Title
A Global Analysis of Tropical Dry Forest Extent and Cover Based on Climatic Definitions

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A Global Analysis of Tropical Dry Forest Extent and Cover Based on Climatic Definitions

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Master of Arts in Geography

by

Jonathan Pando Ocón

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ABSTRACT OF THE THESIS

A Global Analysis of Tropical Dry Forest Extent

and Cover Based on Climatic Definitions

by

Jonathan Pando Ocón

Master of Arts in Geography

University of California, Los Angeles, 2020

Professor Thomas Welch Gillespie, Chair

Tropical dry forests have been estimated to comprise 42% of all tropical forested biomes and are believed to be one of the world's most endangered ecosystems. There is a growing interest in identifying forest extent and forest change in tropical dry forest regions, especially to identify dry forest that deserve a high conservation priority at a global spatial scale. There is currently a debate concerning the classification and extent of tropical dry forest at the global scale. We identify the extent of tropical dry forest regions based on commonly used climatic definitions and datasets to improve global estimates of tropical dry forest extent. We compare climatic definitions of tropical dry forest (Murphy and Lugo, FAO, Dryflor, Aridity Index) using Worldclim, CHELSA, and Global Aridity and PET climatic datasets (1 km) and compare results to the World Wildlife Fund's Terrestrial Ecoregions (Tropical and Subtropical Dry Broadleaf

Forest), as well as 579 field plots identified as tropical dry forest. Understanding the best method to estimate global tropical dry forest extent gives both researchers and policy makers a vital tool to begin protecting this critically endangered and valuable resource. We identify methods that most accurately predicted tropical dry forest extent. The global extents of tropical dry forest regions varied significantly with the Aridity Index predicting the largest extent, Murphy and Lugo and FAO predicting similar extents, and DryFlor predicting the smallest extent regardless of climatic dataset used. Globally, there was low agreement between climatic definitions and WWF Ecoregions. FAO and the Aridity Index climate definitions had the highest agreement with WWF Tropical and Subtropical Dry Broadleaf Forest Ecoregions (57%) while FAO (76%) and Murphy and Lugo (69%) definitions had the highest agreement with field plots. However, extents and accuracy varied significantly by regions, biodiversity hotspots, and island archipelagos. Tropical dry forest region extent varies significantly based on climatic definition but not climatic datasets at a global spatial scale. Nearly half of all tropical dry forests will be missed when only analyzing WWF Ecoregion boundaries and climatic definitions will be needed to estimate dry forest cover and change. There was high heterogeneity among climatic definitions at a regional and local spatial scale suggesting that climate definition can only provide a first order hypothesis about the distribution of dry forests and data on phenology, forest structure, and composition are still needed to compare local tropical dry forest extent.

The thesis of Jonathan Pando Ocón is approved.

Kyle C. Cavanaugh

Michael Edward Shin

Thomas Welch Gillespie, Committee Chair

University of California, Los Angeles

2020

DEDICATION

To Mama and Papa Ocón and Ms. Stephanie Lee

for unconditional support in the pursuit of this degree.

For Mr. Kovu Lee.

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1 INTRODUCTION

Tropical dry forests have been estimated to comprise 42% of all tropical forested biomes and are believed to be one of the world's most endangered ecosystems (Murphy and Lugo, 1986; Janzen, 1988). There is a growing interest in identifying forest extent and forest change in tropical dry forest regions, especially to identify dry forest that deserve a high conservation priority at a global spatial scale (Miles et al., 2006; Schmitt et al., 2009; Sunderland et al., 2015; Banda et al., 2016). Most analyses of tropical dry forests at a global spatial scale use the World Wildlife Fund (WWF) Terrestrial Ecoregion boundaries to establish the geospatial extent of the intended study area (Miles et al., 2006; Schmitt et al., 2009; Gillespie et al., 2012; Crowther et al., 2015; Newbold et al., 2016). WWF ecoregions are defined as relatively large units of land containing a distinct assemblage of natural communities sharing a large majority of species, dynamics, and environmental conditions (Olson et al., 2001). Currently, the WWF has identified 53 Tropical and Subtropical Dry Broadleaf Forests (TSDBF) Ecoregions. However, global analyses of forest cover have included other WWF Ecoregions (e.g. Tropical and Subtropical Grasslands, Savannas and Shrublands) (Miles et al., 2001) and ecoregion data may contain several misclassifications or cartographic errors especially on islands (Daniel et al., 2014; Gillespie et al., 2014). Thus, there is a need to identify the extent of tropical dry forest in order to estimate forest cover and change and better understand threats (fire, climate change) and the conservation status of tropical dry forests at a global spatial scale.

Currently, there are a number of definitions of tropical dry forest based on climatic parameters that can be used to define the global extent of tropical dry forest separate from WWF Ecoregion data. The seminal definition of tropical dry forest comes from Murphy and Lugo (1986) which define tropical dry forest as occurring in frost-free areas where the mean annual temperature is higher than 17˚C with annual precipitation between 250-2000 mm, and dry season(s) of 4 to 7 months (Holdridge, 1967, Murphy and Lugo, 1986). The Food and Agriculture Organization of the United Nations (FAO) defines tropical dry forests as tropical climate, with a dry period of 5 to 8 months, and annual precipitation between 500 to 1500 mm (Sunderland et al., 2015). However, both the Murphy and Lugo and FAO definitions fail to provide a threshold for monthly precipitation during the dry season. Tropical dry forests in the Neotropics have recently been defined as occurring in areas with less than 1800 mm per year and a dry period of 3 to 6 months with less than 100 mm per month (Banda et al., 2016). It is unknown if this Neotropical definition could apply to tropical dry forest regions at a global spatial scale. Recently, drylands and associated tropical dry forest have been defined using a simple aridity index (AI), or the ratio of potential evapotranspiration to annual precipitation in which drylands and associated dry forest cover in areas with an aridity index of less than 0.65 (Bastin et al., 2017). Regions are then subdivided into four categories: “hyperarid” zone (AI < 0.05), “arid” zone (AI = 0.05 to 0.2), “semi-arid” zone (AI = 0.2 to 0.5), and the “dry subhumid” zone (AI = 0.5 to 0.65). However, widespread consensus on the relationship between AI and tropical dry forest extent has not been established (Griffith et al., 2017). To date there have been no studies that compare the potential global or regional extent of tropical dry forest based on these climatic definitions.

There have been a number of advances in global climate and environmental data sets that should improve our understanding of the distribution of tropical dry forests. Worldclim is the most widely used global climatic data set in biogeography. Worldclim data offers 1 km resolution gridded climate data interpolated from a network of weather stations over a 31-year period and quantifies annual and monthly temperature and precipitation (Fick and Hijmans, 2017). The CHELSA (Climatologies at High-resolution for the Earth's Land Surface Areas) data set also offer 1 km resolution climate data on monthly temperature and precipitation climatology for the years 1979–2013 based on a quasi-mechanistically statistical downscaling of global circulation models (Krager et al., 2017). These updated data sets contain monthly estimate of minimum precipitation per month (e.g. 100 mm) that can be used to estimate seasonality. New data sets also have been created that estimate PET and can be used to map aridity index at a 1 km resolution (Trabucco and Zomer, 2019). These climate and environmental data sets could be used to delineate potential tropical dry forest extent at a global scale based on current climatic definitions (Murphy and Lugo, 1986; Sunderland et al. 2015; DryFlor, 2016; Bastin et al., 2017). There have also been significant advances in the spaceborne remote sensing of forest cover and dynamics that may be applied to tropical forests and used for conservation assessments (Miles et al., 2006; Fraser et al. 2009; Gillespie et al. 2014a; Secades et al. 2014). Forest cover can be mapped globally using forest cover change data sets that contain forest cover, gain and loss, and percent forest cover at a 30 m pixel resolution from Landsat imagery for 2000 to 2018 (Hansen et al., 2013). Tropical dry forests have been hypothesized to be one of the world's most endangered biomes and forest types, thus there is a growing interest in identifying tropical forest extent in regions that have a high conservation priority at a global spatial scale and monitoring forest cover and change (Janzen, 1988; Miles et al., 2006; Schmitt et al., 2009; Sunderland et al., 2015; DryFlor, 2016). However, all such analyses are based on accurately defining tropical dry forest extent.

Achieving a consensus would allow for comprehensive conservation assessments of the most critically endangered tropical forest types. Tropical dry forests provide the ecosystem services needed to support millions of subsistence farmers in some of the world's poorest areas, and higher population densities are driving the demand for energy and land leading to quicker deforestation of tropical dry forest over humid forest (Blackie et al. 2014). Additionally, tropical dry forests are considered to be among some of the most diverse communities and their deforestation contributes to the steady erosion of earth's biodiversity (Cabin et al. 2000). Understanding the best method to estimate global tropical dry forest extent gives both researchers and policy makers a vital tool to begin protecting this critically endangered and valuable resource.

This research has three primary research objectives related to the global extent of tropical dry forest. First, we estimate the extent of tropical dry forest across scales based on four current climatic definitions of tropical dry forest. We would expect similar area estimates and high agreement between climatic definitions at a global spatial scale. Second, we assess how well climatic definitions of tropical dry forests overlap with WWF Tropical and Subtropical Dry Broadleaf Forest Ecoregions and field plots defined as tropical dry forest. We would expect significant overlap between climatic definitions, WWF ecoregions, and field plots. Third, we identify the climatic definition in closest agreement with field plots to calculate tropical dry forest cover and change from 2000 to 2018. We would expect that there has been a global decrease in tropical dry forest cover over the last 19 years.

2 MATERIALS AND METHODS

2.1 Study Area

Our study area spans the pantropics, between 30˚N and 30˚S.

2.2 Data Sets

We collected data from three climatic data sets (Worldclim, CHELSA, Global Aridity and PET), biome defining shapefiles (WWF Ecoregions), a compilation of 579 tropical dry forest field plots, as well as the latest forest cover data to estimate the extent for tropical dry forest regions from 2000 to 2018 (Global Forest Change) (Table 1).

Climate data sets

The second version of the Worldclim climate data released in 2016 includes monthly temperature and precipitation measurements from 9,000 and 60,000 weather stations respectively spanning 1970 to 2000. These data were interpolated using thin plate splines with covariates including elevation, distance to the coast and three satellite derived covariates: maximum and minimum land surface temperature as well as cloud cover, obtained with the MODIS satellite platform (Fick and Hijmans, 2017). The data sets include the monthly temperature and precipitation averages, as well as nineteen bioclimatic variables often used in species distribution modeling. The spatial resolution of the data are 30 arc seconds or ~1 km resolution at the equator.

The second climate data set we use is the Climatologies at High resolution for the Earth's Land Surface Area (CHELSA) currently hosted by the Swiss Federal Institute for Forest, Snow and Landscape Research. CHELSA includes monthly mean temperature and precipitation patterns from 1979 to 2013 and is based on a quasi-mechanistically statistical downscaling of the ERA interim global circulation model with a GPCC bias correction (Krager et al., 2017). The data spatial resolutions are also 30 arc seconds or ~1 km resolution at the equator.

We collected the Global Precipitation Measurement Integrated Multi-satellitE Retrievals for Global Precipitations Measurement (IMERG) Level 3 monthly precipitation data (mm/hour) at 0.1˚ spatial resolution (or approximately 11 km at the equator) (Huffman, 2017). However, the 4.25-year time series did not appear long enough to include in the analyses and contained a number of extremely high and low precipitation values.

To find aridity index, or the ratio of potential evapotranspiration to annual precipitation, we collected data from the Global Aridity and PET database, an addition of the Worldclim data set (Trabucco and Zomer, 2019). To obtain the aridity index for CHELSA data, we used the ENVIronmental Rasters for Ecological Modeling (ENVIREM) R-package (Title and Bemmels, 2018) to produce a global annual potential evapotranspiration raster file, which was then used to calculate aridity using the equation: annual precipitation / potential evapotranspiration (Bastin et al., 2017; Trabucco and Zomer, 2019). Drylands and associated dry forest extent has been tested at an aridity index of less than 0.65 (Bastin et al., 2017). We compare the climatic definitions of tropical dry forest against this aridity threshold.

WWF Ecoregions

The ecoregions polygon shapefile includes 867 land units classified into 14 different biomes such as forests, grasslands, or deserts (Olson et al., 2001; WWF, 2019). Each polygon also represents areas of land with an assemblage of species, dynamics, and environmental conditions (WWF, 2019). WWF has identified 53 ecoregions that fall within the Tropical and Subtropical Dry Broadleaf Forest category (Appendix 1). We test the validity of these 53 WWF Ecoregions, but acknowledge that previous studies have established the presence of tropical dry forest in other WWF Ecoregion biomes such as Tropical and Subtropical Grasslands, Savannas and Shrublands (Miles et al. 2006).

Field data sets

We tested predicted extents of tropical dry forest based on climatic definitions against 579 verified locations of tropical dry forest compiled from three primary sources. First, we gathered field plot locations from four separate studies on tropical dry forest ecology and distribution (Fayolle et al., 2014; Dexter et al., 2015; Ibanez et al., 2018; Franklin et al., 2018). Ibanez et al. (2018) presents 438 known forest plots > 0.1 ha from published forest inventory data on Dryad Digital Repository including 79 tropical dry forest plots. Franklin et al. (2018) provides 572 sampled locations of tropical dry forest across 11 sub-regions in the Caribbean, of which 159 we verified as having accurately defined coordinates within 1 km. Dexter et al. (2015) present 41 plots of which we classify India Dry Evergreen Forest and Cambodia Deciduous Forest as tropical dry forests. Fayolle et al. (2014) presents 53 plots of which we classify West African Dry Forests and Coastal East African Forests as tropical dry forest.

