Appendix A: Change Agents

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A-1.1.1 Development

This CA class contains a broad variety of CAs with very different CE effects; we therefore treat them individually:

- Urbanization: Urbanization displaces habitat for CEs, introduces invasive species, and alters ecosystem dynamics (e.g., hydrology, fire).
- Infrastructure (roads, pipelines, transmission lines, water transmission): infrastructure displaces habitat for CEs and creates movement barriers, creates bird collision features & alters predator behavior (e.g., introducing perches in non-forest lands for raptors), alters hydrology, and introduces invasive species.
- Energy development (oil, gas, wind, solar, geothermal & biomass): This CA impacts CEs by destroying or altering habitat, creating bird collision features, introducing invasives, causing ground water pollution or changes, and creating movement barriers.
- Groundwater withdrawals pose significant threats to aquatic CEs in the ecoregion, where basin-fill and bedrock groundwater levels provide crucial baseflows to perennial streams and sustain crucial water levels in spring ecosystems. In many cases, existing rates of withdrawal already threaten many groundwater-dependent ecosystems in the ecoregion; increases in withdrawals could accelerate impacts to already-threatened ecosystems and expand the geographic scope of such impacts. Such impacts could include shrinkage of perennial stream lengths, decreases in stream baseflow and concomitant increases in baseflow temperature, and reduced spring water levels or discharges, all of which would affect hydrologically and temperature-sensitive aquatic species and communities (e.g., Deacon et al. 2007).
- Mining (all minerals and materials): Mining has similar affects to other development along with radical hydrologic changes and increased dust sources.
- Military use/expansion areas: Although military lands hold some of the best protected and managed wildlife habitat, military exercises (depending on type) can have significant impacts on CEs in terms of land cover and soil damage, contamination, dust, & noise and can limit opportunities for other land uses such as recreation and energy development/transmission.
- Air quality impacts (non-attainment areas and dust): Air quality is an outcome of other CAs but where plume/deposition areas are mapped or can be modeled, more specific CE impacts can be assessed such as visual impairment of scenic views & plant growth changes from nitrogen and dust.
- Recreation (OHV use, other intensive recreation, land sales, etc.): OHV use can have significant impacts such as land cover and soil disruption, spread of invasive species, noise pollution causing habitat abandonment, etc.
- Refuse Management (landfills, sewage sludge disposal, nuclear disposal, etc.): This CA can impact CEs through habitat removal or alteration (e.g., hydrologic, fertilization, erosion, dust).

Applying development CAs to MQ analyses largely involved simple footprint analyses where CA maps were overlain with CE maps for example and did not involve complex modeling of the direct, indirect, or synergistic effects. Therefore we believe the results of such analyses should be of confidence proportionate to the confidence in the distribution maps input to those analyses.

A-1.1.2 Invasives**: Terrestrial Plants and Aquatic Species**

Globally terrestrial non-native (aka "exotic") invasive plant species, as well as many invasive native species, can have detrimental effects and some documented positive effects on native ecosystems. From a conservation perspective, where possible, maintaining the native biodiversity of an ecosystem helps the resiliency and resistance of the ecosystem to climate change and other stressors. The presence of terrestrial non-native invasive plant species is a rapidly observed indicator of current or past disturbance and is a direct measure of current plant species composition within an ecosystem. The negative effects of terrestrial non-native invasive plant species on native ecosystems are becoming increasing well documented. They can cause biotic homogenization of ecosystems (Houlahan and Findlay 2004). Non-native invasive species have been documented to have a competitive advantage over native species by altering the rate of decomposition and litter nitrogen loss (Ashton et al. 2005), reducing soil moisture and changing wildfire frequency and intensity (Smith et al. 2008, Wisdom and Chambers 2009). Invasive non-native species have been documented to have larger seed sizes in their introduced range than their native range, indicating a high competitive advantage over local native species (Buckley et al. 2003). Invasive non-native species in grasslands have lowered N availability by outcompeting native plants for mineral N, making it difficult for native species to reestablish and promoting the spread of the non-native invasive over native grass species (Scott et al. 2001).

Within this ecoregional assessment three groups of invasive plant species were the focus: invasive (mostly exotic) annual grasses (e.g.Cheatgrass (*Bromus tectorum*), red brome (*Bromus rubens*)); invasive and noxious forbs (e.g. *Salsola* spp., *Cirsium arevense*), and woody species invasive (mostly exotics) to riparian areas (e.g. Tamarisk (*Tamarix* spp.) and Russian Olive (*Eleagnus angustifolia*)). Each has their own impact on native ecosystems. Cheatgrass (*Bromus tectorum*) begins growth earlier in the spring than most native perennials, depletes soil moisture and causes excessive competition when they emerge with other native species (Smith et al. 2008). Cheatgrass can change the timing and frequency of wildfires in such a way that completely eliminates native sagebrush species (Wisdom and Chambers 2009). Tamarisk (*Tamarix* spp.) causes changes to ecosystem structure, function and animal use. These changes include: supporting fewer bird species and individuals than native trees (Sogge et al. 2008), a reduction in stream flow volume and groundwater levels, an increase wildfire frequency, an increase soil salinity on controlled rivers, reduced agricultural production and drop in recreational use of invested reaches (Lewis et al. 2003). While the amount of water use by tamarisk has been disputed (Stromberg et al. 2009) and the fact that Southwest willow flycatcher, an endangered species, successfully nests in Tamarisk trees (Sogge et al. 2008), efforts to remove this species may better be served by restoring ecosystems processes that supports riparian areas (i.e. flooding) rather than targeting tamarisk removal *per se* (Stromberg et al. 2009). Russian Olive (*Eleagnus angustifolia*) reduces the habitat for some invertebrates which can affect the food chain for aquatic species (Moline and Poff 2008). A reduction in the density of Russian Olive can be beneficial to native lizard populations (Bateman et al. 2008).

<u>Aquatic Invasive Species in Aquatic Resources</u> Impacts from invasive species are considered to be of equal importance with habitat loss and global climate change as the primary factors responsible for the world's rapidly decreasing biodiversity and altered ecosystem functioning (Sala et al. 2000; Lockwood & McKinney 2001; Lodge 2001; Mack *et al.* 2001; McKinney and Lockwood 1999). The level of density or biomass of the invasive aquatic taxon in a CE and watershed is critical to the level of impact it has once it becomes established. Densities also affect dispersal rates with higher densities resulting in increased

‘potential propagules’ (Veltman et al. 1996; Lockwood et al. 2005; Colautti et al.2007). Most data rich invasive species models nearly always incorporate density estimates when available (Shigesada and Kawasaki 1997).

Only one of our databases reported densities for only one single taxon and none of our databases reported biomass. Therefore, our invasive species impact index does not explicitly include level of density or biomass. However, for a location to have been reported the species most likely occurred at densities greater than its detection threshold. Given the recognized negative ecological impacts of aquatic invasive species and the scarcity of aquatic invasive species rapid ecological assessments, we have created an index of aquatic invasive species impact. The index was developed for each Conservation Element (CE) at the 5th level watershed. It consists of three indices: 1) Known Status Index, 2) At Risk Index, and 3) Future Impact Index. The Known Status Index and the At Risk Index were developed based on reported invasive species locations at the time databases were available, whereas the Future Impact Index is the predicted impacts in 2025 based on surrounding conditions.

A-1.1.3 Fire

Fire has historically played a critical role driving the dynamics of many ecological systems in the Mohave Basin and Range Ecoregion. Researchers believe that, prior to European settlement, these systems were largely fuel-limited meaning that the fire regime was controlled by the availability of continuous fuels and not directly by climate. As a result, fires are thought to have been infrequent (or non-existent in some systems) with return intervals of >100 years for *Artemesia tridentata* communities, and potentially longer for other systems (Mensing et al. 2006). However, our understanding of the historical dynamics of the shrub-steppe systems of the Mohave Basin and Range is limited by a number of factors including the lack of data sources (e.g. tree scars or sediment cores). In addition, recent historical observations are confounded by at least 3 interacting drivers. The first is the introduction of domestic livestock which were introduced as early as the 1500s. Livestock, by consuming the grasses and forbs reduced the fine fuels, and as a result increased fire return intervals within some systems. One consequence of this was the expansion of Pinyon Juniper into sagebrush dominated systems (Miller and Rose 1999). Secondly, the introduction of exotic grasses in the late 19th and early 20th centuries has resulted in dramatic changes in the fire regimes of all the native ecosystems in which they are now found (Reid et al. 2008, Rice et al. 2008). Cheatgrass and red brome are now widely distributed in the Mohave. And finally, a changing climate; our first observations of the Great Basin occurred during the end of the 19th century -- at the end of the Little Ice Age (West 1999). Thus, when first observed these systems were adapted to a cooler and wetter climate.

Fire, invasive grasses, and climate change have been shown to interact to effect dramatic ecosystem change throughout the Great Basin and Mojave (Brooks et al. 2004; Pellant 2006). Cheatgrass (*Bromus tectorum)* and red brome (*Bromus rubens*) are the most widespread of these invasive species and have become drivers of the current fire regime. Both are highly competitive, highly invasive, and change soil characteristics to the detriment of native grasses and forbs. Under favorable conditions these species are hugely productive, creating continuous fine-fuel loads across thousands, of hundreds of thousands, of acres. When ignition occurs in these annual grass-invaded communities, fires can rapidly span tens of thousands of acres (Brooks et al. 2004, Zedler 1983). Unlike historic, small patchy fires these annual grass driven fires tend to be uniformly stand-replacing, high severity fires. The resulting exposed soil is rapidly recolonized by annual grass seeds, resulting in more frequent fires that, in turn results in a stable annual grassland state which is extremely difficult to restore back to native vegetation. Red brome is able to colonize, and dominate the understory of undisturbed Mojave systems (Salo 2004), accelerating this process. Prior to the introduction of the annual grasses, most of the

Mojave's shrublands were sparsely vegetated and rarely burned. Fires are now facilitated by the dense continuous fuels created by red brome. The Conservation Elements most at risk are the sagebrush shrubland, Pinyon Juniper, mid-elevation and mixed desert scrub communities (Peters and Bunting 1994, Pellant 1990, Rice et al. 2008). West (1999) estimates that approximately 25% of the original extent of the sagebrush steppe has been converted to annual grasslands.

The interaction between climate and fire regimes becomes more complex as we look into the future. For drought-driven systems (e.g., montane forests) current climatic models suggest more frequent, and larger fires as the frequency and duration of droughts increases (Westerling et al. 2006, Brown et al. 2004). However, for the fuel-limited systems including the Mojave shrublands, the situation is more complicated. Annual grasses are fierce competitors for water in the first few centimeters of the soil. Thus, a precipitation pattern shift toward less frequent and less abundant patterns favors these species. For example, red brome will germinate following 1 cm rainfall, whereas native species require a minimum of 2 cm for germination. Similarly, warmer winters favors these annual grasses that opportunistically germinate in the fall (Abatzoglou and Kolden 2011). Conversely, extended drought may result in longer fire return intervals resulting from a lack of accumulation of annual grass-fuels (Westerling and Bryant 2008, Salo 2004) and decreased dispersal of annual grass seed (Bradley 2009, Brown et al. 2004).

A-1.1.4 Climate Change

Human activities have already generated sufficient greenhouse gas emissions to commit Earth to substantial climate change in the coming decades. Although the current principal driver toward extinction is habitat loss, in the coming decades, climate change is projected to become at least or even more important. A wide range of climate change impacts to species and ecosystems have already been observed, including shifts and contractions in species distributions, changes in phenology, reductions in populations sizes, the decoupling of interactions that had co-evolved, increased spread of wildlife diseases, increased spread of invasive and exotic species, and decreases in habitat due to climate-induced factors such as loss of glacial ice and sea level rise (Heller & Zavaleta 2009). Assessing the biodiversity consequences of climate change is essential to minimize the potential loss of biodiversity and the invaluable goods and services that it provides for human well being.

Data from current and paleontological observations, experiments, and models all indicate that populations often have the capacity to adapt to climate change via a variety of mechanisms, including in situ adaptation and dispersal (Willis & Bhagwat 2009). Habitat heterogeneity providing microclimatic opportunity may play a critical role in building the resilience ecological communities to rapid climate change (Loarie et al 2009). Increasing connectivity to accommodate species range shifts is the single most common recommendation to support biodiversity adaptation to climate change (Heller & Zavaleta 2009). Managers and conservationists clearly require information about which species and habitats are most at risk, and how the adaptive capacities in natural systems can be best leveraged to build resilience and resistance in ecological communities.

Ecological niche models run under alternative climate change projections provide an important tool for assessing species exposure to climate change, where exposure is defined as the extent of climate change likely to be experienced by a given species or location (Dawson et al 2011). This is one step among several required to assess overall vulnerability to climate change. Additional factors for a more complete understanding of vulnerability include assessing sensitivity to climate change, defined as the extent to which a species survival is dependent on climatic factors, and adaptive capacity, defined as species ability to cope with change (Dawson et al 2011). Results from niche modeling under future climates can help prioritize which species may require a more complete assessment of climate change vulnerability.

A-1.2 Spatial Models

A-1.2.1 Development

A-1.2.1.1 Current Scenario

This raster represents development CAs in the MBR for the current scenario (2010). This raster was developed to represent CAs in a clear, combined format and to answer the MQs requiring the scenario-based assessment of CEs. The raster contains 19 classes which represent different types of human infrastructure on the landscape. Some types are easily defined with precise footprints (pipelines, roads, energy development areas) while others are broader land cover types derived from spatial models (development, mining, and refuse areas).

Many CAs overlap and per agreement by the AMT, areas of overlapping CAs were reclassified as "multiple CAs." All input data was rasterized to 30m cells. Exceptions include raster input data which includes Crops/Irrigate Pastures, and Military Urbanized Areas which were derived at 30m from the NLCD 2006 (Fry et al. 2011). Urban/Rural Development, derived directly from the ICLUS/SERGoM was also raster source data. The ICLUS/SERGoM was developed at a 90m resolution. While geographic 'best practice' is to convert the final raster output to 90m, the final assessment raster was maintained at 30m to preserve the higher resolution of most of the input datasets.

This data was visually inspected against input datasets to assure that the thematic and geographical integrity of the inputs were maintained.

Current Scenario Classes and Dependent Data Information

1. No development change agent
2. Multiple change agents. Represents areas of overlapping CAs.
3. Urban/Rural Development. This class was derived from the Integrated Climate and Land Use Scenarios (ICLUS) and its related spatial database, Spatially Explicit Regional Growth Model (SERGoM) (EPA, 2010). SERGoM data uses US Census block housing units, protected lands, groundwater well density, and road accessibility to estimate housing density. This class attempts to apply a footprint to a wide array of housing density classes put forth in the ICLUS/SERGoM dataset. This raster dataset is a classification of base case scenario from ICLUS v1.2 which is produced using the SERGoM v3 model, depicts housing density for the coterminous US in 2000, based on 2000 US Census Bureau block (SF1) datasets. The AMT in Las Vegas, NV in September, 2011 agreed that urban and rural development would be defined as less than 160 acres per housing unit. Areas that are less dense (> 160 acres per unit) are classified undeveloped and therefore are not given a 'footprint' in the analysis.
4. Renewable Energy – Geothermal Energy. Geothermal energy project footprints were obtained from BLM and represent project currently operating or approved as of May, 2011. These were verified by BLM state offices between June and October, 2011. A complete list of these projects can be found in Table A - 6.
5. Renewable Energy – Solar Energy. Solar project footprints were obtained from BLM and represent project currently operating or approved as of May, 2011. These were verified by BLM state offices between June and October, 2011. A complete list of these projects can be found in Table A - 6.

6. Renewable Energy – Wind Energy. Wind project footprints were obtained from BLM and represent project currently operating or approved as of May, 2011. These were verified by BLM state offices between June and October, 2011. A complete list of these projects can be found in Table A - 6.

7. Mines/landfills. This class includes major landscape disturbances, including open pit mines, tailings piles, leach pads, landfills and other refuse areas. See the Mining and landfills section below and full metadata is available for this layer as a modeling product developed by NatureServe for the REA.

8. Oil and Gas Wells. BLM provided state locations of oil and gas wells in the ecoregion. These were point locations assembled from state regulatory agencies.

9. Military Urbanized Areas. This class resulted from the desire to identify an urban footprint within military reservations in the ecoregion, given that the ICLUS/SERGoM excluded these areas from analysis. We extracted the Urban/Developed class using the NLCD 2006 and clipped this to military reservation boundaries.

10. Railroads. BLM provided a current railroad network from the National Transportation Atlas Database (NTAD).

11. Canals/Ditches. This class represents most major water transmission infrastructure- canals, ditches and aquaducts in the ecoregion. This was derived from a corresponding class (canal/ditch) in the National Hydrography Database (NHD) Plus.

12. Utilities – Transmission lines. These are major high voltage transmission lines (generally larger than 115kV which tie major plants to the electrical grid) obtained from BLM. This dataset is part of a larger GIS mapping application (EV Energy Map) for the North American energy industry.

13. Pipelines. The BLM provided a clip from the National Pipeline Mapping System to represent this natural gas pipeline infrastructure.

14. Crops/Irrigated Pastures. This class was derived from the NLCD 2006 to represent areas transformed by row crops, irrigated pastures (including alfalfa and grass) and orchards.

15. Roads- Primary and Secondary. We used the BLM Ground Transportation Linear Features dataset to represent roads. Primary and secondary roads consist of state, county and federal public highways. This class consists largely of interstates and other separated, limited access highways but also major urban thoroughfares that are under state or local government jurisdiction. Roads that directly support the access to primary and secondary roads are also included features like ramps, cloverleaf structures. Vehicular numbers and speeds are generally high.

    Example classes from the BLM GTLF:
    'Primary road with limited access or interstate highway, separated'
    'Secondary and connecting road, state and county highways, major category'
    'Access ramp, the portion of a road that forms a cloverleaf or limited access interchange'

16. Roads- Local, Neighborhood, Rural. This class two consists of light duty roads that are local, neighborhood or rural in nature. The surface of the road in rural areas is commonly composed of dirt or gravel but will often be paved, especially in urban areas. These roads may be public or private. The number and average speed of vehicles transiting this type of road is lower than in primary and secondary roads. This is the most common class of road in the ecoregion. This class has the most overlap with class three and depending on the data source used in the GTLF, there may be significant classification error.

Example classes from the BLM GTLF:
'Local, neighborhood, and rural road, city street, unseparated, underpassing'
'ROAD_ LIGHT-DUTY GRAVEL (CLASS 3B)'
'Private Road for service vehicles logging_ oil fields_ ranches_ etc'

17. Roads- Unimproved, (4-wheel drive). This class of road consists of unimproved or four-wheel drive roads. These roads are almost always dirt or unconsolidated material and rarely, if ever receive any maintenance. Traffic volumes and average speeds are generally low. This class has the most overlap with class two and depending on the data source used in the GTLF, there may be considerable classification error.

    Example classes from the BLM GTLF:
    '4WD_ rough bladed_ 2-track surface'
    'ROAD_ FOUR-WHEEL DRIVE (CLASS 5)_ LOCATION APPROXIMATE'
    'ROAD_ UNIMPROVED (CLASS 4)_ LOCATION APPROXIMATE'
    'Vehicular trail, road passable only by four-wheel drive (4WD) vehicle, major category'
    'trail class 5 4x4'

18. Trails (non-vehicular). The trail class intends to capture all paths or tracks that generally exclude or prohibit vehicular traffic. These include foot paths, bike paths and but may occasionally include trails used by ATVs and other small motorized vehicles (either lawfully or unlawfully). Level of use is unknown and may vary greatly depending on location.

    Example classes from the BLM GTLF:
    'Walkway, nearly level road for pedestrians, usually unnamed'
    'TRAIL'
    'foot_ pack_ bike_ ATV (only type of road in a WSA)'
    'Bike Path or Trail'

19. Roads- Unknown. Some features in the BLM GTLF did not fit one of the four primary categories. This class includes features where the type or description in the attribute table or metadata indicated uncertainty.

    Example classes from the BLM GTLF:
    ‘Cul-de-sac, the closed end of a road that forms a loop or turn around’
    ‘Special road feature, major category used when the minor category could not be determined’
    ‘Road, Parking Area’

Table A - 1. Current Development Scenario Dependent Datasets at a Glance

CA Category	Change Agent	Source	Source Date	Spatial resolution
Infrastructure - Roads	Primary and Secondary Highways	BLM linear features (GTLF)	2011	1:24,000
	Local, neighborhood, rural roads	BLM linear features (GTLF)	2011	1:24,000
	Unimproved roads, 4-wd jeep trails	BLM linear features (GTLF)	2011	1:24,000

CA Category	Change Agent	Source	Source Date	Spatial resolution
	Trails and other non motorized routes	BLM linear features (GTLF)	2011	1:24,000
	Unknown	BLM linear features (GTLF)	2011	1:24,000
Infrastructure – Transmission lines	Transmission lines	USGS SAGEMAP	2008	1:100,000
Infrastructure-Pipelines	Pipelines	National Pipeline Mapping System (NPMS)	2011	1:24,000
Infrastructure-Water Transmission	Canals, ditches	USGS NHDplus	2010	1:24,000
Infrastructure - Railroads	Railroads	NTAD	2010	1:100,000
Developments - Urbanization	Urban/Rural Development	ICLUS/SERGoM 2010	Scenario based on 2000 census	90m pixel/ 1:100,000
Energy Development	Geothermal	BLM Operating & authorized geothermal facilities (2011)	2011	1:24,000
	Solar	BLM Operating & authorized wind facilities (2011)	2011	1:24,000
	Wind	BLM Operating & authorized wind facilities (2011)	2011	1:24,000
	Oil and Gas Wells	BLM Detailed oil and gas maps	2010	30m pixel/ 1:100,000
Mining & Refuse Management	Heavily disturbed areas due to either mining or refuse disposal	NatureServe mines and refuse management model	2011	1:100,000
Military Use	Urbanized areas (urban areas on military land)	National Land Cover Data (2005)	2005	30m pixel/ 1:100,000
Agriculture	Crops and irrigated agriculture	National Land Cover Data (2005)	2005	30m pixel/ 1:100,000

The current scenario renewable energy development includes two different components, existing energy production facilities and those approved in May, 2011. Many of the May, 2011 approved energy production facilities were in the process of construction at the time that this document was published.

