: Grid C3 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

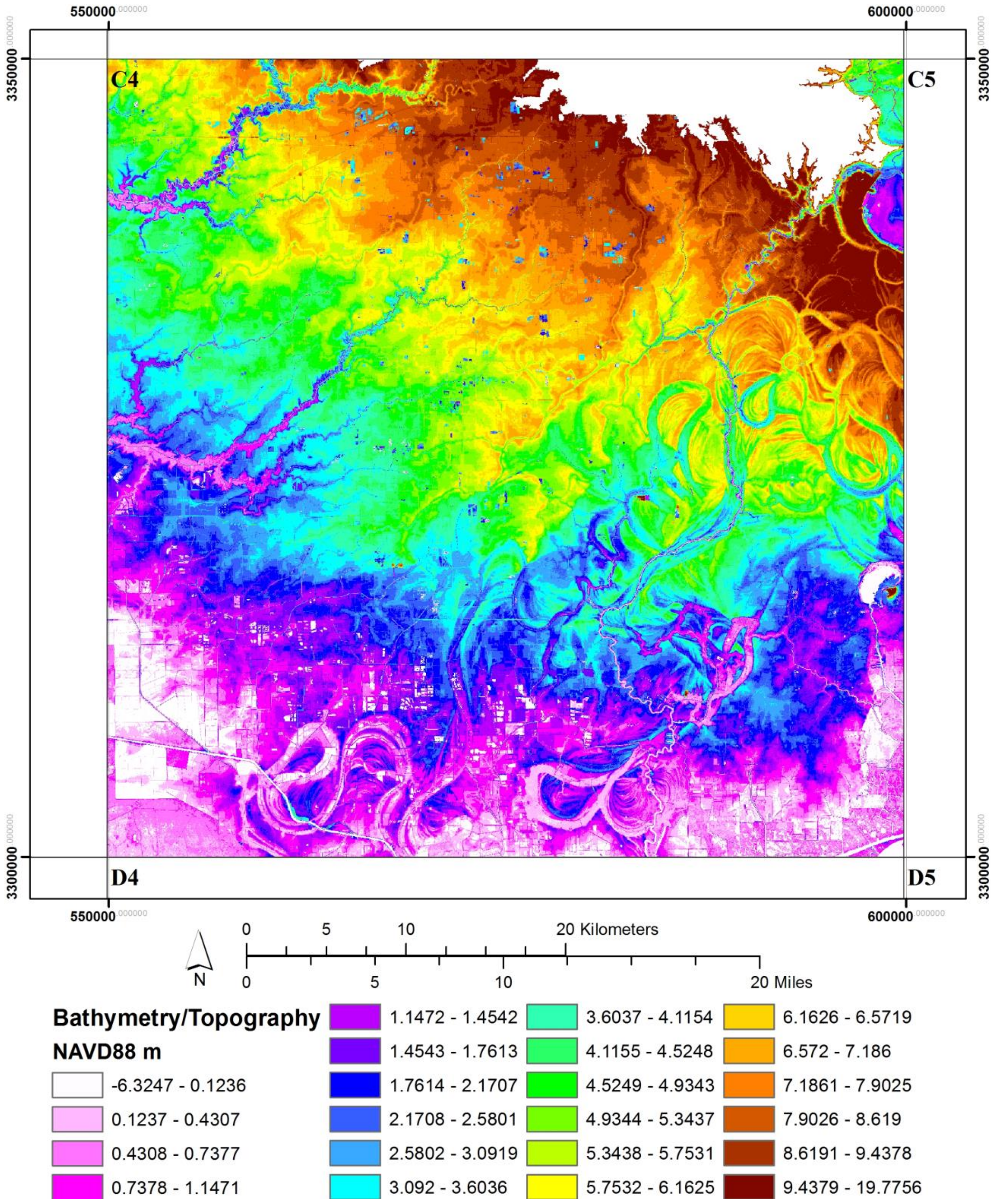


Figure 16: Grid C4 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

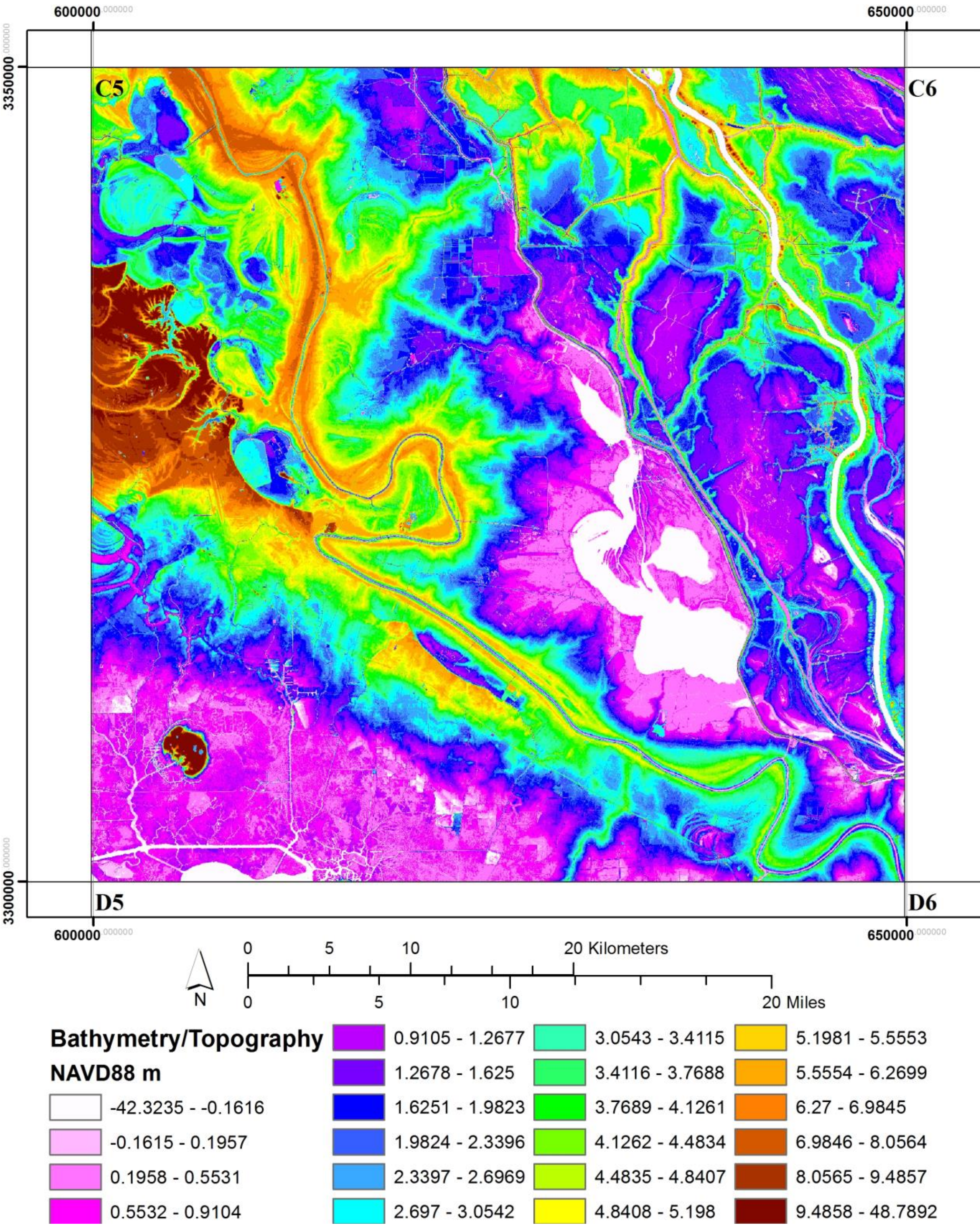


Figure 17: Grid C5 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

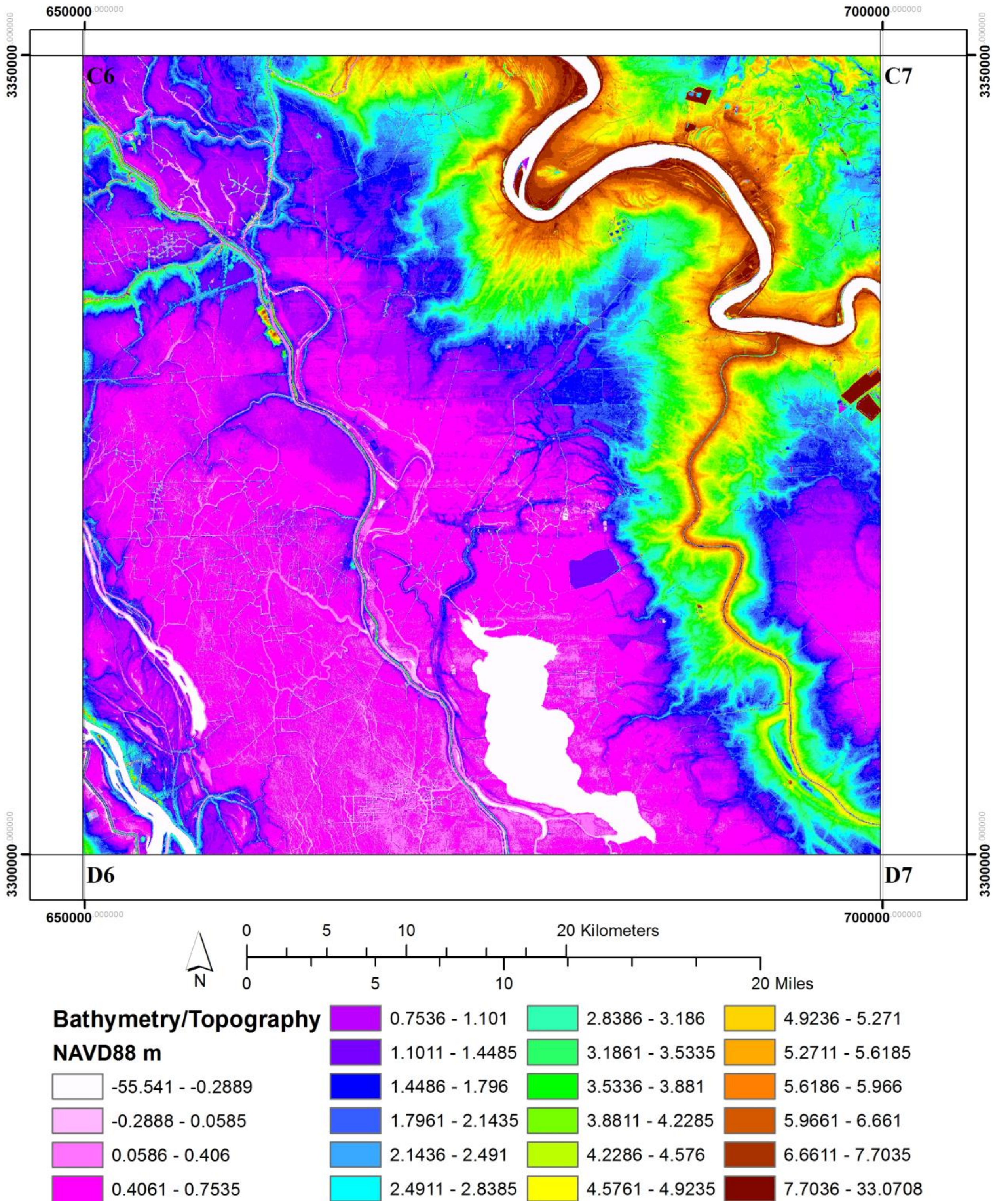


Figure 18: Grid C6 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

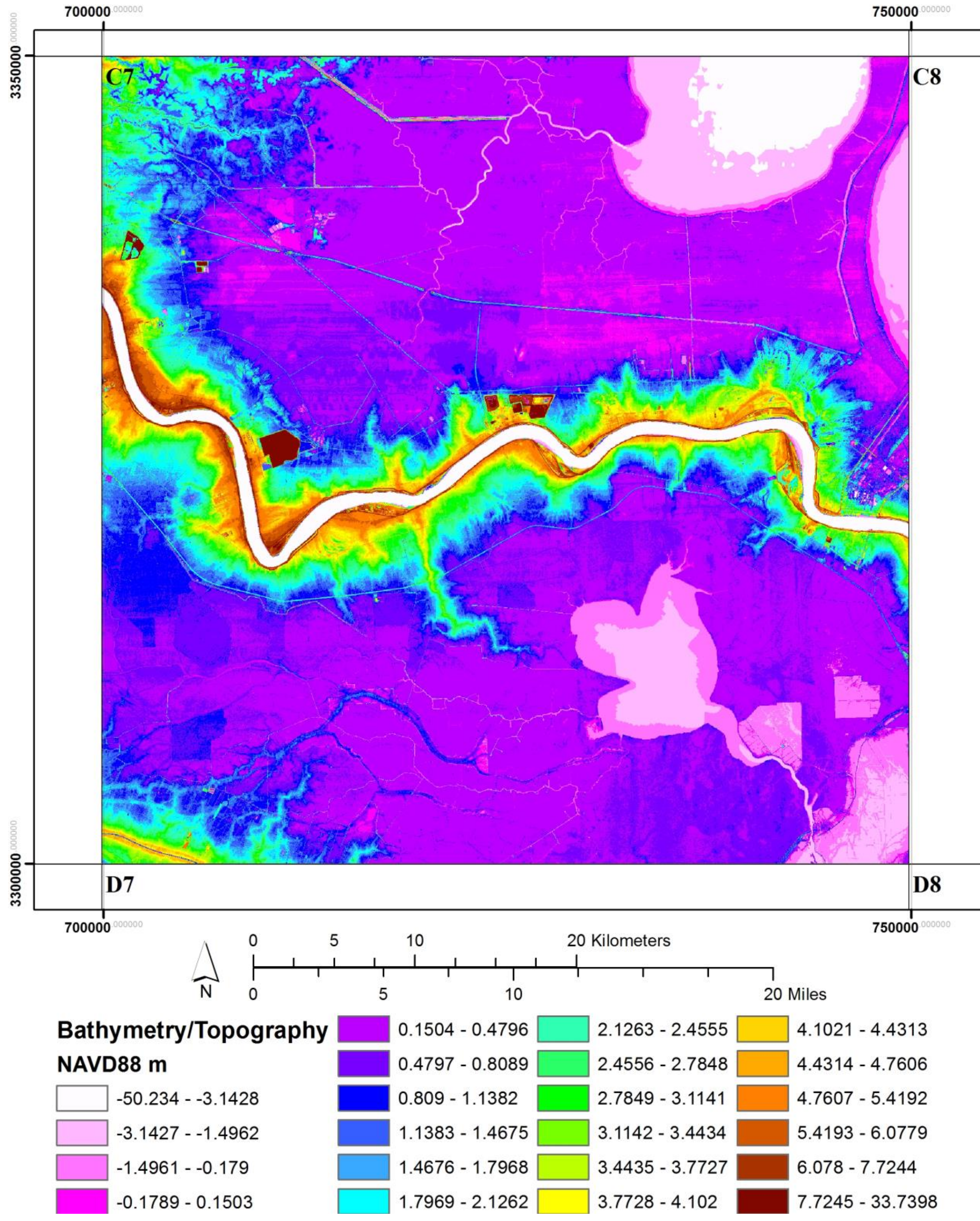


Figure 19: Grid C7 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

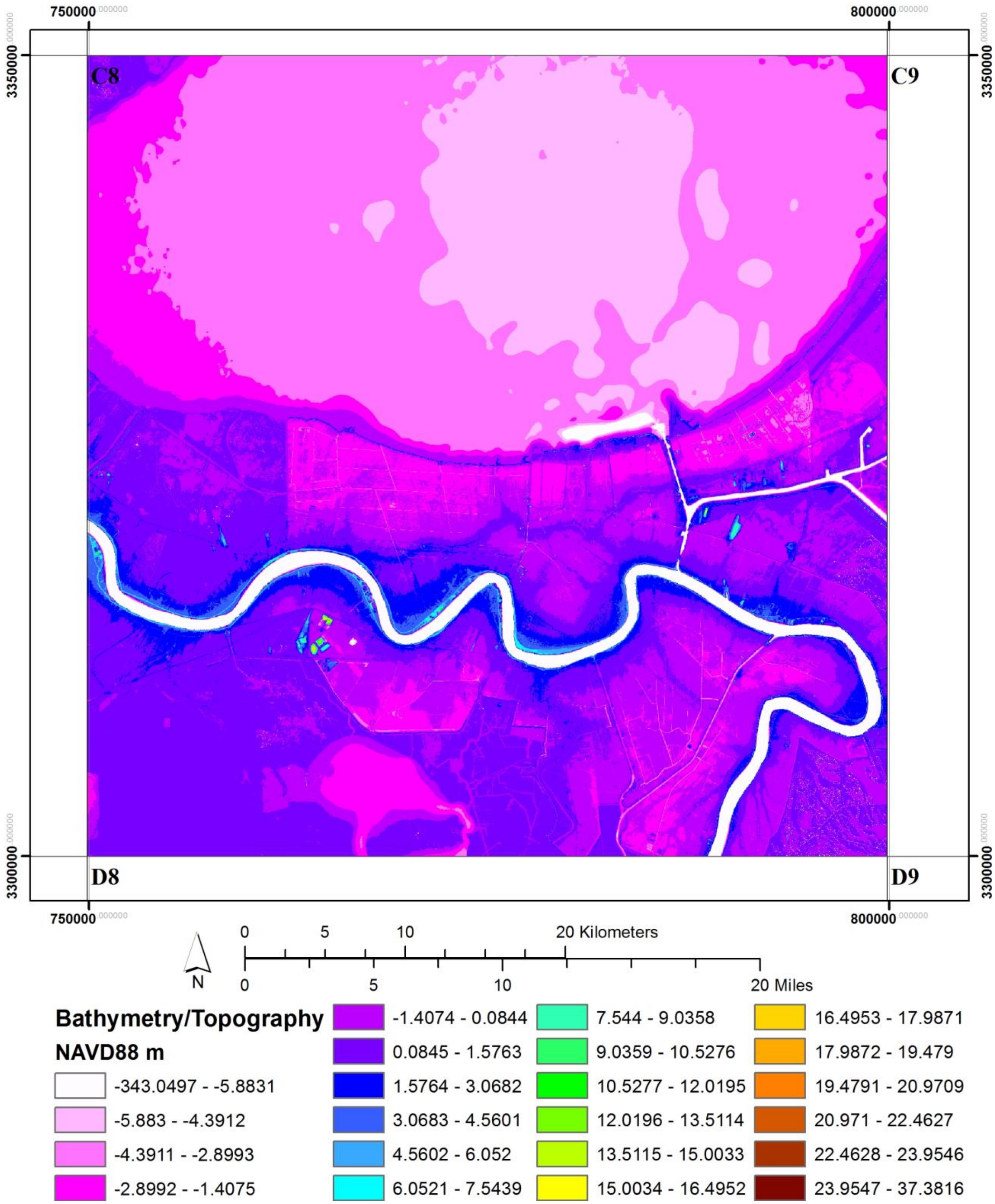


Figure 20: Grid C8 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