Second, we searched Web of Science [v.5.32] (WoS), Scopus, and Google Scholar databases for peer-reviewed articles published between January 1990 and September 2019. We queried titles, abstracts, and keywords for the following terms: tropical*dry* forest* plots*. We selected the peer-reviewed articles based on four criteria: 1) Plots classified as dry forest following author's classifications, 2) Plots had to contain "forest" and not woodlands or savannahs, 3) Articles needed to include published latitude and longitude of plot location that was accurate to within 1 km, and 4) Forest had to be composed of tree species native to the region with riparian or flooded forests excluded. We used Google Earth to verify the coordinates were in closed canopy forest and to establish seasonality using built-in, time-lapse imagery collected since 1984 across varying seasons. This method yielded eight peer-reviewed articles (Dattaraja et al., 2018; Mani and Parthasarathy, 2006; Ramanujam and Kadamban, 2001;

Chaturvedi et al., 2011; Chave et al., 2005; Choat et al., 2005; Tanaka et al., 2008; Almulqu et al., 2018) offering nineteen additional tropical dry forest plots over four regions (South Asia, South East Asia, Australia and Latin America).

Third, we searched four global forest data repositories for sites classified as tropical dry forest. Our search into the Global Biodiversity Information Facility (GBIF), as well as ForestPlots.net, yielded much of the same plot data we had collected from our list of peer-reviewed studies. The Dryad data repository, however, did yield 40 additional dry forest plots from three peer-reviewed articles studying dry forest across Latin America (Prado-Junior et al., 2016; Salas-Morales et al., 2020; Suazo-Ortuno et al., 2018). Additionally, 189 sites were collected from the United States Geological Survey's Forest Inventory and Analysis program covering tropical dry forest from the United States and territories (Hawai'i, Florida, Puerto Rico and US Virgin Islands). The final plot locations validate whether any of the tropical dry forest climatic definitions accurately capture existing definition of dry forest presence (Appendix 2).

Global forest cover and change

Originally launched to provide high-resolution global maps of forest cover change from 2000 – 2012 using Landsat 7 imagery, the Global Forest Change data set has grown to include time series analysis of Landsat 5, 7 and Landsat 8 imagery now covering 2000 – 2018 (Hansen et al., 2013). Each pixel has a spatial resolution of 1 arc second, or roughly 30 m, and unsigned 8-bit values (0-255). We identify areas with > 10% cover (encompasses mosaic of savannas and woodlands) and > 40% cover or forest for the year 2000 and 2018 (Bastin et al., 2017). We utilize this as our primary data set to calculate tropical dry forest cover and loss.

2.3 Data Analyses

Spatial scale

We calculate "global" results within 30˚N and 30˚S. We divided global results into six macro-scale regions (Africa, North and Central America, South America, South Asia, and South East Asia and Asia Pacific). We further sub-divided regions using Biodiversity Hotspots (Myers et al., 2000; Hoffman et al., 2016) and countries (Natural Earth, 2019) for a meso-scale analyses (Appendix 3 and 4). Tropical dry forests on islands are generally combined in global analyses (Miles et al., 2006; Schmitt et al., 2009), however, these islands contain the smallest extents and fragments of tropical dry forest, which emphasizes the need to report the extent of the tropical dry forest on islands to assess global conservation priorities (Sunderland et al., 2015). Thus, we select tropical four island archipelagos (Fiji, Galapagos, Hawai'i, Puerto Rico) as an example of micro-scale archipelago analyses. Tropical dry forest biome and forest types are well known in Puerto Rico and Hawai'i, while Fiji is on the wetter end of the spectrum and the Galapagos is on the drier end.

Climatic definitions

We identify the global and regional extent of tropical dry forest based on four common definitions of tropical dry forest (Murphy and Lugo, FAO, DryFlor, aridity index) (Table 2). For all definitions, we use frost-free regions (> 0 C) in the tropics that also experience a mean annual temperature > 17 C (Murphy and Lugo, 1986). Tropical dry forest extent from Murphy and Lugo were calculated by subsetting areas with 250 to 2000 mm of annual precipitation with a dry season(s) of 4 to 7 months with less than 100 mm of precipitation a month (Holdridge, 1967; Murphy and Lugo, 1986). Tropical dry forest extent from the Food and Agriculture

Organization of the United Nations (FAO) were created by subsetting areas with 500 to 1500 mm of annual precipitation with a dry period of 5 to 8 months with less than 100 mm of precipitation a month (Sunderland et al., 2015). Tropical dry forest extent from DryFlor were calculated as annual precipitation less than 1800 mm with a dry season of 3 to 6 months receiving less than 100 mm per month (Banda et al., 2016). A definition using aridity index was calculated for regions with an index of less than 0.65 (Bastin et al., 2017) for both Worldclim and CHELSA data (Fick and Hijmans, 2017; Karger et al., 2017).

Programming

A combination of geospatial modules were used across three programming languages and software to manage, analyze, and compile spatial data sets for our analysis. Free and open-source Python software (Python Software Foundation, 2019) was used to manipulate raw data to compile binary raster maps representing the fundamental layers (e.g. temperature, precipitation, seasonality) that were then overlaid on top of one another to produce a second and final binary raster for the respective climatic definition. The Python modules used most were GDAL and Rasterio.

Additionally, we used the cloud-based geospatial analysis platform Google Earth Engine (Gorelick et al. 2017) to analyze and calculate global tropical dry forest cover (Hansen et al., 2013). The advantage to using Earth Engine is the computing power needed to process large amounts of forest cover data (over 1 Tb).

We also lacked one raw data set (AI for CHELSA), and used the ENVIronmental Rasters for Ecological Modeling (ENVIREM) R-package (Title and Bemmels, 2018) to compile a GeoTiff raster file of a global aridity index with CHELSA data. Additional R packages used in this study include the Tidyverse, which helped create all data tables, as well as Tmap, which was used in the design and compilation of all figures. All figures were compiled in a WGS84 projection. The code used in our analysis is available in Appendix 6, and all compiled data is provided in the supplementary material.

Geographic extents

Global, regions, Biodiversity Hotspots, countries, and islands level data on area of tropical dry forest extent based on climatic definitions and data sets were examined for a normal distribution using one-sample Shapiro-Wilk normality test for small samples (< 30) and Kolmogorov-Smirnov tests (> 30). Parametric (T-tests) and non-parametric (Wilcoxon rank sum test) tests were used to identify significant differences among climatic definitions and between Worldclim and CHELSA data sets at a global, regional (regions, Biodiversity Hotspots, countries), and local (island archipelagos) spatial scales.

Comparisons with WWF Ecoregions and field plots

WWF has identified 53 ecoregions that contain Tropical and Subtropical Dry Broadleaf Forests. We calculated the area of each WWF Ecoregion (Appendix 1) and compare results with four climatic definitions. We identified the proportion of overlap between WWF Ecoregions and four climatic definitions, which identifies areas where there are overlap with WWF Ecoregions, as well as potential tropical dry forest extent outside of the 53 WWF ecoregions. We identified agreement between field plots and WWF ecoregion and four climatic definitions across spatial scales. The accuracy of the field plot locations was within 1 km and represented in decimal degrees (Appendix 2).

Tropical dry forest cover and change

We select the methods that had the highest agreement with field plots at a global spatial scale and calculate forest cover in 2000 and gross loss from 2001-2018 based on the Global Forest Change data set using a forest cover threshold of > 10% to define open forests and > 40% to define closed canopy forest (Hansen et al., 2013). We also calculate similar results for all tropical forests from Global Forest Cover (30˚N and 30˚S), WWF Tropical and Subtropical Dry Broadleaf Forest, consensus maps of three climatic definitions (Murphy and Lugo, FAO, and DryFlor) using Worldclim and CHELSEA data sets. Finally, we calculate a broad definition of tropical dry forest biome as forests that occur in frost free areas with 2000 mm or less of annual precipitation and a dry season of four or more months with less than 100 mm of precipitation, which encompasses all four climatic definitions (Table 6).

3 RESULTS

Comparisons of climatic definition of tropical dry forest extent

Estimates of tropical dry forest potential extent based on climatic definitions varied globally and by regions (Table 3, Appendix 5: Figure S1). The aridity index (AI < 0.65) estimated the largest extent of dry forest that was two to three times larger than the other three climatic definitions (Table 3). This was largely due to the inclusion of deserts at a global spatial scale (Figure 2). The global area estimates from Murphy and Lugo and FAO definitions were relatively similar, generally around 15,000,000 km2 while DryFlor covered the smallest area estimated around 10,000,000 km2 at a global spatial scale. FAO and aridity index definitions using the Worldclim data set (Table 3, Figures 2a and 3b) estimated larger extents while Murphy and Lugo and aridity index definitions using CHELSA climate data set estimated larger extents (Table 3, Figures 2b and 3a). Worldclim generally showed more continuous or homogenous climatic gradients while CHELSA displayed a more heterogeneous or pixelated patterns near boundaries. However, there was no significant difference between climatic data sets used and extent for the four climatic definitions at a global scale (Wilcoxon rank sum test $p > 0.05$)(Appendix 5: Figure ST4).

The aridity index covered the largest extent in Africa, North and Central America, South Asia, and the South East Asia/Pacific regions, while the Murphy and Lugo definition covered the largest extent in South America (Table 3). There was no significant difference between climatic data sets by regions (Wilcoxon rank sum tests $p > 0.05$)(Appendix 5: Figure ST4). Within Biodiversity Hotspots, Murphy and Lugo's definition generally estimated the largest tropical dry forest extent (Table 3, Appendix 3, Appendix 5: Figure S1). There was no significant difference between climatic data sets used in Biodiversity Hotspots for Murphy and Lugo, DryFlor, and aridity index definitions (Paired T-Test: Murphy and Lugo $p = 0.208$, DryFlor $p = 0.449$, Aridity $p = 0.462$) but a significant difference between climatic data sets used for FAO (Paired T-Test: FAO $p = 0.050$). At the country level, there was a significant difference in climatic data set used for all four definitions (Paired T-Test: Murphy and Lugo $p = 0.004$, FAO $p = 0.012$, DryFlor $p = 0.018$, Aridity $p = 0.005$) (Appendix 5: Figure ST10). There was a great deal of heterogeneity in extent estimates at the scale of island archipelagos (Table 3, Appendix 5: Figures S11 and S12). Only Murphy and Lugo and DryFlor definitions identified tropical dry forest in Fiji while three climatic definitions identified tropical dry forest on the Galapagos, and all four identified tropical dry forest on Hawai'i and Puerto Rico. This suggests that climatic definitions and data sets results in significantly different occurrences and extents at smaller spatial scales (e.g. countries and islands).

Comparisons to WWF Ecoregions

The 53 WWF Ecoregions defined as Tropical and Subtropical Dry Broadleaf Forest extend over an area of 2,918,256 km2 with South Asia having the largest extent and Africa the smallest extent (Figure 1, Table 4). Globally, the aridity index and FAO definitions using Worldclim had the highest overlap with WWF Ecoregions (57%) followed by FAO using CHELSA (56%), and Murphy and Lugo definition and CHELSA (44%) and Worldclim (43%). DryFlor had the lowest overlap when using both Worldclim (22%) and CHELSA (22%). There was high variation among regions. The aridity index, Murphy and Lugo and FAO definitions using Worldclim had the highest overlaps within most WWF Ecoregions. The aridity index using Worldclim had the highest overlap in South Asia (82%). The highest overlap of WWF ecoregion within Biodiversity Hotspots were Murphy and Lugo and FAO definitions. For islands, the highest overlap was for Puerto Rico followed by Hawai'i and Fiji and no Tropical and Subtropical Dry Broadleaf Forest identified by the WWF in the Galapagos.

Comparisons of climatic definitions to field plots

We collected 579 tropical dry forest plots with 61% represented in North and Central America of which 50% were located in the Caribbean. Only 43% of the field plots fell within the WWF Tropical and Subtropical Broadleaf Forest ecoregions and ranged from 0% overlap in Africa to 76% in South East Asia/Pacific (Table 5). At a global scale, FAO definition using CHELSA had the highest agreement (76%) with field plots followed by Murphy and Lugo (69%). FAO (68%), Murphy and Lugo (64%), and the aridity index (61%) using Worldclim accounts for the next three highest overlaps with field plots. DryFlor had the lowest overlap (32-33%). Regionally, Murphy and Lugo and FAO definitions have the highest proportional overlap with field plots. Among the Biodiversity Hotspots and islands, there was wide variation in the number of field plots. FAO (CHELSA) performed best in the Caribbean (89%) based on 287 plots. Murphy and Lugo definition using Worldclim has the highest overlap with field plots in Fiji (44%) and Hawai'i (27%), and using CHELSA in Puerto Rico (87%). Aridity index was the only definition to overlap with field plots on the Galapagos (67%), which makes sense as the archipelago skews much drier.

Estimates of tropical dry forest cover and change

We selected FAO definition using CHELSA and Murphy and Lugo's definition using Worldclim to estimate the open and closed forest cover and change for 2000 (Table 6, Figure 5). We also calculated gross forest loss from 2001 to 2018 to estimate 2018 forest cover. Based on FAO's definition, we estimate 4,440,046 km2 of closed canopy tropical dry forest in 2000 and 3,948,678 km2 of closed canopy tropical dry forest in 2018 or gross forest loss of 491,368 km2 (11%) between 2000 and 2018. Based on Murphy and Lugo's definition, we estimate 6,894,394 km2 of closed canopy tropical dry forest in 2000 and 6,081,931 km2 of tropical dry forest in 2018 and gross forest loss of 812,462 km2 or (12%) between 2000 and 2018. FAO estimates account for 24% of all closed canopy forest cover in the tropics in 2000 and a deforestation rate of 11% between 2000 and 2018 while Murphy and Lugo estimates account for 38% of all closed canopy forest cover in the tropics and a deforestation rate of 12% between 2000 and 2018. Both estimates of closed canopy tropical dry forest are larger than WWF Tropical and Subtropical Dry Broadleaf Forest ecoregion estimates (600,000 km2 or 4% of all tropical forests) and consensus maps based on Murphy and Lugo, FAO, and DryFlor definitions either climatic data sets (approximately 2 millions km2 or 12% to 13% of all tropical forest). Simple climate definitions (no freeze, mean annual precipitation < 2000 mm, four or more months < 100 mm precipitation) resulted in the greatest open and closed forests areas with closed canopy tropical dry forest accounting for 47% to 54% of all tropical forests.