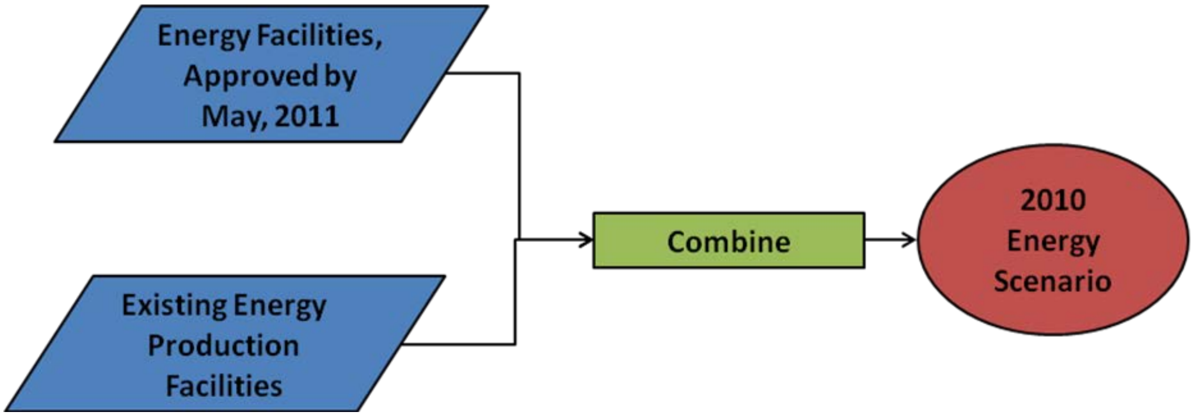

Figure A - 1 Spatial Model of Current Renewable Energy Scenario.

Mining and Landfills Model

<u>Mines and Landfills Model</u>

This dataset shows barren areas that are expected to reflect the locations of active mines, landfills and refuse areas in the MBR. It was developed using five data inputs: the USGS' Mineral Resource Data System (MRDS) containing active mine locations; BLM abandoned mines lands over 2000 acres (Abandoned Mine Lands and Site Cleanup Module); the Nevada Bureau of Mining Regulation and Reclamation (BMRR) data for mine pits, pit lakes, leach pads, and abandoned mine lands (AMLs); USGS SAGEMAP points representing landfills; and the NatureServe national ecological systems layer.

To create the 'footprint' for the mines and landfills model (Figure A - 2) the barren/disturbed cover type in the NatureServe ecological systems raster layer was extracted and vectorized to obtain a dataset showing barren areas. Point locations of mines from the MRDS were combined with point locations of mines (Pits, Pit Lakes, Leach Pads, and AMLs) contained in Nevada's BMRR datasets. Active mines were selected by excluding historic mines from MRDS. Barren polygons within 1000 meters of an active mine were selected and exported. Barren polygons smaller than 2 acres (equivalent to a 90-m pixel (900 m2)) or smaller were removed. Point locations from the source datasets that did not intersect the barren/disturbed areas cover class were buffered by 45m and integrated into the dataset to provide minimal footprints in absence of a footprint provided by the barren/disturbed class.

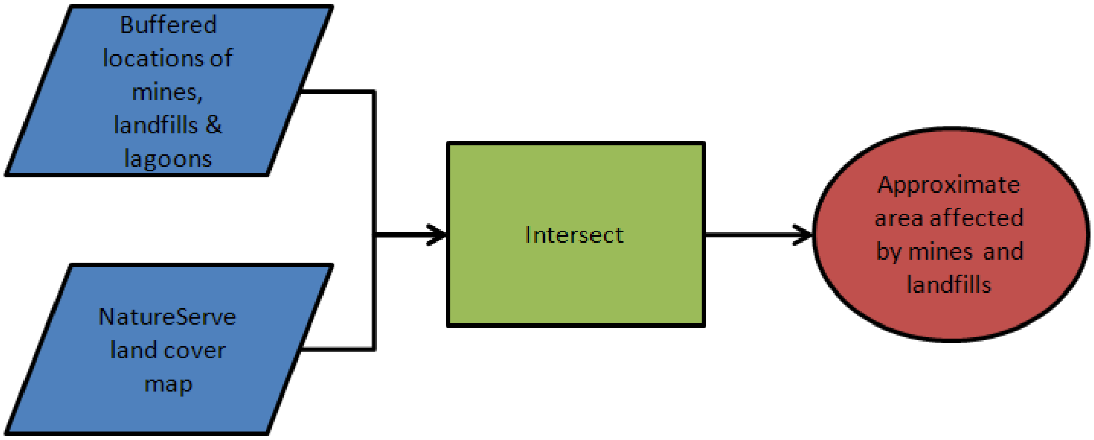

Figure A - 2. Conceptual diagram for mines and landfills model.

Mines and Landfills were intended to be two separate datasets representing the two classes of features independently. However, after accuracy assessment results were presented to the AMT in September, 2011 the AMT elected to combine the two classes to form one theme. The two classes were frequently cross-identified (e.g. tailing piles as landfills). The methodology was altered to accommodate additional data provided by the BLM (large abandoned mine lands (AMLs) and further refinement was done by digitizing over air photos. A final accuracy assessment was conducted by selecting a random sample of 20 input points verifying these places with digital air photos and USGS topographic maps. About 70% of the 'mine/landfill' footprints were correctly identified as areas heavily disturbed by humans: mines, quarries, shooting ranges or junkyards. The remaining 30% of areas were often lightly disturbed areas or naturally disturbed areas: low density urban areas, geothermal areas, scree or dune fields.

Recreation

Recreation is treated separately and not included in the scenarios because the AMT felt that the uncertainty in the modeling was too great to use for conducting assessments of its effects on CEs. This section provides the details on all recreation modeling.

Recreation was modeled by estimating the relative levels of dispersed recreation use through established modeling approaches (e.g., Theobald 2008) that combine data on traffic volume with accessibility. This assumes that the majority of visitors to BLM and other public lands accessed these areas via the road transportation infrastructure via an automobile. The basic approach used to model the spatial pattern of the recreation change agent (RCA) draws on the demand/supply factors of recreation (push/pull) and how recreationists move through the transportation infrastructure by employing an network-based accessibility model (Figure A - 3; Theobald 2008).

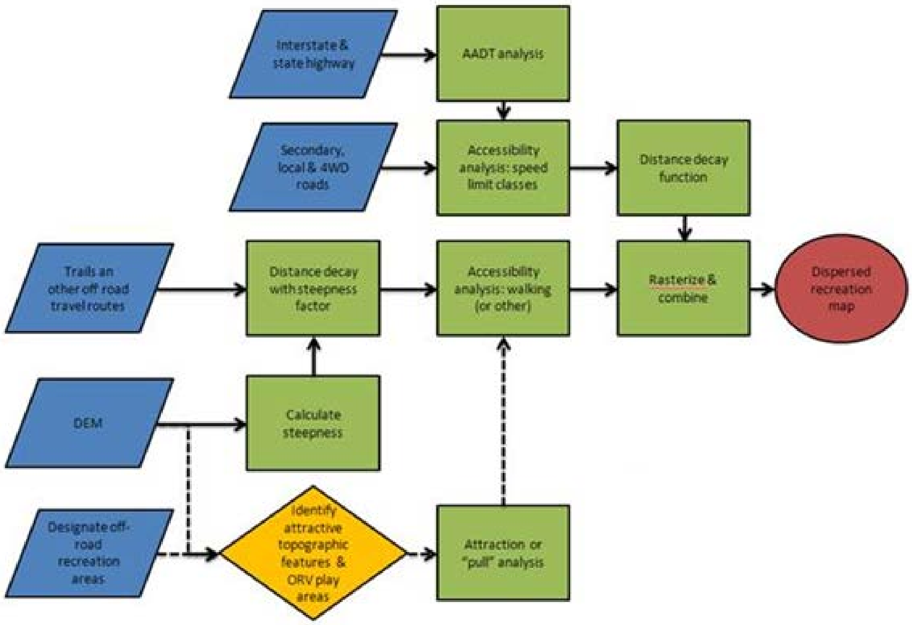

Figure A - 3 Conceptual model of recreational use.

Table A - 2 List of datasets used in the Recreation modeling

Name	**Source**	**Scale**
Population centers	Census places 2008, 2030	1:100k
Roads	Census TIGER 2010	1:100k
Linear disturbances	BLM	1:100k
Slope	USGS National Elevation Dataset	30 m
Land ownership	Protected Areas Database – CBI 2008	1:100k
Trailheads, OHV staging areas, marinas	Colorado State University 2011 -- heads-up digitizing on 2009 NAIP imagery, internet searches	1:10k
Water	National Land Cover Dataset 2006	30 m
Nevada Game Management Units	Nevada Fish and Game	1:100k
Abandoned mines	USGS MRDS	1:100k

The first factor is the demand for recreation – which is tied to the number and location of population of towns and cities (Census places). The number of residents at each population center (town/city) in 2008 (and projected for 2040) was multiplied times the average proportion of residents who recreated in 2007 – which is 20.9% overall for Arizona, California, Nevada, and Utah residents (Cordell et al. 2008; Table A - 3). The population centers (Figure A - 4) were grouped into 6 classes according to a log 10 transformation on the population, placing towns/cities into a separate data layer for each class of population (i.e. class 1 = population of 10 to 100; class 2 = population of 100 to 1000, class 3 = 1,000 to 10,000, etc.). The population centers were used as the "seeds" or starting locations for the cost-distance weighted calculations. That is, cost-distance from population centers was run 6 times, once for each population class.

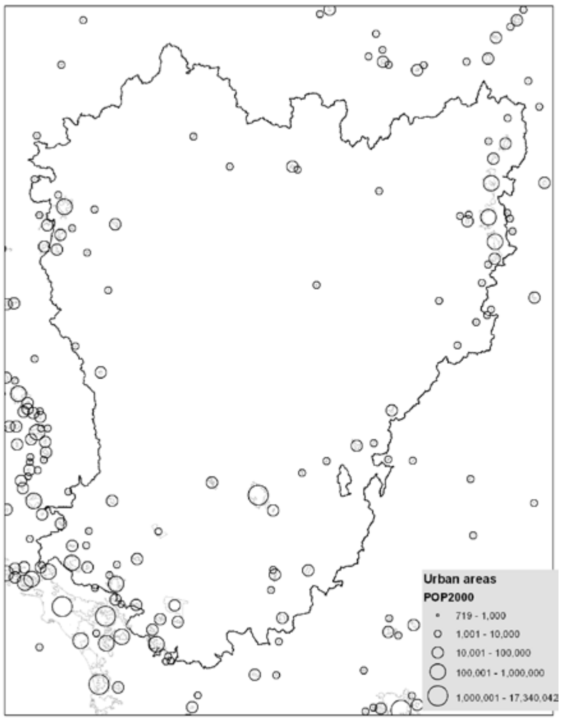

Figure A - 4. Population centers for the Central Basin and Mojave Basin REAs

Table A - 3. The proportion of residents who participated in off-road recreation in 2007.

State	Percent (metro/non-metro)	Participants (metro/non-metro)
Arizona	24.6% / 32.4%	1,019,000 / 163,000
California	17.3% / 31.0%	4,667,000 / 199,000
Nevada	21.5% / 44.9%	365,000 / 89,000
Utah	31.0% / 44.3 %	499,000 / 90,000
	Overall, 20.9% of AZ, CA, NV, UT	

The second factor is the transportation infrastructure that affects the accessibility of those residents of towns/cities to all other locations in the study area. The accessibility values forms the values for the cost weights in the cost-distance calculations. The assumption is that recreationists travel in automobiles along the public transportation infrastructure. Travel time, the amount of time it takes to travel from a given town/city along a road was assigned according to the speed limit assigned for different road types in the Census TIGER 2010 dataset: interstate = 65 mph, highways 55 mph, secondary 45 mph, local 30 mph, and backcountry/4WD 10 mph. Also, BLM linear disturbance features were also included at an assumed speed of 10 mph. For off-road travel, we will estimate travel time based on walking speeds, adjusted by the steepness of the terrain (using Tobler's equations; Theobald et al. 2010).

Roads that travelled through locations closed to public were excluded from the accessibility infrastructure. Each polygon from PAD-US dataset (CBI 2008) was assigned one of 6 values: private, no public access; recreation uses, motorized likely; wilderness, motorized precluded; natural areas, motorized likely excluded (e.g., national parks and monuments); DoD, military, DoE, prison, recreation excluded; and fishing access. To estimate the recreation use (measured in number of recreationists), we assumed that *use* declines by half with each 60 minutes of travel (Theobald 2008). To calculate recreation use in the GIS, the cost-allocation value was assigned the product of the population * 20.9%, and the cost-distance value was assigned the travel time through the transportation infrastructure with off-road (slope) additional weights.

The third factor is supply – the extent and location of various recreation sites, trailheads, etc. A number of types of recreation features were mapped and modeled, to represent different factors that might influence the destination of off-road recreational use. These recreation features included: over 100 OHV staging areas and trailheads, over 150 aquatic access points (including docks and launching areas along major Nevada rivers such as Truckee and Humboldt, and an additional boat ramp from the Lake Havasu FO), and over 25 designated motorized recreation use areas. In addition, campsites, picnics, and day use areas (including LTVAs) were added as "gates". The travel time from these features (e.g., abandoned mines, etc.) was calculated back to the nearest trailhead (or marina/dock for aquatic recreation). These values modified the overall travel time of estimated recreational use.

We differentiated 6 types of recreational use (see Table A - 4). First, the overall recreational use (R) was estimated that assumed that off-road recreation was excluded from wilderness and Defense Department lands. The boater/fisher recreation type (R_a) assumed that travel occurred only on reservoirs and rivers, and travel originated at marinas and boat ramps (so called "gates"). Destinations included any location accessible via water (as defined in the National Land Cover Dataset 2006 water class), such as beaches, fishing holes, and camping spots. Travel time was assumed to occur at 10 mph boat speed. The Off-Highway Vehicle enthusiast (R_e) model assumed that travel was excluded on wilderness and DoD lands and on existing highways. Travel originated at mapped OHV staging areas and trail heads. Presumed destinations would include ravines and washes (which would be preferentially visited because of low-slope). Because no centralized, official, easily-accessible data layers on race courses existed, race courses were not mapped. The hiker/biker/camper type (R_f) assumed that recreation would be excluded from DoD lands, originated from trail heads, and destinations areas included mapped (from USGS GNIS) locations of springs, slot canyons, peaks, and arches. The big game hunter type (R_h) was modeled in a very different fashion than the others (and only for the state of NV). The number of big game visitors for 2008 was tallied by game management unit and then allocated using the accessibility surface. The OHV hunter/rock hunter type was modeled assuming that wilderness and DoD lands were excluded, travel originated from OHV trailheads and staging areas, and destination areas included high densities of caves, mines, and ruins (from USGS GNIS maps).

Table A - 4. Recreation models developed for the REA

Type	**Constraints**	**"Gates"**	**Destinations**
R - general	Non-wilderness, non-DOD	None	None
Ra - Boater/fisher *assume 10 mph boat speed	Reservoirs, rivers, Non-wilderness, non-DOD	Marinas, boat ramps	Beaches, fishing holes, camping spots
Re - OHV enthusiast *assume no highway travel	Non-wilderness, non-DOD	OHV staging areas, trail heads	Race courses, ravines, washes
Rr - OHV rock hounder	Non-wilderness, non-DOD	OHV trail heads	Caves, mines, ruins

Type	Constraints	“Gates”	Destinations
Rh - OHV big game hunter	Restricted to Nevada game management units	OHV trail heads	None
Rf - Hiker/cyclist	Non-DOD	Trail heads	Springs, slot canyons, peaks, arches

A-1.2.1.2 Future Scenario

MQ49 - WHERE ARE AREAS OF PLANNED OR POTENTIAL DEVELOPMENT CAS?

The development footprint is forecasted to increase from 8.8% currently to 9.8% by 2025. The 2025 developed area is cumulative with current so represents current plus added development area. Note that we did not assess increases in non-renewable energy sources due to lack of data. Details on changes in renewable energy area are provided elsewhere.

This scenario has all of the same inputs as the current scenario raster but has four layers that depict planned or modeled infrastructure expected to be on the landscape in the near term future. These layers include an urban growth forecast for the year 2030 by the ICLUS/SERGoM, the Section 368 transmission corridors (West-wide Energy Corridor Programmatic EIS) and currently existing, approved and priority renewable energy projects on federal land that have begun the environmental permitting process with BLM (but are not yet approved as of May 2011). This includes the Solar Energy Programmatic EIS Zones (SEZs). While these models and projects are considered likely to occur, they are not definite or approved by any federal, state or local agency. For additional information on these layers please see the section on attribute information below.

Near Future Scenario (2025) Classes and Dependent Data Information

1. No development change agent

2. Multiple change agents. During planning stages of the REA, we observed that many CAs will overlap and per agreement by the AMT, where overlapping CAs were detected during raster processing these areas were reclassified as “multiple.”

3. Urban/Rural Development. This class is derived from the Integrated Climate and Land Use Scenarios (ICLUS) and its related spatial database, Spatially Explicit Regional Growth Model (SERGoM) (EPA, 2010). SERGoM data uses US Census block housing units, protected lands, groundwater well density, and road accessibility to estimate housing density. This class attempts to apply a footprint to a wide array of housing density classes put forth in the ICLUS/SERGoM dataset. For the near future scenario we used the growth model forecasting an urban/rural footprint for 2030. The AMT in Las Vegas, NV in September, 2011 agreed that urban and rural development would be defined as less than 160 acres per housing unit. Areas that are less dense (> 160 acres per unit) are classified undeveloped and therefore are not given a ‘footprint’ in the analysis.

4. Renewable Energy – Geothermal Energy. Geothermal energy project footprints were obtained from BLM and verified by BLM state offices between June and October, 2011. In the near-future scenario, this class includes existing projects and priority projects (projects in the permitting process). A complete list of these projects can be found in Table A - 6.

5. Renewable Energy – Solar Energy. Solar project footprints were obtained from BLM and verified by BLM state offices between June and October, 2011. In the near-future scenario, this class includes existing projects and priority projects (projects in the permitting process). A complete list of these projects can be found in Table A - 6.

6. Renewable Energy – Wind Energy. Wind project footprints were obtained from BLM and verified by BLM state offices between June and October, 2011. In the near-future scenario, this class includes existing projects and priority projects (projects in the permitting process). A complete list of these projects can be found in Table A - 6.

7. Mines/landfills. This class includes major landscape disturbances, including open pit mines, tailings piles, leach pads, landfills and other refuse areas. See the Mining and landfills section below and full metadata is available for this layer as a modeling product developed by NatureServe for the REA.

8. Oil and Gas Wells. BLM provided state locations of oil and gas wells in the ecoregion. These were point locations assembled from state regulatory agencies.

9. Military Urbanized Areas. This class resulted from the desire to identify an urban footprint within military reservations in the ecoregion, given that the ICLUS/SERGoM excluded these areas from analysis. We extracted the Urban/Developed class using the NLCD 2006 and clipped this to military reservation boundaries.

10. Railroads. BLM provided a current railroad network from the National Transportation Atlas Database (NTAD).

11. Canals/Ditches. This class represents most major water transmission infrastructure- canals, ditches and aquaducts in the ecoregion. This was derived from a corresponding class (canal/ditch) in the National Hydrography Database (NHD) Plus.

12. Utilities – Transmission lines. These are major high voltage transmission lines (generally larger than 115kV which tie major plants to the electrical grid) obtained from BLM. This dataset is part of a larger GIS mapping application (EV Energy Map) for the North American energy industry.

13. Pipelines. The BLM provided a clip from the National Pipeline Mapping System to represent this natural gas pipeline infrastructure.

14. Crops/Irrigated Pastures. This class was derived from the NLCD 2006 to represent areas transformed by row crops, irrigated pastures (including alfalfa and grass) and orchards.

15. Roads- Primary and Secondary. We used the BLM Ground Transportation Linear Features dataset to represent roads. Primary and secondary roads consist of state, county and federal public highways. This class consists largely of interstates and other separated, limited access highways but also major urban thorofares that are under state or local government jurisdiction. Roads that directly support the access to primary and secondary roads are also included features like ramps, cloverleaf structures. Vehicular numbers and speeds are generally high.

Example classes from the BLM GTLF:
'Primary road with limited access or interstate highway, separated'
'Secondary and connecting road, state and county highways, major category'
'Access ramp, the portion of a road that forms a cloverleaf or limited access interchange'

16. Roads- Local, Neighborhood, Rural. This class two consists of light duty roads that are local, neighborhood or rural in nature. The surface of the road in rural areas is commonly composed of dirt or gravel but will often be paved, especially in urban areas. These roads may be public or private. The number and average speed of vehicles transiting this type of road is lower than in primary and secondary roads. This is the most common class of road in the ecoregion. This class has the most overlap with class three and depending on the data source used in the GTLF, there may be significant classification error.