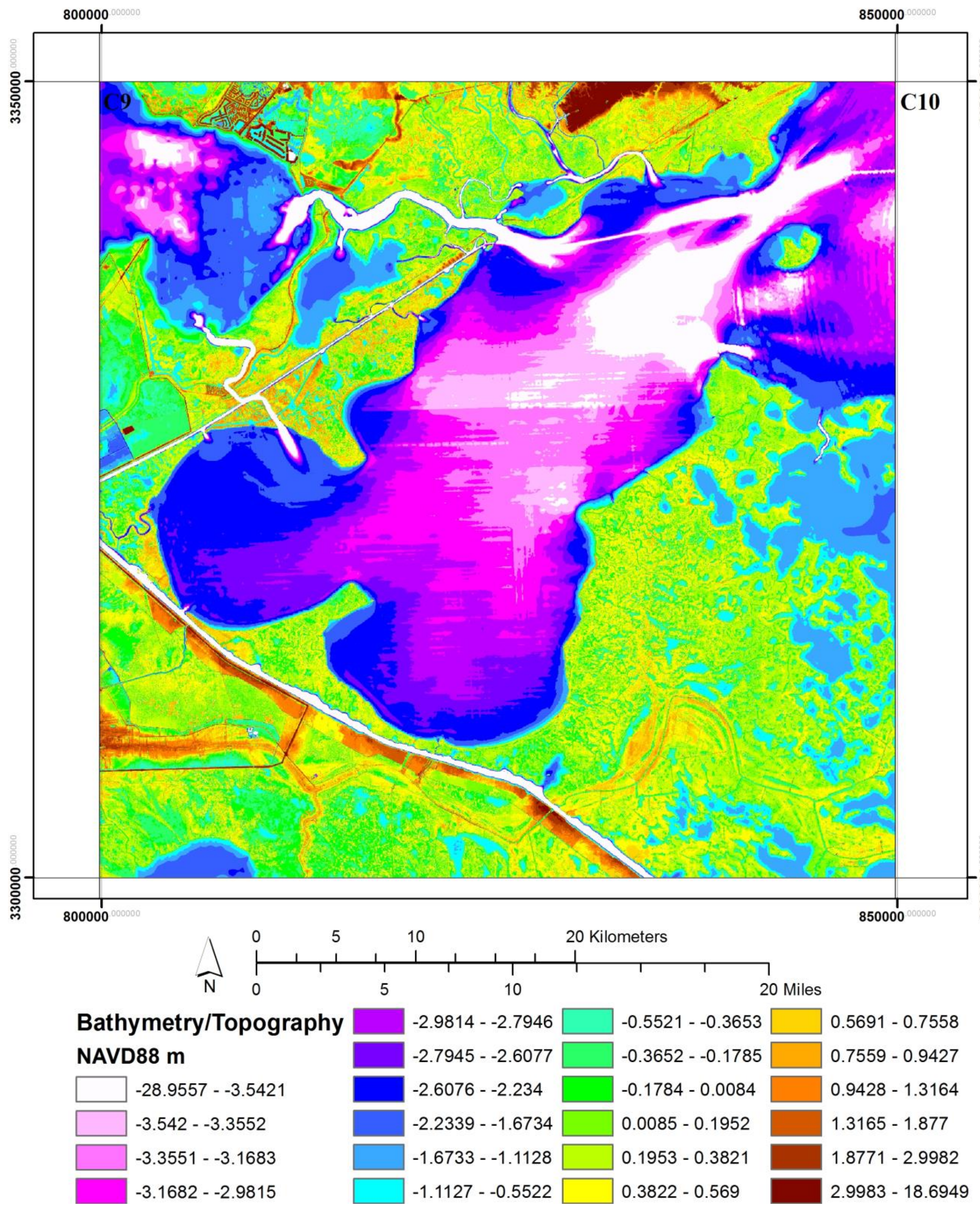


Figure 21: Grid C9 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

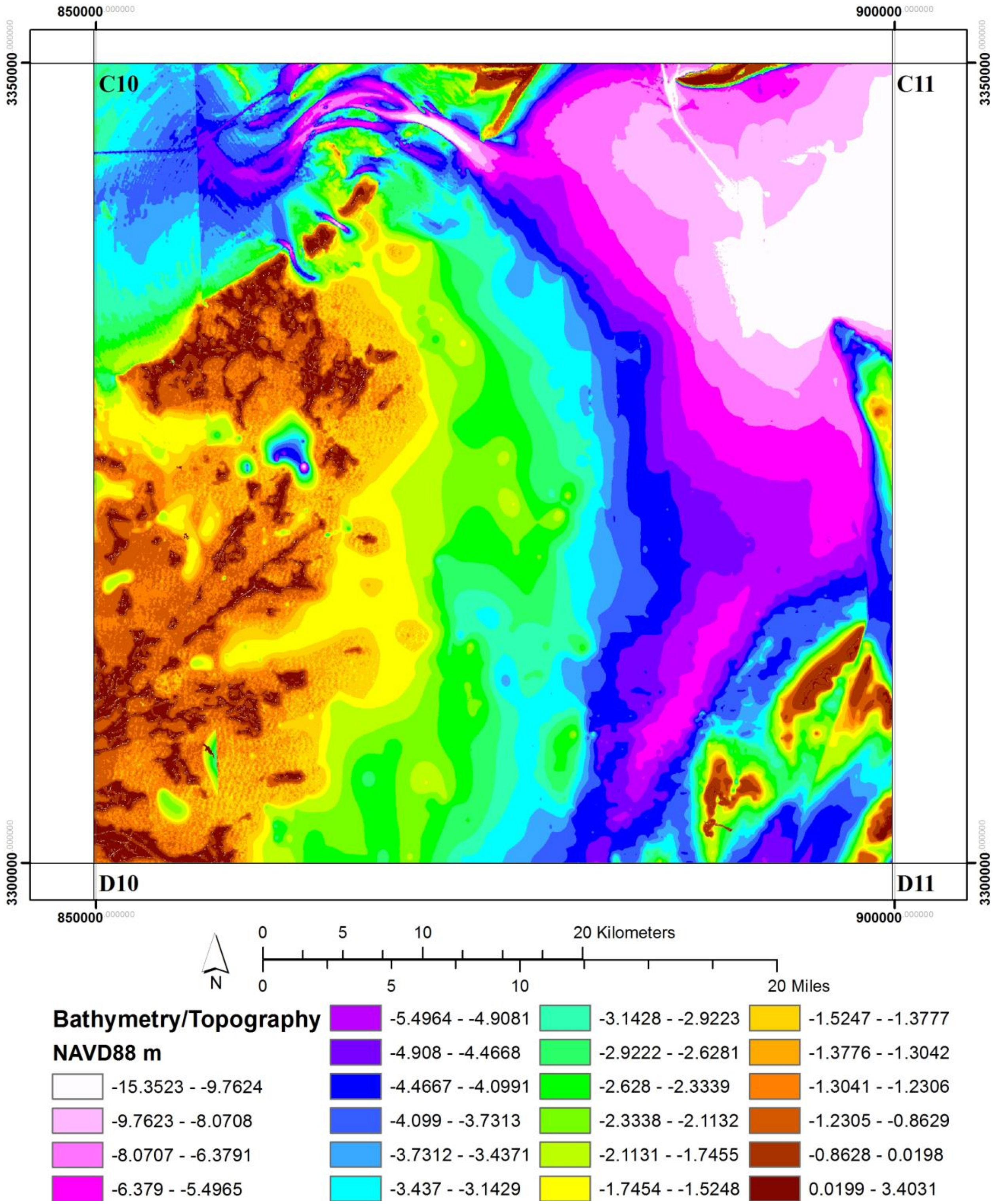


Figure 22: Grid C10 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

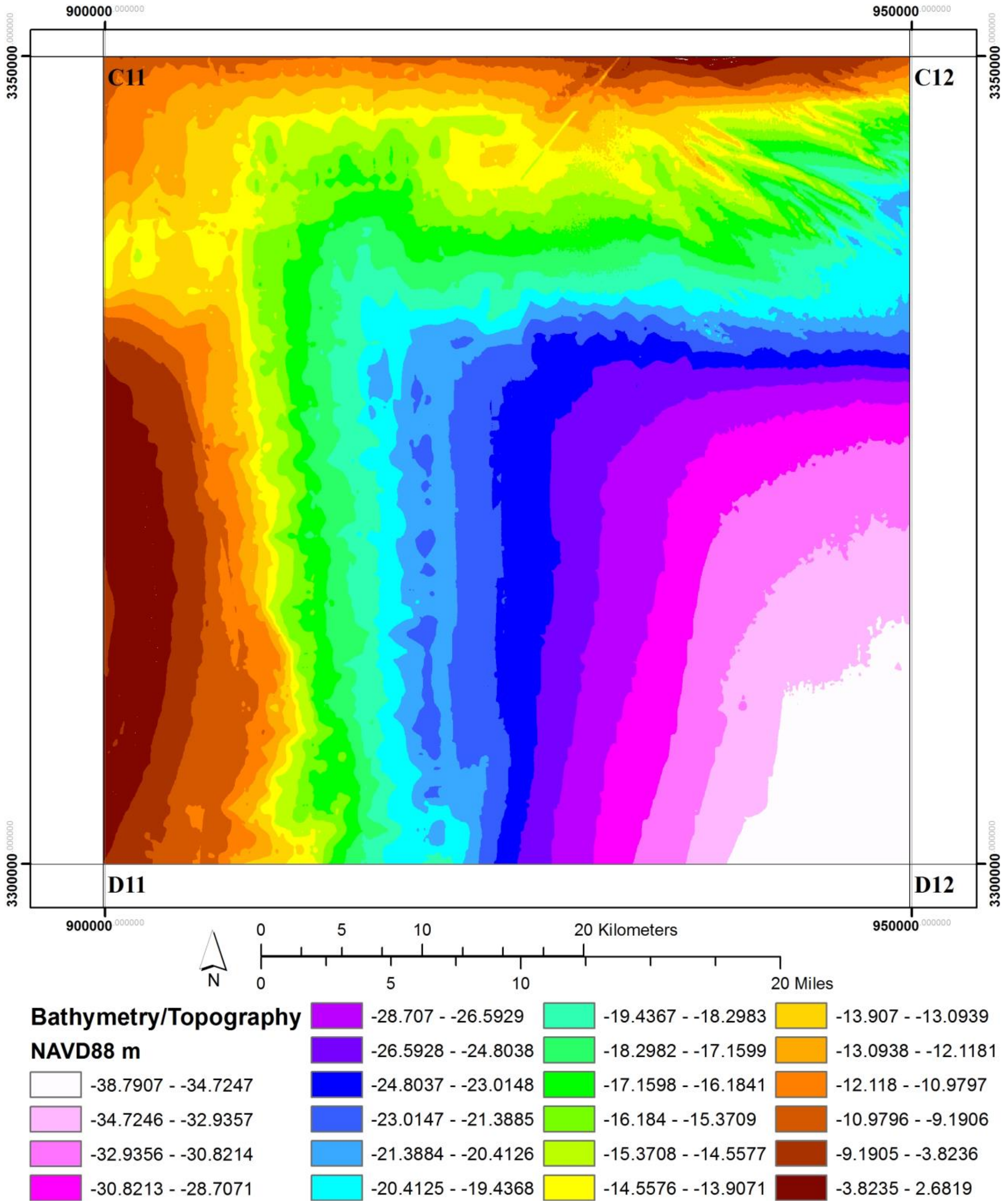


Figure 23: Grid C11 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

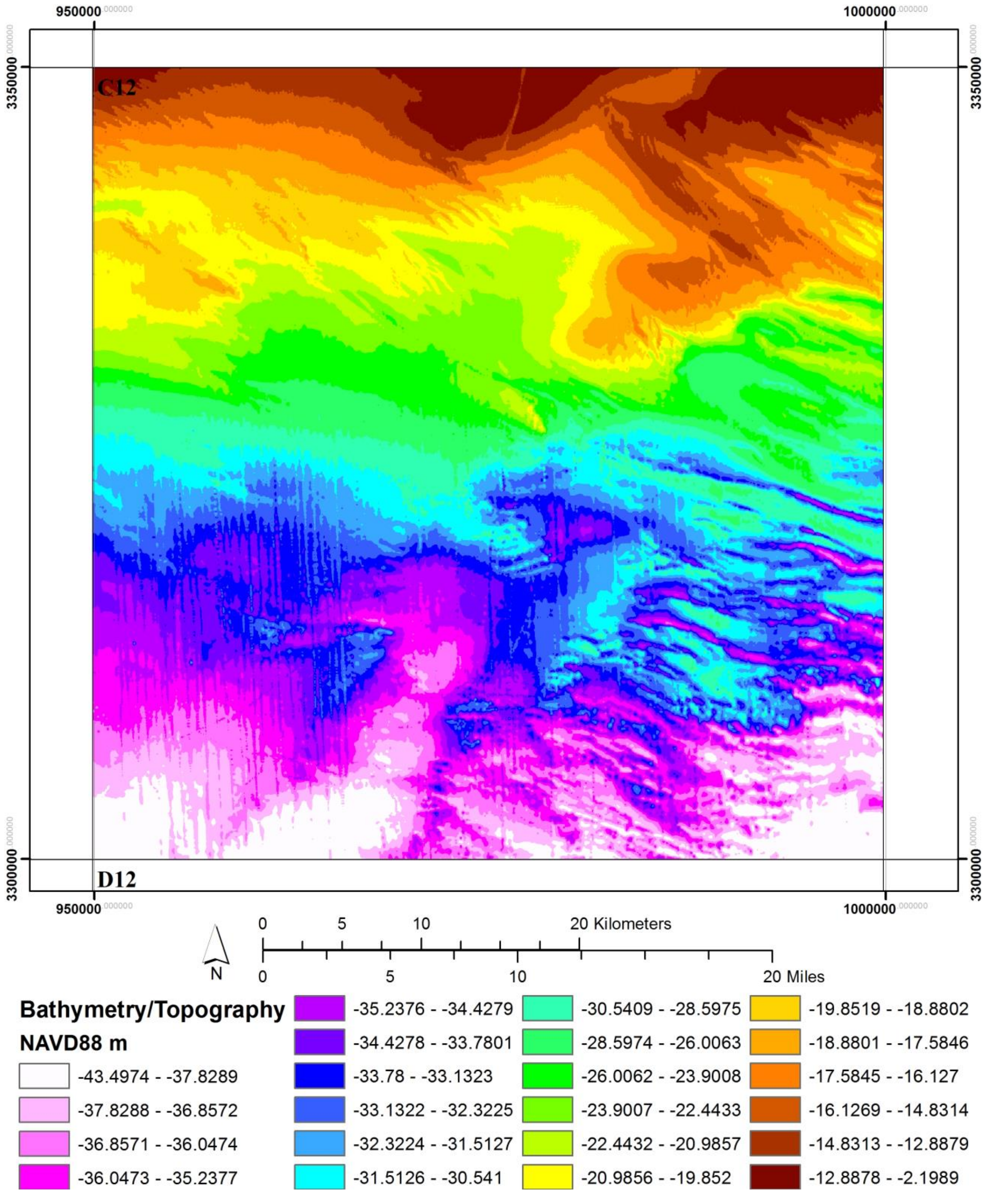


Figure 24: Grid C12 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

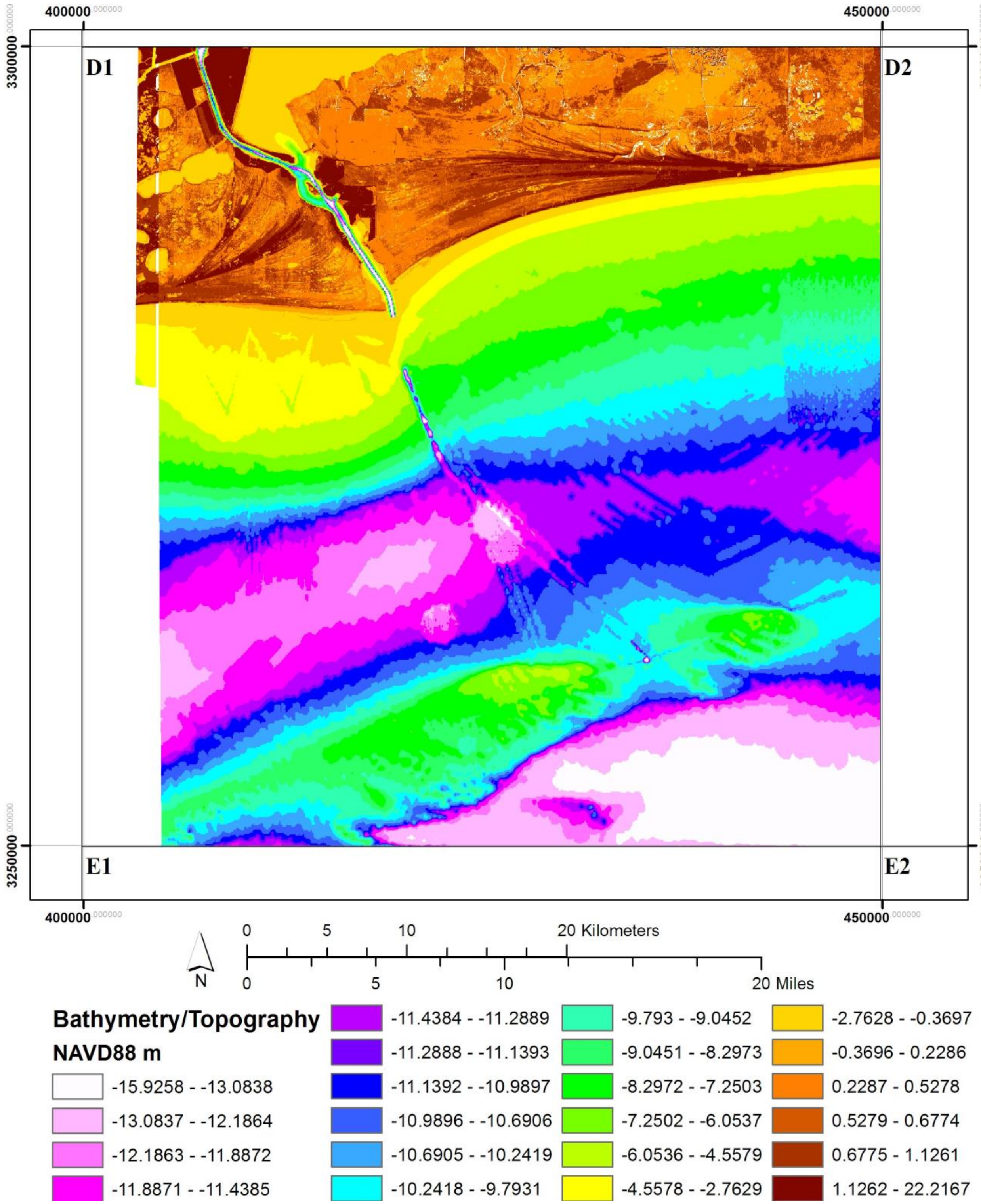


Figure 25: Grid D1 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

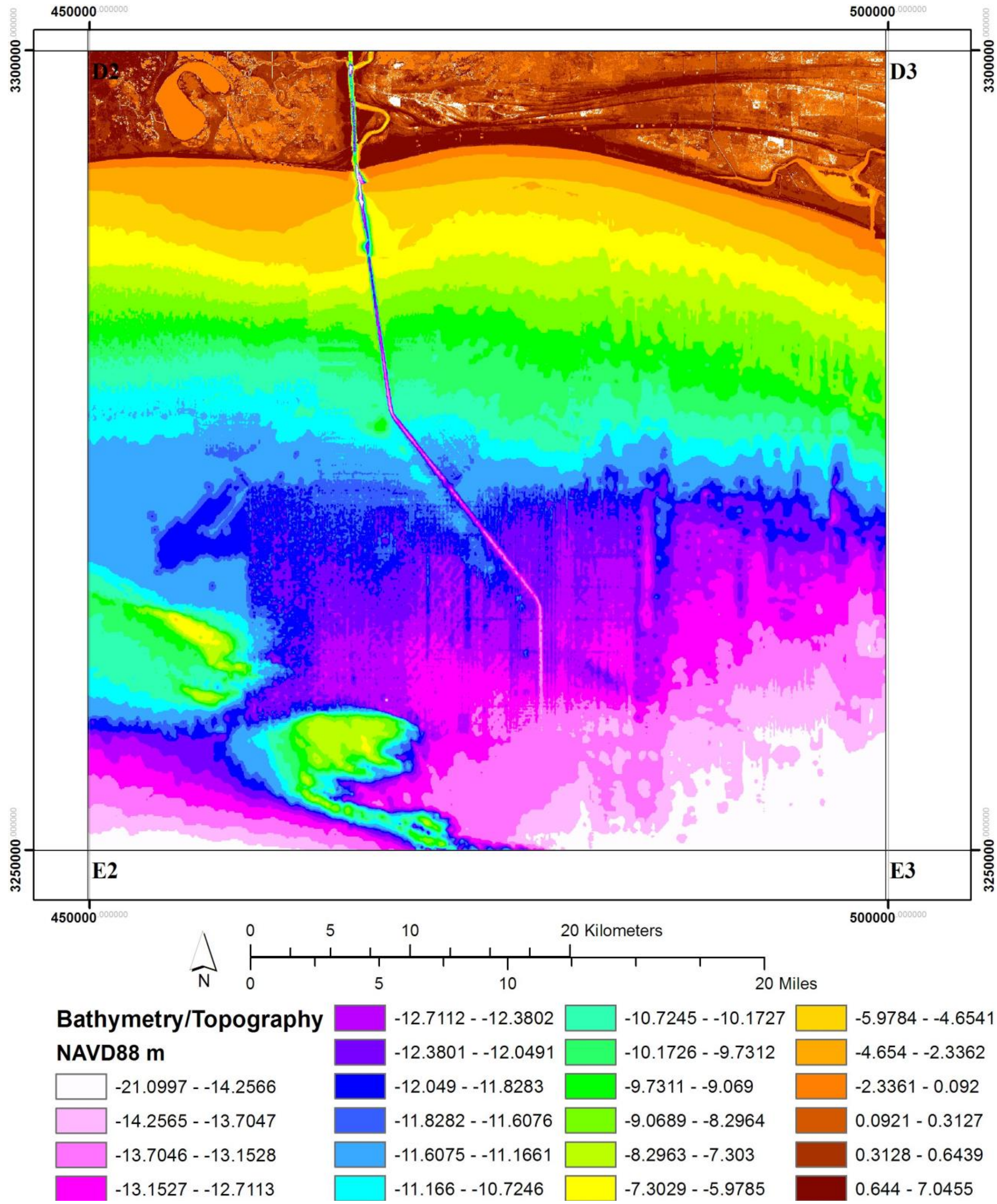


Figure 26: Grid D2 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