4 DISCUSSION

Climatic definitions of tropical dry forest at a global scale

Climatic definitions appear useful for estimating tropical dry forest biome extent and cover at a global, biodiversity hotspot, country, and island scale. In theory, climatic definitions identify the potential extent of biome types (e.g. boreal forest, tropical rainforest) and possibly what vegetation types might have been in a 1 km2 area without the influence of humans. It should be made clear that climatic definitions do not account for different vegetation types such as savannas, shrublands, woodlands, and deciduous to evergreen forests that all overlap within tropical dry forest climatic definitions (Staver et al., 2011; Dexter et al., 2018). Indeed, all these vegetation types can be found within a 1 km2 pixel area. Thus climatic definitions identify the potential extent and provide a starting point for identifying the closed canopy tropical dry forests which is a distinct vegetation type within the biome.

There were significant differences in tropical dry forest extent based on commonly used climatic definitions. FAO and Murphy and Lugo appear to be the best at identifying the potential extent of tropical dry forests with FAO definitions identifying drier regions with more seasonal forests and Murphy and Lugo definition identifying wetter regions with less seasonal forests. The DryFlor definitions worked well in the Neotropics but does not perform well at a global and regional spatial scale. The aridity index estimated the greatest extent because it included desert areas especially deserts in Mexico, South America, Africa, Asia, and Australia (Figure 2). This method does not account for mean annual precipitation or precipitation seasonality and appears to include the drier extremes of what would be considered tropical dry forest. Indeed, although forests that occur within area with AI > 0.65 can be considered “tropical dry forests” because they occur in the tropics and clearly occur in dry conditions, the absence of precipitation and seasonality clearly misses a number of well-known tropical dry forest sites such as tropical dry forests of Costa Rica and Panama (Janzen, 1988; Appendix 4). The aridity index is useful because it does identify the dry extremes of forest and this has important implications because it identifies dry forests and forest that may have been “invisible” in the past (Bastin et al., 2017).

Climatic definitions and consensus maps clearly provide first order hypotheses about the potential existence of tropical dry forest in regions, biodiversity hotspots, countries and individual islands. For instance, there is a consensus from all four tropical dry forest climate definitions regardless of climate data set used that tropical dry forest occurs in twenty-three of the thirty-three Biodiversity Hotspots (Appendix 3) and 75 of the 127 countries and associated territories in the pantropics (Appendix 4). For the four island archipelagos selected, all climate definitions clearly identify the presence of tropical dry forest on Puerto Rico and Hawai'i which is the case and strongly suggest the presence of tropical dry forest in Fiji and the Galapagos (Figures 10 and 11). Thus there are a number of reasons why climatic definitions are useful for assessing tropical dry forest from a global to local scale.

Comparison of climatic data sets

Globally, comparison of Worldclim and CHELSA data sets did not significantly change area estimates based on all four climatic definitions but did identify different extents especially across scales (Figures 2, 3, 4). CHELSA (a downscaled Global Circulation Model) generally had higher mean annual precipitation estimates than Worldclim (based on interpolations of climatic measurements) but there was little difference in temperature estimates (e.g. < 1 C). As analyses proceed to smaller spatial scales from regions to island archipelagos, the climatic data set used becomes more important and results in significantly different estimates of extent. The CHELSA data on tropical dry forest extent best matched personal observations of the authors (Figures 10 and 12c) and offer some advantages over interpolated Worldclim data when assessing the future impacts of climate change. Since CHELSA is a downscaled GCM, it can easily be used to estimate the future climatic variables a 10 km and over last 40 million years at 10 km resolution (Gamisch, 2019).

Comparison to WWF Ecoregions

There was low overlap between climatic definitions of tropical dry forest and WWF Ecoregions defined as Tropical and Subtropical Dry Broadleaf Forest. The climatic condition for tropical dry forest also occurred in other Ecoregions such as Tropical and Subtropical Grassland, Savanna and Shrubland, and Desert and Xeric Shrubland. The WWF Ecoregions are widely used standard for delineating global biomes and estimating forest cover, canopy height, biomass, and stand density (Miles et al., 2006; Schmitt et al., 2009; Crowther et al., 2015; Newbold et al., 2016) and still provides the most standard and repeatable way to assess for forest cover change in the tropics (Appendix 2). Indeed, although there were miss-classifications such as climatic definitions (e.g. Yap is a moist not dry forest), the use of climatic definition does not significantly improve dry forest biome extent enough to warrant their wide use. WWF Ecoregions are appropriate for future global or macro-scale analyses of tropical forests biomes. However, it should be remembered that caution should be used when applying WWF boundaries for regional, country, or island scale analyses. At these scales, higher resolution vegetation maps that identify forests, woodlands, shrublands and grasslands should be used. Furthermore, WWF Ecoregions boundaries may not be appropriate for analyzing the impacts of climate change on tropical dry forests and climatic definitions and data sets should be used instead.

Comparisons to field plots

Globally it is clear that there is a great deal of spatial bias in the number, extent, and density of tropical dry forest field plots. We collected 579 tropical dry forest plots with 61% represented in North and Central America of which 50% were located in the Caribbean. Based on a global assessment of tropical dry forest field plots, it is clear that the Caribbean was over represented in our study and North and Central America and South America have the most tropical dry forest plots (Banda et al., 2016; Miranda et al., 2018). Regions such as North, Central, and South America are well represented along with a number of islands in the Pacific (Gillespie et al., 2014; Ibanez et al., 2019). However, there are relatively few tropical dry forest plots from Madagascar (1 plot), eastern India, Indonesia, and Australia and these areas deserve a high priority for establishing standardize plots in the future (e.g. 1 ha, 0.1 ha).

There was surprisingly high misclassification (57%) between field plots and WWF Ecoregions with only a 43% agreement at a global scale. This is due to a number of dry forests that naturally occurred in other ecoregions such as Subtropical Grassland, Savanna and Shrubland and Deserts. It is common for tropical dry forest to occur as fragments in both these arid environments and among savannas and shrublands. The exception to this is in Hawai’i and Puerto Rico where 85% and 80%, respectively, of field plots overlap with WWF Ecoregions

(Table 5). The majority of the 150 field plots (52 in Hawai'i, 98 in Puerto Rico) come from the US FIA database, which may indicate a sampling bias among field plots in US territories to match WWF Ecoregion boundaries.

Tropical Dry Forest Cover and Changes

The FAO definition using CHELSA and Murphy and Lugo definition using Worldclim estimate 4 to 6 million km2 of closed canopy tropical dry forest in 2000. Miles et al. (2016) estimated 1,048,700 km2 of tropical dry forest (> 40% closed canopy) using MODIS imagery (500 m), while Bastin et al. (2017) estimated 3,200,000 km2 of closed canopy dry forest and 2,030,00 million km2 of open forest. Miles et al. (2016) estimate thus appears very conservative and more in line with our estimates in WWF Ecoregions but still well below estimates of closed canopy cover based on consensus climatic definitions (2 million km2). Bastin et al. (2017) estimates of closed forest cover are more in line with our consensus estimates of tropical dry forest. Direct comparison at a global spatial scale are difficult, however, it is clear from all analyses that open forest (canopy > 10%) account for about half of all forest within dry regions regardless of climatic definition and data set used. Furthermore, it is clear that both open and closed tropical dry forest are experiencing a decline. Estimates based on all definition of tropical dry forest are between 7% and 14% from 2000 to 2018 with closed canopy tropical dry forests experiencing high rates of deforestation and gross forest cover loss (11%, + 2%).

Limitations

There are a number of limitations that should be noted in our analyses. Almost all global climate data sets contain errors especially on islands with few weather stations and high heterogeneity in the landscape (Ibanez et al., 2019). Miranda et al. (2018) found that Worldclim data resulted in the misclassification of 15 to 20% of tropical dry forests in lowland South America while the addition of soil data improved classification by 3%. Deliminating tropical dry forest biome and vegetation type are also complex due to the fact that tropical forest historically occurred across environmental and disturbance gradients, do not have solid boundaries as depicted in GIS, and were a continuum from drier to wetter areas. On the dry end of the spectrum dry forests grade into savannas, shrublands, woodlands within the same climatic condition. The actual extent of vegetation within this region is highly impacted by soil type, soil moisture, and fire (Miranda et al., 2018). On the wetter end of the spectrum, tropical dry forest transition into moister forests, a zonal riparian forests, or swamps with increased canopy heights and an increasing number of tree species that are less susceptible to seasonal drought or dry soil conditions. These gradients clearly existed in the past but have been significantly impacted by humans certainly over the last 2000 and 100 years. It should be remembered that we are currently examining a disturbed landscape. Many dry forest regions are deforested and degraded and it is difficult to precisely identify and delineate their distribution at a local spatial scale.

Thus, climate definitions of tropical dry forest provide only a first order hypothesis and standard and repeatable method for identifying and estimating the spatial extent of tropical dry forest regions. Analyses of vegetation types based on structure such as forests (> 3 m), woodlands (< 40% canopy cover), shrublands (< 3 m), and savannas can be undertaken at a higher resolution such as 30 m from Landsat (Hansen et al., 2013) or very high resolutions < 1 m in Google Earth (Bastin et al., 2017). Indeed, with a 1 km2 area, it is possible to have all four vegetation types.

Future research and applications

Comparative analyses of biogeography, threats, and conservation can be undertaken using FAO (CHELSA) or Murphy and Lugo (Worldclim) boundaries as a baseline. It is well-established that biodiversity is greatly threatened by human activity (Myers et al., 2000; Gaston, 2005) and land cover changes such as those linked to human-induced forest loss, fragmentation, and degradation represent the largest current threat to biodiversity (Chapin et al., 2000; Menon et al., 2001; Gaston, 2005). Miles et al. (2006) identified and included five global threat metrics for tropical dry forest including climate change (300 km), forest fragmentation (500 m), fire (10 km), agrosuitability (10 km), and population (10 km). Since this seminal work, there has been a significant increase in the temporal and spatial resolution of GIS and remote sensing data for these threat metrics, such as predicted future climate change (10 km), forest fragmentation (< 30 m), fire (375 m), agrosuitability and grazing (1 km), and population (1 km) and vegetation type (Small et al., 2005; Giglio et al., 2006; Laurance et al., 2012, Bastin et al. 2017). Thus, there are currently a number of threat metrics that can be analyzed with FAO and CHELSA that might significantly improve our understanding of the health of tropical dry forests.

Twenty-three of the thirty-three Biodiversity Hotspots appear to contain tropical dry forests based on all four climatic definitions of dry forests (Appendix 3), possibly highlighting the importance of this biome and vegetation type. Analyses of protected areas, old growth forest, and threatened and endangered species are also needed within tropical dry forest biome and vegetation type. There has been a rapid increase in the number of protected areas and clearly there is a need to identify how well different regions are protected (Miles et al., 2006). Using time series Landsat and fire data sets since 2000, it should be possible to identify stable closed canopy tropical dry forests that have not experienced fire or forest loss since 2000 (Dexter et al., 2018). These forest areas may be some of the best preserved or relictual forests and contain an increasing rare combination of dry forest species. This may be especially true for regions like Africa, Asia, and Australia where fires are common and closed canopy dry forests are isolated in natural refugia.

5 CONCLUSIONS

Tropical dry forest is clearly a globally important biome occurring in twenty-three of the world's thirty-three biodiversity hotspots. Direct comparison at a global spatial scale are difficult, however, it is clear from all analyses that open canopy forest account for about half of all forest within dry regions regardless of climatic definition and data set used. Furthermore, FAO with CHELSA can identify potential dry forest extent and provide a starting point for identifying closed canopy forests, of which closed canopy tropical dry forest currently occurs in a majority of pantropical countries and has been experiencing high rates of disturbance (11%, ±2%) between 200 and 2018. Identifying these extents are important for future research and understanding the status of the world's tropical dry forest for conservation purposes. As many studies rely on the WWF Ecoregion boundaries to establish dry forest regions, we demonstrate that nearly half of all tropical dry forest will be missed using this method. Instead, we recommend that climatic definitions are needed to estimate dry forest cover and change moving forward. At local scales, climatic definitions show high heterogeneity in estimating dry forest extent, and vegetation data on forest structure and composition are still needed. However, climatic definitions can serve as a first order hypothesis about tropical dry forest distribution, and we found the FAO definition using CHELSA data provides a standard and repeatable way to asses tropical dry forest cover and change at the global and regional scales.

6 TABLES

Table 1: Overview of data sets.

Data Set	Source	Variables	Resolution	Format
Worldclim (1970-2000)	Fick and Hijmans 2017	Precipitation (mm), Temperature (C)	1 km	GeoTiff
Global Aridity and PET (1970-2000)	Trabucco and Zomer 2019	Annual PET (mm), aridity index (ratio); Derived from Worldclim	1 km	GeoTiff
Integrated Multi-satellitE Retrievals for Global precipitation measurement (IMERG) (March 2014 – Present)	Huffman 2017	Interpolation of Global Precipitation Measurement (GPM) satellite microwave precipitation estimates, microwave-calibrated infrared estimates, and precipitation gauges (mm/hour)	11 km	HDF5
Global Forest Change	Hansen et al. 2013	Canopy cover (%)	30 m	GeoTiff
WWF Tropical Dry Forest Ecoregions	Olson et al. 2001	867 units of land representing assemblages of species and environmental conditions	N/A	Polygon shapefile
Tropical Dry Forest Plots	See text for references.	579 verified dry forest locations	N/A	Point shapefile

Table 2: Overview of climatic definitions of tropical dry forest.