    Example classes from the BLM GTLF:
    'Local, neighborhood, and rural road, city street, unseparated, underpassing'
    'ROAD_ LIGHT-DUTY GRAVEL (CLASS 3B)'
    'Private Road for service vehicles logging_ oil fields_ ranches_ etc'

17. Roads- Unimproved, (4-wheel drive). This class of road consists of unimproved or four-wheel drive roads. These roads are almost always dirt or unconsolidated material and rarely, if ever receive any maintenance. Traffic volumes and average speeds are generally low. This class has the most overlap with class two and depending on the data source used in the GTLF, there may be considerable classification error.

    Example classes from the BLM GTLF:
    '4WD_ rough bladed_ 2-track surface'
    'ROAD_ FOUR-WHEEL DRIVE (CLASS 5)_ LOCATION APPROXIMATE'
    'ROAD_ UNIMPROVED (CLASS 4)_ LOCATION APPROXIMATE'
    'Vehicular trail, road passable only by four-wheel drive (4WD) vehicle, major category'
    'trail class 5 4x4'

18. Trails (non-vehicular)-The trail class intends to capture all paths or tracks that generally exclude or prohibit vehicular traffic. These include foot paths, bike paths and but may occasionally include trails used by ATVs and other small motorized vehicles (either lawfully or unlawfully). Level of use is unknown and may vary greatly depending on location.

    Example classes from the BLM GTLF:
    'Walkway, nearly level road for pedestrians, usually unnamed'
    'TRAIL'
    'foot_ pack_ bike_ ATV (only type of road in a WSA)'
    'Bike Path or Trail'

19. Roads- Unknown. Some features in the BLM GTLF did not fit one of the four primary categories. This class includes features where the type or description in the attribute table or metadata indicated uncertainty.
    Example classes from the BLM GTLF:
    'Cul-de-sac, the closed end of a road that forms a loop or turn around'

‘Special road feature, major category used when the minor category could not be determined’
‘Road, Parking Area’

20. Renewable Energy – SEZs. Solar energy zones (Solar Programmatic EIS Zones) were obtained from BLM in September, 2011. In the near-future scenario, this class included in the near-future scenario alongside existing projects and priority projects (projects in the permitting process). A complete list of these areas can be found in Table A - 6.

Table A - 5. Near Future (2025) Development Scenario Datasets at a Glance

CA Category	Change Agent	Source	Source Date	Spatial resolution
Infrastructure - Roads	Primary and Secondary Highways	BLM linear features (GTLF)	2011	1:24,000
	Local, neighborhood, rural roads	BLM linear features (GTLF)	2011	1:24,000
	Unimproved roads, 4-wd jeep trails	BLM linear features (GTLF)	2011	1:24,000
	Trails and other non motorized routes	BLM linear features (GTLF)	2011	1:24,000
	Unknown	BLM linear features (GTLF)	2011	1:24,000
Infrastructure – Transmission lines	Transmission lines	USGS SAGEMAP	2008	1:100,000
Infrastructure – Transmission lines	Transmission lines	Sec 368 PEIS Energy Corridors	2010	1:100,000
Infrastructure-Pipelines	Pipelines	National Pipeline Mapping System (NPMS) (BLM provided)	2011	1:24,000
Infrastructure-Water Transmission	Canals, ditches	USGS NHDplus (BLM provided)	2010	1:24,000
Infrastructure - Railroads	Railroads	NTAD (BLM provided)	2010	1:100,000
Developments - Urbanization	Urban/Rural Development	ICLUS/SERGoM modeled growth for 2030	2008	90m pixel/ 1:100,000
Energy Development	Geothermal	BLM Operating, authorized & priority geothermal facilities	2011	1:24,000
	Solar	BLM Operating, authorized & priority wind facilities	2011	1:24,000
	Wind	BLM Operating, authorized & priority wind facilities	2011	1:24,000
	Oil and Gas Wells	BLM Detailed oil and gas maps	2010	30m pixel/ 1:100,000
Mining & Refuse Management	Heavily disturbed areas due to either mining or refuse disposal	NatureServe mines and refuse management model	2011	1:100,000
Military Use	Urbanized areas (urban areas on military land)	National Land Cover Data (2005)	2005	30m pixel/ 1:100,000
Agriculture	Crops and irrigated agriculture	National Land Cover Data (2005)	2005	30m pixel/ 1:100,000

Table A - 6. Renewable Energy Projects and Solar Energy Zones included in the REA. The near future scenario renewable energy development includes the current scenario projects (existing energy production facilities, energy facilities approved in May, 2011) plus the BLM priority projects and programmatic EIS Solar Energy Zones (SEZs).

Project Name	BLM Code	Commodity	Scenario	REA	BLM Status	Acres (approx)
Amargosa-North, Big Dune Area, Nye County	NVN xxxxxx	Solar Energy Facilities	Future Only	MBR	BLM Priority Projects	9570
Dry Lake Solar	NVN 084052	Solar Energy Facilities	Future Only	MBR	BLM Priority Projects	1978
First Solar - Stateline	CACA 048669	Solar Energy Facilities	Future Only	MBR	BLM Priority Projects	6099
Mohave County Wind Farm	AZA32315	Wind Energy Facilities	Future Only	MBR	BLM Priority Projects	49032
Palen Solar I, LLC - Palen	CACA 048810	Solar Energy Facilities	Future Only	MBR	BLM Priority Projects	361
Silver-State Solar 2nd Phase (combined South and North project)	NVN xxxxxx	Solar Energy Facilities	Future Only	MBR	BLM Priority Projects	8376
Amargosa Valley	Nevada_NA	SEZ	Future Only	MBR	BLM SEZ Future Only	9737
Dry Lake	Nevada_NA	SEZ	Future Only	MBR	BLM SEZ Future Only	6186
Riverside East	California_NA	SEZ	Future Only	MBR	BLM SEZ Future Only	16089
Amargosa Farm Road, Amargosa Valley, Nye County	NVN-084359	Solar Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	6280
BP-Edom Hills Project	CACA 014632	Wind Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	365
Calico Solar, LLC - Calico	CACA 049537	Solar Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	4604
Cameron Ridge, LLC	CACA 009501	Wind Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	546
Chevron Energy Solutions - Lucerne Valley	CACA 049561	Solar Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	461
Desert Wind Energy	CACA 015549	Wind Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	79
DIF Wind Farms V	CACA 037869	Wind Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	39
DIFCO - Whitewater Floodplain	CACA 015562	Wind Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	962
Energy Unlimited Inc. - Eastridge	CACA 017192	Wind Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	77
FPL Energy - Cabazon Wind	CACA 013198	Wind Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	210

Mark Technologies Corp. - Mesa	CACA 041695	Wind Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	277
Navy BLM China Lake	CACA 011402	Geothermal Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	2572
Oak Creek Energy - Tehachapi	CACA 013528	Wind Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	160
PAMC Management Corp. - Alta Mesa	CACA 011688A	Wind Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	874
San Gorgonio Farms - Whitewater Hill	CACA 009755	Wind Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	13
Searchlight Wind Energy, Searchlight, Nevada	NVN-084626	Wind Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	23996
Silver State Solar (combined South and North project)	NVN-085077	Solar Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	7839
Solar Partners I - Ivanpah 2	CACA 048668	Solar Energy Facilities	Current and Future	MBR	Existing & Approved May, 2011	3475

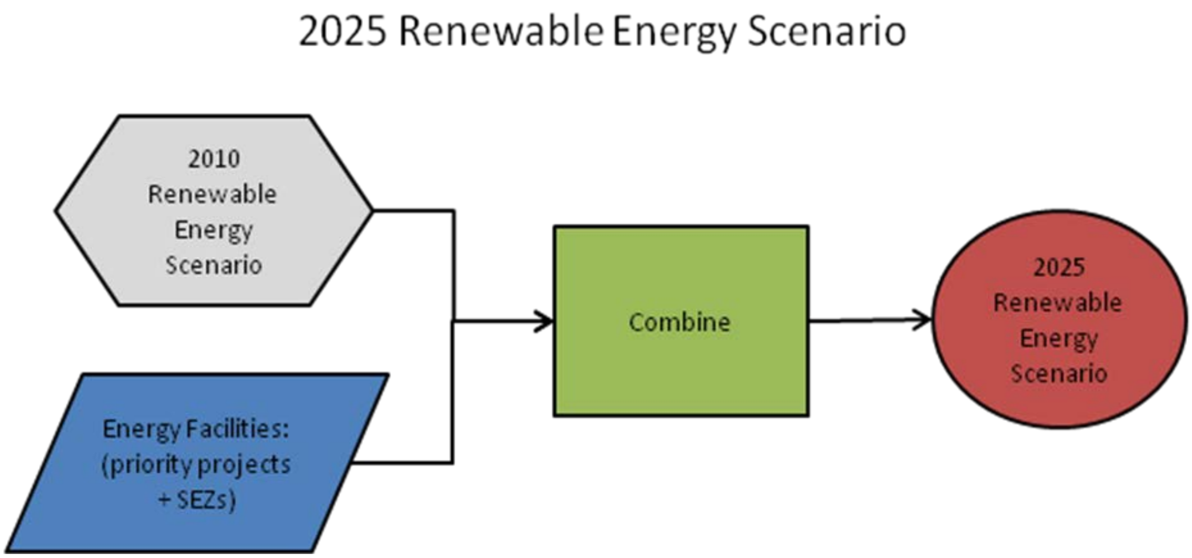

Figure A - 5. Spatial Model of Near-Future (2025) Renewable Energy Scenario.

A-1.2.1.3 Renewable Energy Potential and Priority Areas

This data was developed to support MQs addressing the potential solar energy development free of a specific timeframe and so was not included in the 2025 scenario described above. Solar, geothermal and wind energy were assessed for potential in the ecoregion. Potential renewable energy areas were defined using third-party source data and choosing thresholds that reflected a “high likelihood” that potential exists. Renewable energy facilities are extremely site specific with a complex set of factors that determine suitability and economic feasibility (the latter changing under different economic situations). Wind and geothermal energies in particular depend on micro-siting that requires additional field data, skilled engineering knowledge, and more sophisticated models not suitable for the REA process.. This more basic approach represents a suitable and feasible approach for the REA.

The Southwest US DNI Filtered 5-percent High Resolution (NREL 2005b) was used to represent solar potential. Direct solar insolation is considered high enough in much of the ecoregion for commercial development. The primary limiting factor for solar energy development in the ecoregion is slope and most solar energy developers strongly prefer geographically flat areas for development.

Geothermal potential was defined using data from the Great Basin Center for Geothermal Energy at the University of Nevada, Reno (Coolbaugh et al., 2005). Coolbaugh et al., developed an index of geothermal favorability based on a complex set of integrated analyses. The threshold of values defined as areas with "most favorability" ("Value" >=-594 (0.00594)) was applied as suggested by Coolbaugh et al.

Wind energy potential was derived from state maps at 50m above the ground (AWS TrueWind/NREL 2003) and classified into areas suitable for community and commercial scale development. Metadata for this layer indicated that classes 3 and higher may be suitable for energy development while classes 4 and higher may be most likely. Comparing these maps to planned wind development locations and visually comparing the 50m maps with PDF images of the newer 80m maps indicated that classes 3 and above represented the most likely areas for development. All existing and new wind energy projects in the ecoregion are in class 3 (or higher) zones. Unfortunately the higher accuracy 80m GIS data were not available for REA.

Priority renewable energy sites are those areas that have been designated by the states as priority areas or zones for renewable energy development. While these areas were not directly assessed during the course of the REA, we included them as a data delivery product for follow up use by BLM or its partners. In MBR, this layer represents areas that have been designated by the states of California and Nevada as priority zones for development for renewable energy. These layers were assembled from two sources, the Nevada Renewable Energy and Proposed Interconnections Map (RETAAC) and the California Renewable Energy Transmission Initiative (RETI). Utah did not have priority zones for renewable energy development at the time of this assessment.

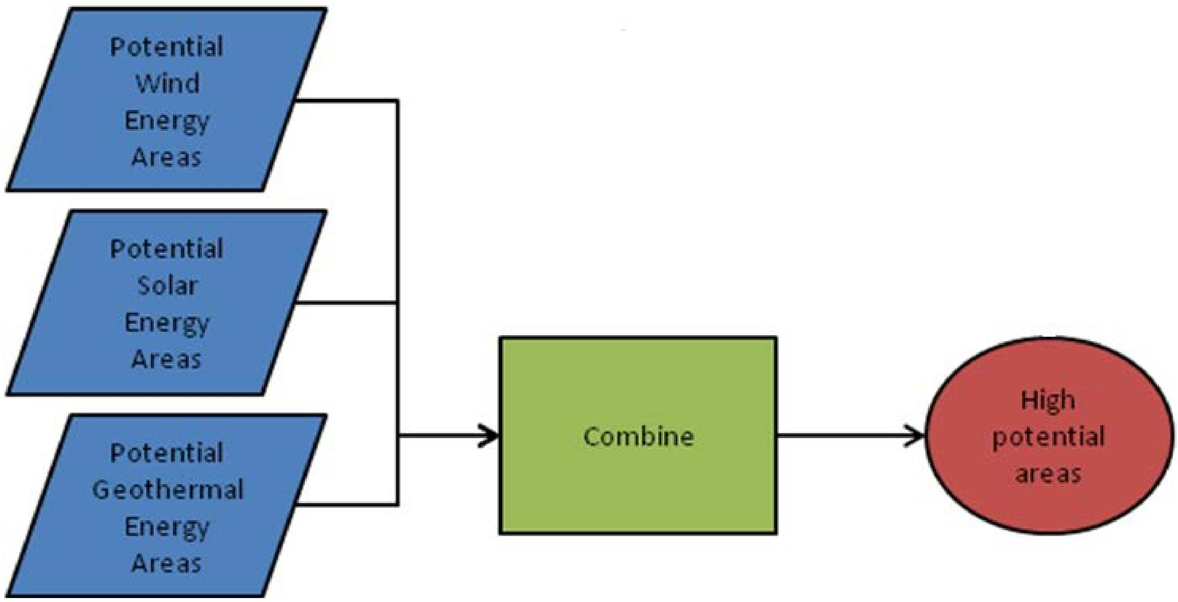

Figure A - 6. Potential Renewable Energy. This data was combined to create an overall area of "high potential" layer that was used to answer management questions answered in Appendix D.

A-1.2.2 Invasives

A-1.2.2.1 Plants: Maxent models

Three models of invasive (mostly exotic) species assemblages (Annual Grasses, Noxious Forbs, and Invasive Riparian) were developed to represent the potential of the REA to experience invasive encroachment using Maximum Entropy (MaxEnt v3.3.3e, Phillips, et al. 2006). These models do not represent the distribution or estimate of cover, but are rather a representation of the biophysical envelope of where invasive potential is most likely to occur.

Models were derived simultaneously for the combined extent of both Central Basin and Mojave Ecoregions and represent continuous probability raster's (Forbs and Woody Riparian) and composite assemblages of five continuous probability surfaces representing separate estimates of the distribution of densities (Annual Grasses). Figure A - 7 represents the modeling convention used to derive each component of the invasive species models.

The invasive models were constructed for both CBR and MBR ecoregions to maximize the number of geo-referenced samples that were inputs to the models, which then produced a more robust model for each group of invasives. For example, for the invasive annual grasses because the sample data used had cover estimates by species, models predicting potential abundance (or cover) of the grasses could be constructed. Limiting the models to either CBR or MBR would have resulted in fewer samples (especially for MBR) and also would have resulted in a heavier weighting in the CBR for samples with higher cover (see Figure A - 8 which shows the spread of samples by annual grass cover across the 2 ecoregions). For the forbs and woody riparian invasives, modeling the 2 ecoregions separately would have markedly reduced the number of sample points; in addition, the primary invasives within these 2 groups are found in both ecoregions.

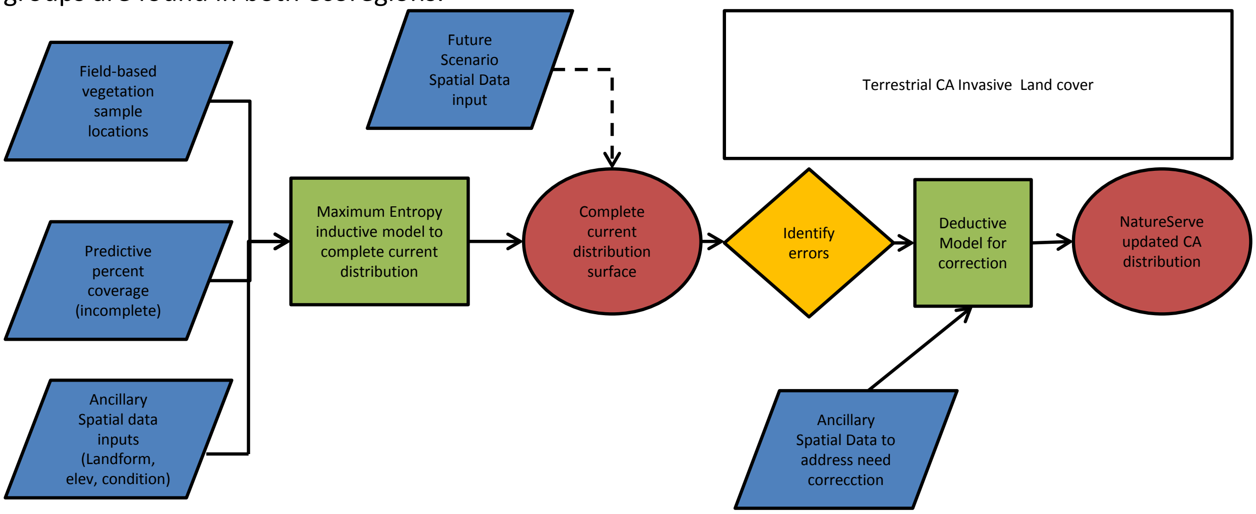

Figure A - 7. Invasive species modeling convention

Annual Grasses

The Annual Grass model is comprised of a mosaic of five separate continuous models representing separate thresholds of absolute cover. All training and validation data were acquired from the July 2011 update of the LANDFIRE Public Sample points data set. A total of 7031 samples were identified as having an invasive annual grass component within the overall species composition of the sample site. A total of 25 separate species were identified within the sample sites, of which 77% of the total samples were comprised of Cheatgrass (*Bromus tectorum*) (Table A - 7). A total of 94% of all samples are comprised of three species when cheatgrass was combined with Red Brome (*Bromus madritensis*) and Mediterranean Grass (*Schismus barbatus*). *Bromus rubens* and *B. madritensis* are listed separately in this table; the NRCS PLANTS database recognizes both as valid taxa, although *B. madritensis* ssp. *rubens* is now considered part of *B. rubens*. The records in the database did not distinguish between *B. madritensis* ssp. *rubens*, and *B. madritensis*. Since all of these sample points were combined into one dataset for the modeling purposes, this taxonomic uncertainty is not problematic.

Table A - 7. Invasive Annual Grasses present within the combined CBR and MBR region.

Invasive Grass Species	Sample Count
Aegilops cylindrica	2
Avena barbata	5
Avena fatua	3
Bromus diandrus	27
Bromus hordeaceus	8
Bromus hordeaceus ssp. hordeaceus	2
Bromus japonicus	3
Bromus madritensis	603
Bromus rubens	335
Bromus tectorum	5388

Invasive Grass Species	Sample Count
Echinochloa crus-galli	1
Eragrostis cilianensis	5
Hordeum murinum	7
Hordeum murinum ssp. leporinum	11
Hordeum vulgare	2
Poa annua	3
Polypogon monspeliensis	1
Schismus arabicus	5
Schismus barbatus	580
Secale cereale	8
Sorghum bicolor	1
Taeniatherum caput-medusae	5
Triticum aestivum	20
Vulpia myuros	5
Zea mays	1
Grand Total	**7031**

The majority of sample points are comprised of a single species of annual grass, but 375 points contain between 2-7 species per sample site. The final sample plot total includes 6622 samples plots with the majority of the samples in the Category 1 and Category 2 levels of density (Table A - 8).

Table A - 8. Sample size per percent cover category.

Annual Grass Category	Sample Count	Minimum Cover	Maximum Cover	Average Cover
1- less than 5%	3674	0.02	5.00	2.62
2 - 5-15%	1434	5.20	15.00	10.82
3 - 15-25%	635	15.50	25.00	21.03
4 - 25-45%	554	27.00	45.00	34.62
5 - greater than 45%	325	49.90	100.00	64.30
Grand Total	**6622**	**0.02**	**100.00**	**11.87**

Independent spatial layers used in the MaxEnt analysis consist of both continuous and thematic feature types (Table A - 9). Landforms, Surficial Lithology, Ombrotype and Thermotype were extracted from the existing USGS GEOS national data layers. All others variables were derived from either the 10m Digital Elevation Model (scaled to 30m), or the updated soils CEs as described in the sensitive soils results of this report. There is not a remote sensing component which would be required to fully map the distribution of invasive plants.

The bulk of high density sites are located within the CBR boundary; only 20% of the overall sample points occur within the MBR region; and 98% of the >45% cover of annual grasses category are in CBR (Figure A - 8). Proportionally, the Category 1 points are evenly distributed throughout both ecoregions equally with 35% of the points occurring within the MBR.