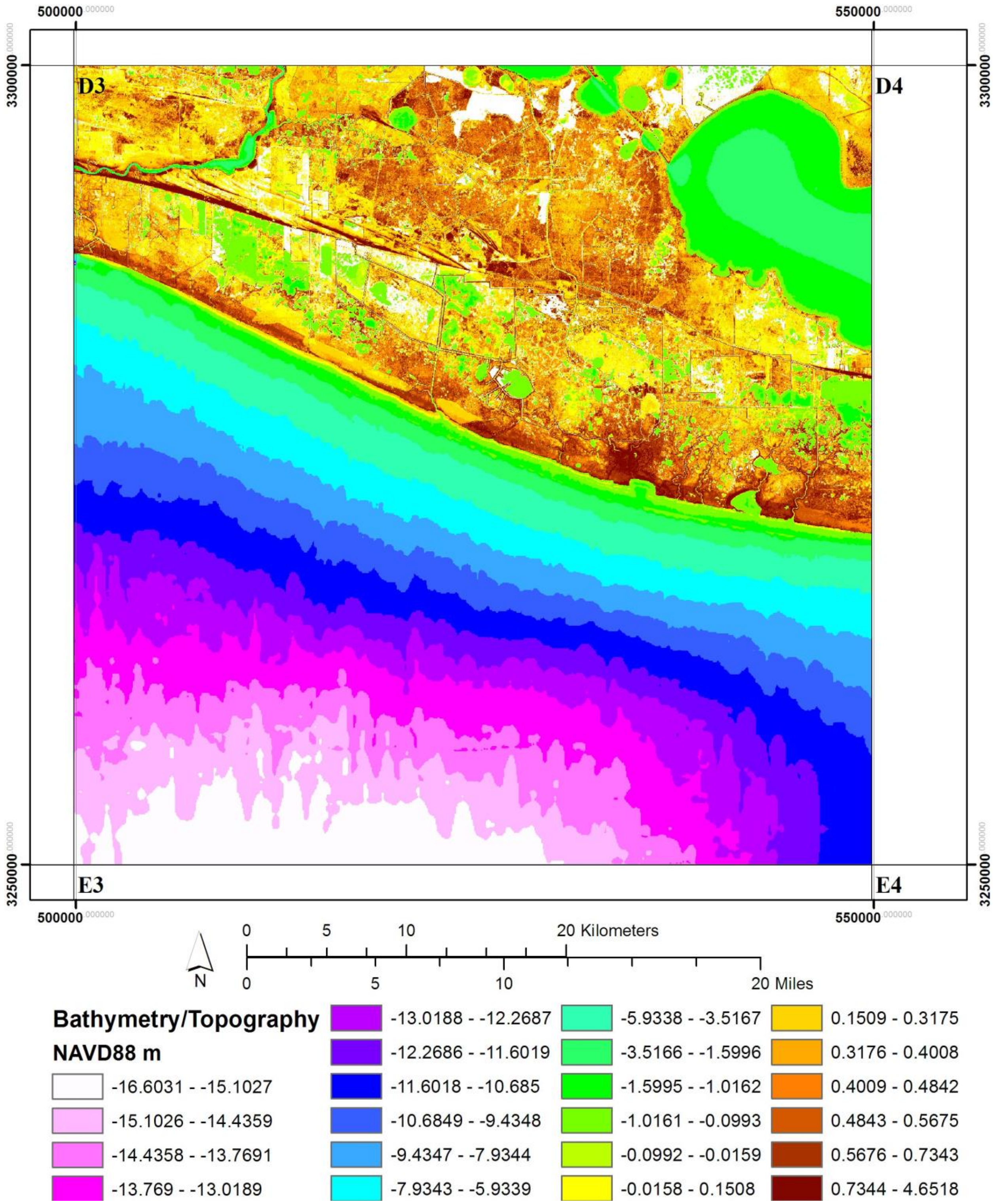


Figure 27: Grid D3 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

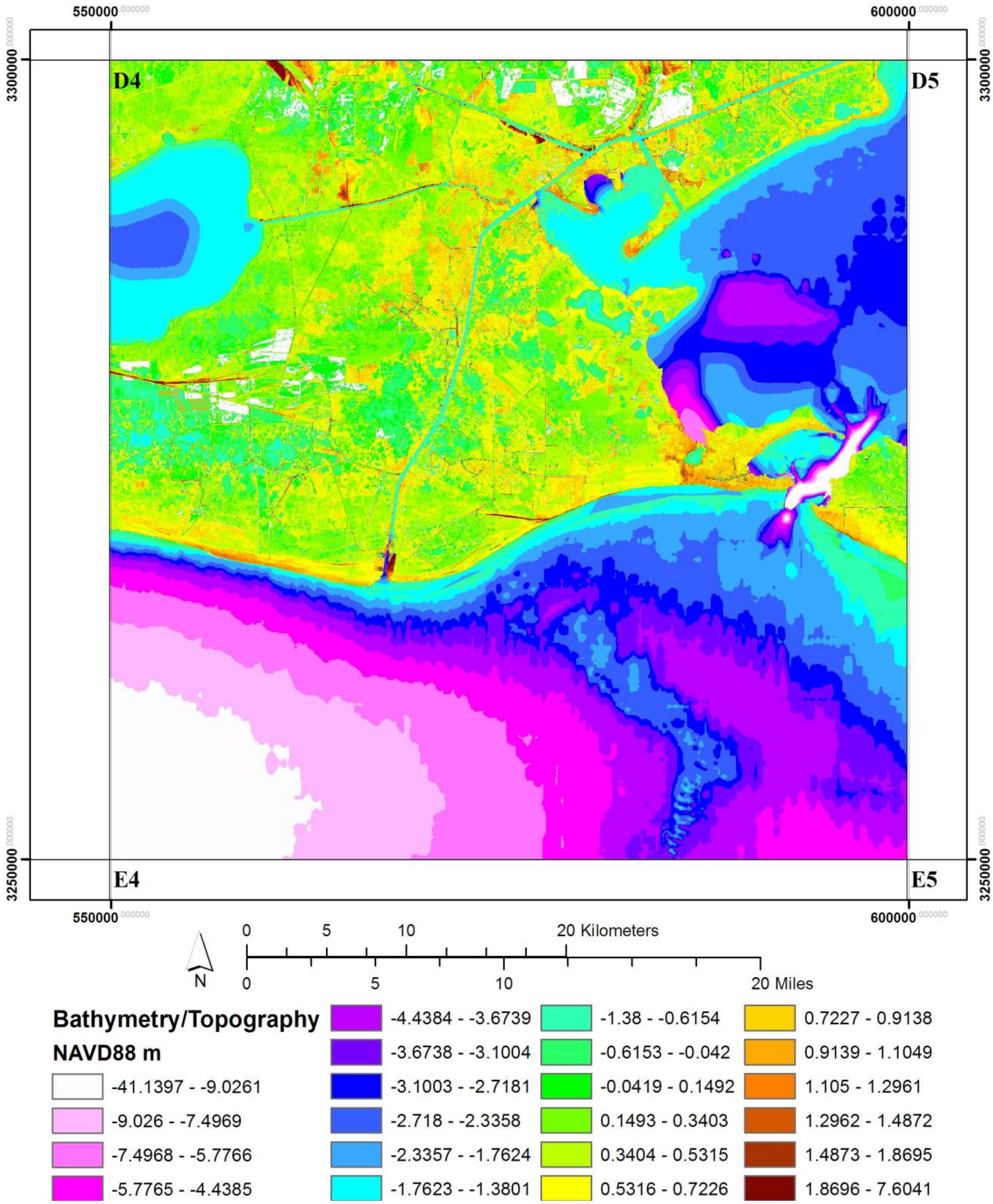


Figure 28: Grid D4 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

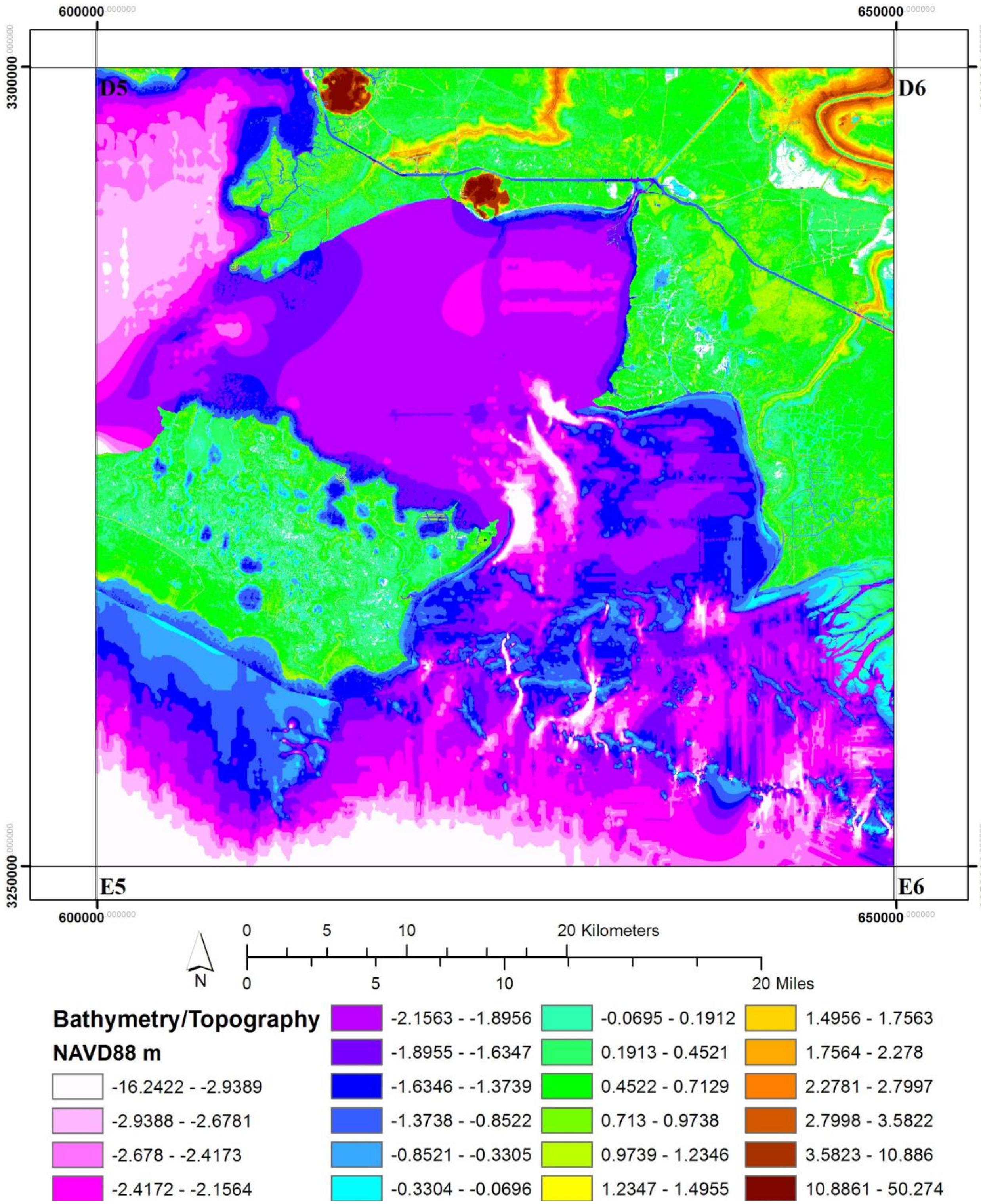


Figure 29: Grid D5 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

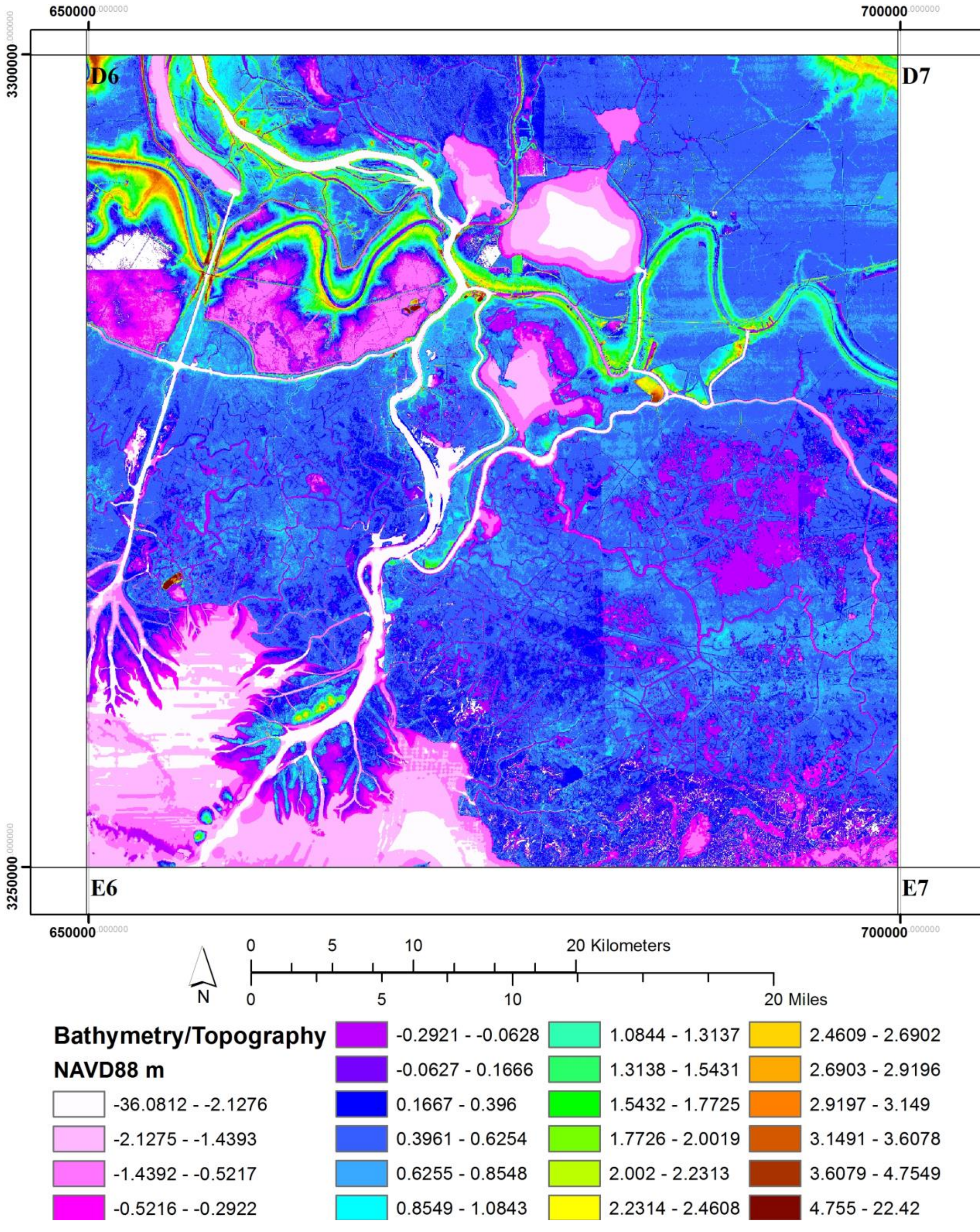


Figure 30: Grid D6 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

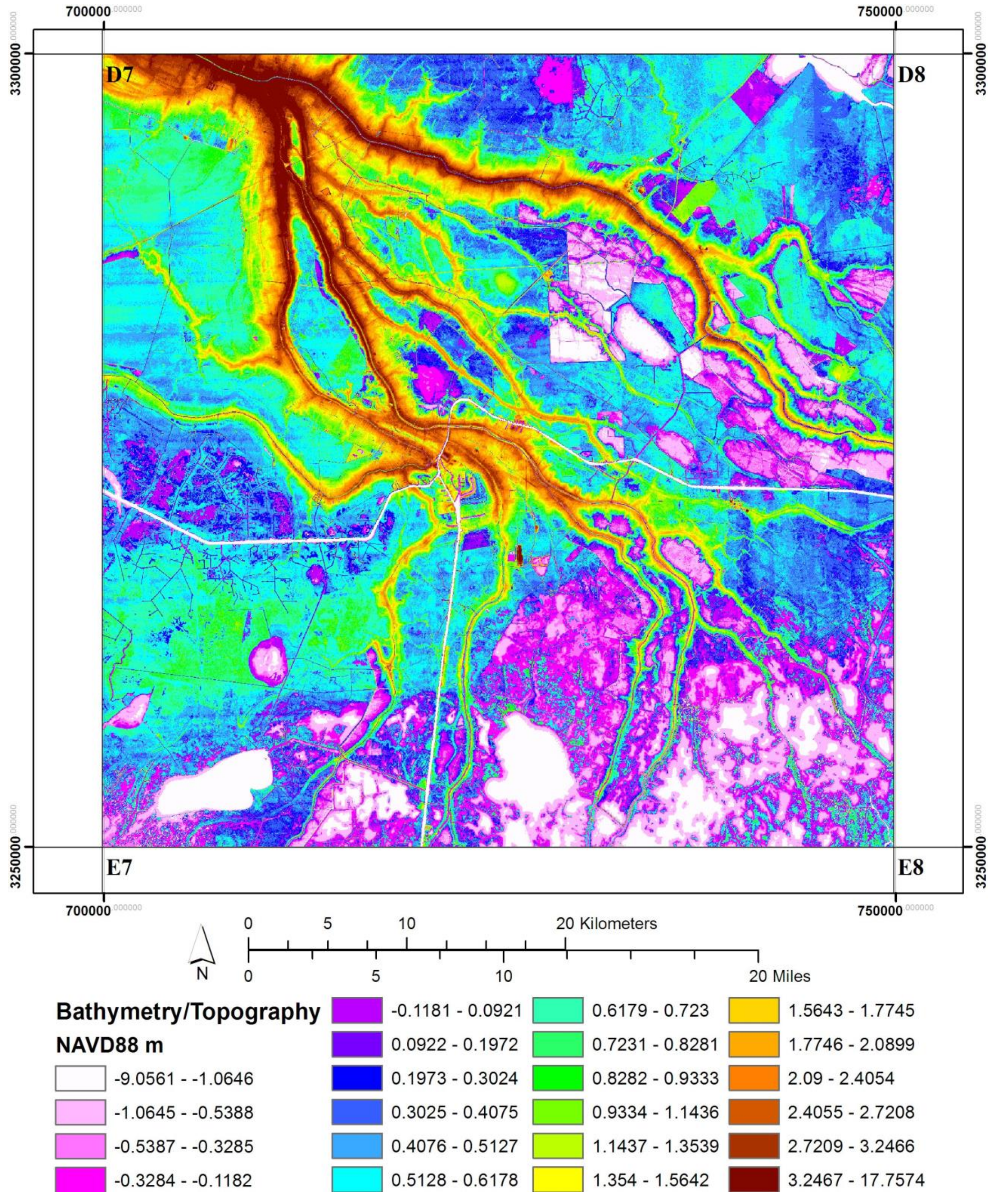


Figure 31: Grid D7 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

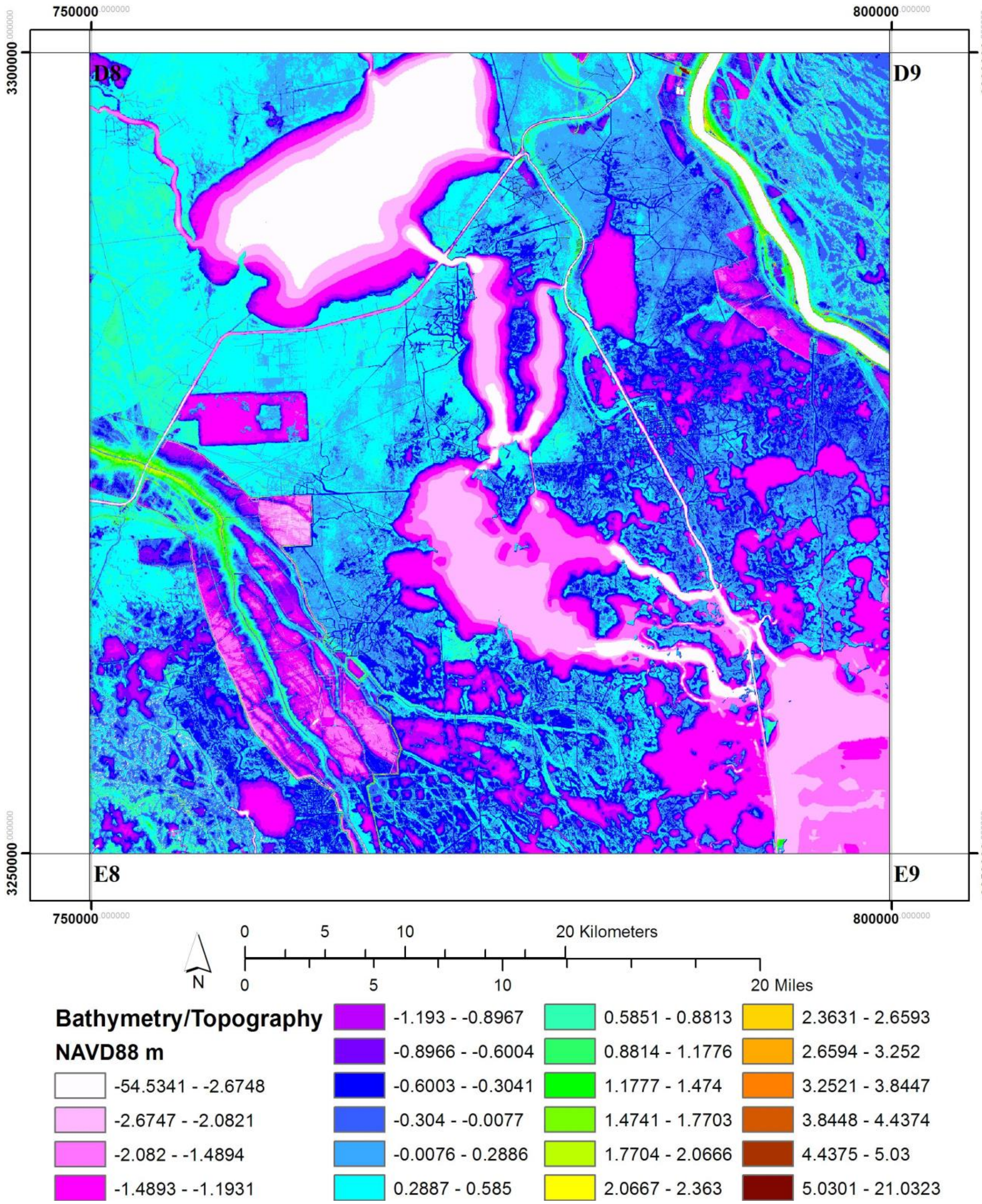