Climatic Definition	Source	Annual Precipitation, Dry Season
Murphy and Lugo	Murphy and Lugo 1986	250-2000 mm, 4-7 months ≤100 mm
FAO	Sunderland et al. 2015	500-1500 mm, 5-8 months ≤100 mm
Dryflor	Banda et al. 2016	≤1800 mm, 3-6 months ≤100 mm
aridity index	Bastin et al. 2017	N/A

Table 3. Estimate of tropical dry forest extent (km^2) per three climatic definitions and aridity index using Worldclim (Fick and Hijmans, 2017) and CHELSA (Karger et al., 2017) climate data sets. Areas (km^2) for Worldclim data presented atop CHELSA results. Largest extents are in bold.

Regions	Murphy & Lugo	FAO	Dryflor	Aridity
Global	15,300,143	15,514,946	10,370,038	**31,669,174**
	16,123,939	15,177,193	10,820,627	**28,718,601**
Africa	6,825,248	7,480,815	5,005,193	**19,942,762**
	7,237,338	7,700,711	5,243,736	**17,910,375**
North and Central America	590,609	689,325	284,154	**1,208,399**
	652,516	811,289	326,525	**1,231,216**
South America	**5,736,592**	3,134,372	3,958,243	2,374,338
	6,042,593	3,774,250	4,023,236	2,459,142
South Asia	437,803	1,261,394	112,170	**2,421,884**
	481,186	1,230,178	153,111	**1,935,105**
South East Asia/Pacific	1,709,888	1,687,644	1,010,275	**5,721,788**
	1,710,303	1,660,763	1,074,017	**5,182,761**
Biodiversity Hotspots				
Caribbean	162,833	138,720	144,585	58,301
	170,746	148,366	147,604	4,297
East Melanesia	25	0	2	0
	984	51	745	0
Madagascar and Indian Ocean	**278,131**	257,610	24,819	218,423
	248,325	177,914	25,066	136,381
New Caledonia	8,774	3,474	7,523	29
	9,911	6,988	8,077	0
Polynesia and Micronesia	4,548	3,074	3,362	3,334
	7,722	3,801	5,744	248
Sundaland and Nicobar of India	**41,193**	5,016	28,093	103
	31,078	1,433	23,439	0
Tumbes Choco Magdalena	43,168	30,883	27,211	**60,951**
	58,017	43,467	36,398	49,217
Wallacea	83,276	46,315	61,228	10,695
	84,470	53,245	68,884	0
Archipelagos				
Fiji	814	0	216	0
	3,606	0	1,778	0
Hawai'i	3,041	2,666	2,268	3,221
	3,255	**3,433**	2,712	244
Galapagos	0	0	0	**7,348**
	14	1,321	0	0
Puerto Rico	2,780	1,446	2,551	1,110
	4,599	2,619	**5,107**	0

Table 4. Extent of World Wildlife Fund's Tropical and Subtropical Dry Broadleaf Forest ecoregions (km^2) and overlap (%) with climatic definitions and aridity based on Worldclim (Fick and Hijmans, 2017) and CHELSA (Karger et al., 2017) climate data sets. Overlap (%) for Worldclim data presented atop CHELSA results. Highest agreement are in bold.

Regions	Ecoregions Area	Murphy & Lugo	FAO	Dryflor	Aridity
Global	2,918,256	43%	**57%**	22%	**57%**
		44%	**56%**	22%	35%
Africa	185,624	**70%**	69%	3%	48%
		60%	56%	1%	13%
North and Central America	511,057	45%	63%	23%	**67%**
		46%	64%	24%	41%
South America	642,243	58%	47%	31%	43%
		60%	51%	28%	32%
South Asia	983,944	9%	60%	2%	**82%**
		11%	61%	2%	56%
South East Asia/Pacific	593,608	75%	53%	49%	24%
		76%	49%	51%	4%
Biodiversity Hotspots					
Caribbean	82,472	88%	88%	74%	38%
		89%	85%	75%	3%
East Melanesia	0	0%	0%	0%	0%
		0%	0%	0%	0%
Madagascar and Indian Ocean	146,130	**68%**	63%	3%	37%
		53%	47%	1%	7%
New Caledonia	3,934	**81%**	50%	57%	1%
		54%	79%	34%	0%
Polynesia and Micronesia	12,970	17%	11%	11%	13%
		34%	13%	21%	1%
Sundaland and Nicobar of India	0	0%	0%	0%	0%
		0%	0%	0%	0%
Tumbes Choco Magdalena	61,434	5%	19%	0%	78%
		4%	27%	0%	75%
Wallacea	78,786	**79%**	54%	56%	13%
		76%	61%	52%	0%
Archipelagos					
Fiji	6,496	10%	0%	2%	0%
		43%	0%	24%	0%
Galapagos	0	0%	0%	0%	0%
		0%	0%	0%	0%
Hawai'i	6,370	23%	22%	19%	**26%**
		25%	27%	19%	2%
Puerto Rico	1,183	61%	75%	28%	81%
		84%	**89%**	39%	0%

Table 5. Plots defined as tropical dry forest in this study and agreement (%) with World Wildlife Fund's ecoregions (Tropical and Subtropical Broadleaf Forest) and climatic definitions based on Worldclim (top) and CHELSA (bottom) climate data sets. Highest agreement with plots in bold.

Regions	# TDF Plots	Ecoregions Agreement	Murphy & Lugo	FAO	Dryflor	Aridity
Global	579	43%	64%	68%	32%	61%
			69%	**76%**	33%	5%
Africa	54	0%	76%	**83%**	52%	41%
			81%	76%	44%	11%
North and Central America	350	42%	63%	74%	26%	78%
			73%	**86%**	30%	4%
South America	48	33%	**79%**	62%	58%	42%
			79%	77%	58%	8%
South Asia	35	57%	91%	91%	34%	77%
			89%	**94%**	31%	14%
South East Asia/Pacific	86	76%	**38%**	26%	30%	9%
			31%	24%	23%	1%
Biodiversity Hotspots						
Caribbean	287	40%	60%	71%	23%	82%
			79%	**89%**	29%	1%
East Melanesia	0	0%	0%	0%	0%	0%
			0%	0%	0%	0%
Madagascar and Indian Ocean	1	0%	0%	0%	0%	**100%**
			0%	0%	0%	100%
New Caledonia	6	83%	83%	50%	67%	0%
			83%	**100%**	67%	0%
Polynesia and Micronesia	69	67%	**28%**	19%	20%	7%
			17%	16%	12%	0%
Sundaland and Nicobar of India	0	0%	0%	0%	0%	0%
			0%	0%	0%	0%
Tumbes Choco Magdalena	7	71%	0%	0%	0%	29%
			0%	0%	0%	0%
Wallacea	3	100%	67%	**100%**	33%	33%
			100%	67%	33%	0%
Archipelagos						
Fiji	9	22%	**44%**	0%	33%	0%
			44%	0%	11%	0%
Galapagos	3	0%	0%	0%	0%	**67%**
			0%	0%	0%	0%
Hawai'i	52	85%	**27%**	25%	17%	10%
			15%	21%	10%	0%
Puerto Rico	98	80%	51%	64%	23%	76%
			87%	78%	39%	0%

Table 6. Comparisons of best methods for estimating tropical dry forest extent and forest cover in 2000 and 2018 with open (>10% open canopy) and closed (>40% closed canopy) canopies between *30˚N and 30˚S*.

Definition	Source	Canopy type	Forest Cover 2000 (km^2)	Estimated Forest Cover 2018 (km^2)*	Gross Forest Cover Loss 2001-18 (km^2)
Pantropics	GFC	Open Closed	25,266,262 18,208,694	23,180,676 16,352,729	2,085,587 1,855,965
FAO	CHELSEA	Open Closed	8,981,537 4,440,046	8,337,834 3,948,678	643,703 491,368
Murphy & Lugo	Worldclim	Open Closed	10,674,741 6,894,394	9,723,467 6,081,932	951,274 812,462
WWF TSDBF	WWF	Open Closed	943,298 684,608	837,028 586,806	106,269 97,801
Consensus maps (3 No AI)	CHELSA	Open Closed	4,098,172 2,425,711	3,798,012 2,189,051	300,160 236,660
Consensus maps (3 No AI)	Worldclim	Open Closed	3,661,147 2,114,311	3,401,829 1,914,954	259,318 199,357
Simple Climate Definition	CHELSA	Open Closed	16,418,675 9,799,834	15,115,605 8,706,535	1,303,070 1,093,299
Simple Climate Definition	Worldclim	Open Closed	14,933,368 8,523,651	13,736,791 7,529,630	1,196,578 994,021

* Denotes estimated forest cover in 2018 using gross forest cover loss. Forest gain data available from 2001-2012 with no equivalent for 2013-2018 (Hansen et al., 2013).

Table 7: Comparison of estimated global tropical dry forest cover.

Base Layer	Source	Methodology	Extent (km^2)
WWF Ecoregions	Miles et al. 2006	Ecoregion biomes thought to contain TDF* $\geq$40% closed canopy MODIS	1,048,700
aridity index	Bastin et al. 2017	$\leq$0.65 aridity index (1) $\geq$10% open canopy; (2) $\geq$40% closed canopy	(1) 13,260,000 (2) 7,770,000

*Sub/tropical dry broadleaf forest; Sub/tropical grassland, savanna and shrubland; Mediterranean forest, woodland and scrub; Desert and xeric shrubland.

7 FIGURES

Figure 1. Global distribution of 579 tropical dry forest plots based on primary sources from four separate studies on tropical dry forest ecology and distribution; queried studies from WoS, Google Scholar, and Scopus; and data sets from three repositories (DRYAD, ForestPlots.net, GBIF).

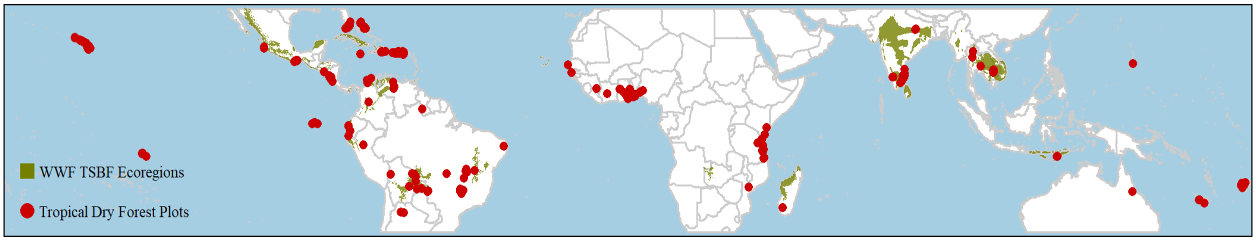
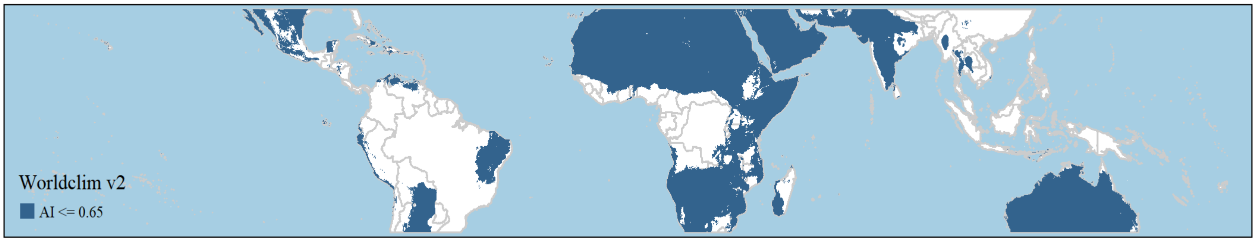
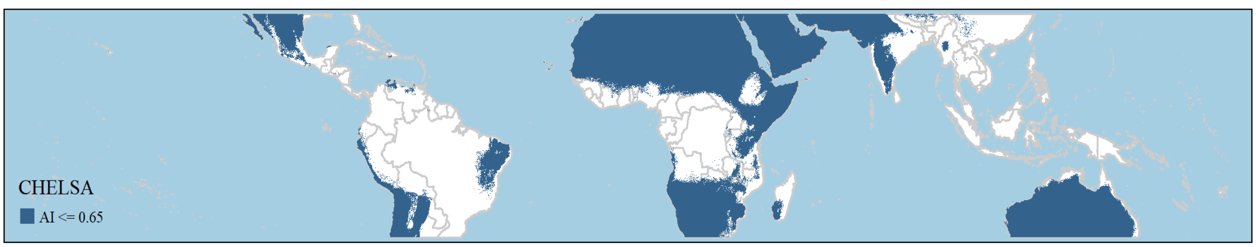


Figure 2. Global distribution of potential tropical dry forest extent based on Aridity Index ($\leq$ 0.65) derived for (a) Worldclim, (b) CHELSA and (c) overlap of Aridity Indices.

a.



b.



c.