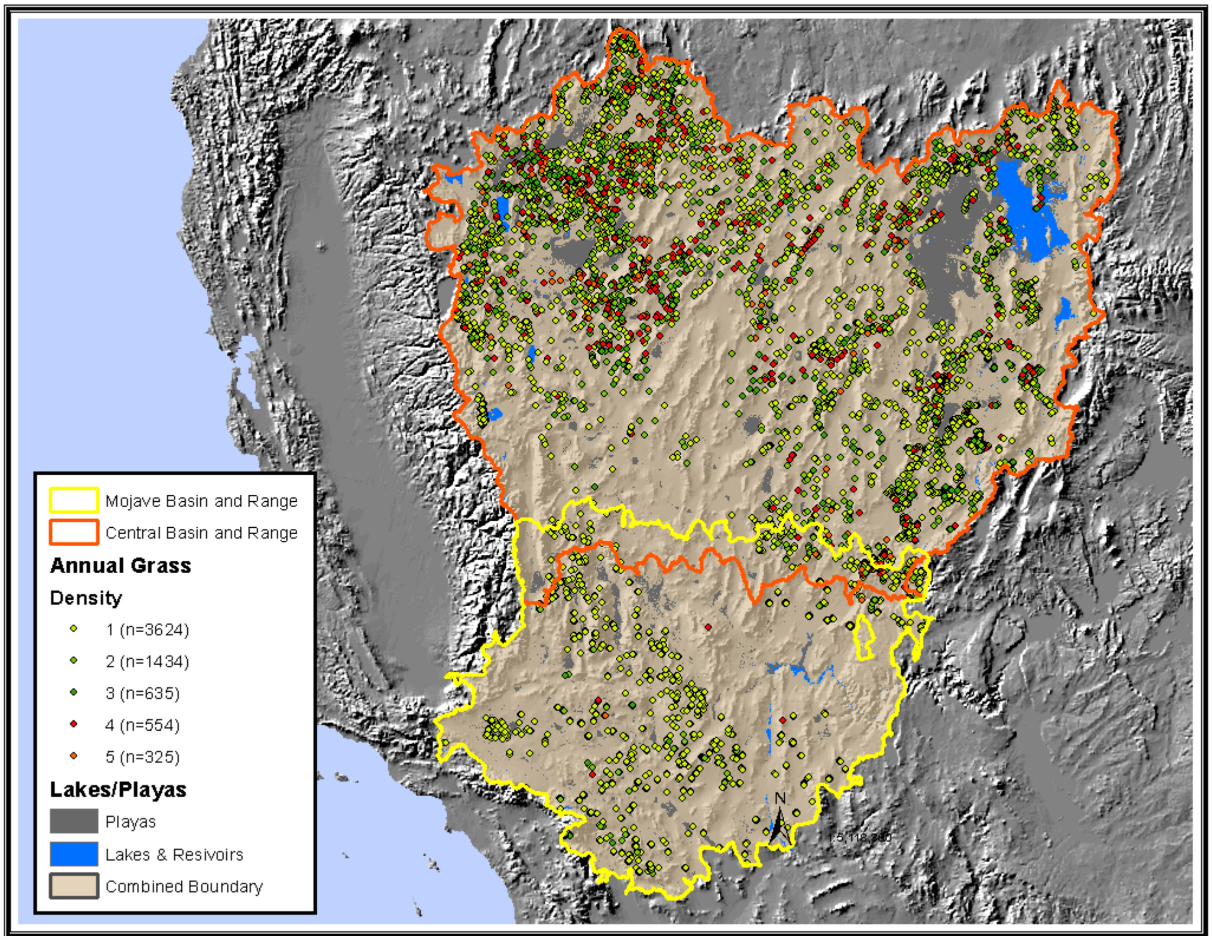

Figure A - 8. Distribution of samples for annual grasses in the combined CBR and MBR ecoregions. Density classes include: 1= <5% cover of annual grass in the sample; 2=5-15% cover of annual grass; 3=15-25% cover; 4=25-45% cover; 5=>45% cover.

In order to maximize the number of samples applied to the model, a two part modeling approach was utilized to determine the model performance. In addition to the final models which consist of all available sample points, a separate analysis was performed utilizing a series of 10 replicate models with random withholding of 10% of total samples for model validation. The average AUC score from the receiver operating characteristics (ROC) score was used to determine the model validity.

Table A - 9. Independent variables used to model Annual Grasses. * Not used with riparian invasive models.

Landforms	Flat Plains	Smooth Plains	Irregular Plains	Escarpments	Low Hills	Hills	Breaks	Low Mountains	High Mountains/ Deep Canyons	Drainage Channels											
Surficial_Lithology	Carbonate (sedimentary/metasedimentary), generally porous, and generally >6pH	Karst	Non-Carbonate (sedimentary/metasedimentary), generally porous, generally <6pH	Alkaline Intrusive Volcanic, generally non-porous, generally >6 pH	Silicic (including most/all granites and non-alkaline intrusive volcanics), generally non-porous, generally <6pH	Ultramafic	Extrusive Volcanic, generally porous	Colluvium (Talus & Scree Slopes, Boulder Fields)	Glacial Till-Clay	Glacial Till-Loamy	Glacial Till Coarse Textured	Glacial Outwash/Ice-Contact Features	Glacial Lake Plain, Fine Textured	Glacial Lake Plain, Coarse Textured	Hydric-Peat&Muck	Aeolian Sediments-Sand Dune, Coarse Textured	Aeolian Sediments-Loess, Fine Textured	Non-Glacial Alluvium-Saline	Non-Glacial Alluvium-Other, Fine Textured	Non-Glacial Alluvium-Other, Coarse Textured	Volcanic Tuff/Mudflows
Ombrotypes	Arid	Semiarid	Dry	Subhumid	Humid	Hyperhumid															
Thermotypes	Lower Inframediterranean	Upper Inframediterranean	Lower Thermomediterranean	Upper Thermomediterranean	Lower Mesomediterranean	Upper Mesomediterranean	Lower Supramediterranean	Upper Supramediterranean	Lower Oromediterranean	Upper Oromediterranean	Infratemperate	Lower Thermotemperate	Upper Thermotemperate	Lower Mesotemperate	Upper Mesotemperate	Lower Supratemperate	Upper Supratemperate	Lower Orotemperate	Upper Orotemperate	Lower Cryorotemperate	
Slope (degree)	0-78.5																				
Elevation (m)	193-4337																				
Aspect (degree)	360																				
Distance to Fire*	Continuous																				
Hydric Soil Distance	Continuous																				
intermitant Ditance	Continuous																				
Perennial Distance	Continuous																				
Soil ph	ph * 10																				
Local Road Density*	Continuous																				
Minor Road Density*	Continuous																				

Final models for each density categories where complied from the five independent models using the threshold where occurs equal training sensitivity and specificity (Table A - 10). This value in all model categories was the most restrictive threshold value. The final composite model is comprised of each individual model layered in order of lowest percent coverage to highest percent coverage with each increasing percent cover layer superseding all underlying data values (Figure A - 9).

Table A - 10. Maximum entropy thresholds

Annual Grass Category	Threshold
1- less than 5%	0.479
2 - 5-15%	0.47
3 - 15-25%	0.449
4 - 25-45%	0.434
5 - greater than 45%	0.39

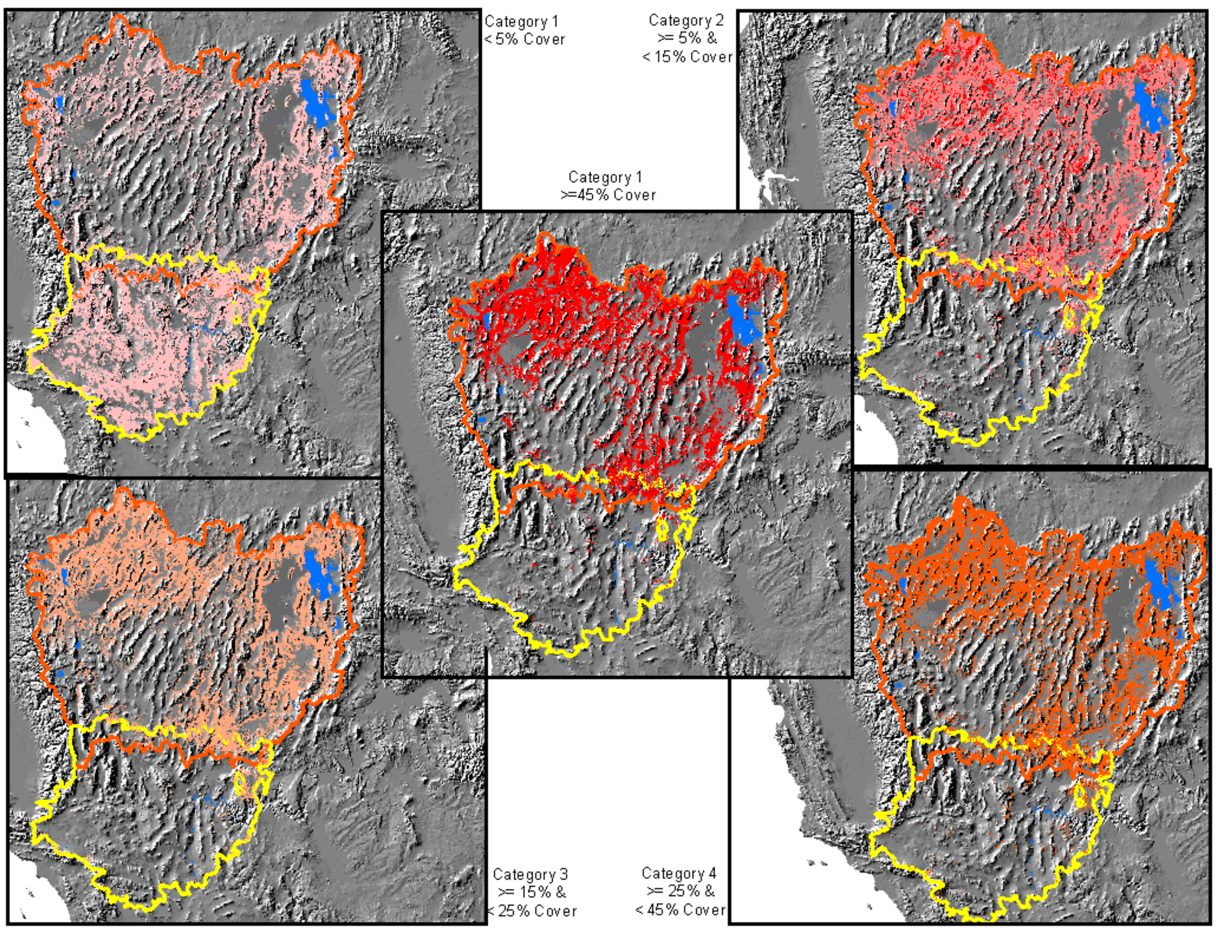

Figure A - 9. Five models for invasive/exotic annual grasses for the combined CBR and MBR ecoregions. Each model represents projected density (cover) of annual grasses. Category 1 (upper left, < 5% cover) indicates much of the Mojave is at risk for low cover of invasive annual grasses; while the other categories suggest the Central Basin and Range ecoregion is at risk of having large areas with high abundance of invasive grasses (>5% to over 45% cover).

Overall model performance was acceptable with ranges in AUC score from 0.69 to 0.806 and with standard deviations ranging from 0.014 to 0.029 (Figure A - 10). The composite model performance as such is not defined beyond the component inputs.

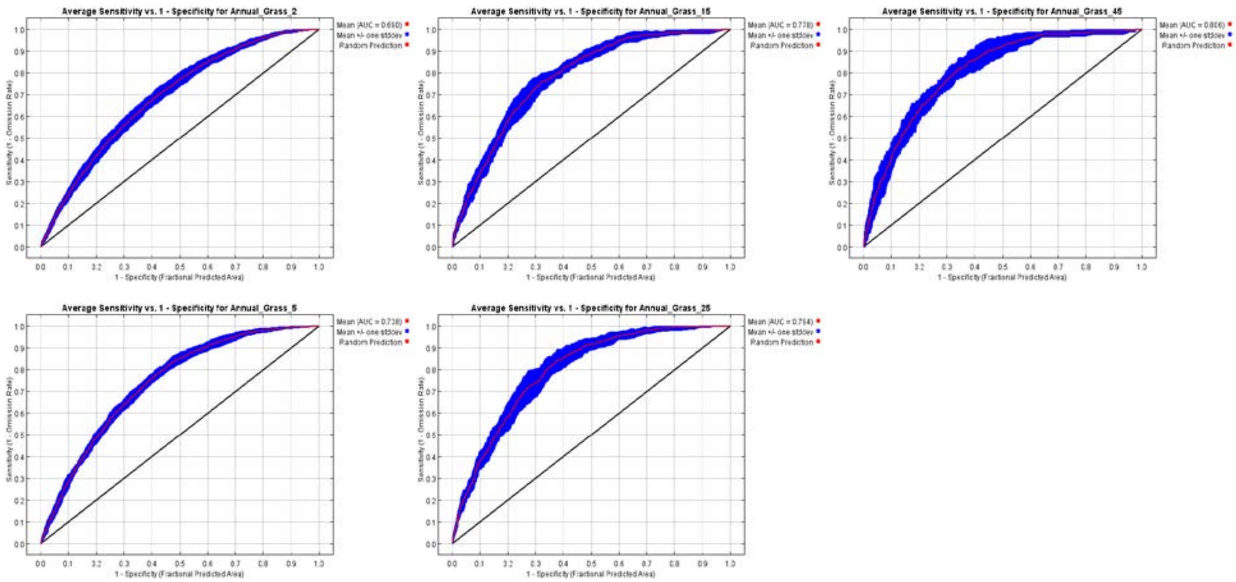

Figure A - 10. Receiver operating characteristic (ROC) curves for the individual annual grass models.

The variable contributions to individual models was constant across the majority of the cover class with Thermotype and fire distance comprising 42-55% of the model explanation (Table A - 11). While we did not perform future projection of invasive potential, the importance of the thermotype variable suggests the potential to perform projections of invasive species at finer scales. Bradley et al. (2008) suggest considerable changes in invasive species distributions in relation to climatic variance but the scale of the analysis is not suitable below the continental scale.

Confidence in the modeling results is relatively high and the models performed with ranges from moderate (< 5% cover) to moderate/high (>=5%-15%, >=15%-25%, >=25%-45%, >=45%) for the composite models. The source data used to train the models is generally well vetted, but the multiple source nature of the data does contain multiple scales of sampling effort and different sampling designs. However, the model intent is not to represent actual ground cover of invasive annual grass, but rather the potential (risk) of the landscape to be affected by varying densities of annual grass cover. As such, the model may act with reasonable confidence as a surrogate for actual annual grass cover in planning and risk assessment analysis.

Table A - 11. Variable contribution by individual cover models

1-5% Cover		5-15% Cover		15-25% Cover		25-45% Cover		>=45% Cover	
Variable	**Percent contribution**	**Variable**	**Percent contribution**	**Variable**	**Percent contribution**	**Variable**	**Percent contribution**	**Variable**	**Percent contribution**
landform	24.3	thermotype	27.5	thermotype	27.7	thermotype	23.1	thermotype	28.3
dem	18.9	landform	16.1	fire_dist	16.7	fire_dist	19.2	fire_dist	26.5
ph1to1	9	fire_dist	15.5	dem	16	dem	13.2	road2_den	11.9
fire_dist	6.9	dem	13.7	ombrotype	6.6	landform	7.7	dem	7
sand_t	6.3	road2_den	6.6	landform	6.6	road2_den	7.1	landform	4.8
geology	6.2	intermit_d	3.3	aspect	5.7	aspect	6.6	intermit_d	4.8
thermotype	5.5	geology	3.1	road2_den	5.3	ombrotype	4.7	geology	3.4
road34_den	4.6	perenn_d	2.9	geology	2.9	intermit_d	4.4	ph1to1	3
intermit_d	4.1	ph1to1	2.6	intermit_d	2.8	sand_t	2.7	road34_den	2.4
perenn_d	3.4	slope	2.1	hydric_dist	2.5	perenn_d	2.7	sand_t	1.8
hydric_dist	3.3	hydric_dist	1.9	road34_den	1.8	road34_den	2.4	slope	1.5
road2_den	3	road34_den	1.8	slope	1.7	ph1to1	2.4	aspect	1.5
ombrotype	2.4	sand_t	1.7	ph1to1	1.5	geology	1.3	perenn_d	1.4
slope	1.1	aspect	0.8	perenn_d	1.1	slope	1.2	hydric_dist	1
aspect	0.7	ombrotype	0.6	sand_t	1.1	hydric_dist	1.2	ombrotype	0.6

Noxious Forbs

Unlike the Annual Grasses model, the forbs model consists of a continuous raster and does not represent a specific threshold value. The user of the data may specify a threshold that is suitable for the analysis. The distribution of noxious forbs is highly skewed toward the CBR and only 13% of all point samples are in the MBR (Figure A - 11).

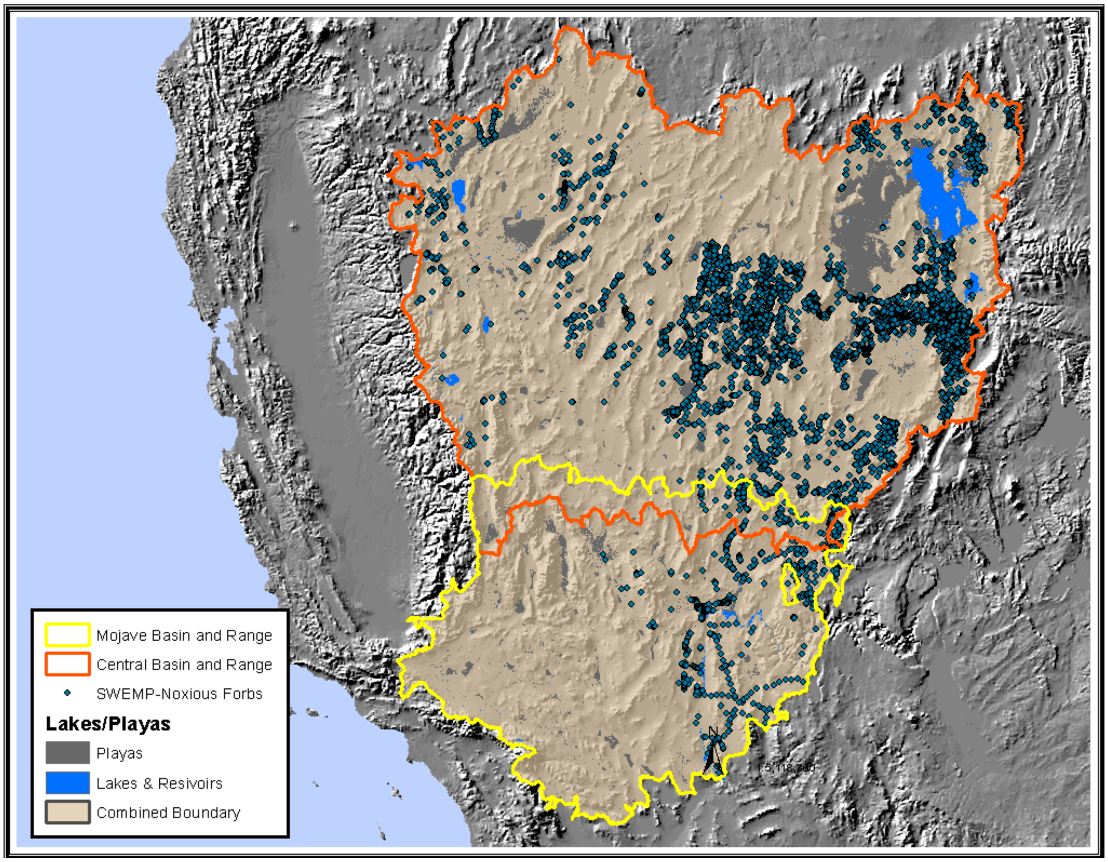

Figure A - 11. Distribution of samples for modeling Noxious Forbs.

Samples used to develop the Noxious Forbs model were extracted from the Southwest Exotic Plant Mapping Program (SWEMP) data layer. A total of 897 exotics species were identified within both the combined Ecoregions, but not all species are considered Noxious. The noxious weed list for each state was acquired from the USDA-Natural Resources Conservation Services "Invasive and Noxious Weeds" database and combined to filter the SWEMP samples for only those species listed as Noxious (Table A - 12). All samples for *Halogeton glomeratus* were excluded from the model as per the AMT group discussion (L. Bryant, pers comm., Las Vegas, NV, Nov 2011). While it was by far the most numerous of the noxious forbs in the dataset, it would have resulted in a model of "*Halogeton*" distribution; a preliminary model was run using the *Halogeton glomeratus* samples, but it yielded poor results (AUC was only 0.623). *Salsola kali* and *S. tragus*, are listed separately in this table; the NRCS PLANTS database recognizes both as valid taxa, although *Salsola kali* ssp. *tragus* can be considered part of *S. tragus*. The records in the database did not distinguish between *Salsola kali* and *S. tragus*. Since all of these sample points were combined into one dataset for the modeling purposes, this taxonomic uncertainty is not problematic. The final sample size for model development was 800 points.

Table A - 12. Noxious forbs used in model development. * Note Halogenton glomeratus was not used.

Scientific Name	Sample	Comment
Acroptilon repens	6	
Cardaria draba	10	
Centaurea	1	
Centaurea diffusa	1	
Chorispora tenella	19	
Cirsium arvense	27	
Conium maculatum	4	
Convolvulus arvensis	11	
Coronopus squamatus	18	
Cuscuta	23	
Cynoglossum officinale	6	
Gaura coccinea	1	
Halogeton glomeratus	983	Not used in model
Iris missouriensis	27	
Iva axillaris	17	
Onopordum acanthium	3	
Orobanche cooperi	2	
Portulaca oleracea	23	
Salsola kali	351	S. kali is also called S. tragus - taxonomy is dependent on ssp.
Salsola paulsenii	3	
Salsola tragus	247	

The independent layer variables used to model noxious forbs were identical to those used in modeling Annual Grasses. As with annual grasses the analysis model represents the entire sample training points with additional modeling preformed to address model validation.