Figure 32: Grid D8 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

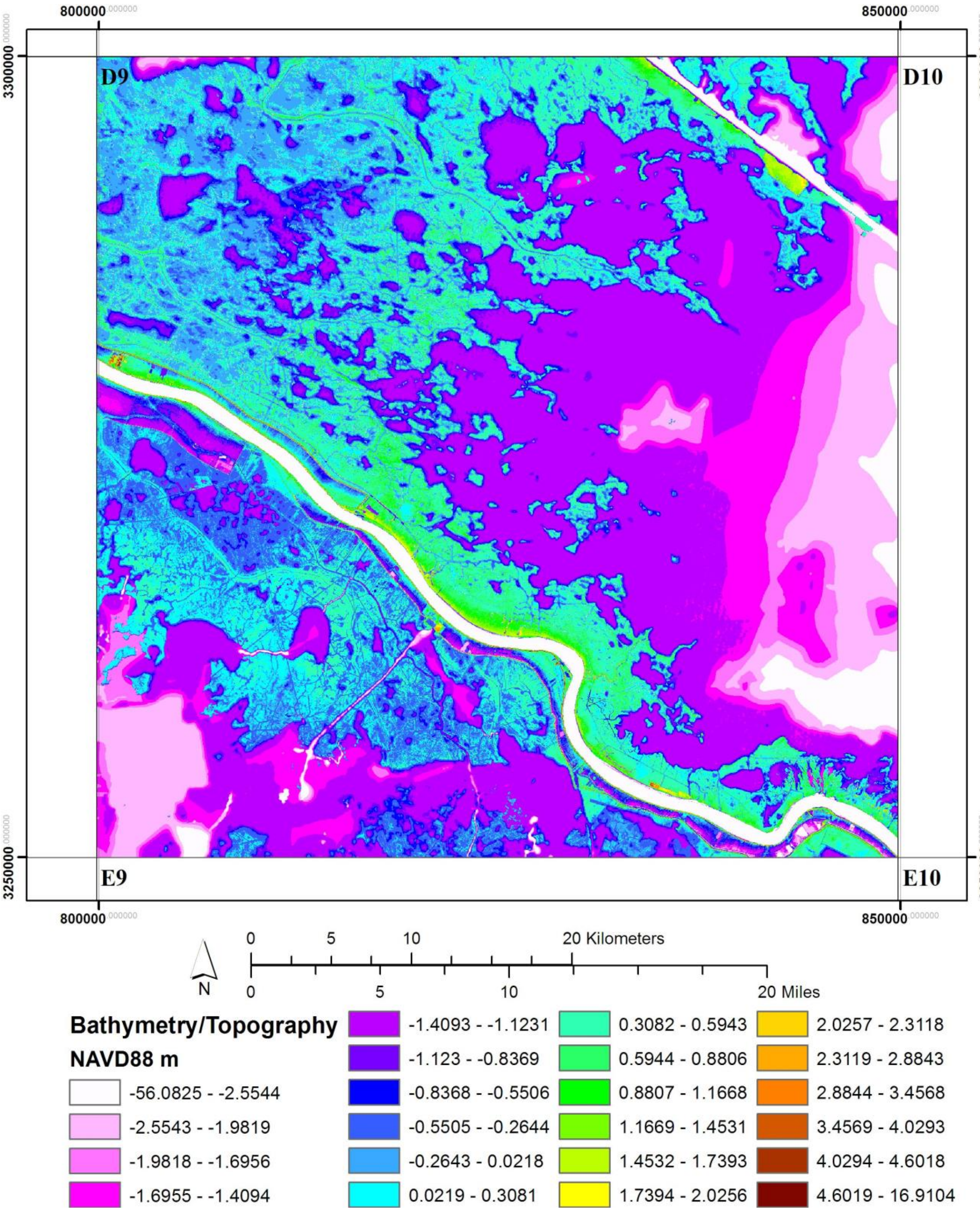


Figure 33: Grid D9 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

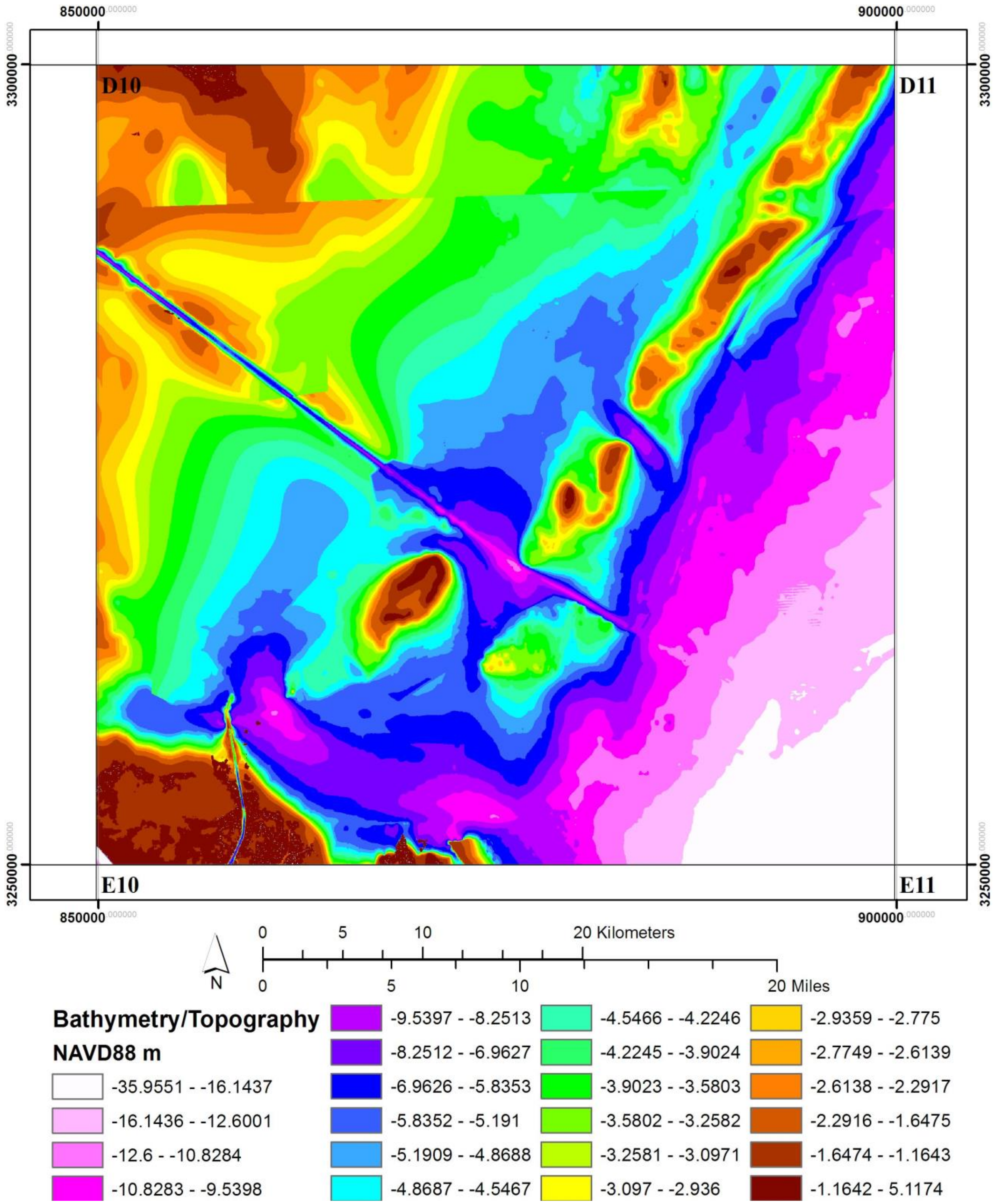


Figure 34: Grid D10 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

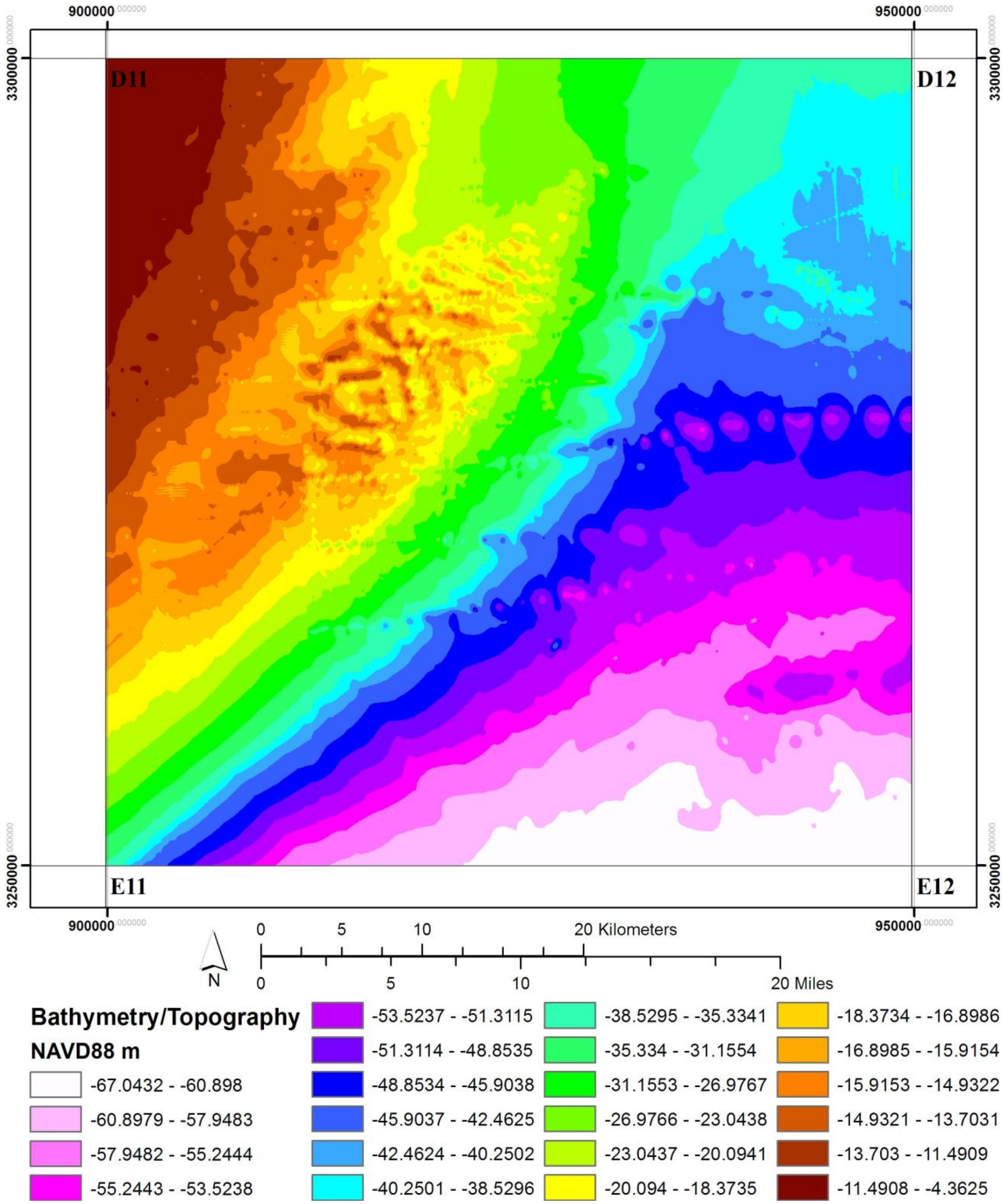


Figure 35: Grid D11 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

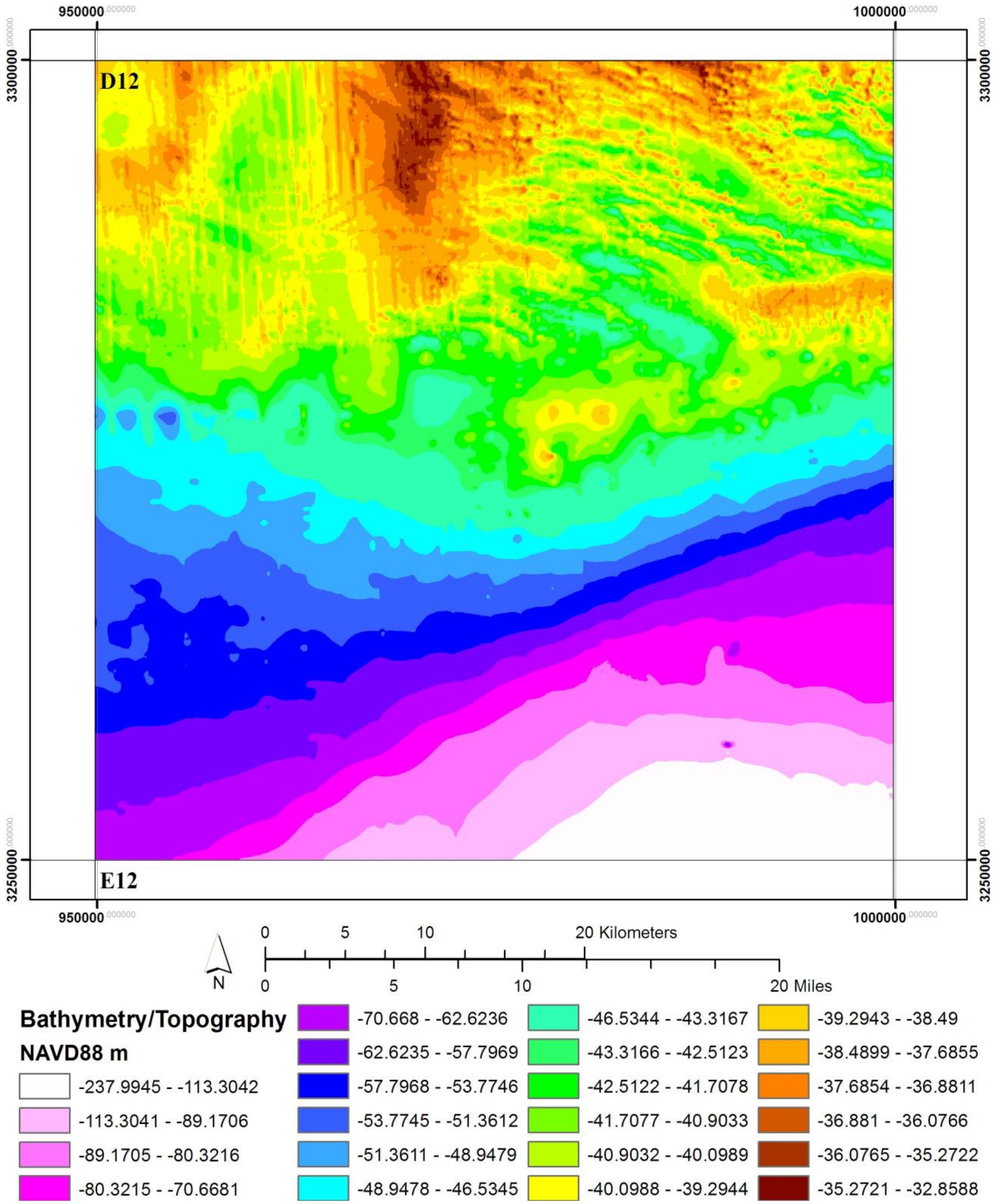


Figure 36: Grid D12 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

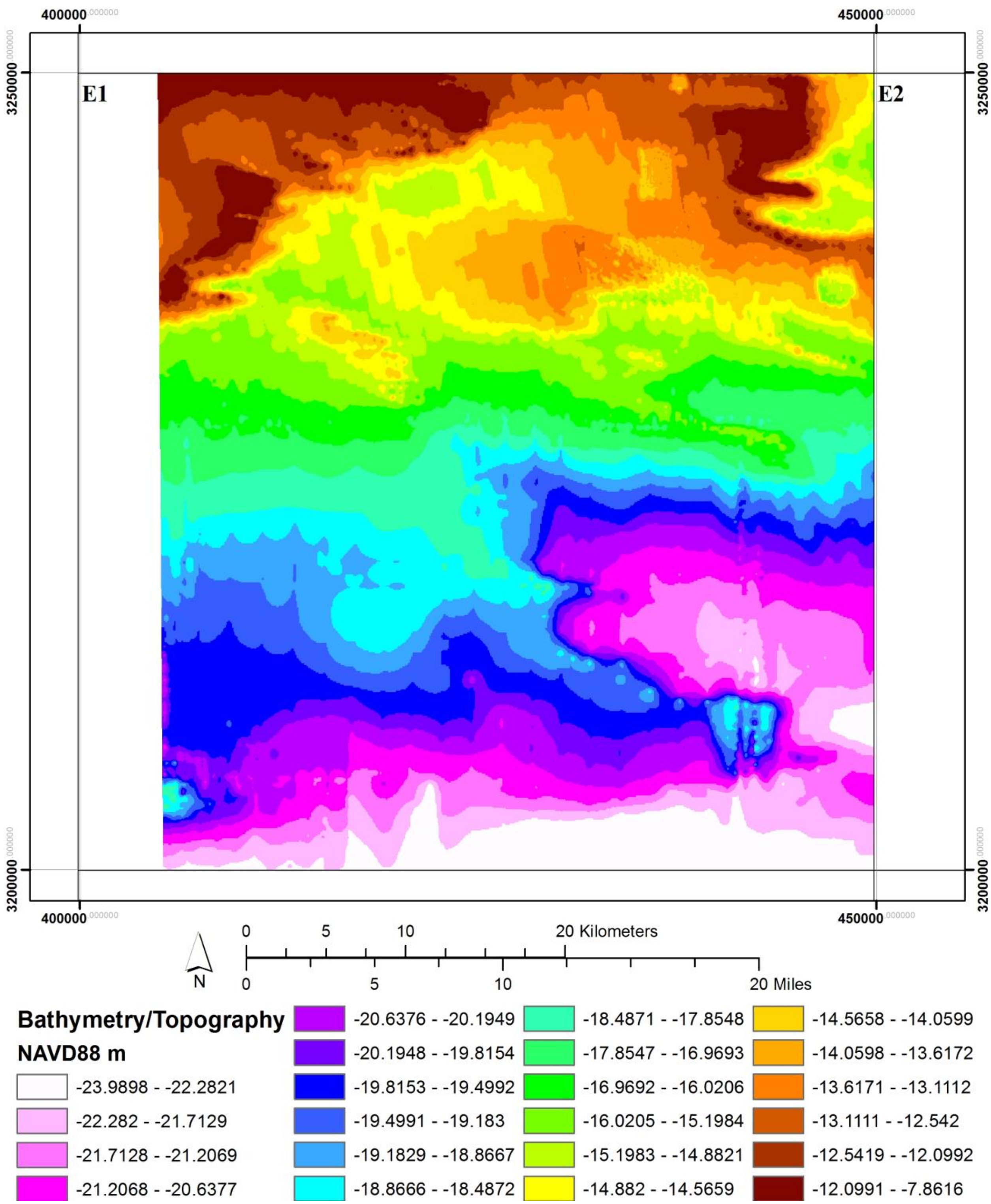


Figure 37: Grid E1 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