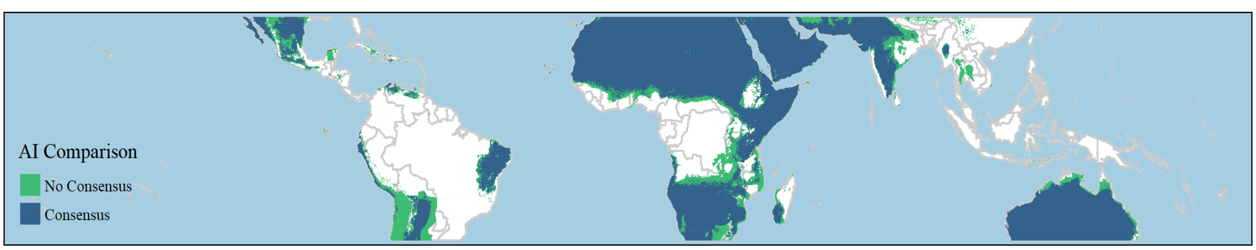
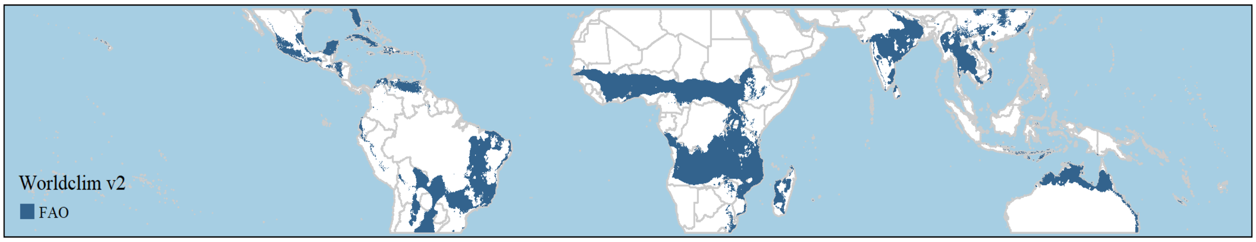


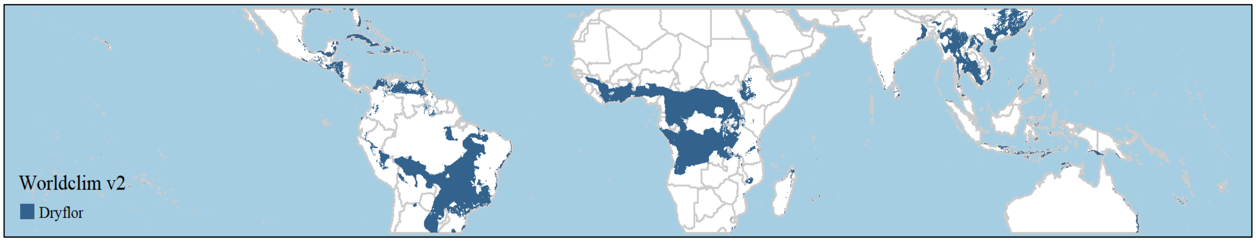
Figure 3. Global distribution of tropical dry forest regions based on: (a) Murphy and Lugo, (b) FAO, (c) DryFlor and (d) overlap of all three climatic definitions using Worldclim.

a.

b.



c.



d.

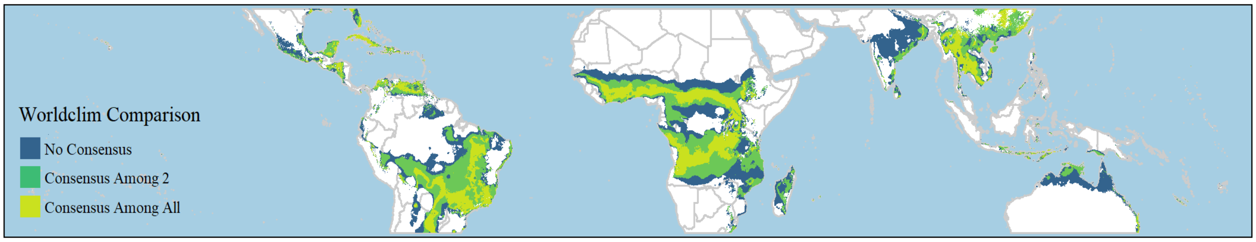
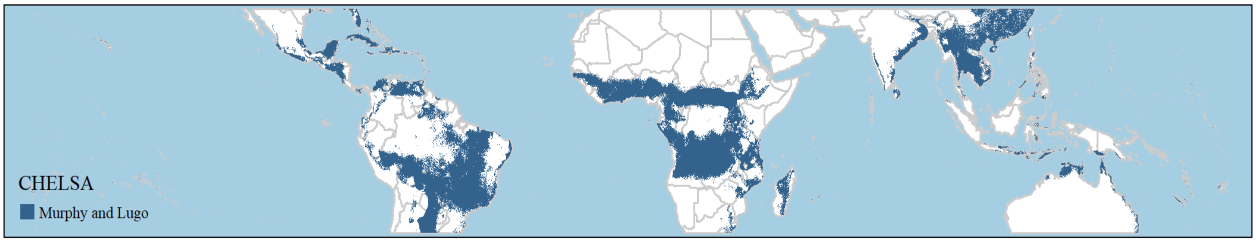
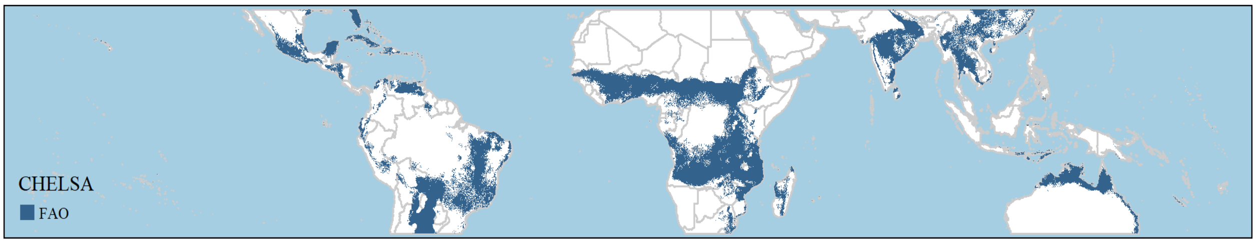


Figure 4. Global distribution of tropical dry forest regions based on: (a) Murphy and Lugo, (b) FAO, (c) DryFlor and (d) overlap of all three climatic definitions using CHELSA.

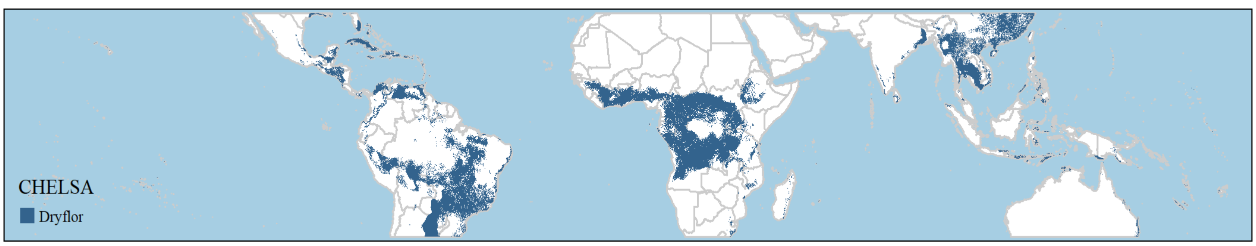
a.



b.



c.



d.

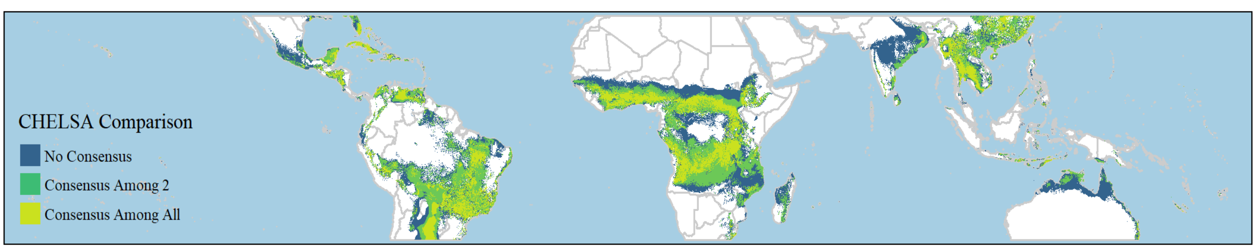
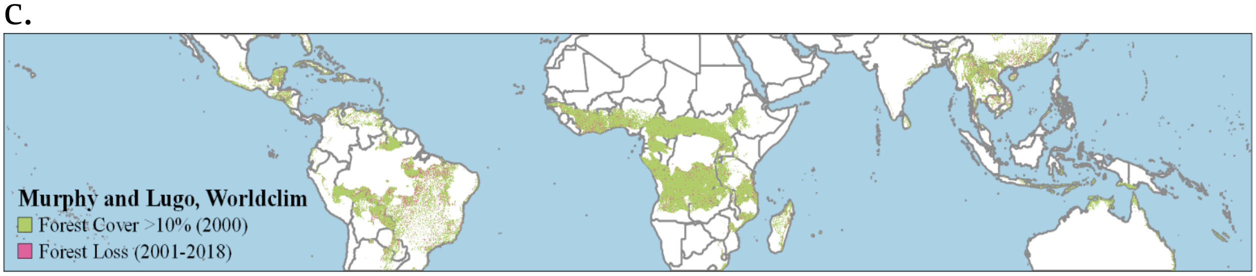


Figure 5. Forest cover change for (a) FAO using CHELSA at ≥ 10% canopy cover, (b) FAO using CHELSA T ≥ 40% canopy cover, (c) Murphy and Lugo using Worldclim at ≥ 10% canopy cover, and (d) Murphy and Lugo using Worldclim at ≥ 40% canopy cover.

a.

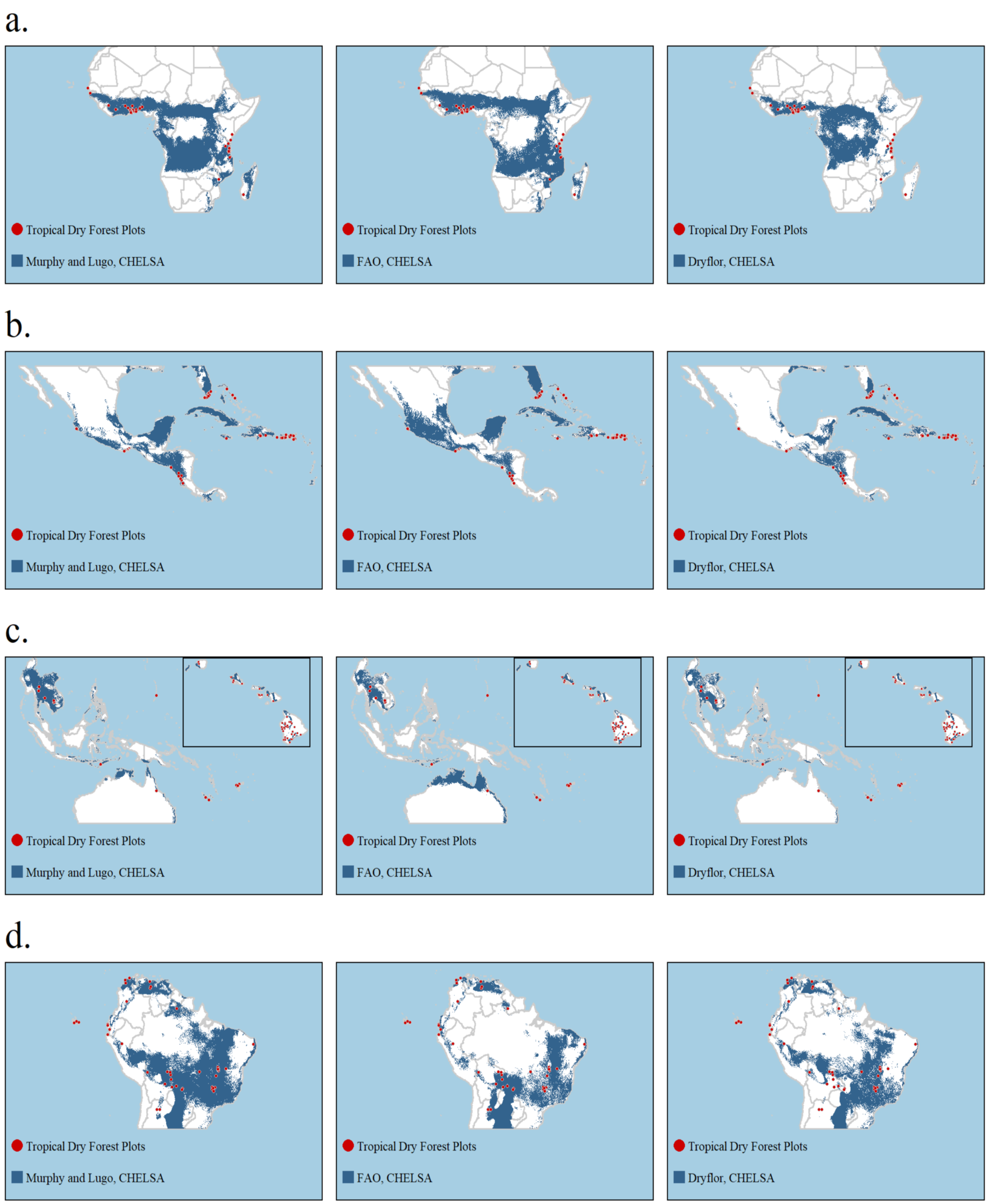
b.

c.



d.

Figure 6. Estimate of tropical dry forest extent (km^2) across subcontinents per climatic definitions (a-e) using CHELSA.



e.