The distribution of noxious forb probability (risk) is limited primarily to the CBR with 83% (78% unique) of watersheds with probability of noxious forbs being present (Figure A - 12). Relatively few watersheds in the MBR have risk of noxious forbs, at least as predicted by this model.

Model performance was relatively high with AUC=0.846 (Figure A - 13). Similar to the individual annual grasses models, the Thermotype variable was the dominate driver of the model result, but unlike these models the density of the secondary roads in the landscape and the physical characteristics of the landscape were nearly equal in describing the model development (Table A - 13).

Confidence in the model is moderately high with overall model performance moderately high with an acceptable range in AUC score of 0.814 in validation subsamples and with standard deviation of 0.010 (Figure A - 13). Confidence in the complete data sample modeling results is relatively high and performed with model performance was high with an AUC=0.867 (Figure A - 13) . The source data used to train the models is generally well vetted, but the multiple source nature of the data does contain multiple scales of sampling effort and different sampling designs. However, the model intent is not to represent actual ground cover of noxious forbs, but rather the potential (risk) of the landscape to be affected by varying densities forb cover. As such, the model may act with reasonable confidence as a surrogate for forb cover in planning and risk assessment analysis. The distribution of noxious forb probability (risk) is limited primarily the CBR with 83% (78% unique) of watersheds with probability of noxious forbs being present (Figure A - 12).

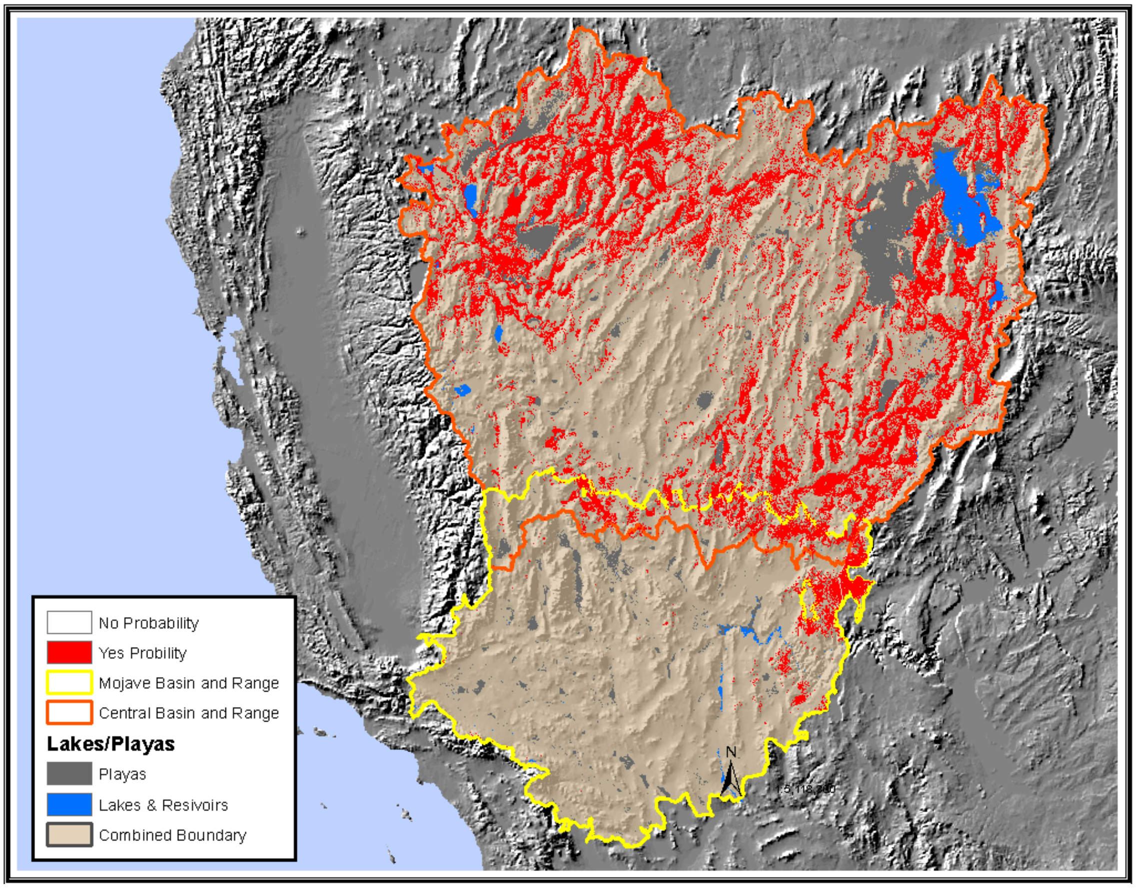

Figure A - 12. Distribution of noxious forb potential in the combined CBR and MBR area

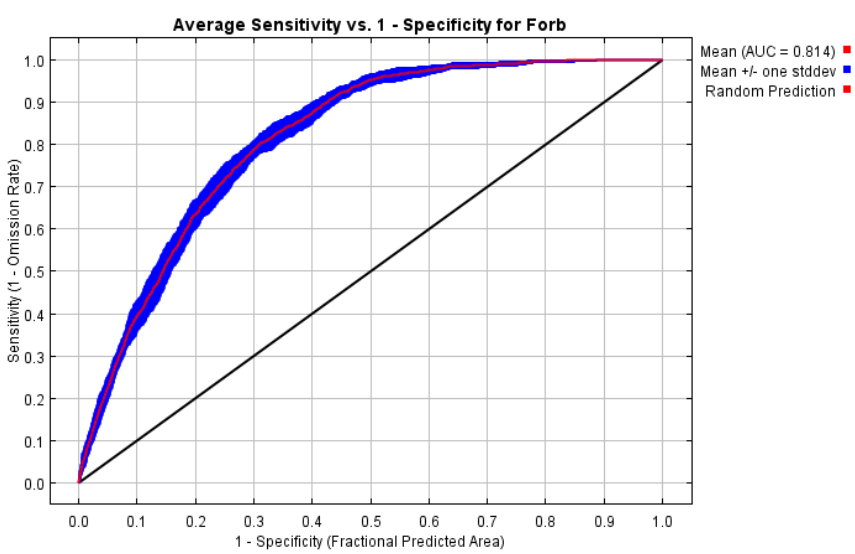

Figure A - 13. Noxious forb model performance

Table A - 13. Variable contribution to the noxious forbs model

Variable	Percent contribution
thermotype	25.2
road2_den	14.2
dem	13.7
slope	12.8
hydric_dist	8.4
fire_dist	7.6
landform	5.2
sand_t	4.7
road34_den	2.5
ph1to1	1.7
intermit_d	1.1
aspect	0.9
perenn_d	0.9
geology	0.6
ombrotype	0.5

Species Invasive to Riparian Areas

Similar to Noxious Forbs, the Invasive Riparian model is represented by a continuous surface of probability of occurrence. The SWEMP data layer was used to identify samples for modeling. There were nine riparian invasive species with document records in the SWEMP, but 95% of the sampoles for modeling distribution were comprised of Tamarisk/Saltcedar with 4,062 recorded occurrences (Table A - 14).

Table A - 14. Riparian invasive species *Note Saltcedar and Tamarisk were combined.

Common Name	Sample Size
Athel Tamarisk	1
Russian Olive	83
Saltcedar	3213
Tamarisk	849
Siberian Elm	3
Tracy's Willow	30
Tree Of Heaven	2
Water Hemlock	86
Water Speedwell	2
Total	4269

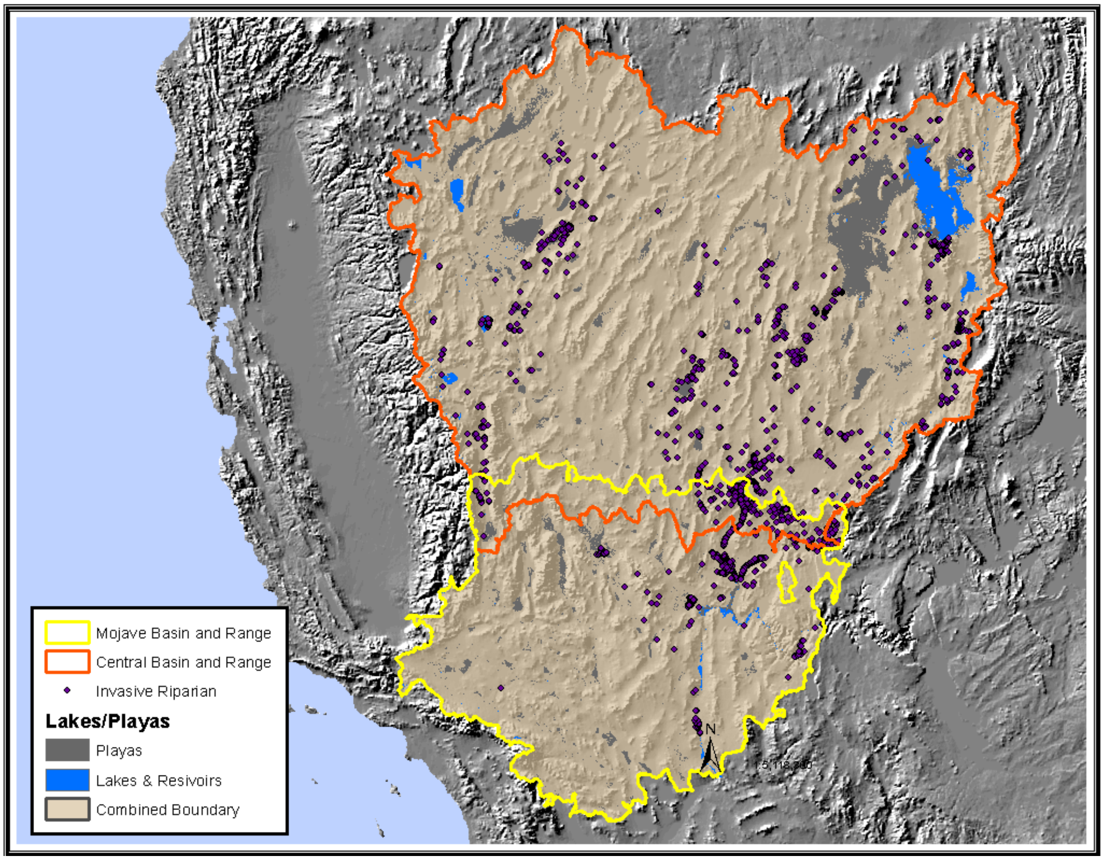

Figure A - 14. Distribution of samples used in modeling species invasive to riparian areas (tamarisk and Russian olive, primarily).

Unlike both Annual Grasses and Noxious Forbs, the independent variables used to model the distribution of the Invasive Riparian probability were limited to only biophysical variables and did not include representation of human caused input via roads or effects of fire (Table A - 15).

The modeled extent of riparian invasive is more evenly distributed across the 2 ecoregions with 38% of the overall extent present within the MBR. Noticeable with the model extent are regions beyond the water channel and typically surround playas, greasewood flats and desert washes (Figure A - 15).

Model performance is acceptably high with a validation score of AUC=0.838 (Figure A - 16a). As expected, the proximity of hydric soils is the primary contributor to the overall performance of the model (Table A - 15). Additionally, the position in the landscape is critical with lower elevation (Figure A - 16b) sites within the drainage channels (Cat 10 in Figure A - 16c).

Confidence in the model performance in subsample validation data is acceptably high with a validation score of AUC=0.838 and a standard deviation of 0.008 (Figure A - 16a). Confidence in the complete data sample modeling results is high and model performance was high with an AUC=0.816. As expected, the proximity of hydric soils is the primary contributor to the overall performance of the model (Table A - 15). Additionally, the position in the landscape is critical with lower elevation (Figure A - 16b) sites within the drainage channels (Cat 10 in Figure A - 16c).

The source data used to train the models is generally well vetted, but the multiple source nature of the data does contain multiple scales of sampling effort and different sampling designs. However, the model intent is not to represent actual ground cover of woody riparian species, but rather the potential (risk) of the landscape to be affected by varying densities woody riparian cover. As such, the model may act with reasonable confidence as a surrogate for woody riparian cover in planning and risk assessment analysis.

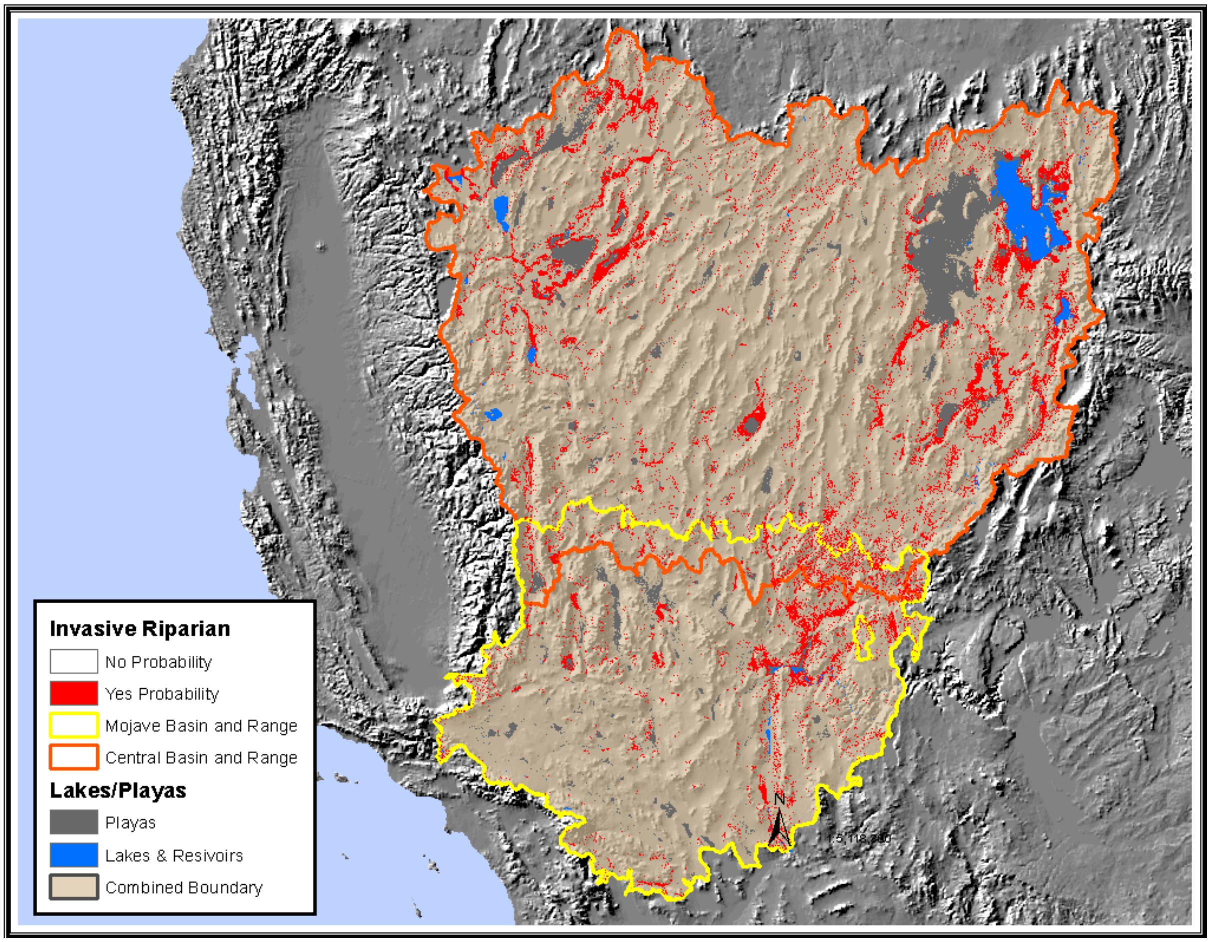

Figure A - 15. Modeled distribution of plants (especially tamarisk and russian olive) invasive to riparian areas

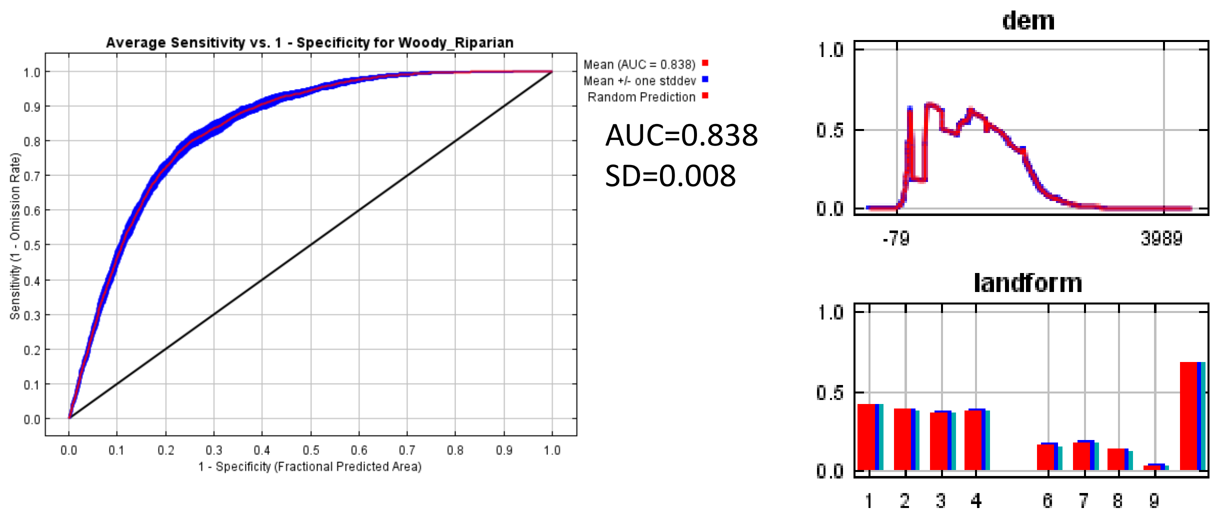

Figure A - 16. AUC score for riparian invasive (a. ROC statistics, b. elevation range, c. landform)

Table A - 15. Variable contribution to the riparian invasive model

Variable	Percent contribution
hydric_dist	34.6
landform	22.7
dem	12.9
perenn_d	8.7
thermotype	6.7
intermit_d	4.3
sand_t	4.2
ph1to1	2.9
ombrotype	1.3
geology	0.7
slope	0.5
aspect	0.4

A-1.2.2.2 Invasive Aquatic Species

Aquatic Invasive Species Impact Index

The aquatic invasive species[1] impact index includes metrics that focus on the more important ecological and landscape factors identified in invasive species life history, ecological, and invasion theory (Barney and Whiltlow 2008; McKinney and Lockwood 1999; Parker et al. 1999; Pimm 1989; Shigesada and Kawasaki 1997; and Williamson 1996). Metrics were incorporated into three indices: 1) Known Status Index, 2) At Risk Index, and 3) Future Impact Index. The Known Status Index and the At Risk Index

[1]The terms species, taxa, and taxon are used throughout this narrative. The term species is often used interchangeably with taxa or taxon. Taxa is the plural form of taxon and refers to taxonomic categories. For example, this assessment combines all species of mollies and guppies into one taxon and all species of carp into one taxon.

were developed based on reported invasive species locations in the databases used, whereas the Future Impact Index is the predicted impacts in 2025. We did not develop a Future Impact Index for the year 2050 because of the very limited amount of reported data available. However, we discuss potential aquatic invasive impacts in 2050 later in this report.

INFESTATION LEVELS AND RELATIVE TAXA IMPACT

The level of infestation (density/biomass) of the invasive taxon in a CE and HUC is critical to the level of impact it has once it becomes established. Densities also affect dispersal rates with higher densities resulting in increased 'potential propagules' (Veltman et al. 1996; Lockwood et al. 2005; Colautti et al.2007). Most data rich invasive species models nearly always incorporate density estimates when available (Shigesada and Kawasaki 1997). However, only one of our databases reported densities for only one single taxon and none of our databases reported biomass. Therefore, our invasive species impact index does not explicitly include level of infestation. However, for a location to have been reported the species most likely occurred at densities greater than its detection threshold.

INDEX DEVELOPMENT BASED ON HUC RESOLUTION

Species invasions are primarily determined by ecological interactions occurring at the landscape level. Invasion theory is solidly based on the first law of geography "everything is related to everything else, but near things are more related than distant things" (Tobler 1970), the theory of island biogeography (MacArthur and Wilson 1967), and the field of landscape ecology. Thus, the selection of metrics and scoring criteria for an aquatic invasive index is directly dependent on the 'grain size' or area of resolution of the hydrological unit used. We developed the aquatic invasive species impact index based on lowest practical sized area, the watershed level [HUC10 (Level 5)]. Hence, if these indices are to be used for larger sized areas they will need to be modified.

METRIC SELECTION AND SCORING

Although it is generally recognized that certain metrics are more important measures of invasive impact levels than others; their importance can often differ between taxa and as stated earlier are dependent on densities of the invasive taxon. Given these restrictions, each metric score was divided into three categories (values): no data = 'undetermined', transitioning = 0.67 or degraded < 0.67. It should be noted that almost all metric scores in any rapid assessment are highly subjective. Metric scores require careful thought and consideration before selection and need to be scrutinized and validated after their selection.