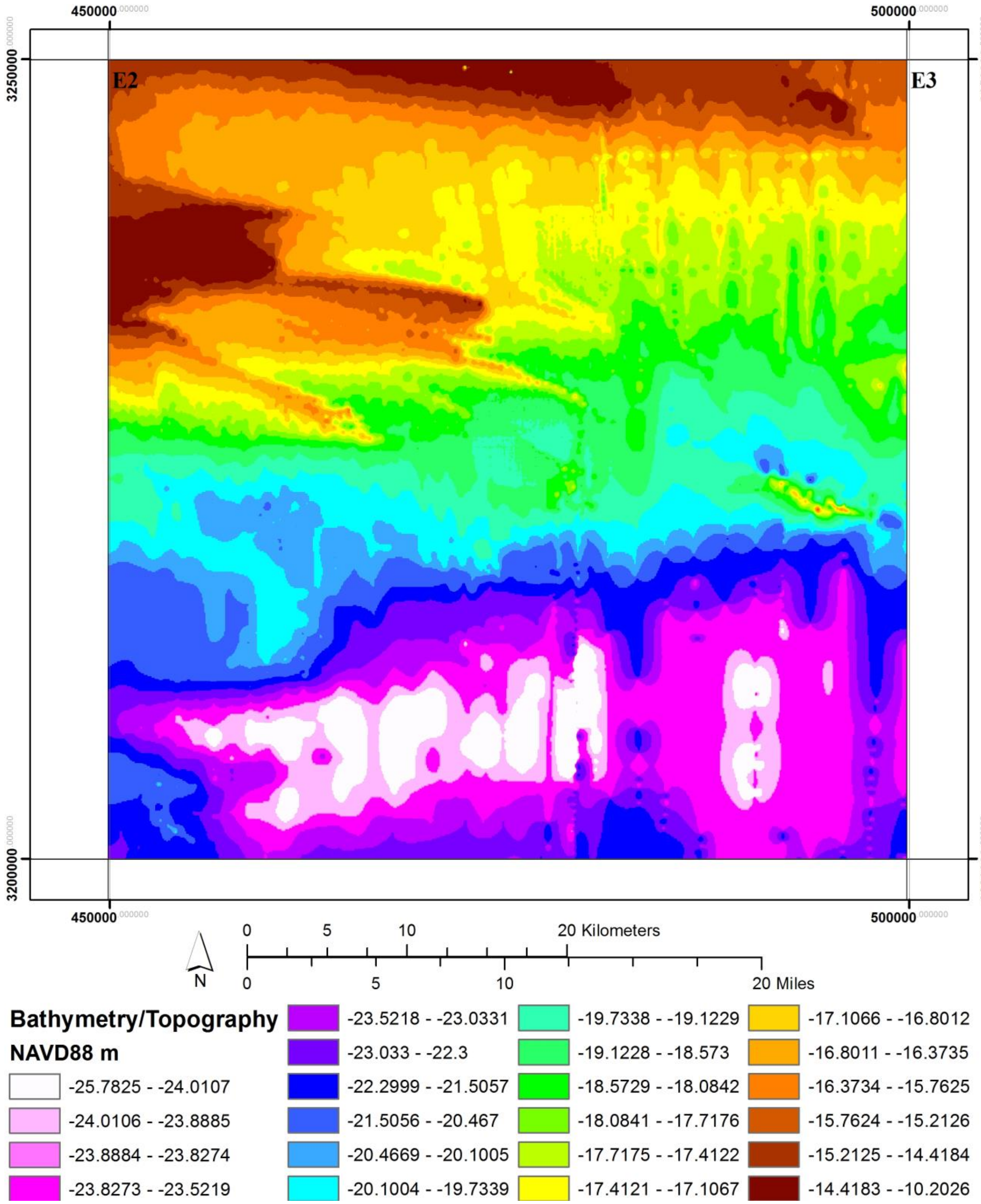


Figure 38: Grid E2 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

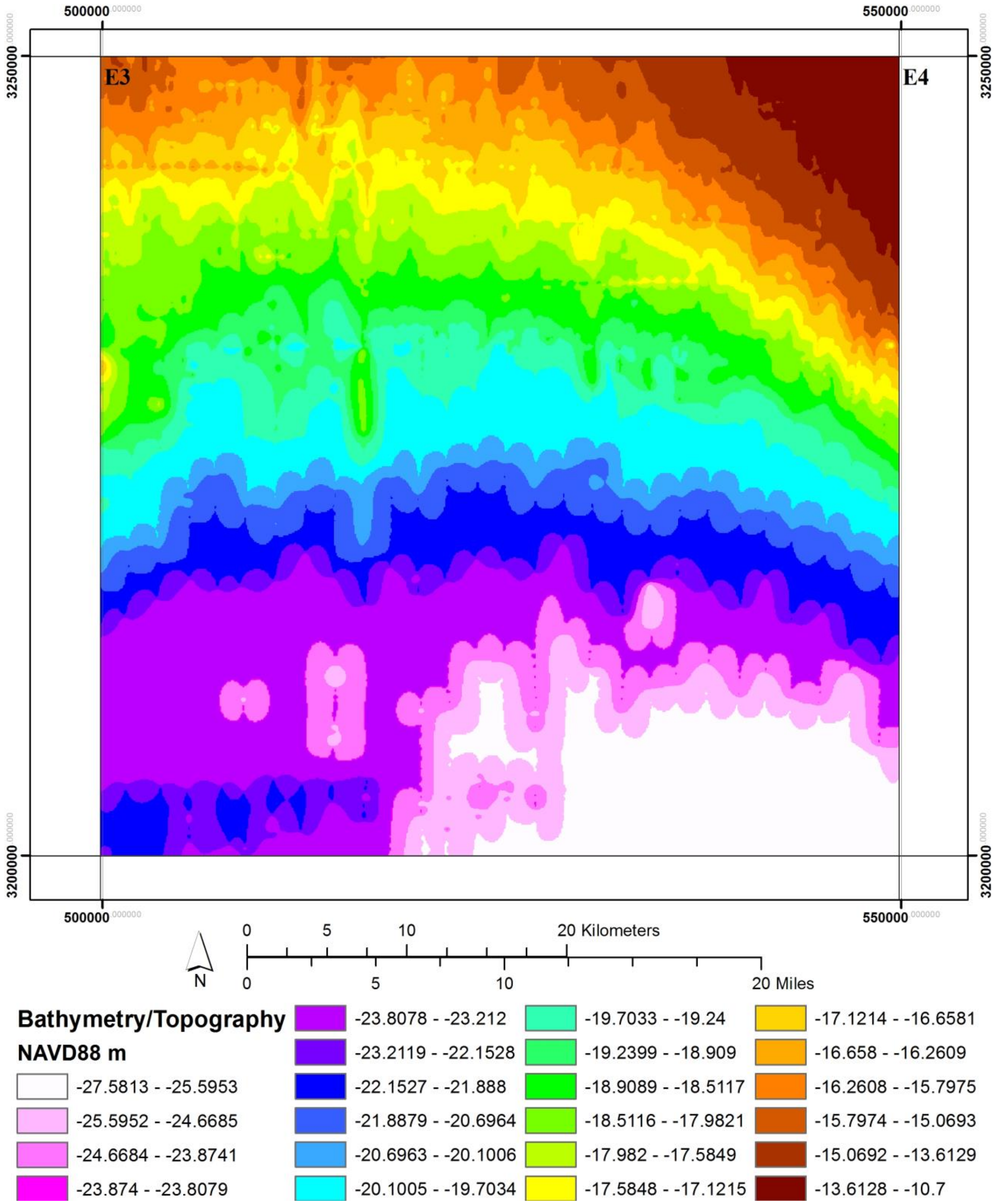


Figure 39: Grid E3 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

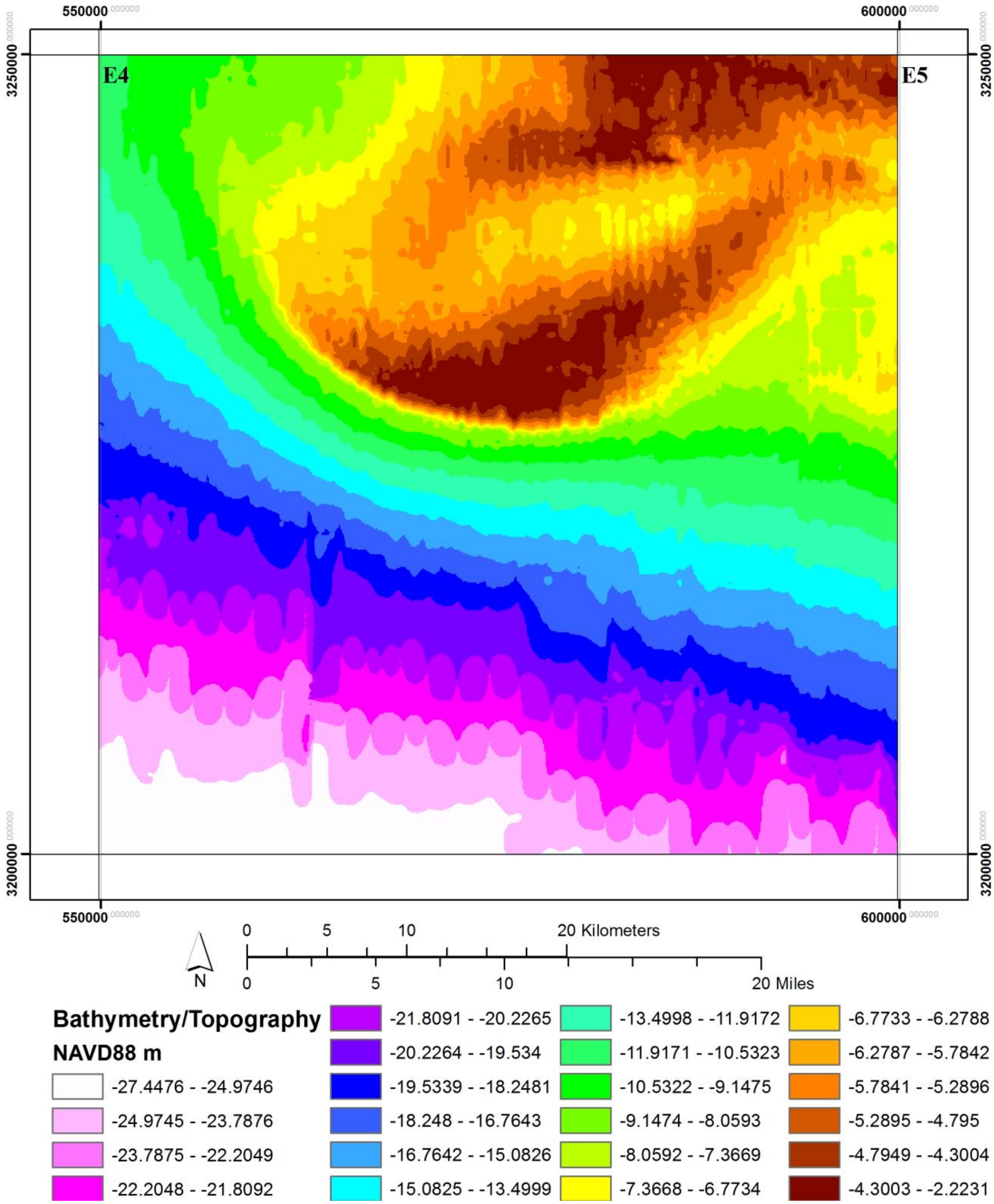


Figure 40: Grid E4 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

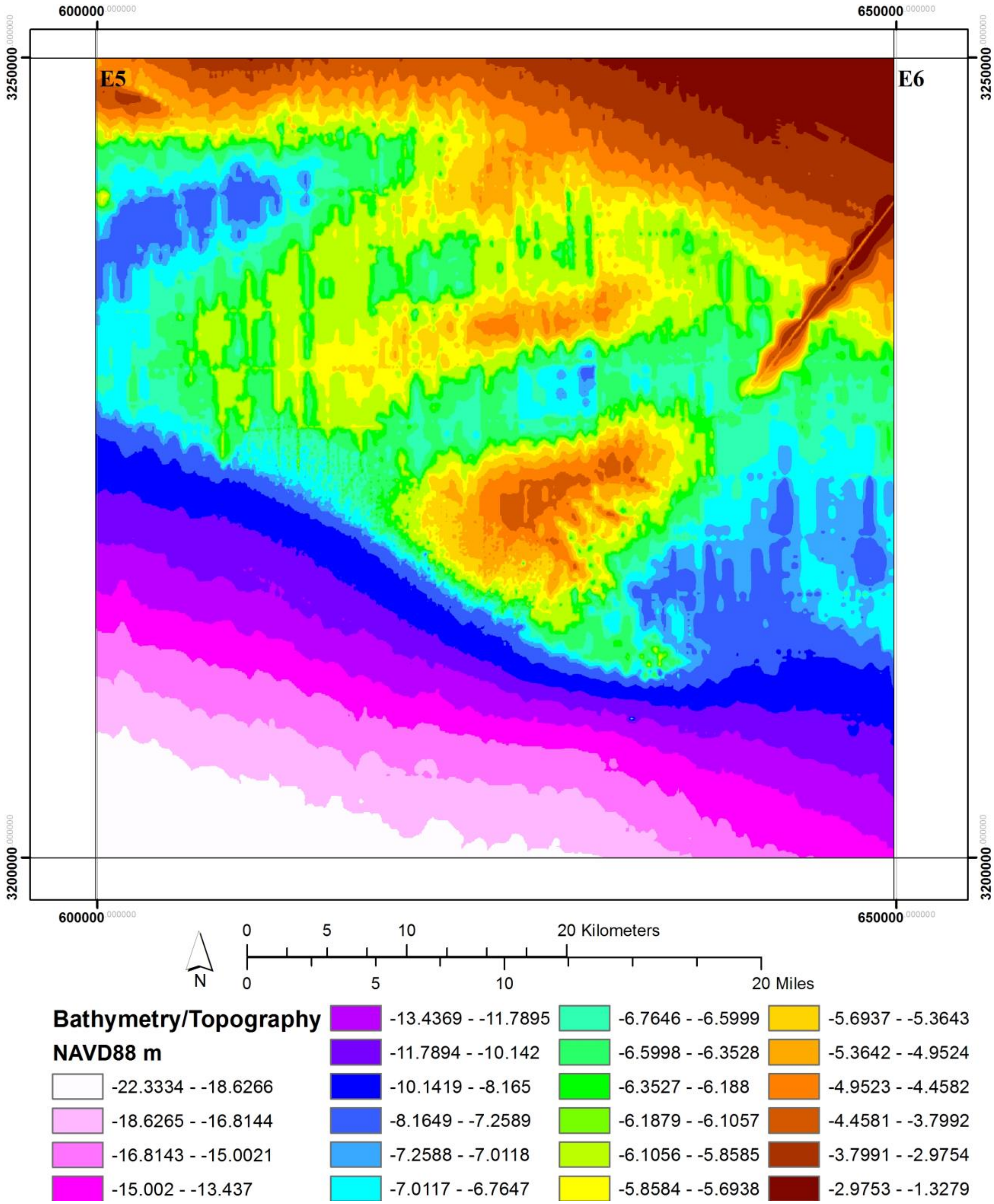


Figure 41: Grid E5 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

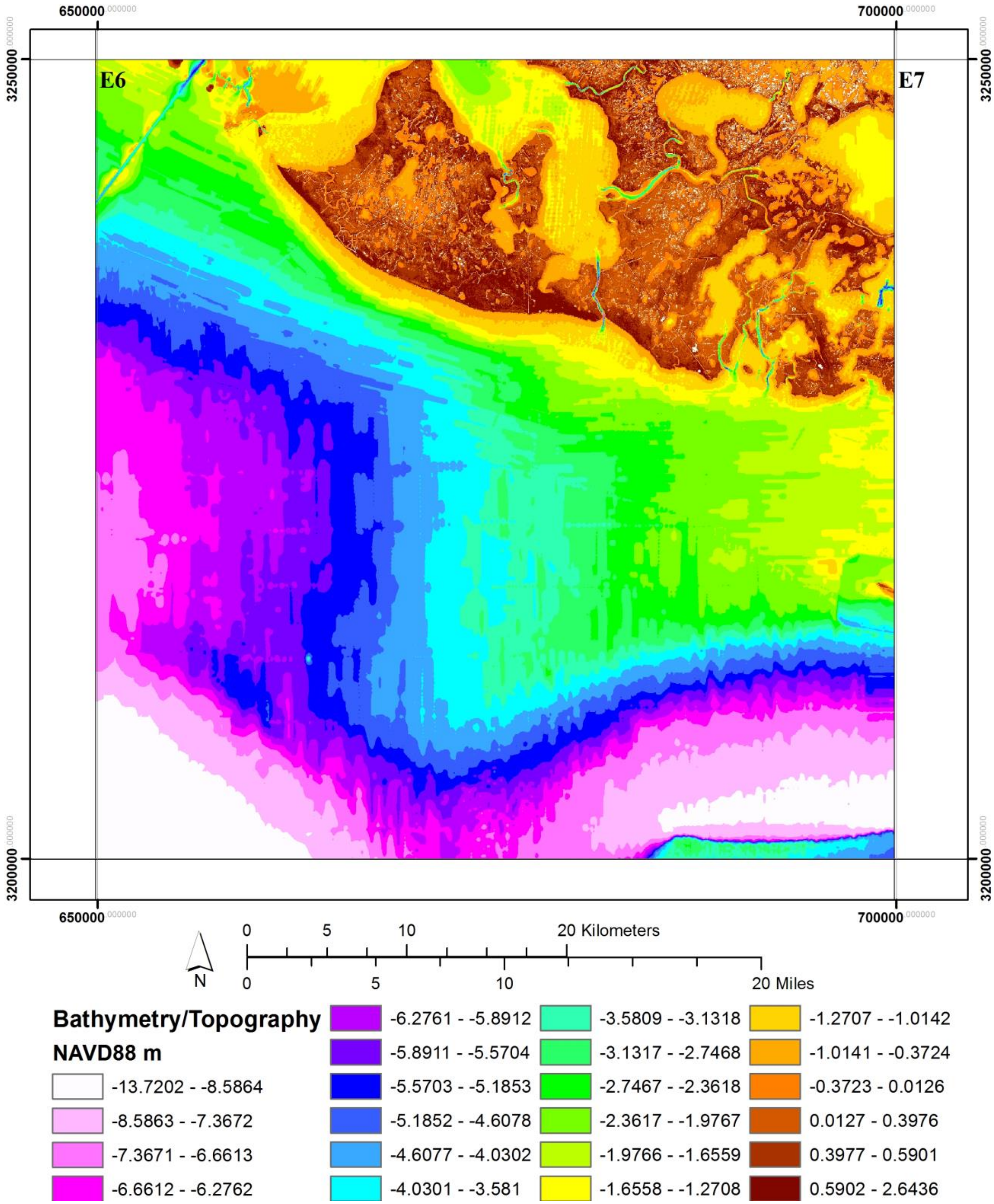


Figure 42: Grid E6 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

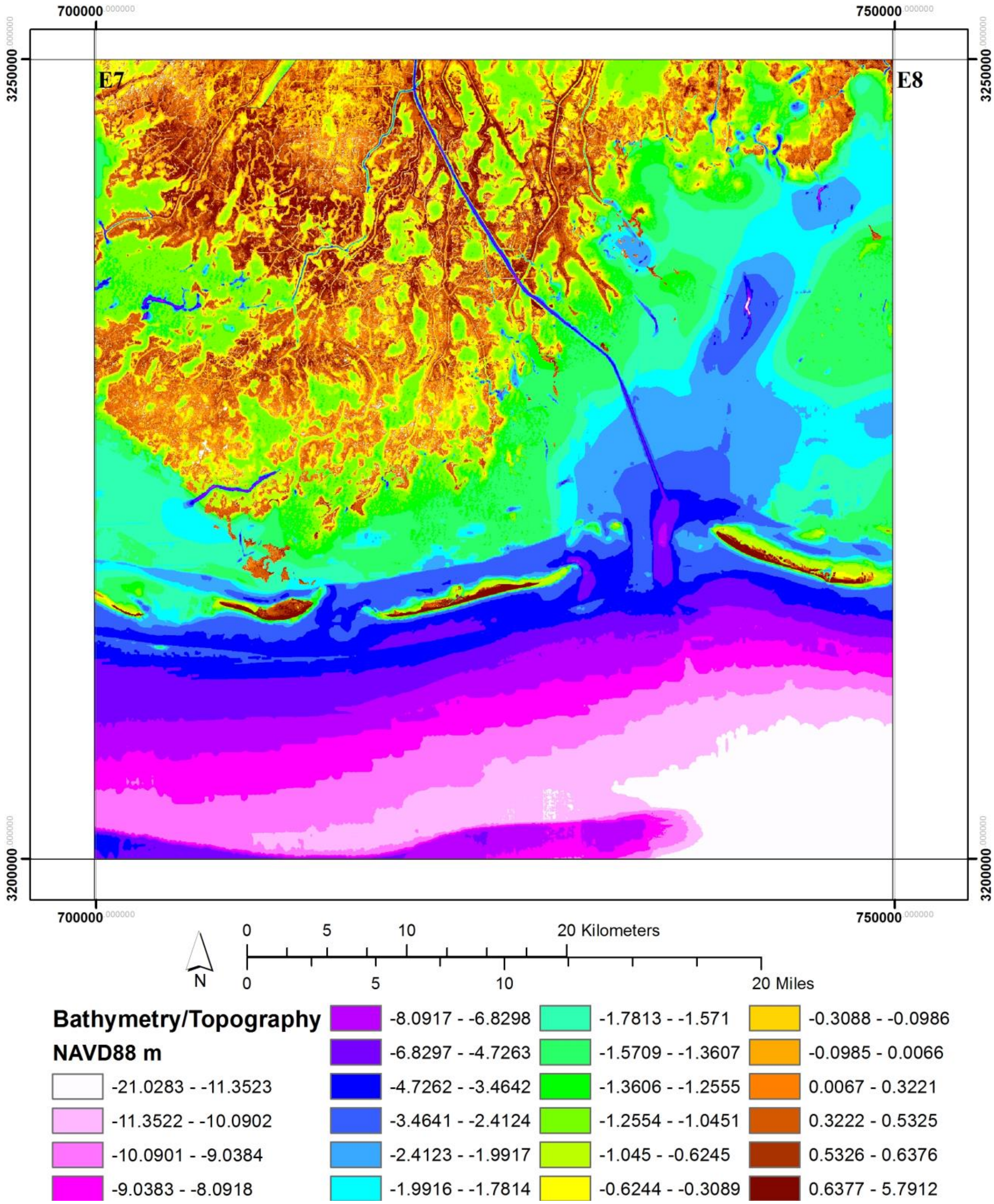
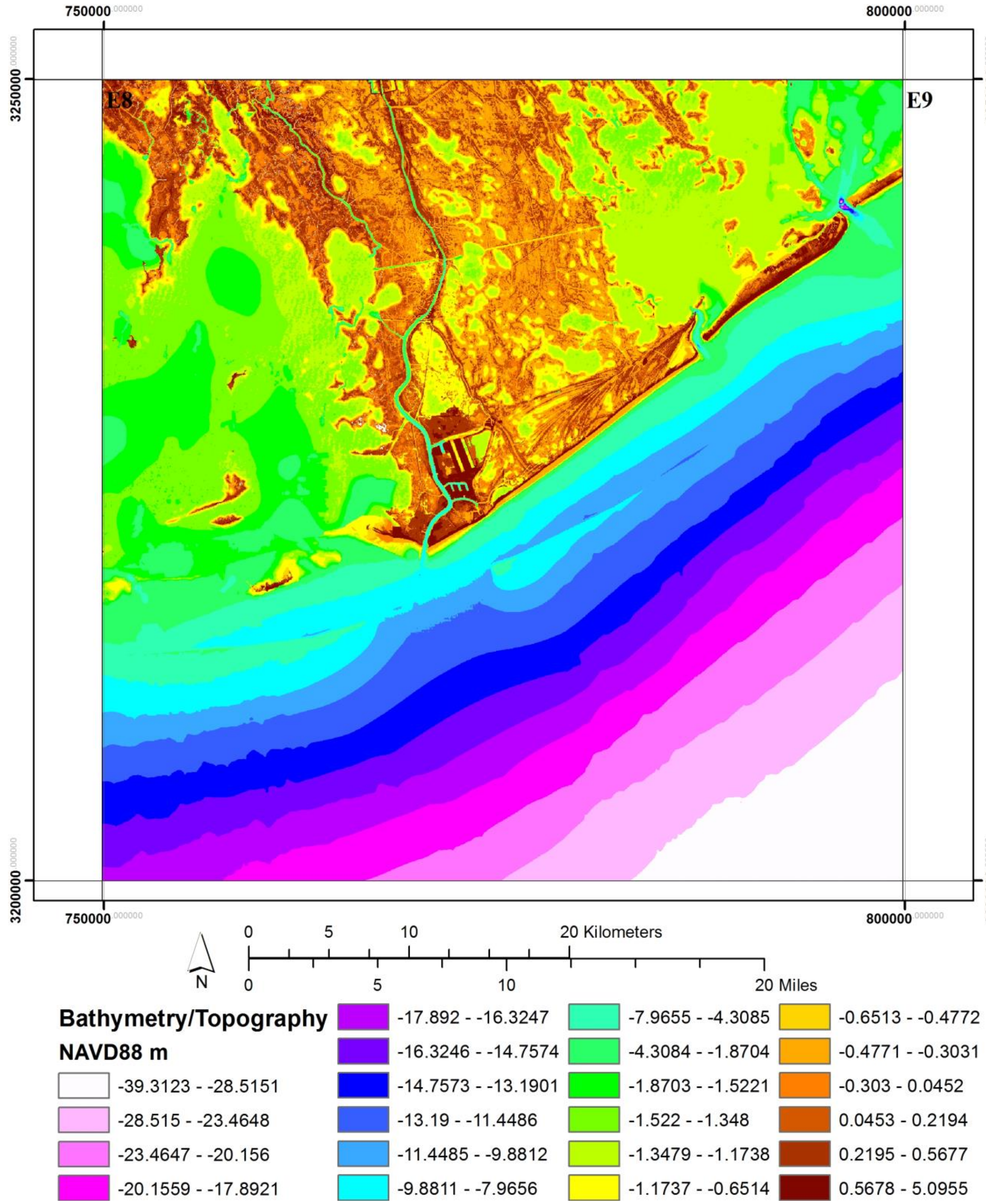