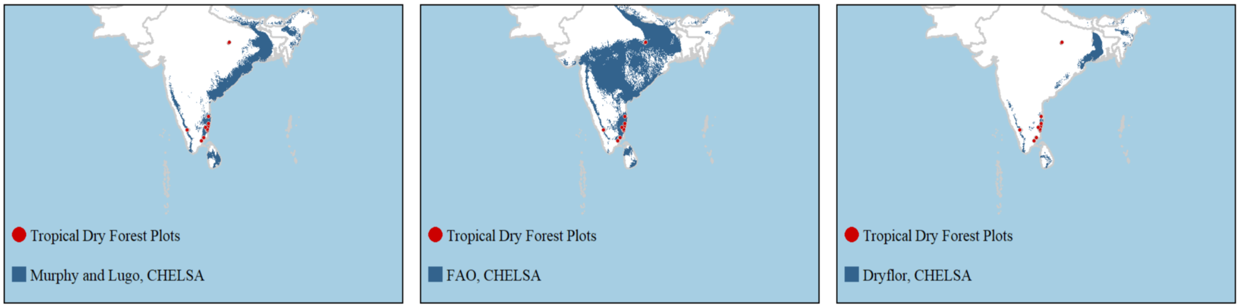
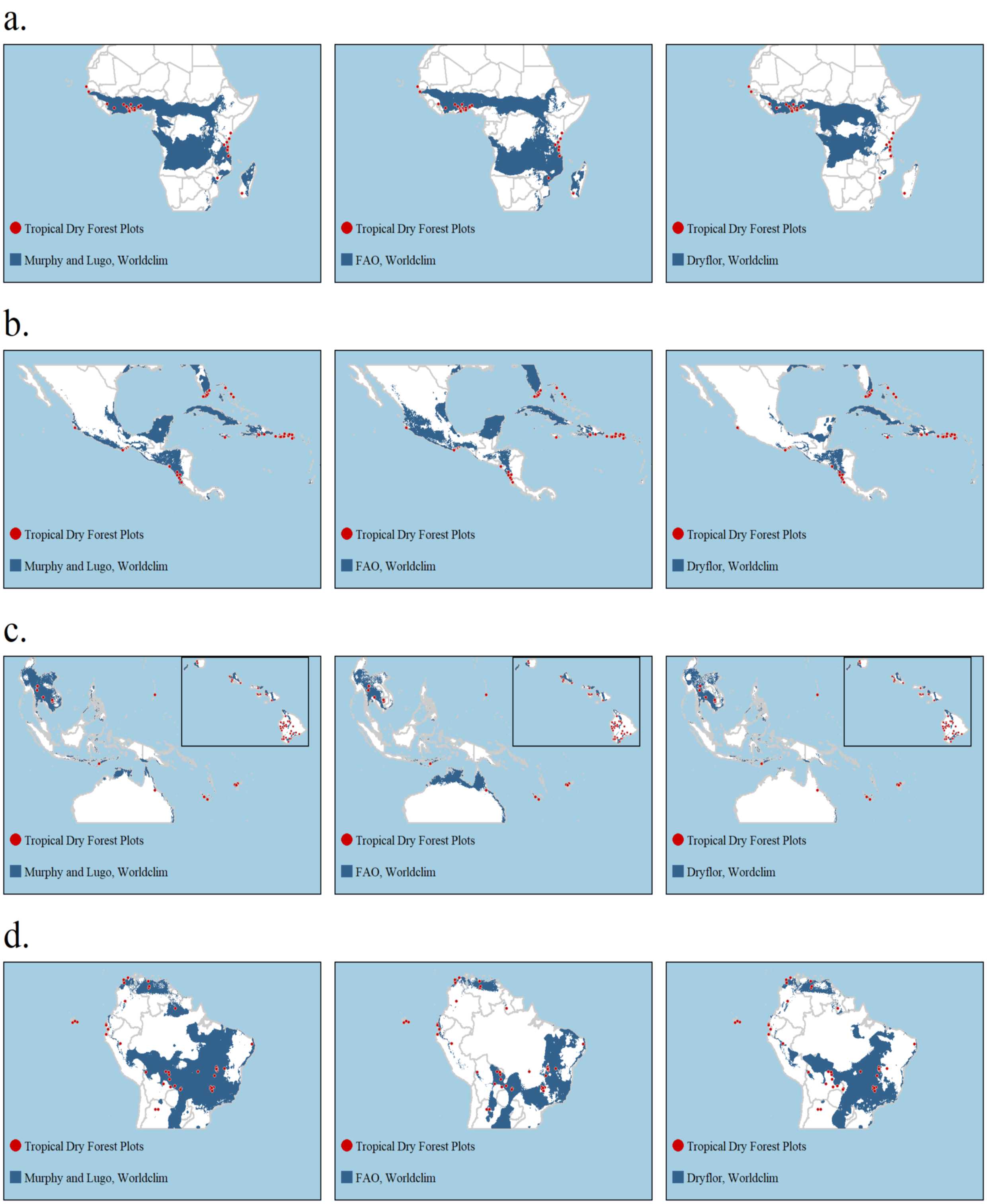

Tropical Dry Forest Plots
Murphy and Lugo, CHELSA
Tropical Dry Forest Plots
FAO, CHELSA
Tropical Dry Forest Plots
Dryflor, CHELSA

Figure 7. Estimate of tropical dry forest extent (km^2) across subcontinents per climatic definitions (a-e) using Worldclim.



e.

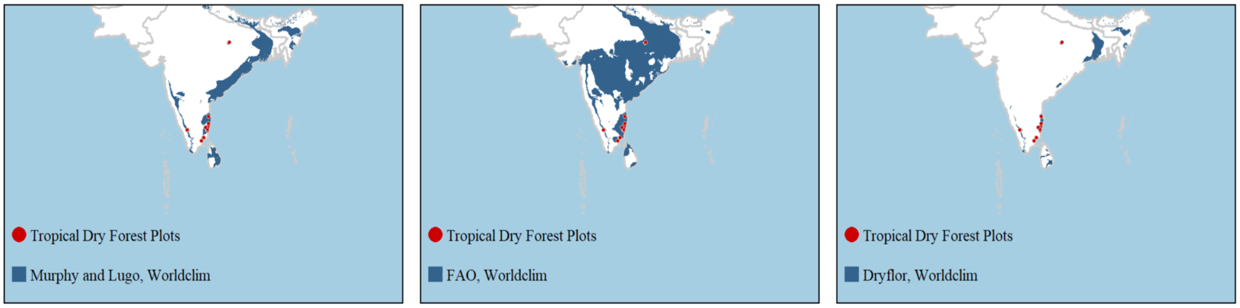
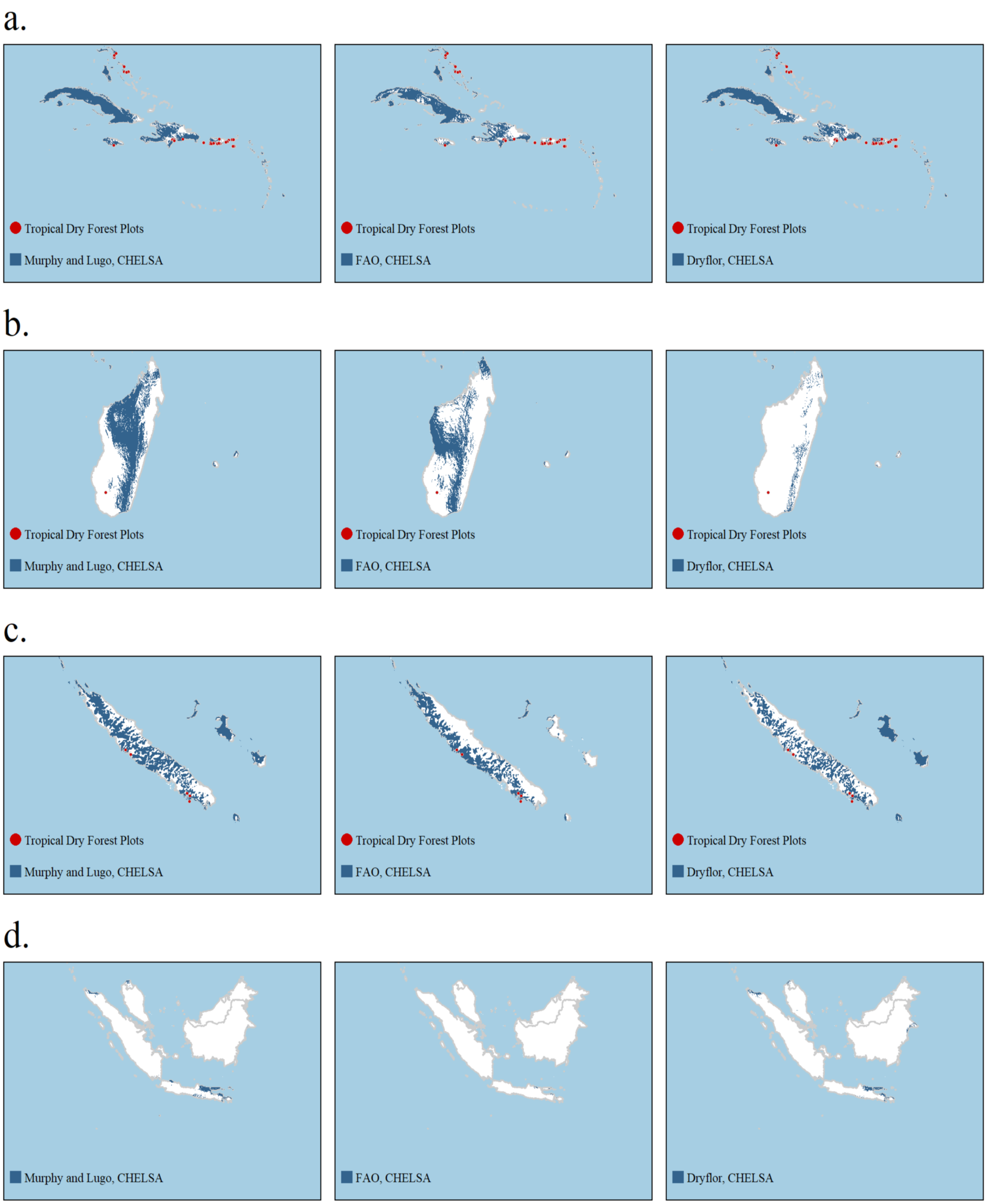
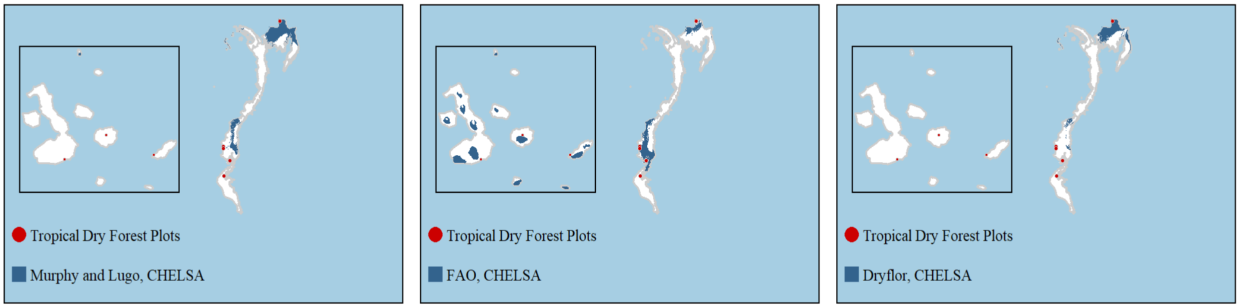

Tropical Dry Forest Plots
Murphy and Lugo, Worldclim
Tropical Dry Forest Plots
FAO, Worldclim
Tropical Dry Forest Plots
Dryflor, Worldclim

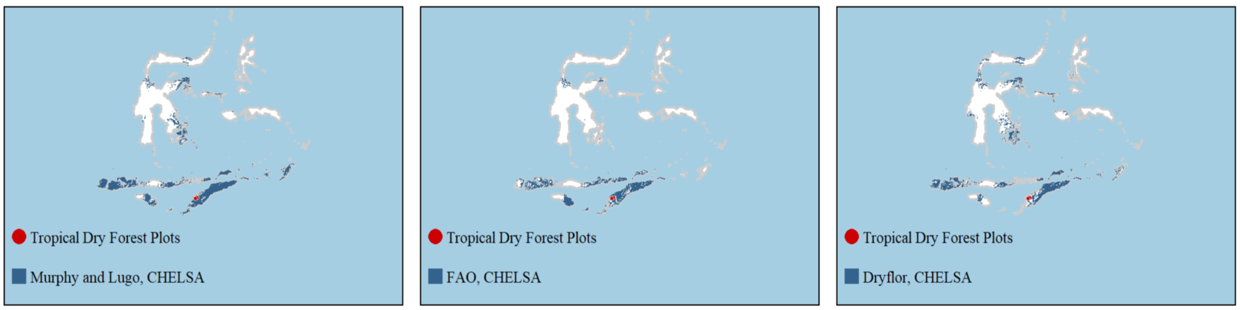
Figure 8. Estimate of tropical dry forest extent (km^2) across biodiversity hotspots per climatic definitions (a-g) using CHELSA.



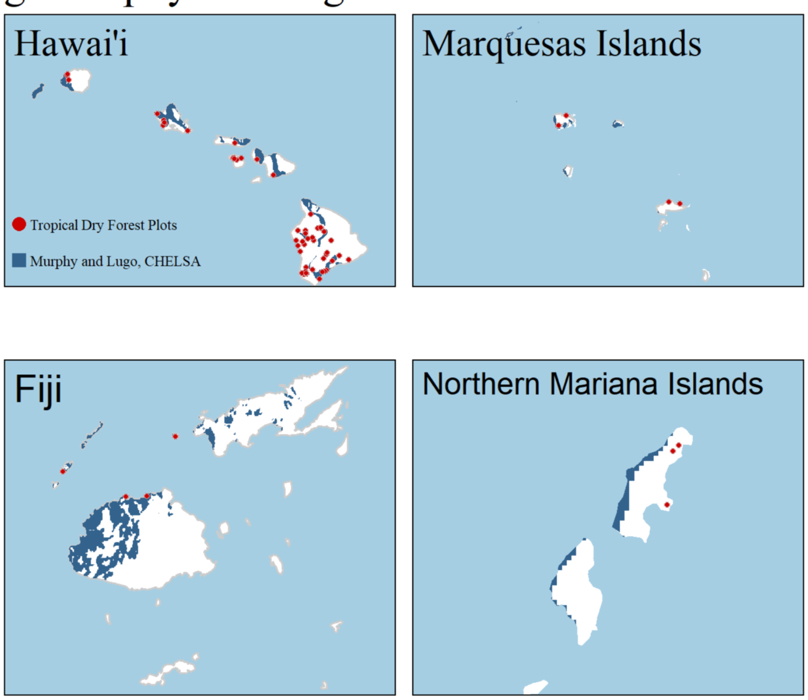
e.