A-1.2.2.2.1 Known Status Index

NUMBER OF INVASIVES

The most important metric (and most heavily weighted) in the entire suite of metrics is the number of invasive taxa present. This is simply because the greater the number of invasive taxa there are in a CE; the greater the loss of 'ecological integrity'. Obviously, if no invasive taxa are in a CE within a HUC there is no invasive impact to that CE although there is always future potential.

The Known Status Index (Table A - 16) contains a single metric 'the number of invasive taxa in a CE'. Other than the didymo database, which also included absence data, available databases only contained reported presence sites. Unreported sites do not infer absences. If a taxon was reported in our database then the taxon was most likely well established and had reached some detection threshold. Unreported sites could have been a result of two factors; 1) no surveys were conducted or 2) surveys were below detection threshold levels of invasive taxa. Detection threshold is a function of observer survey methods and skills, amount of search effort used, observability of the taxon (e.g. some taxa are more easily observed than others ex. carp vs. didymo), and the density of the taxon. There were no metadata available relating survey methods or amount of search effort used for any of our invasive taxa data points in the database. We assume that many different types of survey methods and amounts of search effort were used and were not standardized. This most likely resulted in reported false absences or in locations not being reported. Also, timeliness (time lag) of reporting, lack of awareness of centralized invasive species databases, or failure to understand the importance of a centralized database, were also factors that most likely resulted in under reporting of invasive taxa in the databases. Thus the number of invasive taxa metric should be considered as under representative. Most likely the number of invasive taxa in CEs and HUCS in the ecoregions are much higher. The Known Status Index metric was scored conservatively to take these factors into consideration.

Table A - 16. Aquatic Invasive Species Impact Index scoring criteria for Known Status for each CE within a 5th level watershed. NA = not reported = unknown; 0.67 = transitioning; 0.33 = degraded.

Known Status Index					
Type of Indicator	**Metric category**	**Metric**	**Justification**	**Data Source**	**Evaluation and score**
Biotic	**Number of invasives**	1. Number of invasive taxa present in CE	The greater the number of invasive taxa there are in a CE, the greater the impairment	USGS NAS, USGS didymo database, Natural Heritage Programs attributed to specific CEs (~90% of the records). + Assignment of records in datasets that lack specific CE attributes (~ 10% of data) based on CE invasive potential (Appendix 1) and closest CE.	0 taxa = NA 1 taxon = 0.67 > 1 taxa = 0.33

A-1.2.3 Fire

A-1.2.3.1 Succession class (SClass) updates

The LANDFIRE SClass data layers are a critical component to the application of the VDDT models and estimate of fire regime departure. As part of the data development for the MBR analysis we examined both the fire perimeter boundaries (MTBS Perimeters) and the annual grasses potential models as sources to apply to the current LANDFIRE SClass data layer for updates.

The fire perimeter boundaries were not used individually to modify the SClass distribution. An ecoregion wide modification of SClass values with the fire perimeter data was not possible without further information on the in-perimeter location and documentation of fire intensity. Additionally, the fire effects in a transition to an invasive dominance state varies by the vegetation type and proximity to the existing invasive concentrations.

Updates to the annual grasses component of SClass were performed using the 15-25% Annual Grasses potential model used in development of the Annual Grasses Composite layer. The model was intersected with the current ecological systems map and systems documented in the literature to have associations with annual grass invasion (Table A - 17). Those pixels identified as at risk were used to modify the underlying SClass values to “Uncharacteristic Exotic Vegetation”. References cited in the below table were copied in from Zouhar (2003), and are not in the references cited section at the end of this appendix.

Table A - 17. Elevation and precipitation ranges for communities in which cheatgrass may be dominant or codominant , as reported by state or province (From Zouhar 2003). References are those provided in the Zouhar (2003) table, and appear duplicative but are not.

State	Plant community dominants or codominants	Elevation	Mean annual precipitation	References
CO	Utah juniper/mountain snowberry (*Symphoricarpos oreophilus*)	7,200 feet (2,183 m)	----	Komarkova 1988
ID	basin big sagebrush/cheatgrass	mostly below 7,000 feet (2,120 m); on south aspects as high as 7,800 feet (2,360 m)	----	Schlatterer 1972
NV	shadscale	4,320 to 5,400 feet (1,310-1,640 m)	6.7 to 11.4 inches (168-285 mm)	Blackburn et al 1969, Blackburn et al. 1968, Blackburn et al. 1969.
	spiny hopsage/green rabbitbrush (*Chrysothamnus viscidiflorus*)	5,250 to 5,500 feet (1,590-1,670 m)	8.4 inches (210 mm)	Blackburn et al 1969, Blackburn et al. 1968, Blackburn et al. 1969, Blackburn et al. 1969.
	black sagebrush	4,900 to 6,400 feet (1,485-1,940 m)	7.6 to 17.1 inches (190-428 mm)	Blackburn et al 1969, Blackburn et al. 1968, Blackburn et al. 1969.
	big sagebrush and various codominants	4,590 to 7,350 feet (1,390-2,230 m)	6.8 to 14.9 inches (170-373 mm)	Blackburn et al 1969, Blackburn et al. 1968, Blackburn et al. 1969.
	mountain snowberry-mountain big sagebrush/bluebunch wheatgrass	7,260 to 10,230 feet (2,200-3,100 m)	----	Tueller and Eckert 1987.
	Utah juniper	5,500 to 6,200 feet (1,670-1,880 m)	11.4 to 17.7 inches (285-443 mm)	Blackburn et al. 1969, Blackburn et al. 1969.
	ponderosa pine/rubber rabbitbrush	5,600 to 5,900 feet (1,700-1,790 m)	16.6 inches (415 mm)	
	desert peach/shrub live oak (*Prunus andersonii*/*Quercus turbinella*)	6,125 feet (1,860 m)	16.7 inches (418 mm)	Blackburn et al

Changes in the SClass classification were primarily limited to the early succession classes (Table A - 18). Late successional classes and highly altered landscapes were not substantially affected by the modifications. Figure A - 17 and Figure A - 18 show the results.

Table A - 18. Change in SClass value by applying invasive annual potential.

Sclass Code	DESCRIPTION	HA_Base	HA_Update	Delta_HA	Delta%
1	Succession Class A	4917963.1	4728554.37	189408.69	-3.85%
2	Succession Class B	13360070	11293509.42	2066560.11	-15.47%
3	Succession Class C	6487157	4450737.06	2036419.92	-31.39%
4	Succession Class D	1906813.2	1565570.34	341242.83	-17.90%
5	Succession Class E	1679978.3	1633371.12	46607.22	-2.77%
6	Uncharacteristic Native Vegetation Cover / Structure / Composition	5395009.1	4745675.97	649333.08	-12.04%
7	Uncharacteristic Exotic Vegetation	8689553.6	14082755.85	-5393202.3	62.07%
111	Water	790506.63	810073.62	-19566.99	2.48%
112	Snow / Ice	1123.74	1118.43	5.31	-0.47%
120	Urban	650755.98	645975.18	4780.8	-0.73%
131	Barren	2474525.6	2445292.44	29233.17	-1.18%
132	Sparsely Vegetated	2758058.1	2747423.16	10634.94	-0.39%
180	Agriculture	1029020	992161.62	36858.33	-3.58%

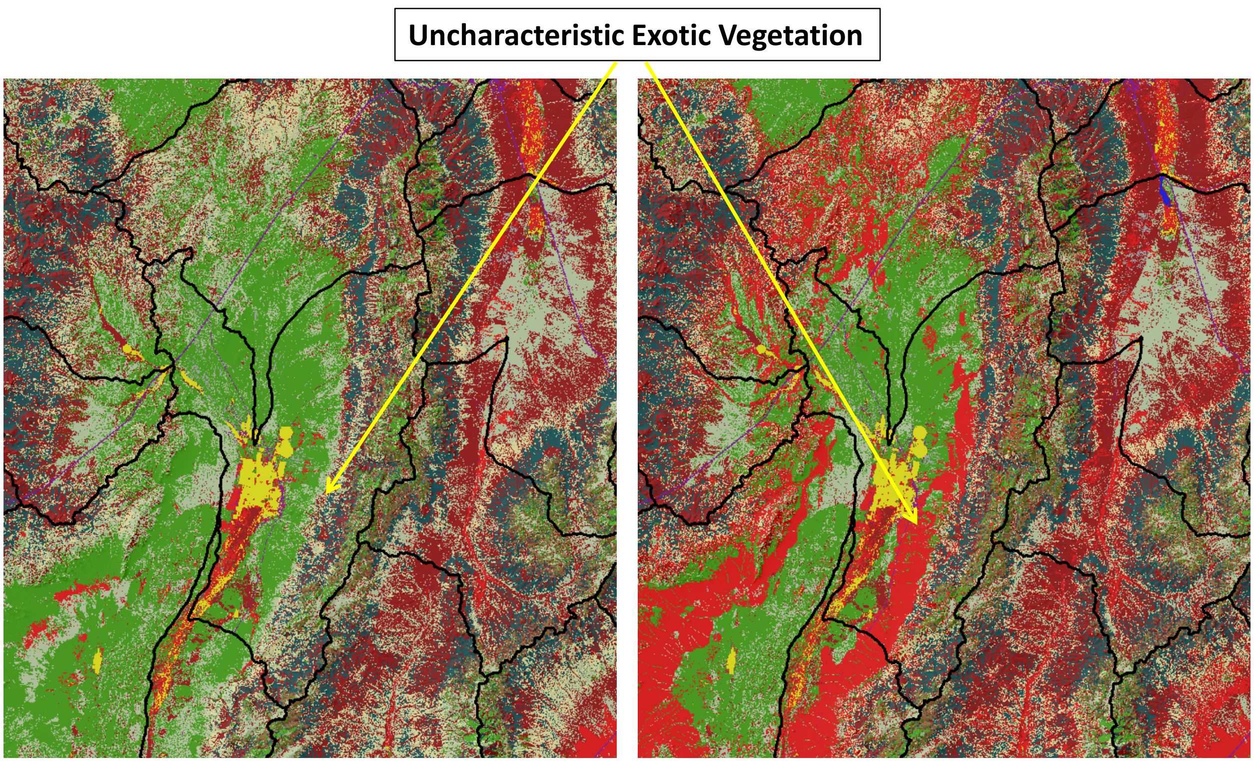

Figure A - 17. Extent of change in Uncharacteristic Exotic Vegetation (Red).

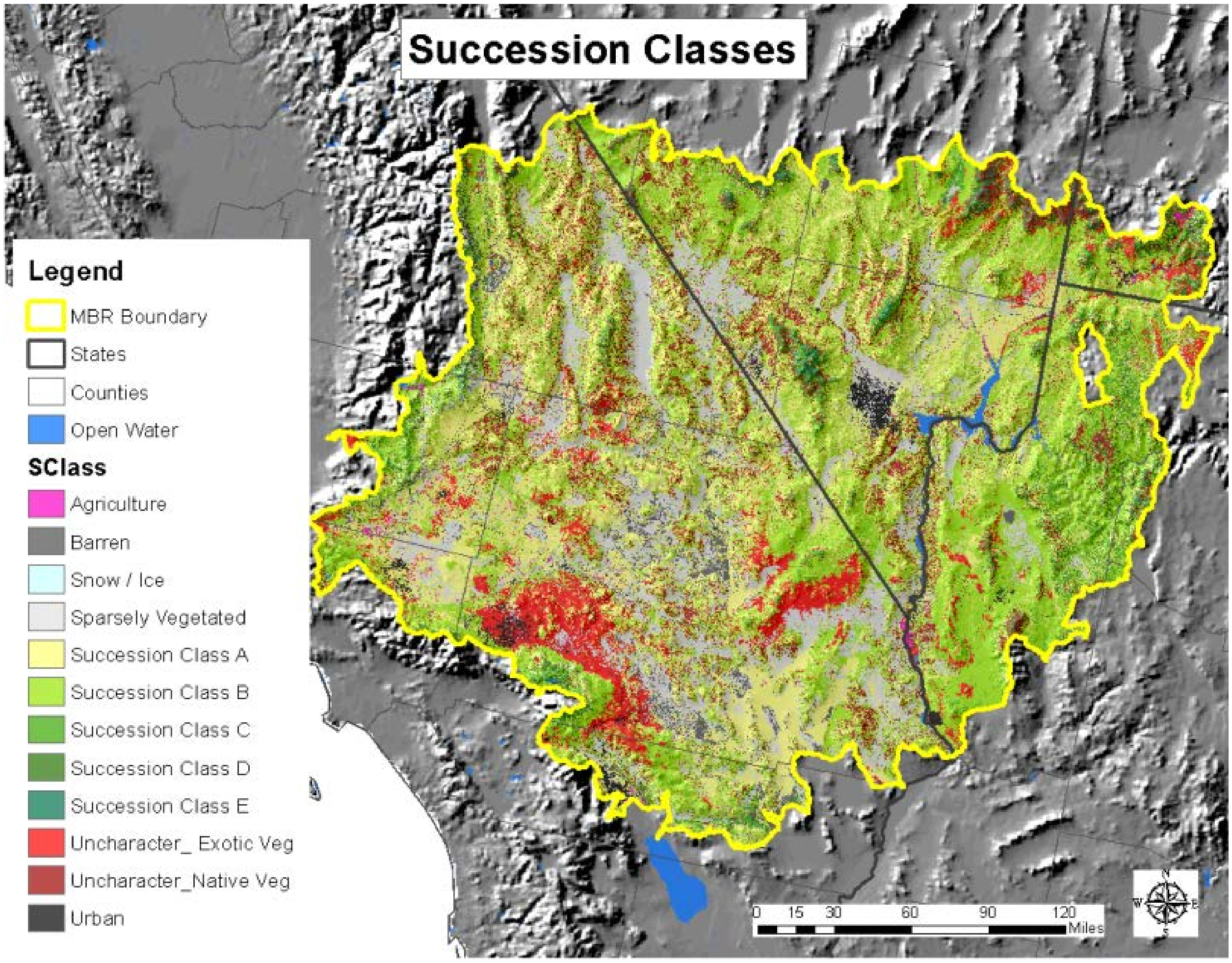

Figure A - 18. Updated succession classes for the MBR. These succession classes (SCLass) describe the stages within an ecological system's ecological cere. SClasses are defined by relative age and canopy closure, so for example Succession Class A captures all early seral stages whereas Class E captures late seral - closed canopy systems. Not all systems are divided into all 5 classes; Two, Three, and Four class systems are common.

Confidence in the modifications made by NatureServe are moderately high, but are limited to the overall model performance as completed by LANDFIRE. The modifications of SClass made by NatureServe are applied based upon the overlap of the invasive annual grasses model representing the 15-25% cover model, which has high model performance (AUC=0.811), and the base SClass data layer as received from LANDFIRE. Due to the modeling protocol followed by LandFire it is difficult to define an overall model performance of the complete SClass data layer.

A-1.2.3.2 State-Transition Modeling and Fire regime Departure Calculations

Ecological communities are dynamic systems with ecological succession moving occurrences toward older states, and disturbances "resetting" these systems back to earlier seral stages.

Westoby et al. (1989) and Bestelmeyer et al. (2004) championed the use of state and transition models for describing the system dynamics within range land and arid land ecosystems. In brief, these models are based upon the premise that ecological communities exist as a mosaic made up of different patches. At any given time, each patch exists as a unique seral state, and over time these patches change as a result of ecological succession and natural disturbance. Therefore, an important landscape scale description of an ecological community is the relative areal extent of each seral class within a study area. Under natural disturbance regimes in ecological system reaches an equilibrium where a relative extent of each seral class does not change over time. This is referred to as the natural range of variation (NRV).

Changes in the relative areal extent of all seral classes represent potentially significant changes within the ecological community. For example, an increase in fire frequency results in a larger proportion of the ecological community being in earlier seral classes. Conversely, fire suppression often results in the ecological community being overrepresented by older Seral stages. Ecological departure (ED) is a measure of how different a current, or modeled, ecological community is when compared to an NRV. ED is essentially a measure of the dissimilarity between NRV and a specific occurrence of a community. In this study ED was calculated as:

$$1 - \sum_{class=A}^{F} Min(class\_abundance_{NRV}, class\_abundance_{Time\,X})$$

This index is used by LANDFIRE, The Nature Conservancy, and others. We tested the performance of this index relative to several other dissimilarity indices and did not find significant differences in performance for this purpose. ED varies from zero to one, with one being the most departed. However, to maintain consistency with the other indices reported in this project, ED was transformed so that, herein, zero reflects the most departed and one, least.

Over the past 10 years the USFS, The Nature Conservancy, and others have built upon the STM theory have used state and transition models broadly to describe the current condition of forested and arid land systems throughout North America.

To simulate vegetation change over time within each of the 11 coarse-filter CEs, we used quantitative state-and-transition models (STMs) developed by The Nature Conservancy – Nevada Chapter (Provencher and Anderson 2011). These STMs were developed for the Mojave region of Nevada as part of the revision of Nevada's Strategic Wildlife Action Plan. The models are extensively referenced and had been widely reviewed. The set of modeled CEs (Table A - 19) covered all of the major upland ecological systems in the ecoregion.

Table A - 19. Conservation Elements (CEs) modeled in the Mojave Basin and Range Ecoregion. Not every CE occurs in every 5th order HUC and no HUC heads every model CE.

Great Basin Pinyon-Juniper Woodland
Great Basin Xeric Mixed Sagebrush Shrubland
Inter-Mountain Basins Mixed Salt Desert Scrub
Mogollon Chaparral
Mojave Mid-Elevation Mixed Desert Scrub-Mesic
Mojave Mid-Elevation Mixed Desert Scrub-Thermic
Sonora-Mojave Creosotebush-White Bursage Desert Scrub
Sonora-Mojave Mixed Salt Desert Scrub
Sonora-Mojave Semi-Desert Chaparral
Sonoran Mid-Elevation Desert Scrub-Mesic
Sonoran Mid-Elevation Desert Scrub-Thermic

STMs were built using the Vegetation Dynamics Development Tool (VDDT) and run in the Path Landscape Model (ESSA Technologies and ApexRMS). Separate VDDT and Path databases were built for historic and current conditions which allowed modeling team to incorporate modern uncharacteristic vegetative states (e.g., annual grassland) in to the models of current condition. These conceptual models, their state descriptions, and transition probabilities are provided in the DB of Conceptual Models for Conservation Elements.

To generate model output, VDDT models were imported into Path. To generate NRV, ten replicate models were each run for 1000 years. These models included only seral classes identified to be part of the historic ecological cere and disturbances and transition probabilities representative of historic conditions. For every CE the distribution of seral state classes had stabilized within 500 years and showed no further changes. Therefore we are confident using these distributions as representative of the natural range of variability.

Unfortunately, it was not possible to model each CE occurrence within the ecoregion; there are 1352 individual occurrences of the modeled CEs identified in the MBR. Thus, it was necessary to reduce the number of models run to a manageable number. This was accomplished through a three step process outlined below:

First, the spatial extent of each CE within each HUC was calculated from the LANDFIRE data. Each observation was then inspected and those occurrences in the smallest 5% were deleted from the data set. By and large, this excluded those occurrences that appeared in such small spatial extents as to be most likely classification errors, and those whose extent was less than the minimum dynamic area for that CE. This step was necessary in order to ensure that our initial starting conditions, based on these observed data, were not unduly biased by these relatively small occurrences.

The remaining occurrences were then clustered to identify a suite of initial conditions that was representative of all HUCs. These analyses were performed in two stages. In the first stage we performed a hierarchical cluster analysis based on the relative proportion of each is class within each HUC, for every modeled CE. The goal of this analysis was to identify an appropriate number of groups to model. Unfortunately, there is no standard analytical method for identifying the ideal number of groups within such an analysis; there is an art as well as a science in doing this. For every CE we examined the Root Mean Squared Standard Deviation index, the Pseudo F Index, and the Pseudo T^2 index for common patterns. Any root mean square deviation index one looks for a dramatic drop in values. In contrast one looks for a peak value in the pseudo F index, and one looks for a dramatic jump in values in the Pseudo T^2 index. Figure A - 19 shows these three plots for the Inter-Mountain Basins Mixed Salt Desert Scrub CE. In this instance the three plots support the conclusion that 3 groups is the appropriate number capture the variation within the CE.

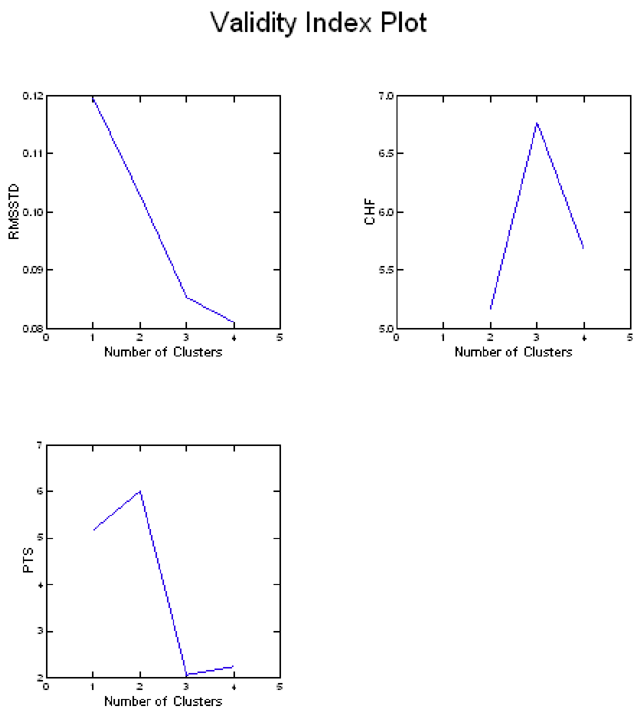

Figure A - 19. Validity Index Plots for the Intermountain Basins Mixed Salt Desert Scrub CE. The three plots together indicate that the appropriate number of clusters is 3 (indicated by the break in RMSSTD and Pseudo F, and Pseudo T^2).