Figure 43: Grid E7 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.



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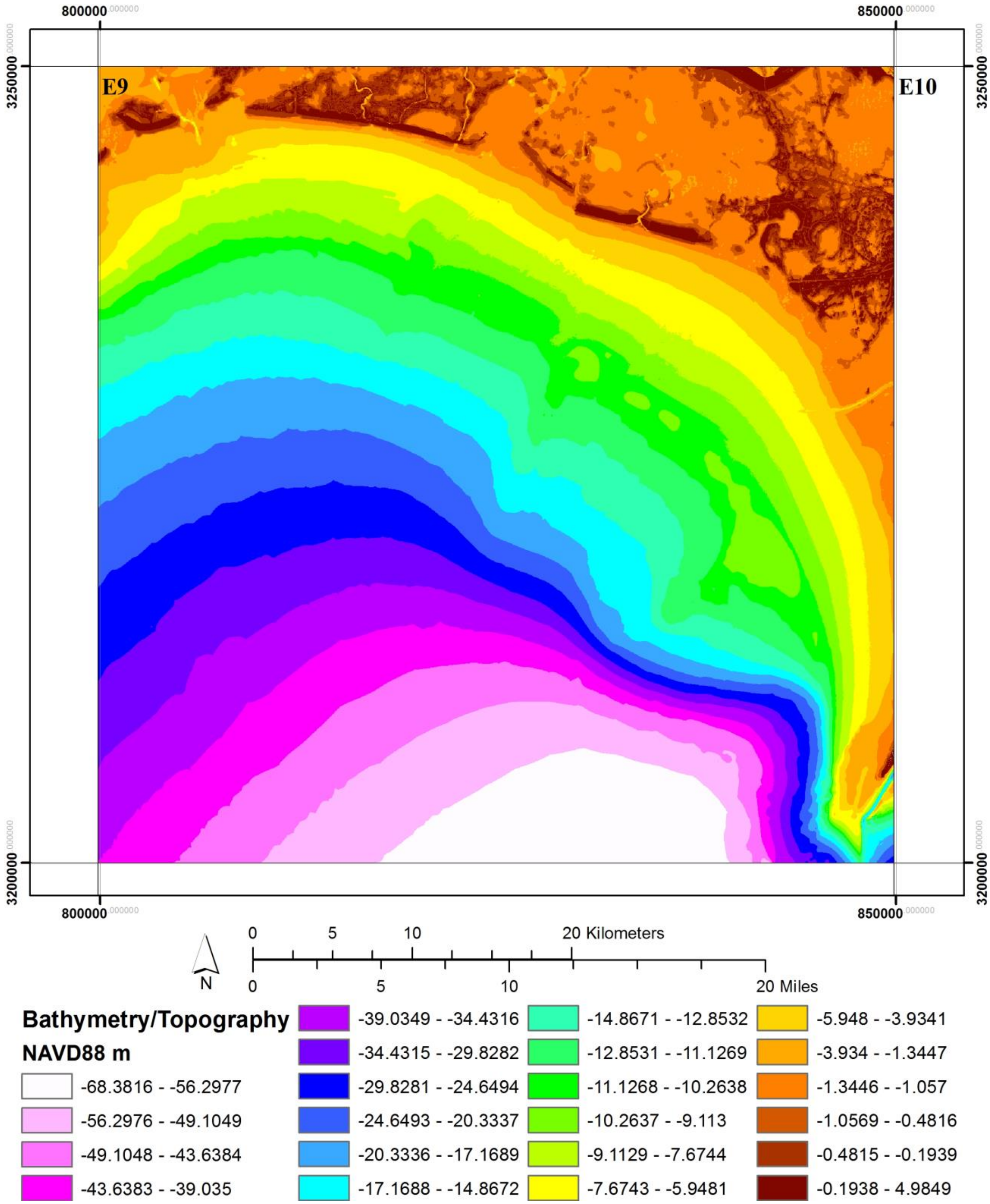

Figure 45: Grid E9 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

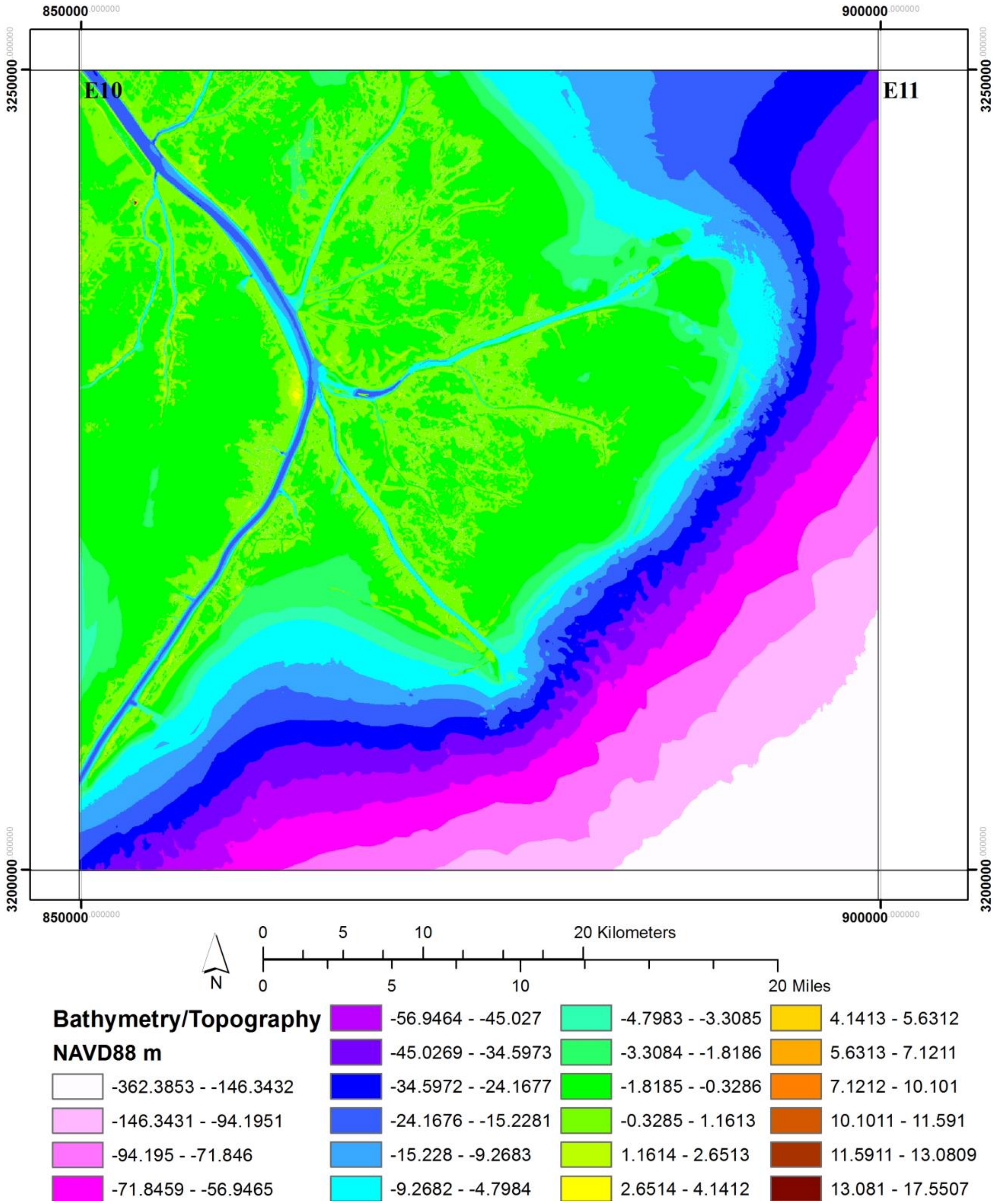

Figure 46: Grid E10 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

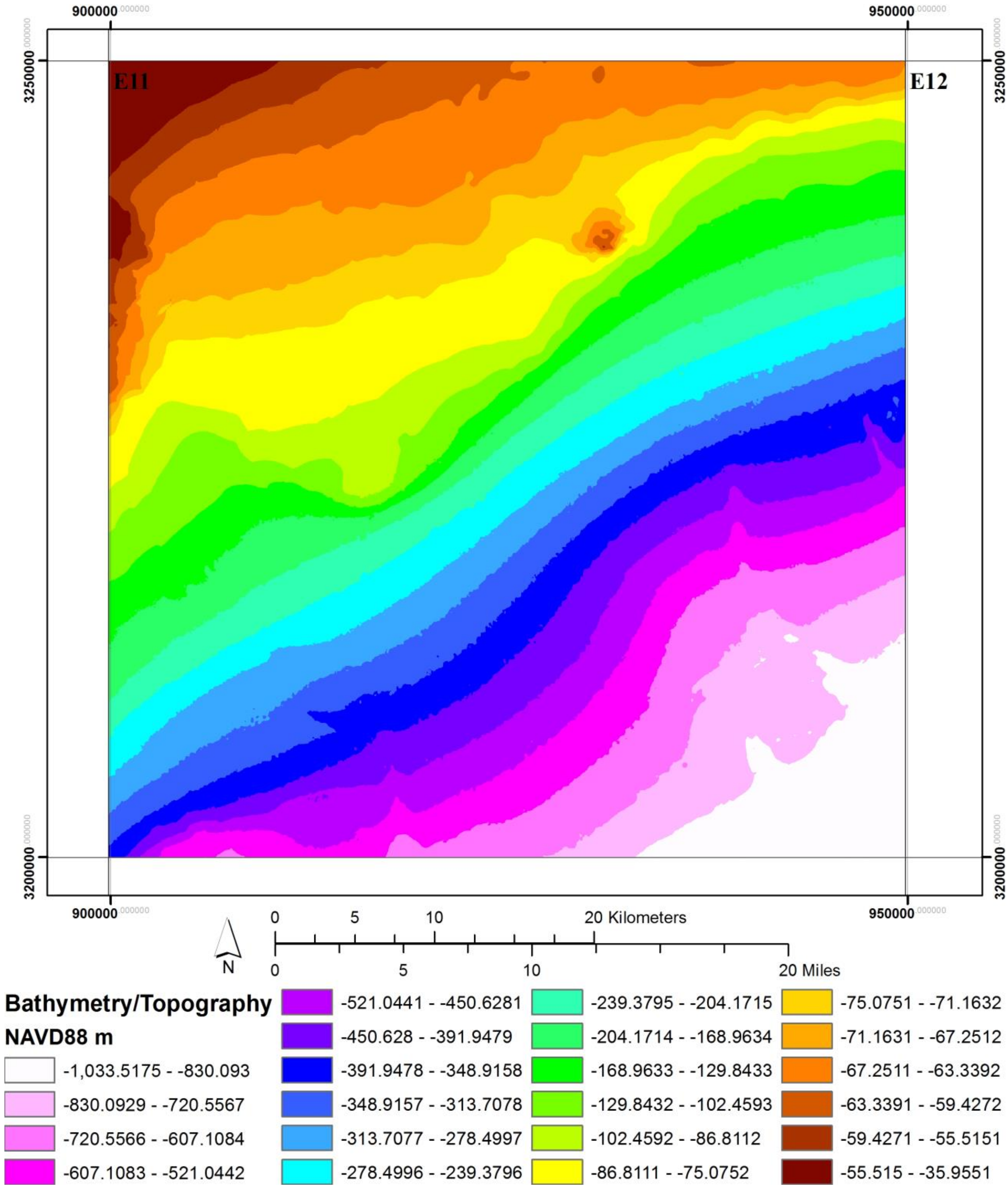

Figure 47: Grid E11 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

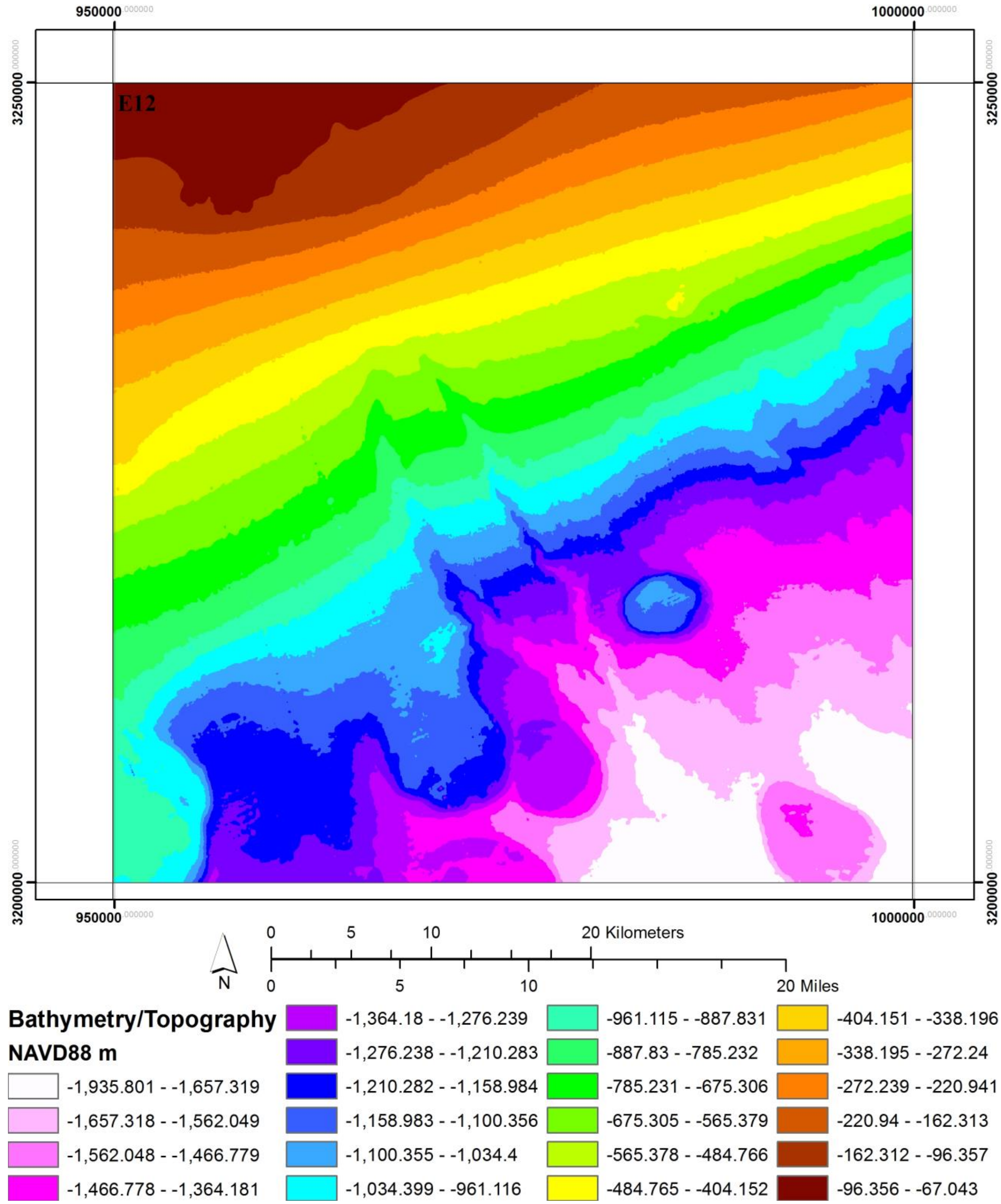

Figure 48: Grid E12 of the 2017 Coastal Master Plan Integrated Bathymetry/Topography Base Condition Dataset. Grid units are UTM WGS84 Zone 15N.