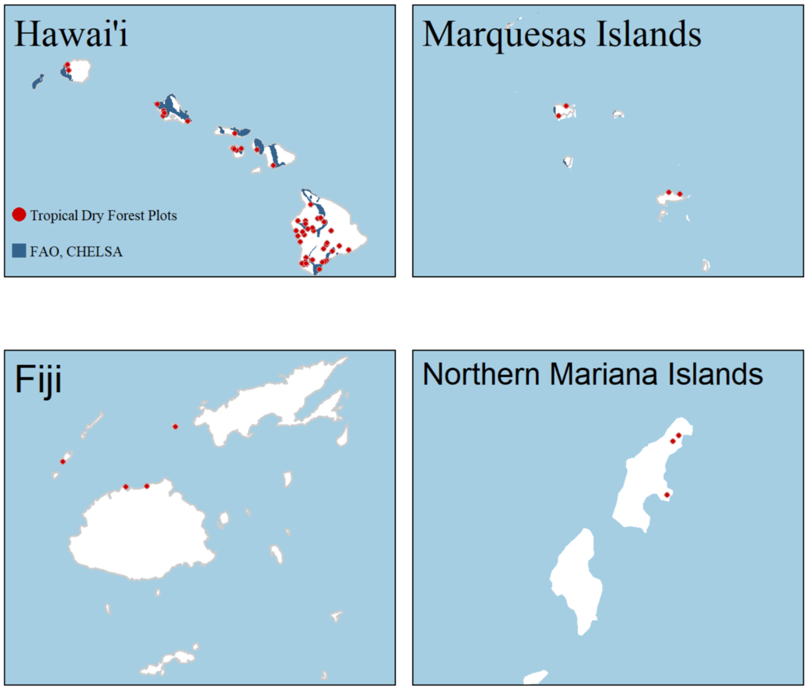
f.



g. Murphy and Lugo



g. FAO



g. Dryflor

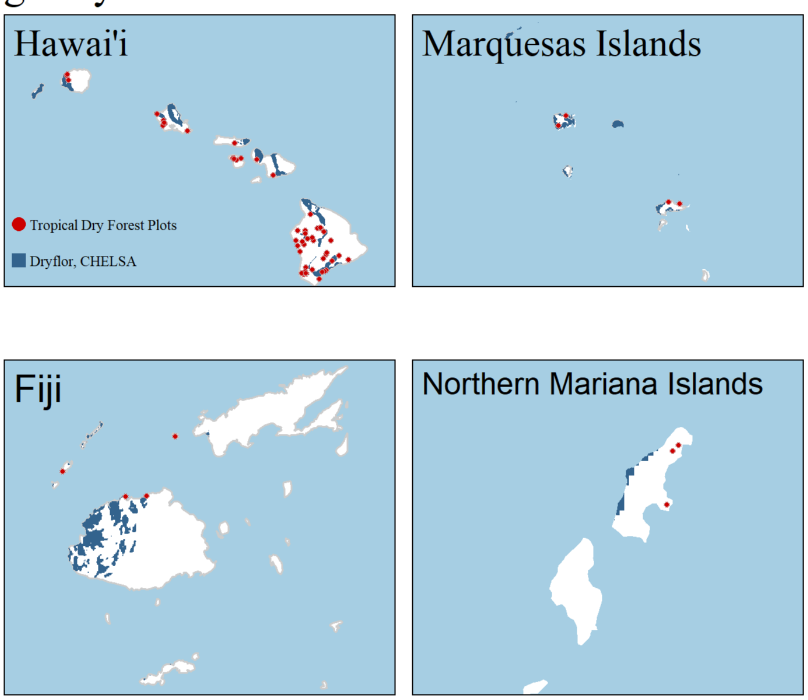
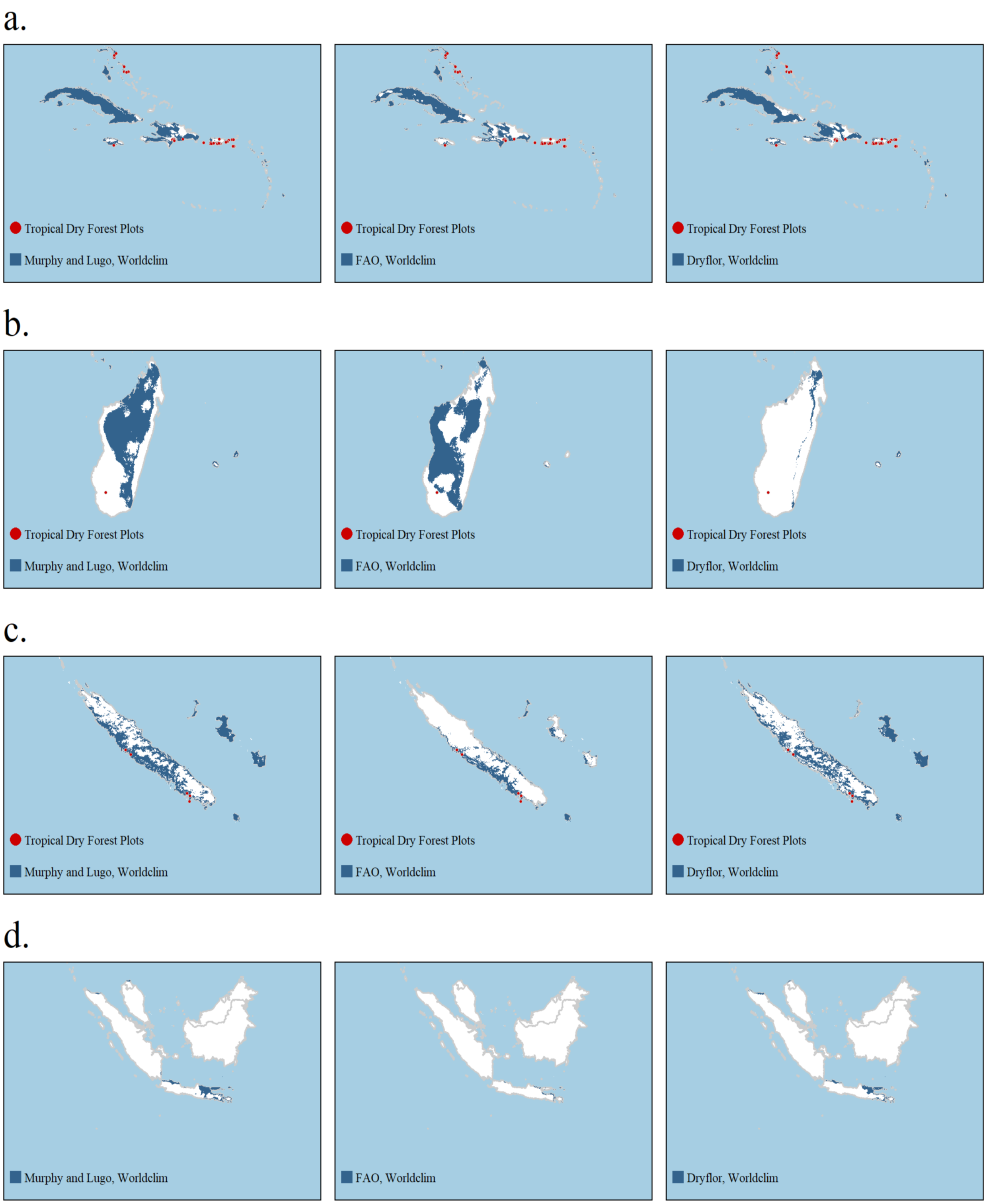
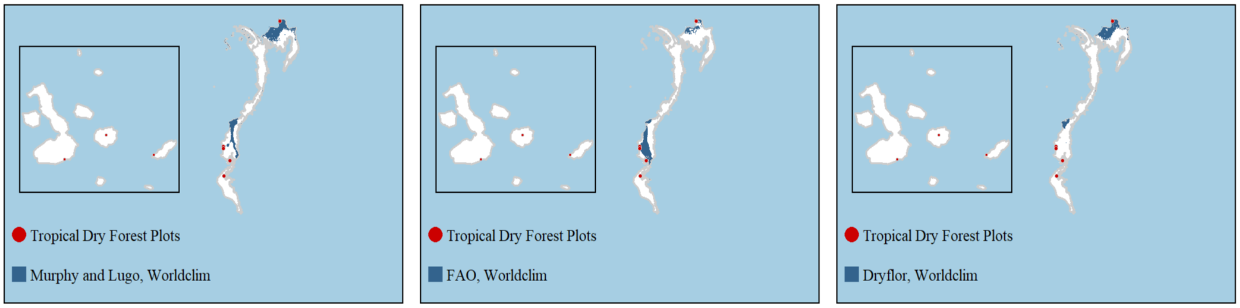


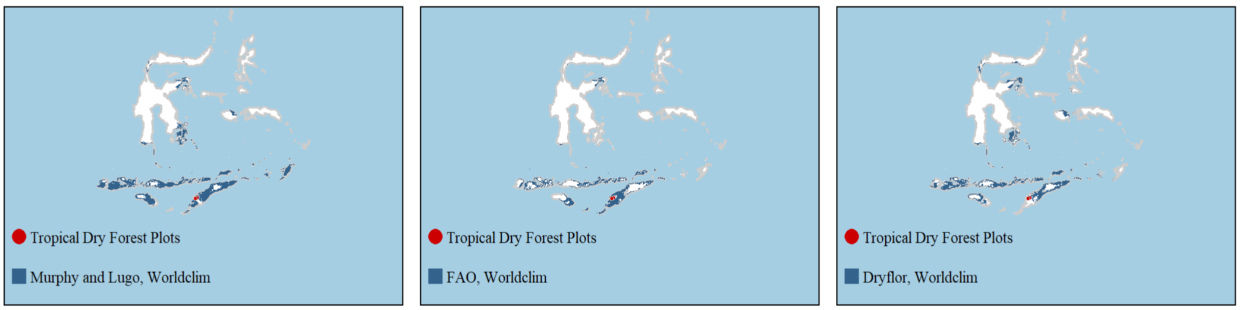
Figure 9. Estimate of tropical dry forest extent (km^2) across biodiversity hotspots per climatic definitions (a-g) using Worldclim.



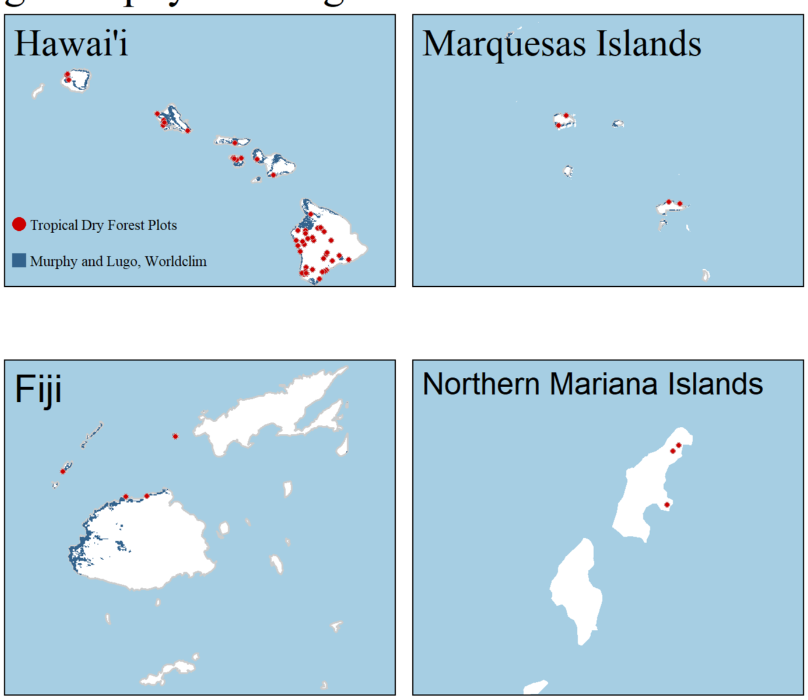
e.