Unfortunately, the three indices to not always agree. In these cases the number of groups was selected based upon the majority of evidence. Table A - 20 shows the number of groups identified for each CE.

Once the number of groups was identified for each CE, each dataset was clustered a second time using a K-means procedure. This clustering procedure aggregates the data into a specified number of groups and provides the values of all variables for each cluster centroid. K-means clustering identifies clusters in a manner that maximizes the differences among clusters will minimizing the variation within. By doing so each cluster's members are more similar to other members in their group than they are to any other observation within the data set. Therefore by using this clustering algorithm we were able to identify a specific number of groups whose member had SCLASS distribution were all very similar. The centroid values for each group were then used as the initial conditions for modeling future conditions for each CE. This resulted in a total of 45 models being used in the PATH modeling process.

Table A - 20. Groups identified by the Hierarchical Cluster Analyses.

Conservation Element	**Number of Groups**
Great Basin Pinyon-Juniper Woodland	5
Great Basin Xeric Mixed Sagebrush Shrubland	4
Inter-Mountain Basins Mixed Salt Desert Scrub	3
Mogollon Chaparral	4
Mojave Mid-Elevation Mixed Desert Scrub-Mesic	4

Mojave Mid-Elevation Mixed Desert Scrub-Thermic	5
Sonora-Mojave Creosotebush-White Bursage Desert Scrub	4
Sonora-Mojave Mixed Salt Desert Scrub	5
Sonora-Mojave Semi-Desert Chaparral	4
Sonoran Mid-Elevation Desert Scrub-Mesic	4
Sonoran Mid-Elevation Desert Scrub-Thermic	3

In the Path model, we supplied initial conditions for each of the 45 models described above. Transition multipliers were used to deactivate all management transitions built into the models. Output was generated as a .csv file written to a separate folder. 10 Monte Carlo runs were simulated across approximately 8,000 simulation cells per model run, using arbitrary cell size and total acre values. For current models, models were run for 60 years starting with current conditions supplied from LANDFIRE (Table A - 21).

Table A - 21. Assignment of model state classes for each coarse-fliter CE modeled. LANDFIRE mapped states included successional states A-E based on LANDFIRE reference condition models. They also included barren, UE (uncharacteristic exotic) and UN (uncharacteristic native). In some cases, a LANDFIRE state might be allocated into multiple state classes (e.g. UN/2 means that the area mapped to UN was divided equally into two model state classes to provide initial conditions).

Ecological System Name	Variant	State and Transition Model	Model State Class	LANDFIRE Map State
Great Basin Pinyon-Juniper Woodland		GBPinyonJuniper	PJ-A:AL	A
Great Basin Pinyon-Juniper Woodland		GBPinyonJuniper	PJ-B:OP	B
Great Basin Pinyon-Juniper Woodland		GBPinyonJuniper	PJ-C:OP	C
Great Basin Pinyon-Juniper Woodland		GBPinyonJuniper	PJ-D:OP	D+E
Great Basin Pinyon-Juniper Woodland		GBPinyonJuniper	PJ-U:AG	UE
Great Basin Pinyon-Juniper Woodland		GBPinyonJuniper	PJ-U:TA	UN
Great Basin Xeric Mixed Sagebrush Shrubland		GBXericMixSage	LBS-A:AL	A
Great Basin Xeric Mixed Sagebrush Shrubland		GBXericMixSage	LBS-B:OP	B
Great Basin Xeric Mixed Sagebrush Shrubland		GBXericMixSage	LBS-C:CL	C
Great Basin Xeric Mixed Sagebrush Shrubland		GBXericMixSage	LBS-D:OP	D+E
Great Basin Xeric Mixed Sagebrush Shrubland		GBXericMixSage	LBS-U:AG	UE/4
Great Basin Xeric Mixed Sagebrush Shrubland		GBXericMixSage	LBS-U:DP	UN/3

Great Basin Xeric Mixed Sagebrush Shrubland		GBXericMixSage	LBS-U:ES	UN/3
Great Basin Xeric Mixed Sagebrush Shrubland		GBXericMixSage	LBS-U:SA	UE/4
Great Basin Xeric Mixed Sagebrush Shrubland		GBXericMixSage	LBS-U:SAP	UE/4
Great Basin Xeric Mixed Sagebrush Shrubland		GBXericMixSage	LBS-U:TA	UE/4
Great Basin Xeric Mixed Sagebrush Shrubland		GBXericMixSage	LBS-U:TE	UN/3
Inter-Mountain Basins Mixed Salt Desert Scrub		IMBSaltDesertScrub	MSD-A:AL	A
Inter-Mountain Basins Mixed Salt Desert Scrub		IMBSaltDesertScrub	MSD-B:OP	B+C
Inter-Mountain Basins Mixed Salt Desert Scrub		IMBSaltDesertScrub	MSD-C:OP	D+E
Inter-Mountain Basins Mixed Salt Desert Scrub		IMBSaltDesertScrub	MSD-U:AG	UE/2
Inter-Mountain Basins Mixed Salt Desert Scrub		IMBSaltDesertScrub	MSD-U:SAP	UN
Inter-Mountain Basins Mixed Salt Desert Scrub		IMBSaltDesertScrub	MSD-U:SD	UE/2
Mogollon Chaparral		MogollonChaparral	Chp-A:AL	A+B
Mogollon Chaparral		MogollonChaparral	Chp-B:CL	C+D+E
Mojave Mid-Elevation Mixed Desert Scrub	Mesic	MojMidElevDesertScrub-Mesic	BM-A:AL	A
Mojave Mid-Elevation Mixed Desert Scrub	Mesic	MojMidElevDesertScrub-Mesic	BM-B:CL	B+C
Mojave Mid-Elevation Mixed Desert Scrub	Mesic	MojMidElevDesertScrub-Mesic	BM-C:OP	D+E
Mojave Mid-Elevation Mixed Desert Scrub	Mesic	MojMidElevDesertScrub-Mesic	BM-U:AG	UE/3
Mojave Mid-Elevation Mixed Desert Scrub	Mesic	MojMidElevDesertScrub-Mesic	BM-U:BG	BARREN
Mojave Mid-Elevation Mixed Desert Scrub	Mesic	MojMidElevDesertScrub-Mesic	BM-U:SAP	UN
Mojave Mid-Elevation Mixed Desert Scrub	Mesic	MojMidElevDesertScrub-Mesic	BM-U:SD	UE/3
Mojave Mid-Elevation Mixed Desert Scrub	Mesic	MojMidElevDesertScrub-Mesic	BM-U:TA	UE/3
Mojave Mid-Elevation Mixed Desert Scrub	Thermic	MojMidElevDesertScrub-Thermic	BT-A:AL	A+B
Mojave Mid-Elevation Mixed Desert Scrub	Thermic	MojMidElevDesertScrub-Thermic	BT-B:CL	C+D+E
Mojave Mid-Elevation Mixed Desert Scrub	Thermic	MojMidElevDesertScrub-Thermic	BT-U:AG	UE

Mojave Mid-Elevation Mixed Desert Scrub	Thermic	MojMidElevDesertScrub-Thermic	BT-U:BG	BARREN
Mojave Mid-Elevation Mixed Desert Scrub	Thermic	MojMidElevDesertScrub-Thermic	BT-U:SAP	UN
Sonora-Mojave Creosotebush-White Bursage Desert Scrub		SonMojCreosoteBursageScrub	CB-A:OP	A+B
Sonora-Mojave Creosotebush-White Bursage Desert Scrub		SonMojCreosoteBursageScrub	CB-B:CL	C+D+E
Sonora-Mojave Creosotebush-White Bursage Desert Scrub		SonMojCreosoteBursageScrub	CB-U:AG	UE
Sonora-Mojave Creosotebush-White Bursage Desert Scrub		SonMojCreosoteBursageScrub	CB-U:BG	BARREN
Sonora-Mojave Creosotebush-White Bursage Desert Scrub		SonMojCreosoteBursageScrub	CB-U:SAP	UN
Sonora-Mojave Mixed Salt Desert Scrub		SonMojSaltDesertScrub	MSD-A:AL	A
Sonora-Mojave Mixed Salt Desert Scrub		SonMojSaltDesertScrub	MSD-B:OP	B+C
Sonora-Mojave Mixed Salt Desert Scrub		SonMojSaltDesertScrub	MSD-C:OP	D+E
Sonora-Mojave Mixed Salt Desert Scrub		SonMojSaltDesertScrub	MSD-U:AG	UE
Sonora-Mojave Mixed Salt Desert Scrub		SonMojSaltDesertScrub	MSD-U:SAP	UN/2
Sonora-Mojave Mixed Salt Desert Scrub		SonMojSaltDesertScrub	MSD-U:SD	UN/2
Sonora-Mojave Semi-Desert Chaparral		SonMojChaparral	Chp-A:AL	A+B
Sonora-Mojave Semi-Desert Chaparral		SonMojChaparral	Chp-B:CL	C+D+E
Sonora-Mojave Semi-Desert Chaparral		SonMojChaparral	Chp-U:SAP	UN+UE
Sonoran Mid-Elevation Desert Scrub	Mesic	SonMidElevDesertScrub-Mesic	BM-A:AL	A
Sonoran Mid-Elevation Desert Scrub	Mesic	SonMidElevDesertScrub-Mesic	BM-B:CL	B+C
Sonoran Mid-Elevation Desert Scrub	Mesic	SonMidElevDesertScrub-Mesic	BM-C:OP	D+E
Sonoran Mid-Elevation Desert Scrub	Mesic	SonMidElevDesertScrub-Mesic	BM-U:AG	UE
Sonoran Mid-Elevation Desert Scrub	Mesic	SonMidElevDesertScrub-Mesic	BM-U:BG	BARREN
Sonoran Mid-Elevation Desert Scrub	Mesic	SonMidElevDesertScrub-Mesic	BM-U:SAP	UN
Sonoran Mid-Elevation Desert Scrub	Mesic	SonMidElevDesertScrub-Mesic	BM-U:SD	UE

Sonoran Mid-Elevation Desert Scrub	Thermic	SonMidElevDesertScrub-Thermic	BT-A:AL	A+B
Sonoran Mid-Elevation Desert Scrub	Thermic	SonMidElevDesertScrub-Thermic	BT-B:CL	C+D+E
Sonoran Mid-Elevation Desert Scrub	Thermic	SonMidElevDesertScrub-Thermic	BT-U:AG	UE
Sonoran Mid-Elevation Desert Scrub	Thermic	SonMidElevDesertScrub-Thermic	BT-U:BG	BARREN
Sonoran Mid-Elevation Desert Scrub	Thermic	SonMidElevDesertScrub-Thermic	BT-U:SAP	UN

Table A - 22 provides a starting CE SCLASS distribution for all 45 model groups. It also provides the NRV SCLASS distribution for all CEs.

Table A - 22. NRV and Initial conditions for all modeled CE Groups.

Great Basin Pinyon-Juniper Woodland											
Group	PJ-A:AL	PJ-B:OP	PJ-C:OP	PJ-D:OP	PJ-U:AG	PJ-U:TA					
HRV	2%	4%	13%	81%							
1	6%	27%	43%	11%	1%	12%					
2	19%	38%	19%	12%	1%	12%					
3	45%	23%	10%	20%	3%	1%					
4	10%	21%	20%	35%	1%	15%					
5	3%	9%	52%	6%	0%	29%					
Great Basin Xeric Mixed Sagebrush Shrubland											
Group	LBS-A:AL	LBS-B:OP	LBS-C:CL	LBS-D:OP	LBS-U:AG	LBS-U:DP	LBS-U:ES	LBS-U:SA	LBS-U:SAP	LBS-U:TA	LBS-U:TE
HRV	17%	48%	23%	11%							
1	22%	41%	14%	4%	0%	7%	7%	0%	0%	0%	7%
2	41%	30%	4%	1%	0%	7%	7%	0%	0%	0%	7%
3	65%	23%	0%	0%	0%	7%	7%	0%	0%	0%	7%
4	24%	30%	2%	0%	0%	7%	7%	0%	0%	0%	7%
Inter-Mountain Basins Mixed Salt Desert Scrub											
Group	MSD-A:AL	MSD-B:OP	MSD-C:OP	MSD-U:AG	MSD-U:SAP	MSD-U:SD					
HRV	8%	83%	8%								
1	10%	77%	6%	0%	7%	0%					
2	8%	53%	3%	17%	3%	17%					
3	53%	44%	1%	0%	2%	0%					

Mogollon Chaparral											
Group	Chp-A:AL	Chp-B:CL									
HRV	8%	92%									
1	57%	36%									
2	27%	35%									
3	68%	14%									
4	49%	35%									
Mojave Mid-Elevation Mixed Desert Scrub-Mesic											
Group	BM-A:AL	BM-B:CL	BM-C:OP	BM-U:AG	BM-U:BG	BM-U:SAP	BM-U:SD	BM-U:TA			
HRV	26%	42%	32%								
1	18%	71%	2%	1%	1%	5%	1%	0%			
2	15%	27%	0%	27%	1%	3%	27%	0%			
3	48%	36%	0%	2%	3%	8%	2%	0%			
4	24%	44%	4%	0%	0%	26%	0%	0%			
Mojave Mid-Elevation Mixed Desert Scrub-Thermic											
Group	BT-A:AL	BT-B:CL	BT-U:AG	BT-U:BG	BT-U:SAP						
HRV	5%	95%									
1	89%	1%	3%	1%	7%						
2	34%	0%	62%	2%	3%						
3	89%	4%	3%	1%	4%						
4	78%	0%	5%	1%	16%						
5	88%	0%	5%	1%	6%						
Sonora-Mojave Creosotebush-White Bursage Desert Scrub											
Group	CB-A:OP	CB-B:CL	CB-U:AG	CB-U:BG	CB-U:SAP						
HRV	9%	91%									
1	88%	0%	3%	4%	6%						
2	9%	0%	88%	2%	0%						
3	72%	0%	4%	2%	22%						
4	85%	3%	3%	1%	8%						
5	52%	0%	38%	5%	6%						
Sonora-Mojave Mixed Salt Desert Scrub											
Group	MSD-A:AL	MSD-B:OP	MSD-C:OP	MSD-U:AG	MSD-U:SAP	MSD-U:SD					
HRV	8%	82%	10%								
1	80%	12%	0%	5%	2%	2%					
2	2%	4%	0%	92%	1%	1%					
3	58%	36%	0%	1%	2%	2%					

4	45%	14%	0%	37%	2%	2%					
5	48%	25%	0%	3%	12%	12%					
Sonora-Mojave Semi-Desert Chaparral											
Group	Chp-A:AL	Chp-B:CL	Chp-U:SAP								
HRV	17%	83%									
1	90%	3%	7%								
2	28%	35%	37%								
3	1%	1%	98%								
4	86%	5%	10%								
Sonoran Mid-Elevation Desert Scrub-Mesic											
Group	BM-A:AL	BM-B:CL	BM-C:OP	BM-U:AG	BM-U:BG	BM-U:SAP	BM-U:SD	BM-U:TA			
HRV	27%	43%	30%								
1	8%	87%	3%	1%	0%	1%	1%	0%			
2	5%	54%	0%	20%	0%	1%	20%	0%			
3	2%	28%	0%	35%	0%	1%	35%	0%			
4	7%	86%	4%	0%	0%	2%	0%	0%			
Sonoran Mid-Elevation Desert Scrub-Thermic											
Group	BT-A:AL	BT-B:CL	BT-U:AG	BT-U:BG	BT-U:SAP						
HRV	5%	95%									
1	90%	7%	1%	1%	2%						
2	84%	5%	5%	1%	5%						
3	95%	0%	1%	0%	3%						

A-1.2.4 Climate Space Trends

A-1.2.4.1 Climate Space Trends Introduction

Climate space is defined as the range of values that occur across a defined landscape in a defined time period for a given combination of climatic variables, such as monthly maximum and minimum temperature or monthly total precipitation. The variables analyzed and the time slices chosen to describe climate space are determined by the management question being addressed and spatial and temporal climate data availability. Analyses of climate space require digital, time series spatial data, and the resolution of the spatial climate data determines the resolution of the analysis. Using spatial climate data interpolated from observations, such as continuous weather station records, recent trends in climate space can be analyzed against a user-defined baseline to reveal the nature, rate, magnitude, and distribution of changes in climate that are already occurring. To understand how future climate change may affect a landscape, downscaled outputs from global or regional climate models can be statistically analyzed relative to a climatological baseline. When analyzing climate model outputs, the baseline is predetermined by the downscaling process.

An essential component of climate space trend analysis is that it incorporates a measure of the natural variability in climate in determining if recent or future climate change is statistically significant. Recent and future trends in climate space are analyzed with respect to natural climatic variability to understand how observed or projected changes may depart from the range of variability to which biodiversity is already adapted in the landscape of management interest. The degree to which natural climatic variability can be quantified is entirely dependent on the availability of time series spatial climate data from interpolated observations, such as PRISM (Daly et al. 2002) or downscaled global or regional climate model outputs (Hamilton et al. in prep; Hostetler et al. 2011).

For the buffered boundary of the Mojave Basin and Range ecoregion, we present three sets of climate space trend analyses using three spatial climate datasets. Current trends in climate space of monthly maximum and minimum temperature and monthly total precipitation are analyzed based on the PRISM 4km^2 spatial climate dataset for the period 1900-2010. Future trends in climate space are examined with two alternative downscaled climate model datasets. Using a 6 model average from the EcoClim 4km^2 dataset, we analyze monthly maximum and minimum temperature and monthly total precipitation projections for two future time slices, the 2020s and the 2050s, as compared to the 1950-1999 baseline, which is defined by the downscaling process. Using a 3 model average of dynamically downscaled regional climate model outputs recently released by the USGS (Hostetler et al. 2011), we analyze climate space trends at 15km^2 resolution between a midcentury 2045-2060 time slice and a 1968-1999 baseline for seven monthly and annual variables related to climate and hydrology. As predetermined by the scope of this REA, all downscaled global and regional model outputs refer to the A2 emissions scenario only. This comprehensive set of climate space trends supports an understanding of the spatial and temporal nature of climate in the MBR, and summarizes forecasts of future change relative to a baseline characterization of natural climatic variability.

A-1.2.4.2 Climate space trends Methods

For analysis of landscape trends in climate space, we used the PRISM spatial climate data (Daly et al. 2002) and two alternative datasets of future climate projections. At 4km^2 resolution, we created a 6 GCM ensemble average of the models listed in Table 1 to examine trends in monthly maximum temperature, monthly minimum temperature, and monthly total precipitation among 3 time periods: a 1900-1979 baseline derived from PRISM, a near-term future (2020s) and a midcentury future (2050s). At 15km^2 resolution, we created an average value across three climate models from 3 dynamically downscaled regional climate model outputs (Hostetler et al. 2011). The baseline climatology is defined as 1968-1999, which is determined by the downscaling process. For the 15km2 dataset, the baseline data is derived from a model, called NCEP, that is forced by observations (Hostetler et al. 2011). To correct for the bias of each GCM, the modeled current (1968-1999) was subtracted from the modeled future (2045-2060) to generate a value of change per GCM, for each month and each variable in each 15km^2 pixel. These 3 values were then averaged to create a future model ensemble value per month/variable/pixel, which was compared to the baseline NCEP run and its standard deviation, similar to the approach with the EcoClim4km2 dataset. With this coarser spatial dataset, we examined climate space trends in evapotranspiration, soil moisture, winter snow water equivalent, and soil runoff, in addition to monthly maximum and minimum temperature and monthly total precipitation. For both spatial climate datasets, the analysis establishes a baseline value for each pixel, for each variable, for every month, and compares these baseline values to projections for that same pixel/variable/month to investigate the amount of change that models forecast between the present and future conditions.

Below are the names of the 6 GCMs downscaled to 4km^2 and used for bioclimatic envelope modeling and climate space trend analysis.

- BCCR_BCM2_0

- CSIRO_MK3_0
- CSIRO_MK3_5
- INMCM3_0
- MIROC3_2_MEDRES
- NCAR_CCSM3_0

An essential component of climate space trend analysis is to incorporate a measure of natural climatic variability when identifying the timing, nature and spatial distribution of significant change. While ‘natural climatic variability’ would ideally be defined with sufficient paleoclimate data to characterize climate variation over longer time scales, available data restricts our ability to quantify natural variability at the spatial scale of the REA and the temporal scale of resource management over the coming decades. Here, we quantify variability as the standard deviation of the baseline average. For the $4km^2$ EcoClim data, this is the standard deviation per pixel, per variable, per month, of the average value from 1950-1999. For the $15km^2$ USGS/Hostetler dataset, this is the standard deviation per pixel, per variable, per month, of the average value from 1968-1999. When projections of the future values for a given pixel/variable/month exceed the baseline value plus or minus at least one standard deviation, we conclude that future conditions are estimated to exceed the natural range of that variable for that time frame.

Climate space trends have been calculated for two time frames in the future: a near term time frame, approximately the 2020s, and a midcentury time frame, approximately the 2050s. The exact time frames differ between the EcoClim $4km^2$ dataset, which has decadal averages for every decade through 2100, and the USGS/Hostetler $15km^2$ dataset, which created a 15 year midcentury average specifically for the REA process: 2045-2059. All climate models from which future variables are derived have been run with the A2 greenhouse gas emissions scenario (IPCC 2000). This means the near term and midcentury futures examined here are restricted to the model outputs associated with a specific set of values for future greenhouse gas concentrations. If global emissions exceed these values, impacts could be greater.