3.3. Vegetation Community Type Classification

The resulting 2014 Vegetation Community Type Classification is provided in

Figure 49. While broad differences in vegetation types can be observed in this figure, the dataset contains too many classes for each to be distinguishable by the human eye.

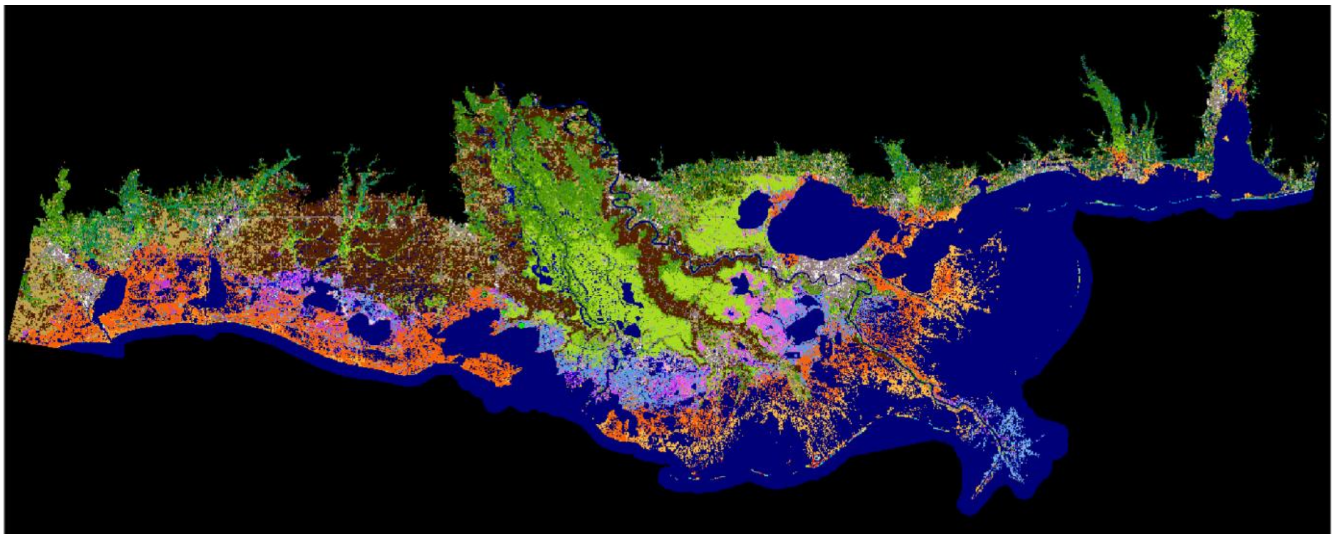

Figure 49: Landscape Scale View of the 2014 Base Conditions Vegetation Community Type Dataset.

A legend has been purposefully omitted from this figure as the colors would be indiscernible for most classes. For this reason, vegetation types must be visualized individually and such, individual visualizations are provided in Figure 50 through Figure 58.

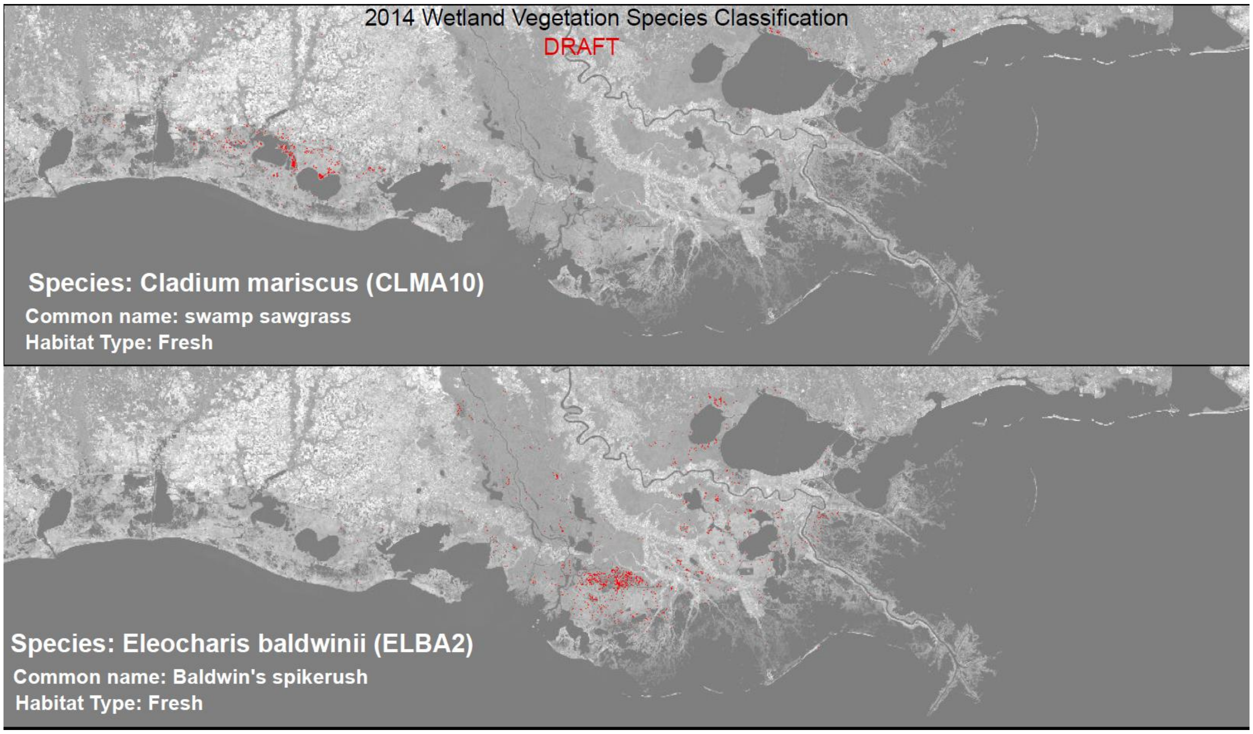

Figure 50: Vegetation Community Type Classification: Dominant Species CLMA10 and ELBA2.

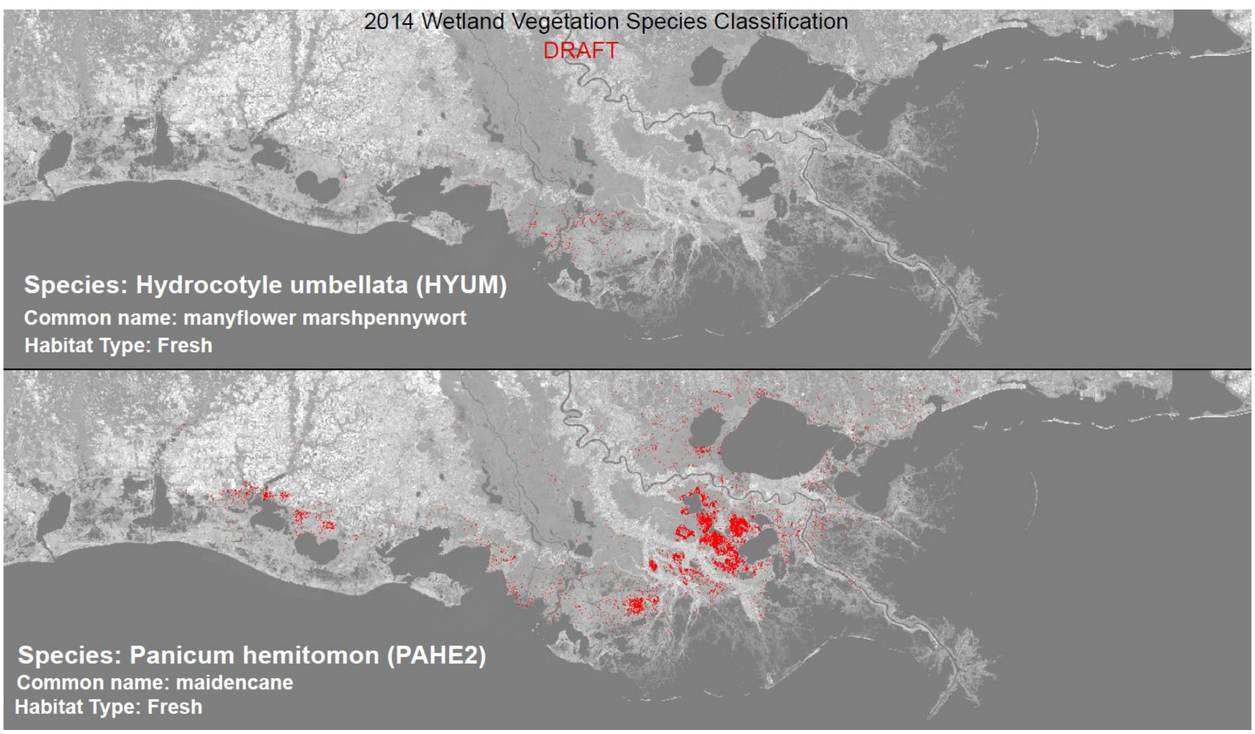

Figure 51: Vegetation Community Type Classification: Dominant Species HYUM and PAHE2.

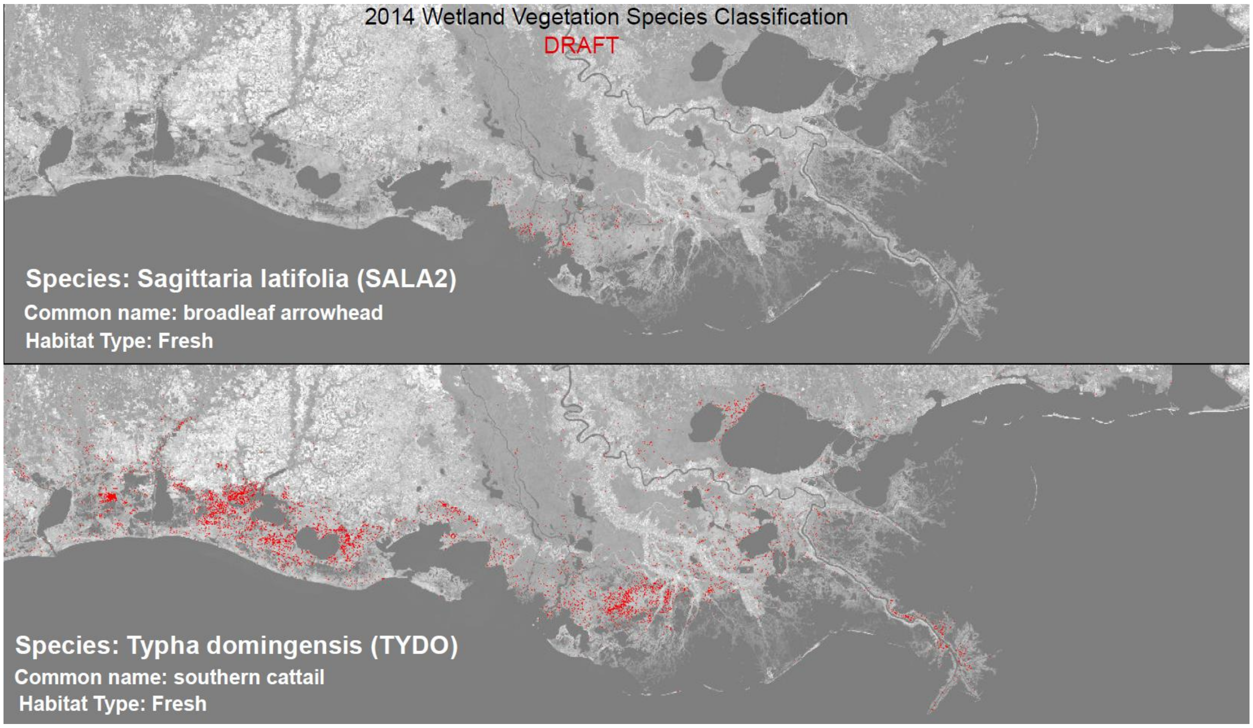

Figure 52: Vegetation Community Type Classification: Dominant Species SALA2 and TYDO.

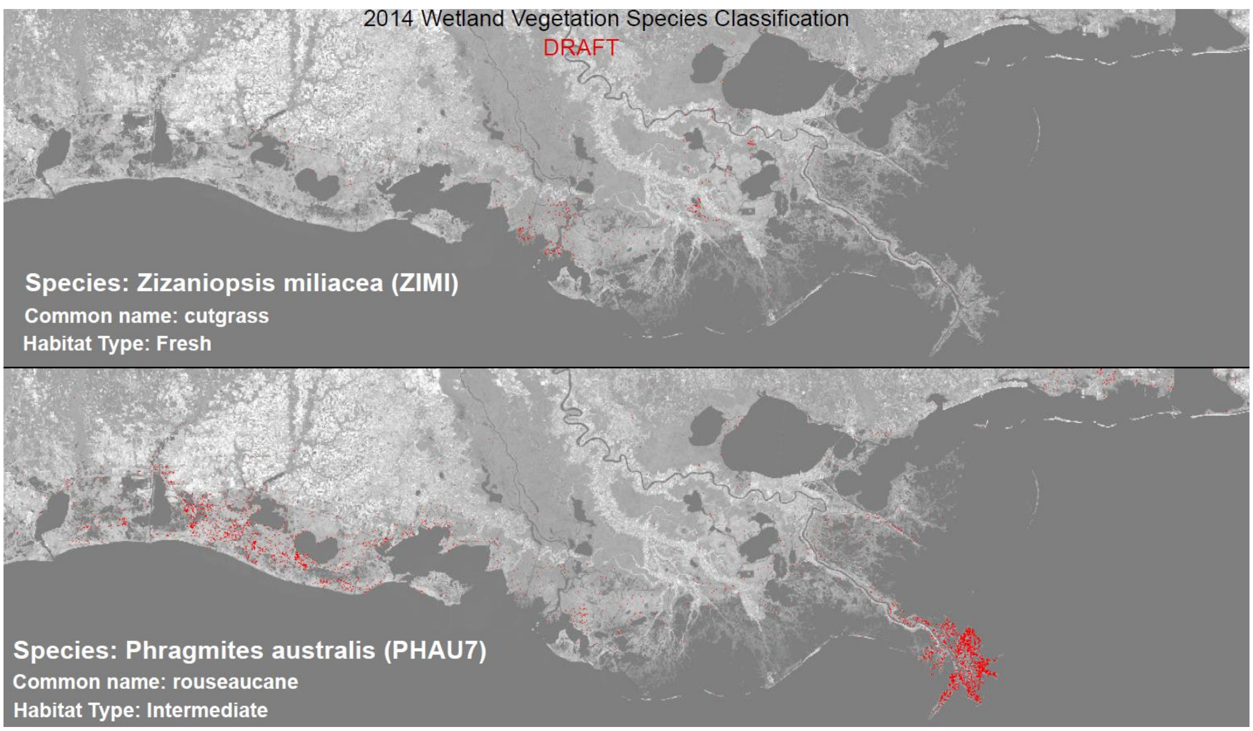

Figure 53: Vegetation Community Type Classification: Dominant Species ZIMI and PHAU7.

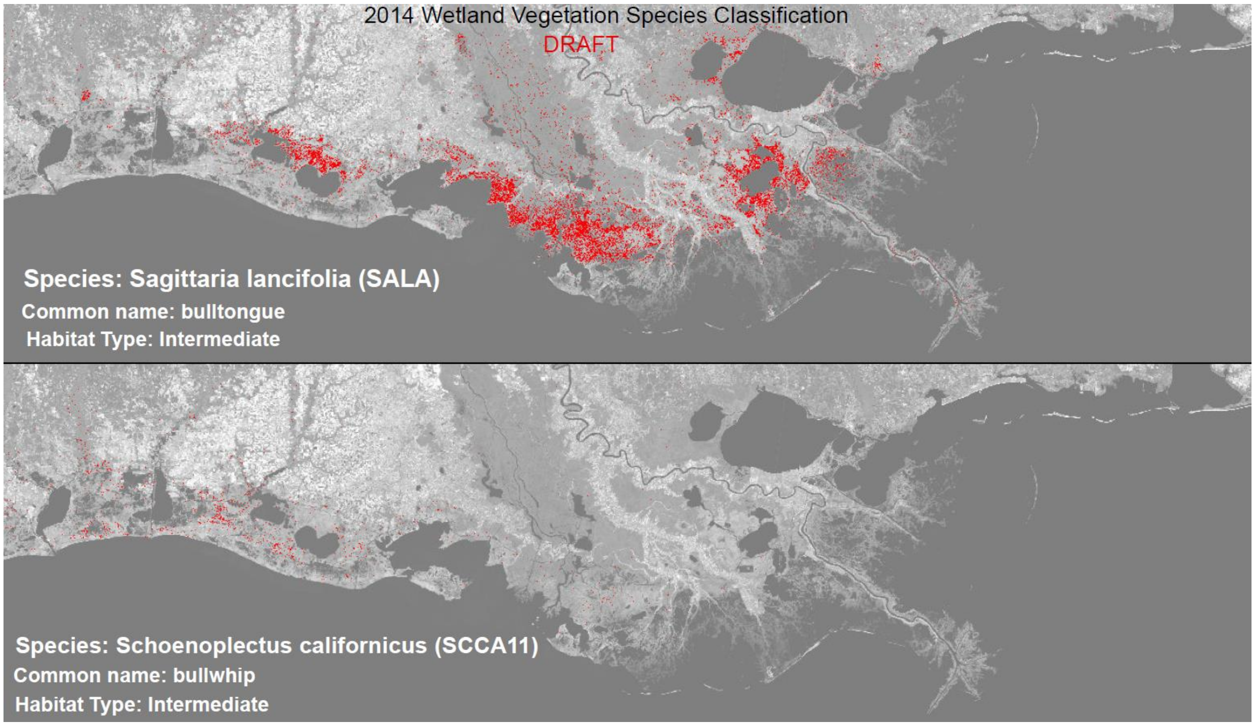

Figure 54: Vegetation Community Type Classification: Dominant Species SALA and SCCA11.

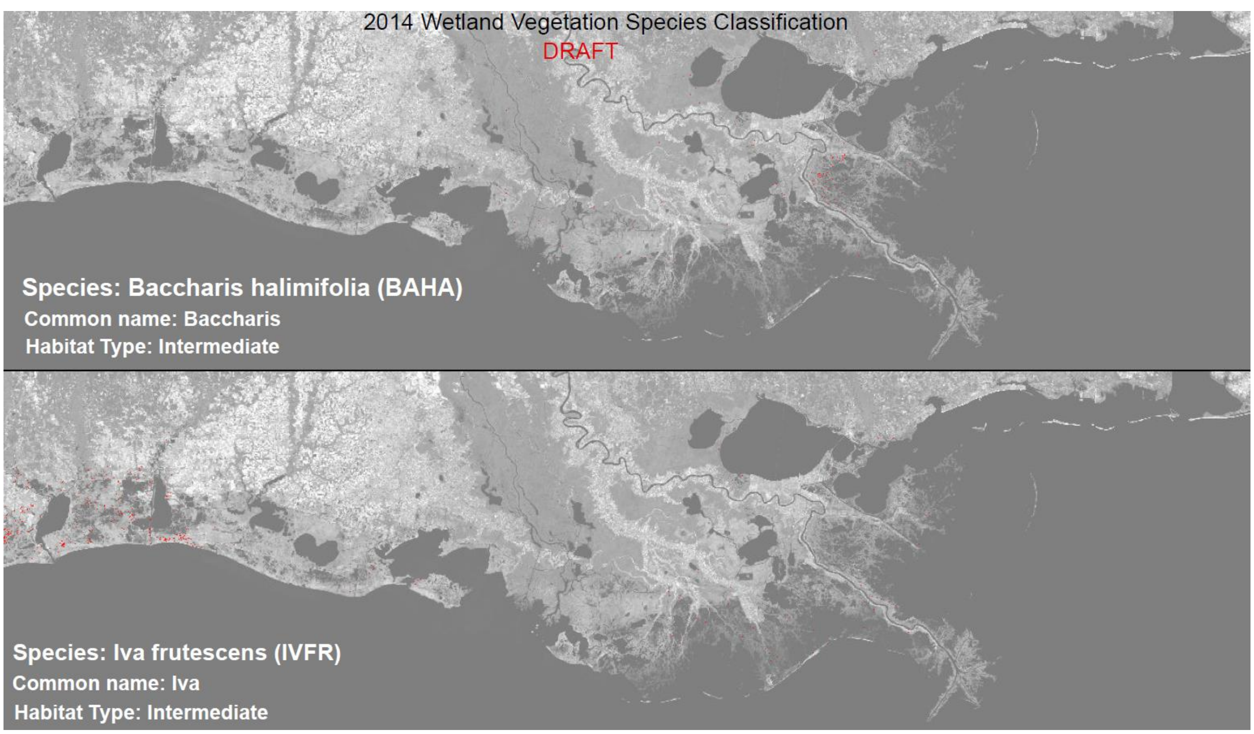

Figure 55: Vegetation Community Type Classification: Dominant Species BAHA and IVFR.