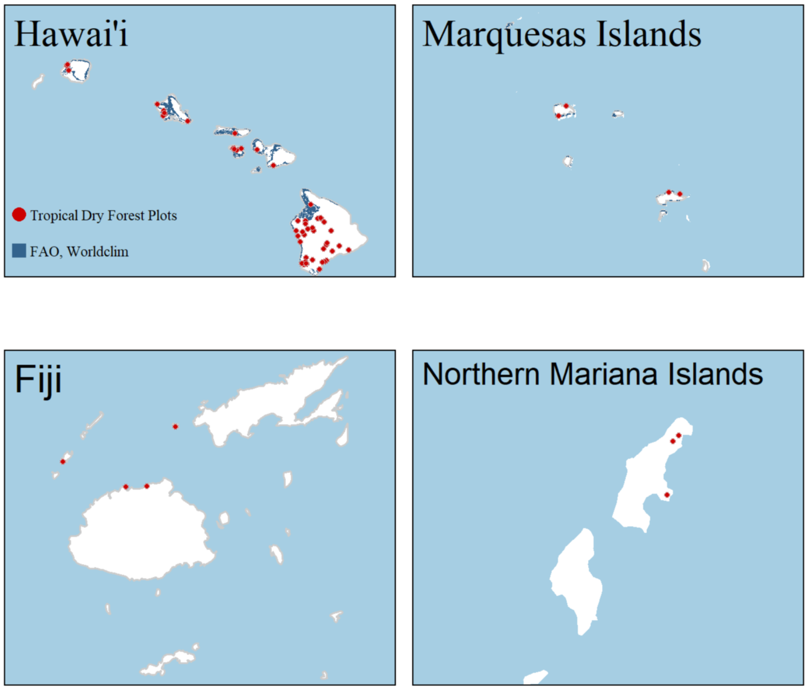
f.



g. Murphy and Lugo



g. FAO



g. Dryflor

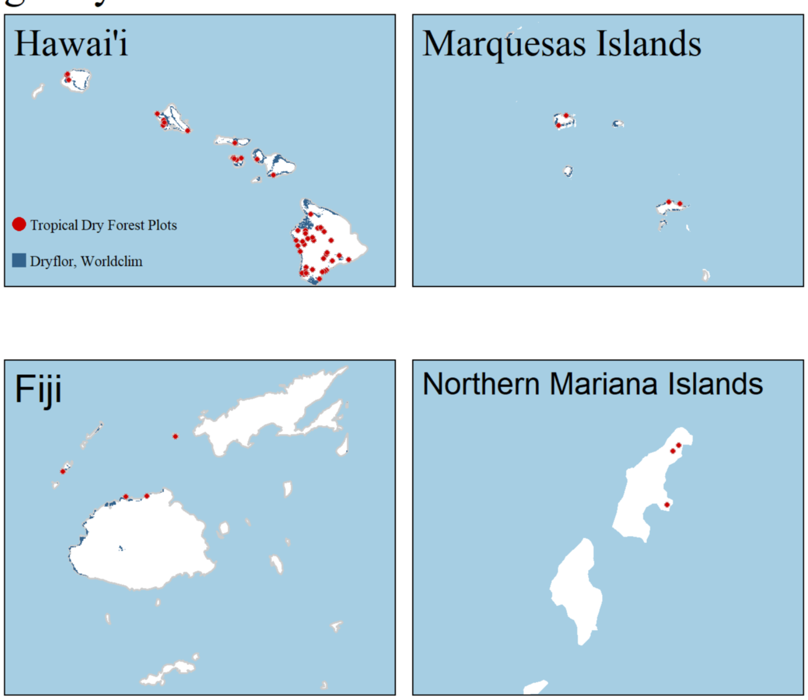


Figure 10. Estimate of tropical dry forest extent (km2) across archipelagos per climatic definitions (a-d) using CHELSA.

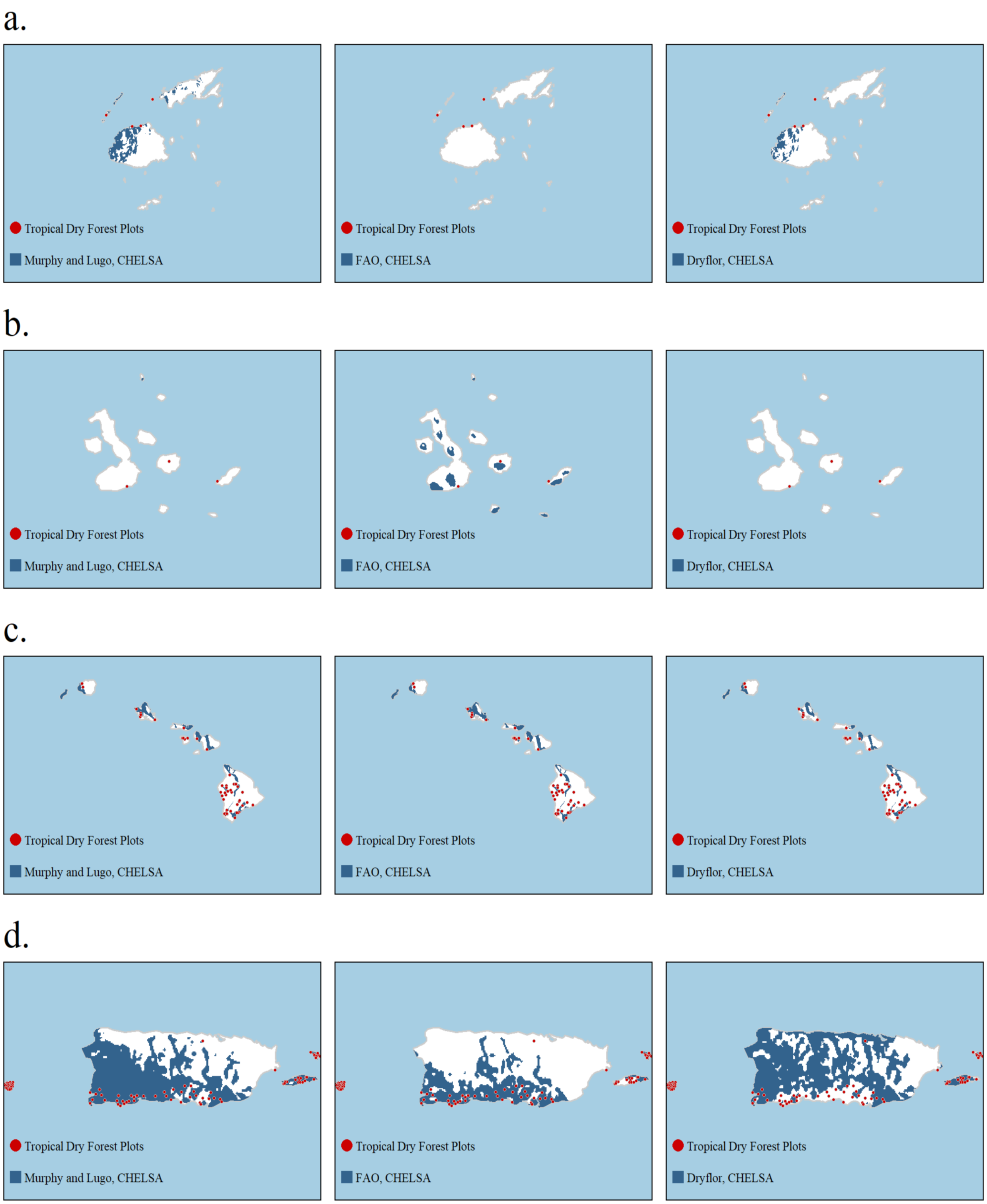


Figure 11. Estimate of tropical dry forest extent (km2) across archipelagos per climatic definitions (a-d) using Worldclim.

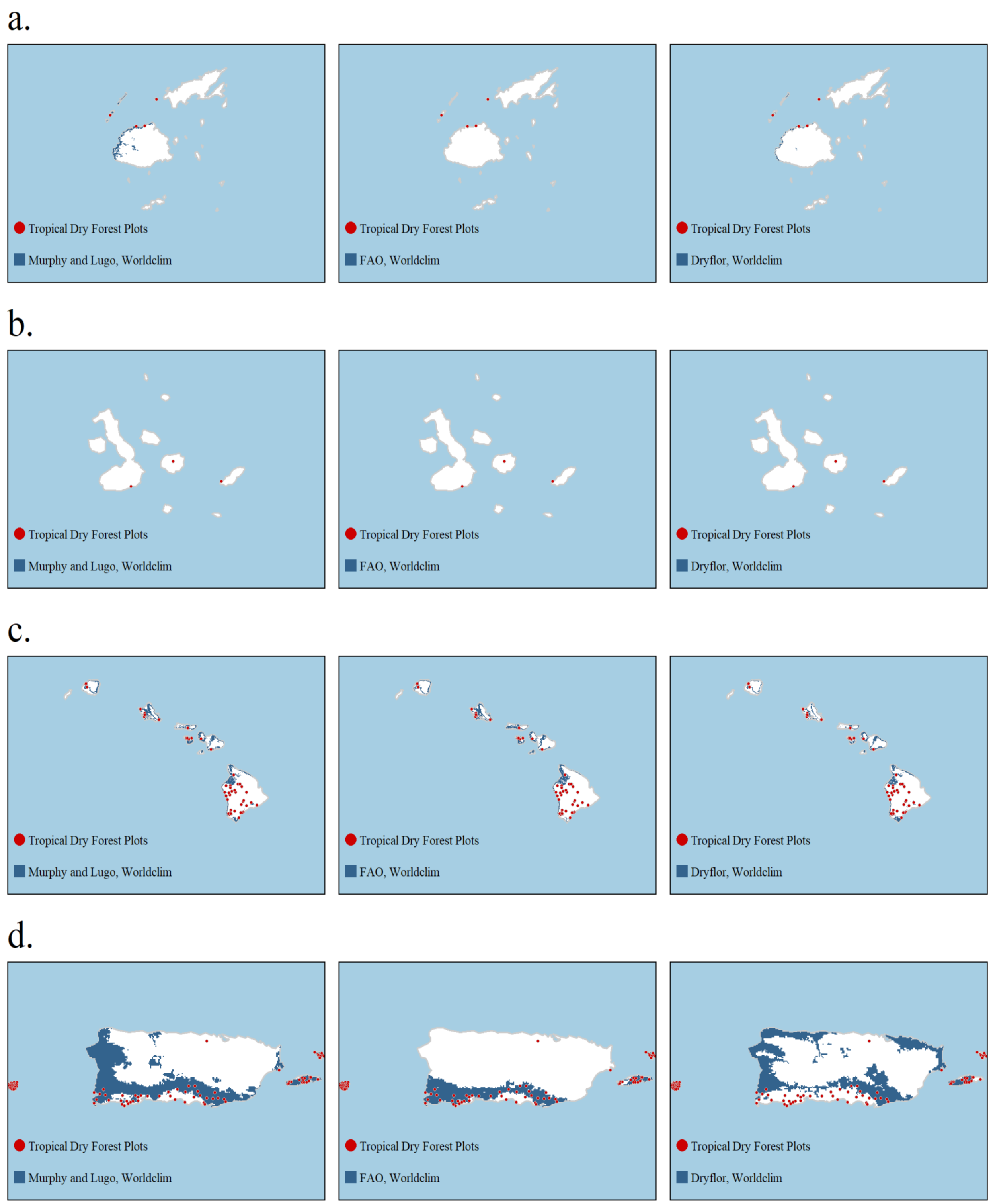
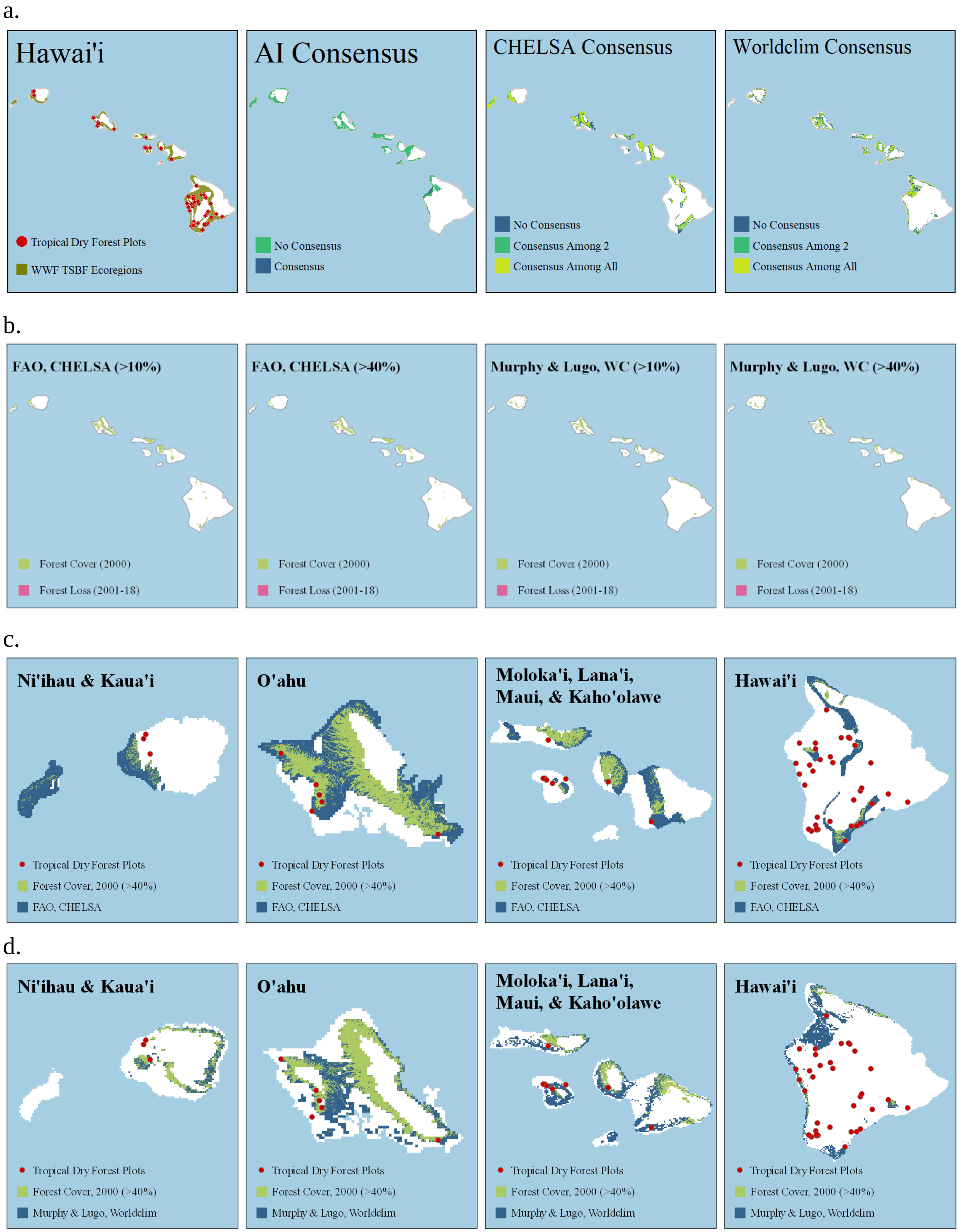


Figure 12. Comparison of tropical dry forest extent across Hawai'i with (a) consensus of climatic definitions; (b) forest cover; and (c & d) overlay of climatic definitions, forest cover and plots.



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