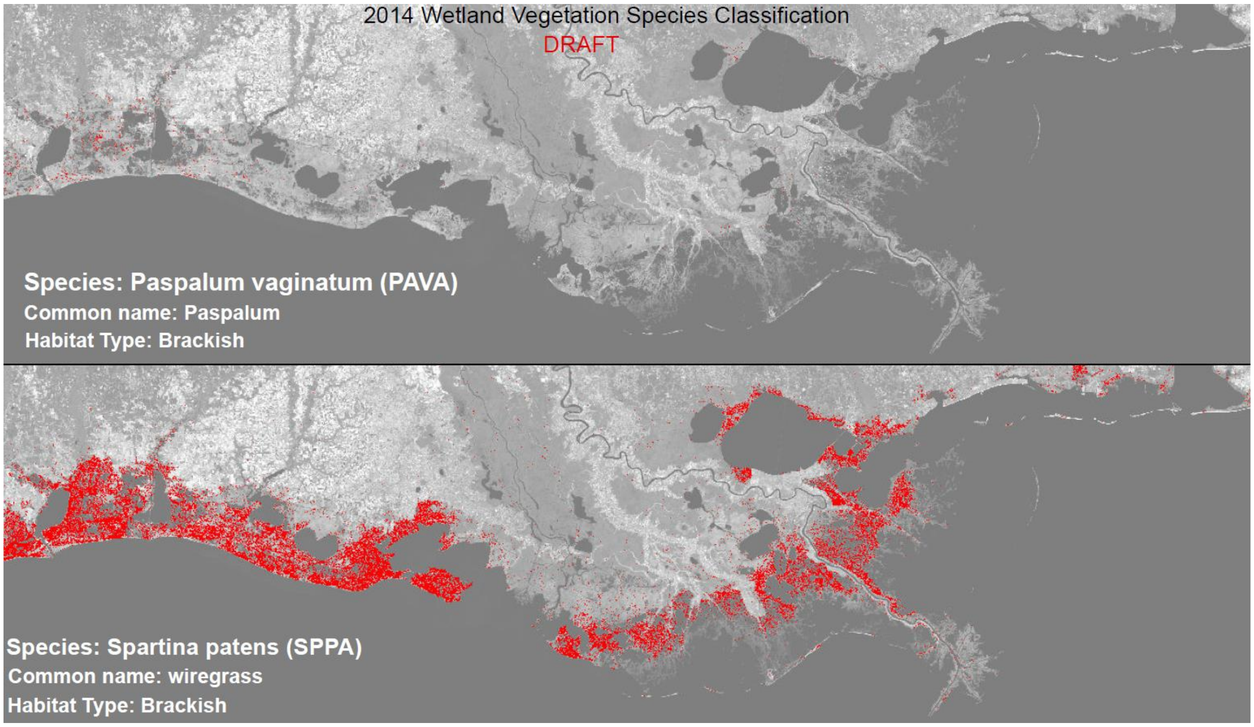

Figure 56: Vegetation Community Type Classification: Dominant Species PAVA and SPPA.

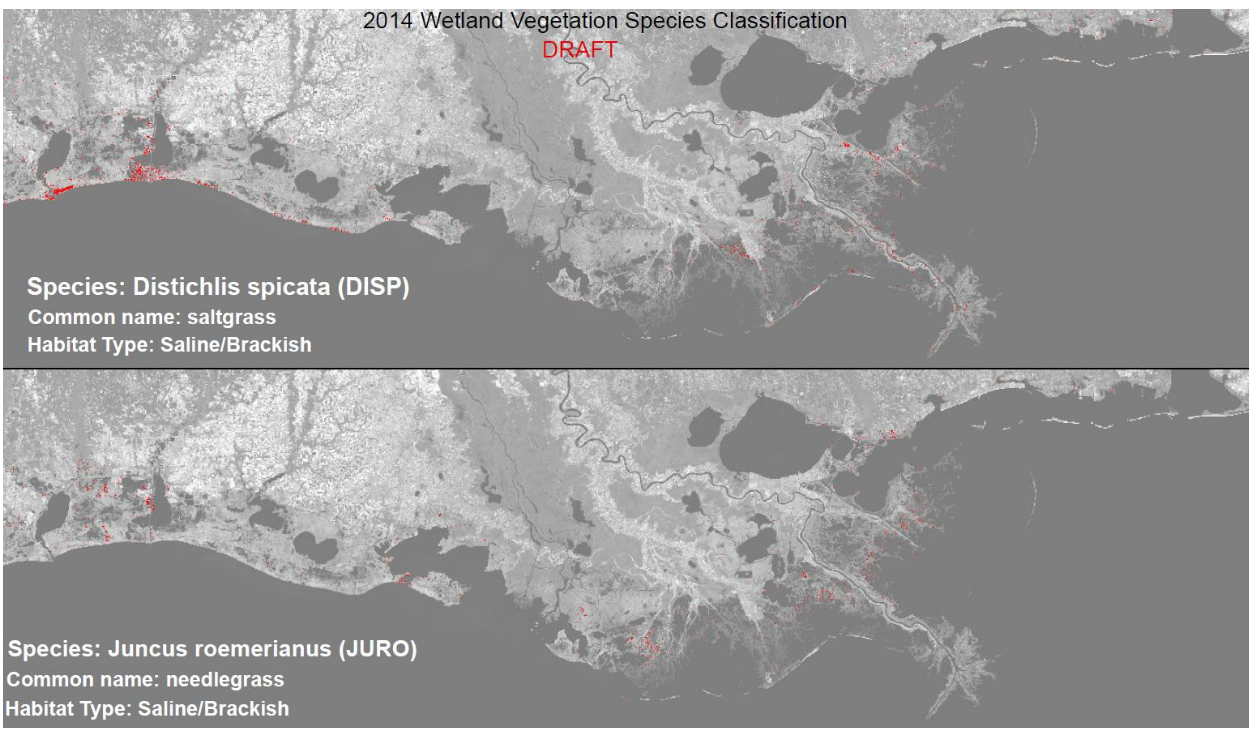

Figure 57: Vegetation Community Type Classification: Dominant Species DISP and JURO.

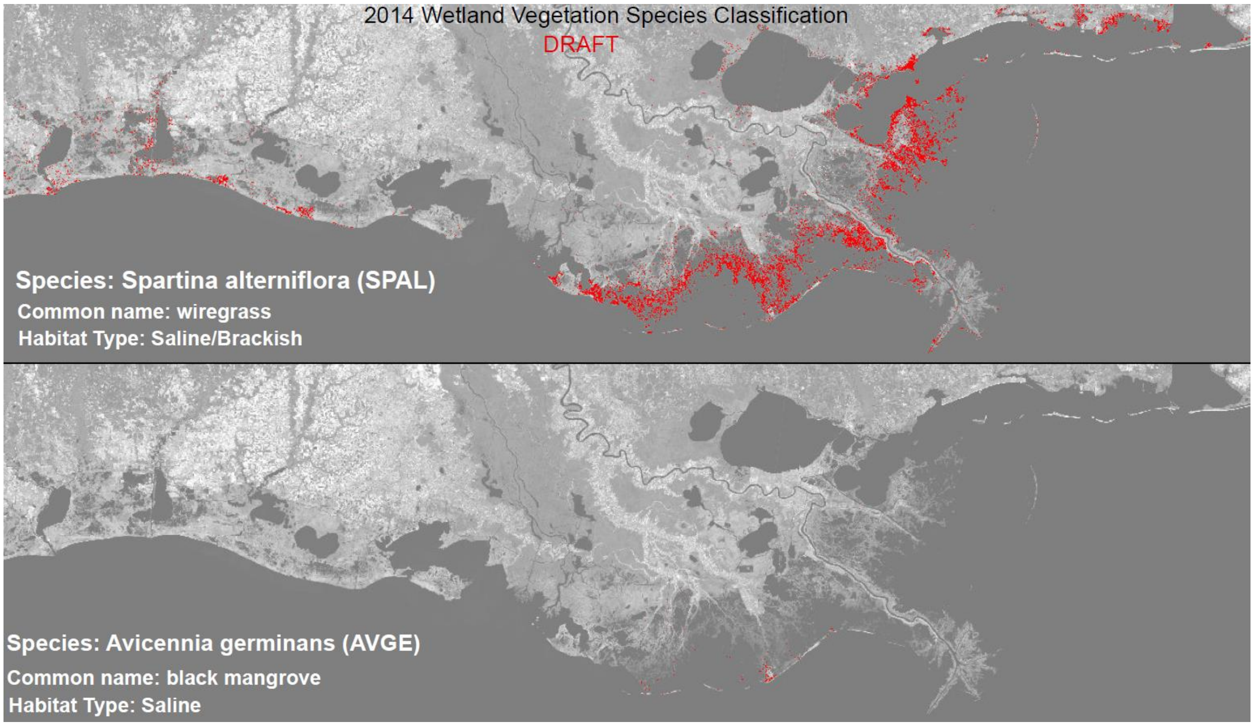

Figure 58: Vegetation Community Type Classification: Dominant Species SPAL and AVGE.

3.3.1. Accuracy Assessment

Remotely sensed classifications are commonly assessed on the basis of an accuracy assessment. Accuracy assessments are a quantitative analysis used to judge the accuracy of a classification at known points, in this case, helicopter survey points, which were not used as training, but were rather held in reserve for accuracy assessment. In this effort, an assumption was made that vegetation types were consistent over a 60 m radius under the direct point over which the observers assessed vegetation types. All pixels that fell in that buffer were candidates for training and validation, and as such, the population of the training and accuracy assessment sample far exceeds the original 3856 sites from the helicopter survey.

A random but stratified 1/3 sample was taken for accuracy assessment and the classification results were compared to the reference helicopter points. The results of that comparison are shown in the confusion matrix in Table 3 below.

Table 3: Confusion Matrix of Wetland Vegetation Community Types.

		Classified																			
		PAHE2	CLMA10	SALA	SPPA	TYDO	SPAL	PAVA	JURO	PHAU7	IVFR	SCCA11	ZIMI	MOCE2	ELBA2	DISP	BAHA	HYUM	SALA2	AVGE	SANI
Reference	PAHE2	1921	4	100	13	72	0	0	1	5	0	7	4	19	9	0	0	0	3	0	0
	CLMA10	2	274	13	5	6	1	0	0	0	0	6	0	0	0	0	0	0	0	0	0
	SALA	115	41	2748	122	225	1	4	3	32	0	25	28	35	10	5	17	25	8	0	0
	SPPA	40	46	169	9873	297	371	93	122	271	66	113	24	6	0	195	3	3	0	1	3
	TYDO	37	44	69	69	1849	3	22	0	37	12	49	19	15	5	10	0	3	6	0	0
	SPAL	9	0	4	263	4	4228	2	248	27	36	0	0	0	0	71	14	0	1	8	0
	PAVA	0	1	2	5	2	3	172	0	0	0	0	0	0	0	0	0	0	0	0	0
	JURO	0	0	1	8	0	6	0	286	1	0	0	0	0	0	5	0	0	0	0	0
	PHAU7	0	5	11	40	43	12	3	0	1369	8	16	0	0	0	4	2	0	0	0	17
	IVFR	0	0	0	2	0	0	1	0	0	74	5	0	0	0	1	0	0	0	0	0
	SCCA11	0	1	3	14	8	0	1	0	3	0	286	1	0	0	0	0	0	0	0	0
	ZIMI	1	0	1	4	2	1	0	0	0	0	0	112	0	0	0	0	0	0	0	0
	MOCE2	2	1	5	1	9	0	0	0	1	0	0	3	172	15	0	0	4	1	0	0
	ELBA2	0	0	6	0	14	0	0	0	0	0	2	0	0	249	0	0	5	3	0	0
	DISP	0	0	0	18	5	10	0	0	2	1	1	0	0	0	421	0	0	0	1	0
	BAHA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	12	0	0	0	0
	HYUM	0	0	7	1	2	0	0	0	0	0	0	0	0	2	0	1	91	2	0	0
	SALA2	1	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	96	0	0
	AVGE	0	0	0	0	0	3	0	0	0	0	0	0	0	0	6	0	0	0	81	0
	SANI	3	0	2	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	29

In this table, correct classification results are shown in the diagonal line of cells denoted in green. These cells list the number of points at which the classifier labeled a particular vegetation type, and the helicopter survey data confirmed that the vegetation type was indeed present at that location. All other cells in the confusion matrix represent an inaccuracy. This representation enables assessment of how often the classifier is right and wrong, but more importantly, it identifies the classes that it tends to label incorrectly.

The greatest value of the confusion matrix is providing information on where the confusion is occurring among classes. For overall figures on the accuracy of the dataset however, it is better to look at the producers, users, and overall accuracy detailed in Table 4 below:

Table 4: Accuracy of Wetland Vegetation Community Types (total, producers, and users).

Class	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
PAHE2	2151	2158	1921	89.31%	89.02%
CLMA10	420	307	274	65.24%	89.25%
SALA	3185	3444	2748	86.28%	79.79%
SPPA	10533	11696	9873	93.73%	84.41%
TYDO	2611	2249	1849	70.82%	82.21%
SPAL	4721	4915	4228	89.56%	86.02%
PAVA	311	185	172	55.31%	92.97%
JURO	672	307	286	42.56%	93.16%
PHAU7	1769	1530	1369	77.39%	89.48%
IVFR	209	83	74	35.41%	89.16%
SCCA11	519	317	286	55.11%	90.22%
ZIMI	206	121	112	54.37%	92.56%
MOCE2	254	214	172	67.72%	80.37%
ELBA2	298	279	249	83.56%	89.25%
DISP	747	459	421	56.36%	91.72%
BAHA	53	13	12	22.64%	92.31%
HYUM	134	106	91	67.91%	85.85%
SALA2	120	100	96	80.00%	96.00%
AVGE	92	90	81	88.04%	90.00%
SANI	50	38	29	58.00%	76.32%
Totals	29055	28611	24343		
Overall Classification Accuracy = 83.78%					

Table 4 lists both a producer's and user's accuracy. These two types of accuracy result from the two types of misclassification errors in remotely sensed classifications; errors of omissions, and errors of commission. Errors of commission reflect the inclusion of a vegetation type in a location in which it should not have been included and are represented by user's accuracy. Conversely, errors of omission reflect the omission of a vegetation type in a location in which it should have been included and are represented by the producer's accuracy. Overall, the classification as a whole achieved an accuracy of 83.78%, which is generally considered to be exceptional for remotely sensed classifications, particularly when so many classes are included. Indeed, the creators of the dataset caution that there is a possibility that this figure may be somewhat inflated due to the use of the 60 m radius around each point, and the assumption that all pixels in that area are the same vegetation type.

Finally, the kappa statistic measures the probability that the results differ significantly from random. The kappa statistic ranges from -1 to 1, though negative values are only theoretically possible. The kappa value generally ranges from 0 to 1, with values closer to 1 representing increased significance of a deviation from a random assignment. The overall kappa statistic attained in the classification was 0.7964 (Table 5), which again, is generally considered exceptional in a classification with this many classes.

It is also important to note that this classification was hierarchical in approach, meaning earlier classifications of land and water for instance were first used to define the land area upon which the vegetation classification would take place. Any errors in that dataset are not reflected in these accuracy results, and therefore, these values may be slightly inflated. These data represent an improvement over the vegetation community classification dataset used in the 2012 Coastal Master Plan both in accuracy and in thematic resolution (number of vegetation types).

Table 5: Kappa Statistics of Wetland Vegetation Community Types.

Class	Kappa
PAHE2	0.8814
CLMA10	0.8909
SALA	0.773
SPPA	0.7555
TYDO	0.8046
SPAL	0.8331
PAVA	0.929
JURO	0.93
PHAU7	0.8879
IVFR	0.8908
SCCA11	0.9004
ZIMI	0.9251
MOCE2	0.802
ELBA2	0.8914
DISP	0.915
BAHA	0.9229
HYUM	0.8578
SALA2	0.9598
AVGE	0.8997
SANI	0.7627
Overall Kappa Statistics = 0.7964	

4.0 Conclusions

Data is a foundational component of any modeling effort. A model can have every formula representing every process correctly, but if the starting point is incorrect, so too will be the results. While no dataset is completely accurate, the data created as part of this effort represent not only the best data available, but also the best data ever created and used in a coast wide, long-term modeling effort in coastal Louisiana.

The elevation data is improved as compared to the datasets that were used in the 2012 Coastal Master Plan as a result of newly available LIDAR being used in many coastal areas. The land/water datasets are improved as a result of better identification and incorporation of floating marsh. And finally, the vegetation community type layer has been improved with regard to the number of classes of vegetation identified and the accuracy of the classification.

Datasets as well as the methods used to collect them will be constantly updated and improved. Future efforts should strongly consider the need for improved bathymetry data, particularly in shallow, coastal waters.

5.0 References

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6.0 Appendix - LA CoNED/TBDEM Metadata

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Publication_Date: 18880101
Publication_Time: April 2015
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Geospatial_Data_Presentation_Form: raster digital data
Publication_Information:
Publication_Place: Sioux Falls, SD USA
Publisher: USGS Earth Resources Observation and Science (EROS) Center
Online_Linkage: https://lta.cr.usgs.gov/coned_tbdem
Description:
Abstract: Accurate, high-resolution elevation information is vital to understanding highly dynamic U.S. coastal regions. The new dataset consists of a detailed and highly accurate elevation model incorporating the best available multi-source topographic and bathymetric elevation data. The Coastal National Elevation Database (CoNED) Project - topobathymetric digital elevation models (TBDEMs) integrate hundreds of different data sources including topographic and bathymetric LIDAR point clouds, hydrographic surveys, side-scan sonar surveys, and multibeam surveys obtained from multiple agencies. The LIDAR and bathymetry surveys were sorted and prioritized based on survey date, accuracy, spatial distribution, and point density to develop a model based on the best available elevation data. Because bathymetric data is typically referenced to tidal datums (such as Mean High Water or Mean Sea Level), all tidally-referenced heights were transformed into orthometric heights that are normally used for mapping elevation on land (based on the North American Vertical Datum of 1988).
Purpose: Physical processes in the coastal environments are controlled by the geomorphology of both "over-the-land" topography and "underwater" bathymetry; therefore, many applications of geospatial data in coastal environments require detailed knowledge of near-shore topography and bathymetry (topobathymetry). The CoNED Project is a collaboration between the U.S. Geological Survey (USGS) Coastal and Marine Geology Program (CMGP), the National Geospatial Program (NGP), and the National Oceanic and Atmospheric Administration (NOAA) National Geophysical Data Center (NGDC). This coastal elevation database integrates disparate light detection and ranging (LIDAR) and bathymetric data sources into common databases aligned both vertically and horizontally to common reference systems. CoNED Project TBDEMs provide a required seamless elevation product for science application studies such as shoreline delineation, coastal inundation mapping, sediment-transport, sea-level rise, storm surge models, tsunami impact assessment, and analysis of the impact of various climate change scenarios on coastal regions.
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Ending_Date: 2013
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Temporal:

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Access_Constraints: Any downloading and use of these data signifies a user's agreement to comprehension and compliance of the USGS Standard Disclaimer. Insure all portions of

metadata are read and clearly understood before using these data in order to protect both user and USGS interests.

Use_Constraints: There is no guarantee of warranty concerning the accuracy of these data. Users should be aware that temporal changes may have occurred since the data was collected and that some parts of these data may no longer represent actual surface conditions. Users should not use these data for critical applications without a full awareness of their limitations. Acknowledgement of the originating agencies would be appreciated in products derived from these data. Any user who modifies the data set is obligated to describe the types of modifications they perform. User specifically agrees not to misrepresent the data set, nor to imply that changes made were approved or endorsed by the U.S. Geological Survey. Please refer to http://www.usgs.gov/privacy.html for the USGS disclaimer.

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Contact_Person: lta@usgs.gov
Contact_Organization_Primary:
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Contact_Person: lta@usgs.gov
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Address: Long Term Archive (LTA,), U.S. Geological Survey (USGS)
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47914 252nd Street

City: Sioux Falls
State_or_Province: SD
Postal_Code: 57198
Country: USA
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Hours_of_Service: 0800 - 1600 CT, M-F, -6 GMT
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Contact_Person: lta@usgs.gov
Contact_Position: Long Term Archive (LTA) Representative
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Address: Long Term Archive (LTA,), U.S. Geological Survey (USGS)
Earth Resources Observation and Science (EROS) Center
47914 252nd Street

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State_or_Province: SD
Postal_Code: 57198
Country: US
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Contact_Person: lta@usgs.gov
Contact_Position: Long Term Archive (LTA) Representative
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Earth Resources Observation and Science (EROS) Center
47914 252nd Street

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Metadata_Contact:
Contact_Information:

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Metadata_Use_Constraints: None
Metadata_Security_Information:
Metadata_Security_Classification_System: None
Metadata_Security_Classification: Unclassified
Metadata_Security_Handling_Description: None