The main results of both sets of climate space trend analyses are delivered in the form of a geodatabase. For each $4km^2$ or $15km^2$ pixel in the Central and Mojave basins, the geodatabase provides a rapid summary of which future pixel values fall either one or two standard deviations above or below the baseline mean, for every month and every variable. Because the values are connected to a unique lat/long coordinate for every pixel, the spatial distribution of statistically significant climate change for each month and each variable can be visualized (Figure A - 20)

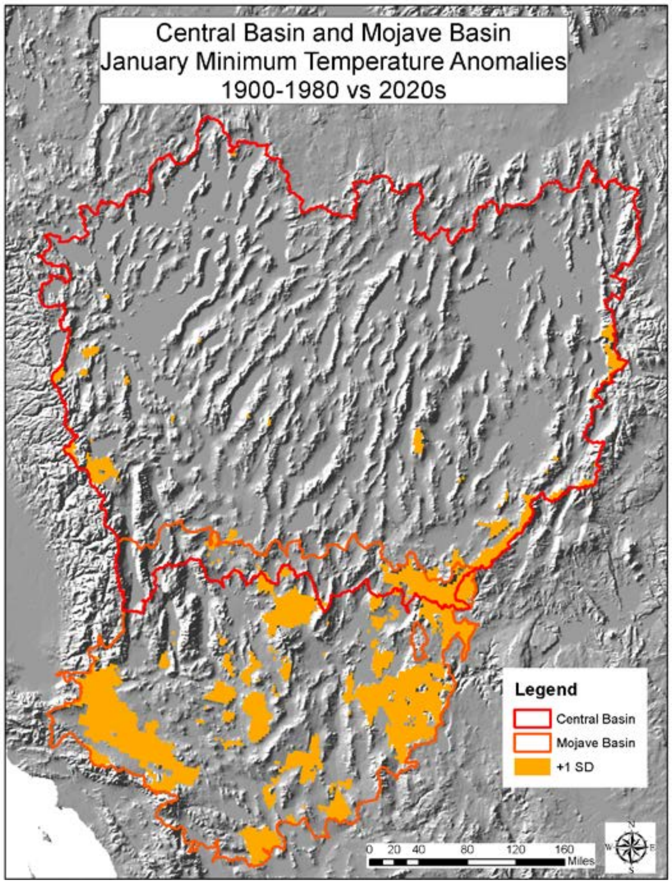

Figure A - 20. Near term (2020s) projected trends in climate space for January minimum temperatures in the CBR/MBR region. The orange area represents each 4km^2 pixel which has a value projected to exceed one standard deviation beyond the eighty year baseline mean for January minimum temperatures. This analysis suggests that southern areas of the basin and range region will be the first to feel the effects of large changes in winter minimum temperatures, and demonstrates that winter minimum temperatures are projected to increase in southern areas first.

A-2 Findings in terms of Management Questions

A-2.1.1 Development – General

MQ48 - WHERE ARE CURRENT LOCATIONS OF DEVELOPMENT CAS?

Less than 9% of the ecoregion is currently occupied by development CAs (see Table A - 23 and Figure A - 21 for enlarged area example).

Table A - 23. Current (2011) proportion of the ecoregion occupied by each development CA.

Change Agent Name	(1000) Acres	Percent
No Development Change Agent	*36,991*	*91.20*
Urban Development	2,237	5.51
Multiple Change Agents	572	1.41
Roads Rural Neighborhood or Private	400	0.99
Crops or Irrigated Pasture	66	0.16

Change Agent Name	(1000) Acres	Percent
Primary Electric Utility Line	63	0.16
Roads Unimproved 4wd	60	0.15
Roads Principal or Secondary	42	0.10
Pipeline	30	0.07
Renewable Energy Wind	26	0.06
Renewable Energy Solar	22	0.05
Railroad	14	0.03
Military Urbanized Area	11	0.03
Roads Unknown Type	11	0.03
Mine or Landfill	7	0.02
Water Canal or Ditch	4	0.01
Non motorized trail	3	0.01
Renewable Energy Geothermal	2	0.01
Oil or Gas Well	<1	0.00

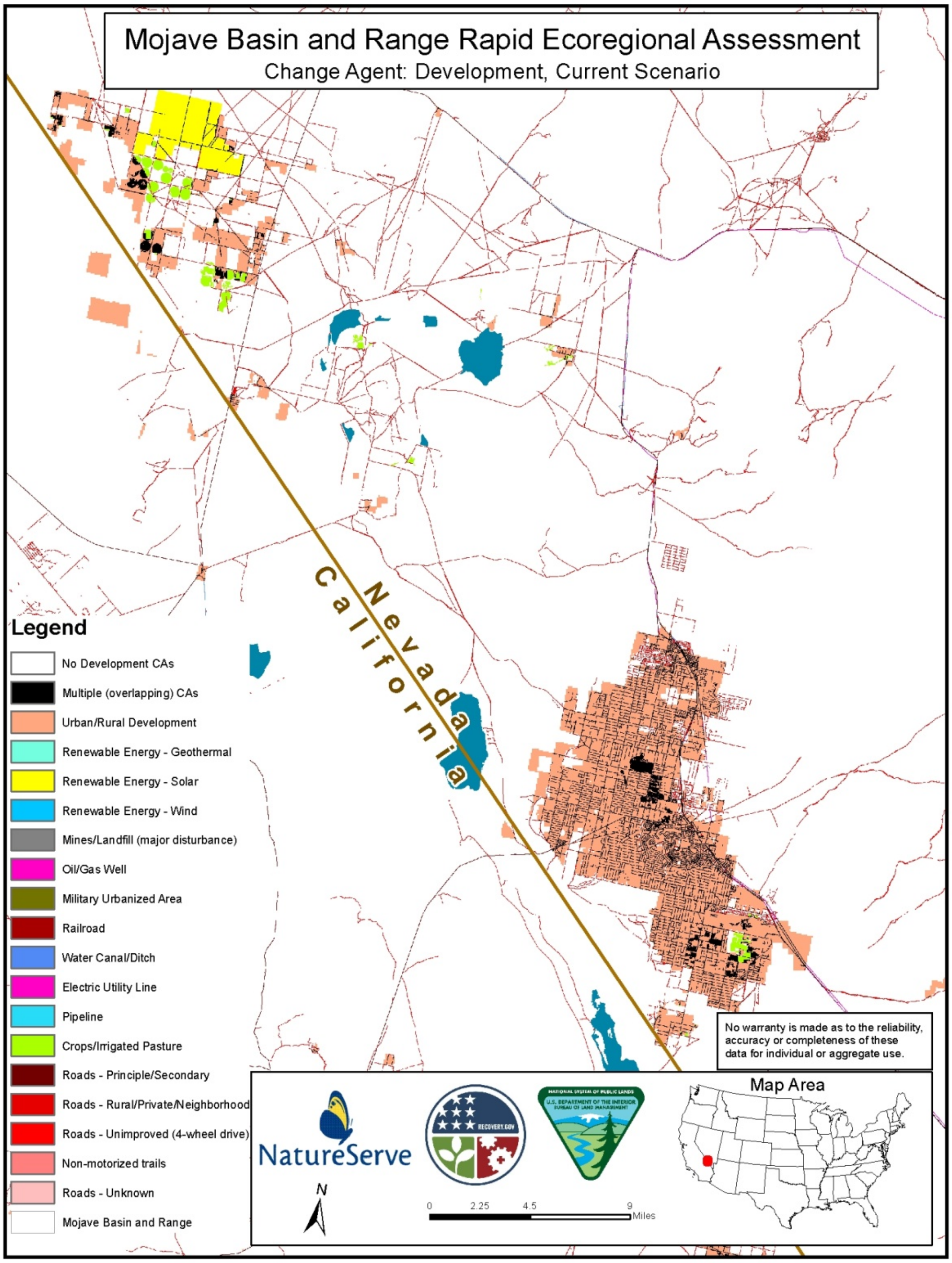

Figure A - 21. Current development change agent distribution around Pahrump, NV.

Confidence in these results is relatively high. The source data used to represent the development CAs will contain mapping and classification errors but generally the ecoregion enjoys high quality data representing these features. The BLM linear features map was assembled from various sources, merging national and state data with layers from the BLM field offices. NatureServe did some additional QA/QC on the layer received from BLM but the team noted duplicate and missing features in the final layer. Locally this may result in some erroneous results in products that used the roads layer including the landscape condition model and the development change agent footprint analyses. In addition, there is some distortion incorporated by reprojecting data and representing vector data as raster data. Also see the development change agent sections above for more information and the general uncertainty statements in the main report for common issues affecting uncertainty.

A-2.1.2 Energy development Management Questions

MQ83 - WHERE ARE THE CURRENT LOCATIONS OF OIL, GAS, AND MINERAL EXTRACTION?

Oil and gas extraction is very small component of the ecoregion. The REA didn't differentiate between mines and refuse areas such landfills due to the difficulty distinguishing these features using existing information. Approximately 0.02% (7,013 acres) of the ecoregion are open pit mines or landfills. California's largest open pit mine, the US Borax Boron Mine is located in western Mojave. See the overview of development change agents above for additional information about mines and landfills. A map is not provided because the features on not readily identifiable at the scale of the REA.

MQ87 - WHERE ARE THE CURRENT LOCATIONS OF RENEWABLE ENERGY DEVELOPMENT (SOLAR, WIND, GEOTHERMAL, TRANSMISSION)?

Renewable energy sources occupy 50,474 acres or 0.13% of the ecoregion. Wind energy development accounts for 26,363 acres or a little over half the combined area of solar and geothermal energy. See Figure A - 22 below for current and future distribution statistics by renewable energy type. Figure A - 23 below shows the locations of these projects and see Table A - 6 for a complete list of projects included in the assessment.

MQ81 - WHERE WILL LOCATIONS OF RENEWABLE ENERGY [DEVELOPMENT] POTENTIALLY EXIST BY 2025?

By 2025 the renewable energy footprint is forecasted to increase relative to current while remaining a small proportion overall. Renewable energy sources increase by nearly 3x in area from the current 0.13% of the ecoregion to 0.36% with significant increases in solar and wind energy types. Geothermal energy is largely confined to the northwest portion of the ecoregion and is not expected to grow significantly. The solar SEZ in particular adds 28,456 acres to the 2025 renewable energy footprint. Figure A - 23 below shows the locations of these projects and see Table A - 6 for a complete list of projects included in the assessment.

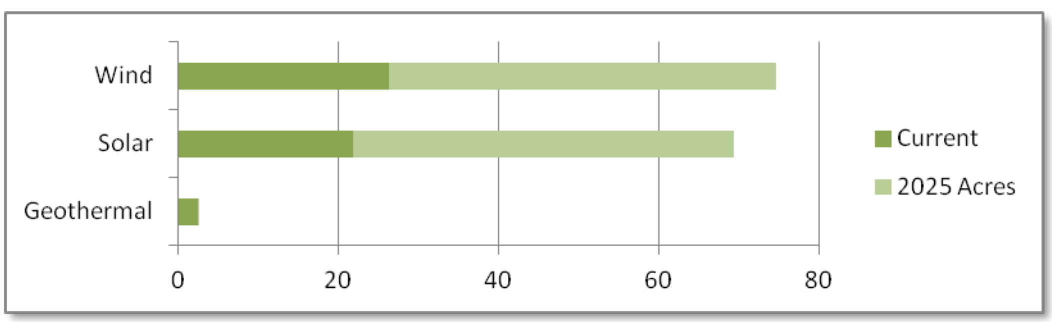

Figure A - 22. Current and future renewable energy area in thousands of acres. Dark shade is current, light shade is additional area added by 2025.

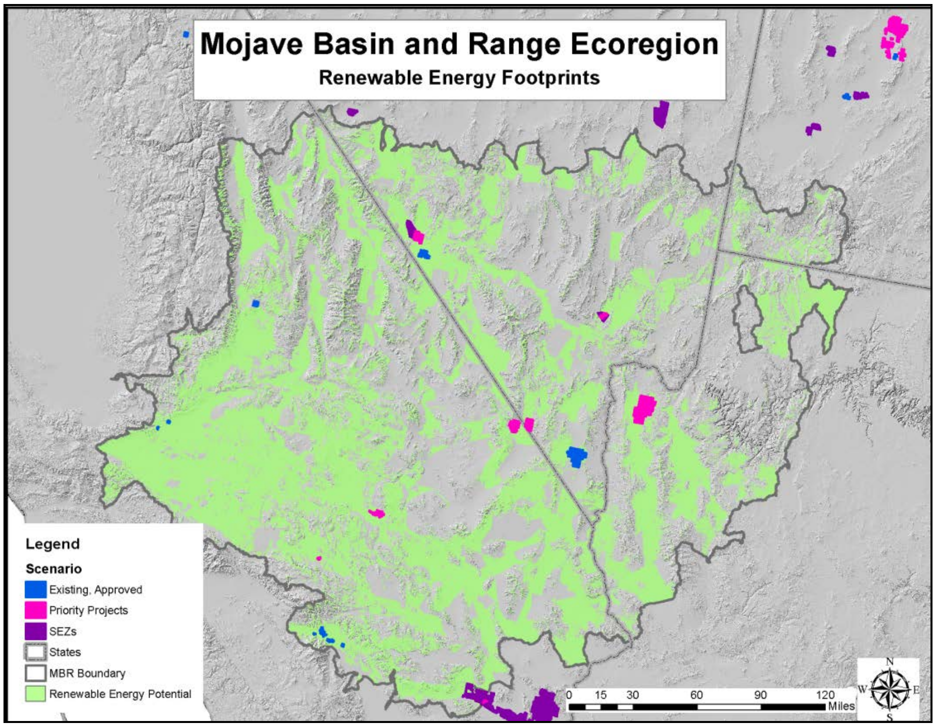

Figure A - 23. Current and 2025 Scenario Renewable Energy Projects and potential energy footprint.

MQ 88 - WHERE ARE THE AREAS IDENTIFIED BY NREL AS POTENTIAL LOCATIONS FOR RENEWABLE ENERGY DEVELOPMENT?

This assessment was free of any particular timeframe but instead mapped the total renewable footprint based on the NREL capability maps. Renewable energy has the potential to increase dramatically in this ecoregion. However, the potential is based on sampled and modeled data by NREL and many other factors such as accessibility to roads and transmission and conflicts with other values will affect the location and amount of areas actually developed. The area of priority renewable energy zones expressed in state zone maps is considerably smaller than the total potential footprint. Methods for developing the renewable energy potential footprint are described above in the section on Renewable Energy Potential and Priority Areas. Figure A - 23 above shows areas with renewable energy potential and results by renewable energy type are provided in Figure A - 24.

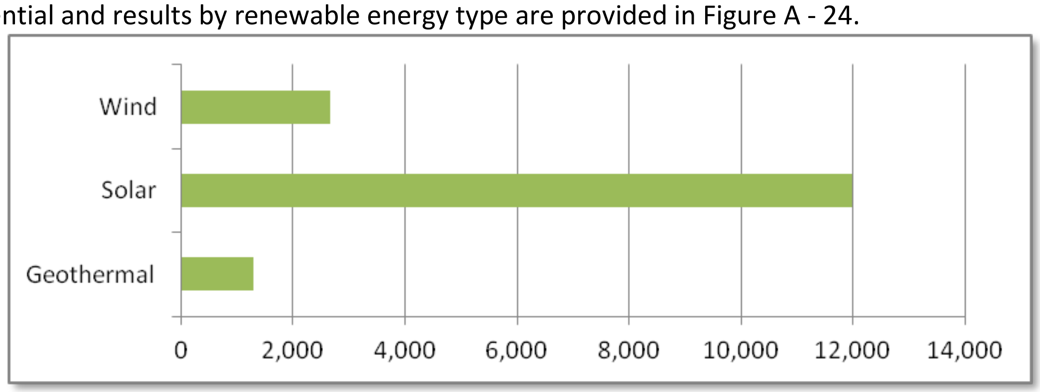

Figure A - 24. Potential future renewable energy area in thousands of acres.

A-2.1.3 Recreation

MQ52 - WHERE IS RECREATION?

High levels of recreation use (here defined as >1000 visitors/year) is occurring within the Central Basin and Range and Mojave Basin and Range ecoregions (Figure A - 25). Not surprising, recreation levels are highest surrounding the urban regions of Los Angeles, Las Vegas, Reno, and Salt Lake City. High visitation levels occur especially in the Mojave because of the proximity and accessibility due to the transportation infrastructure. Areas of significant use from OHV enthusiasts (Re) (Figure A - 26) are more narrowly constrained, and notably in the Mojave basin south of Las Vegas area. Areas of high use from OHV rock hounders (Figure A - 27) includes more remote areas with high densities of abandoned mines, particularly in the Central Basin. Areas of high use for aquatic recreationists (Figure A - 28) are on the western end of Lake Mead. Areas of high use by hiker/biker recreationists (Figure A - 29) include more remote areas northeast of Las Vegas and surrounding urban areas. Areas of high recreation by big game hunters (Figure A - 30) are mostly in the Central Basin and Range ecoregion, particularly in the north and eastern portions of the state of Nevada.

Known limitations and uncertainties

We received limited spatial data from BLM that specified a few motorized recreation areas (e.g., Little Sahara in Utah), but it is likely that there are additional designated motorized recreation areas that were not included in our analysis, and therefore the map on OHV enthusiast would have some localized mis-representations. In an effort to minimize these, we did however augment the OHV staging area/trailhead location dataset by conducting a series of online searches of BLM websites as well as OHV-related club and organizations. We found numerous sites describing various OHV races, but the maps that were provided online were often for previous years (with different courses) and were simply a graphic image that did not allow us to easily extract the spatial information of the course to incorporate in our spatially-explicit model.

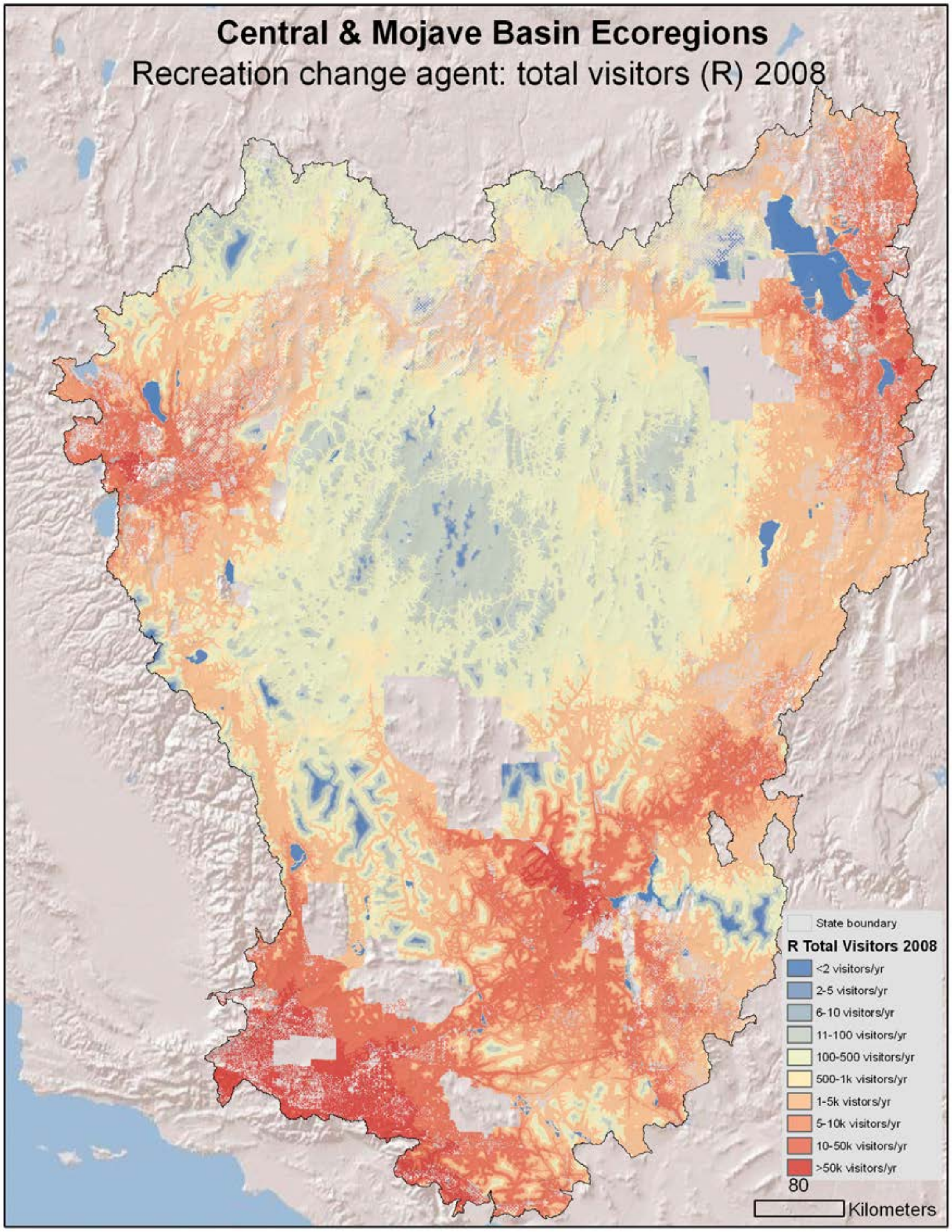

Figure A - 25 Recreation total visitors in 2008

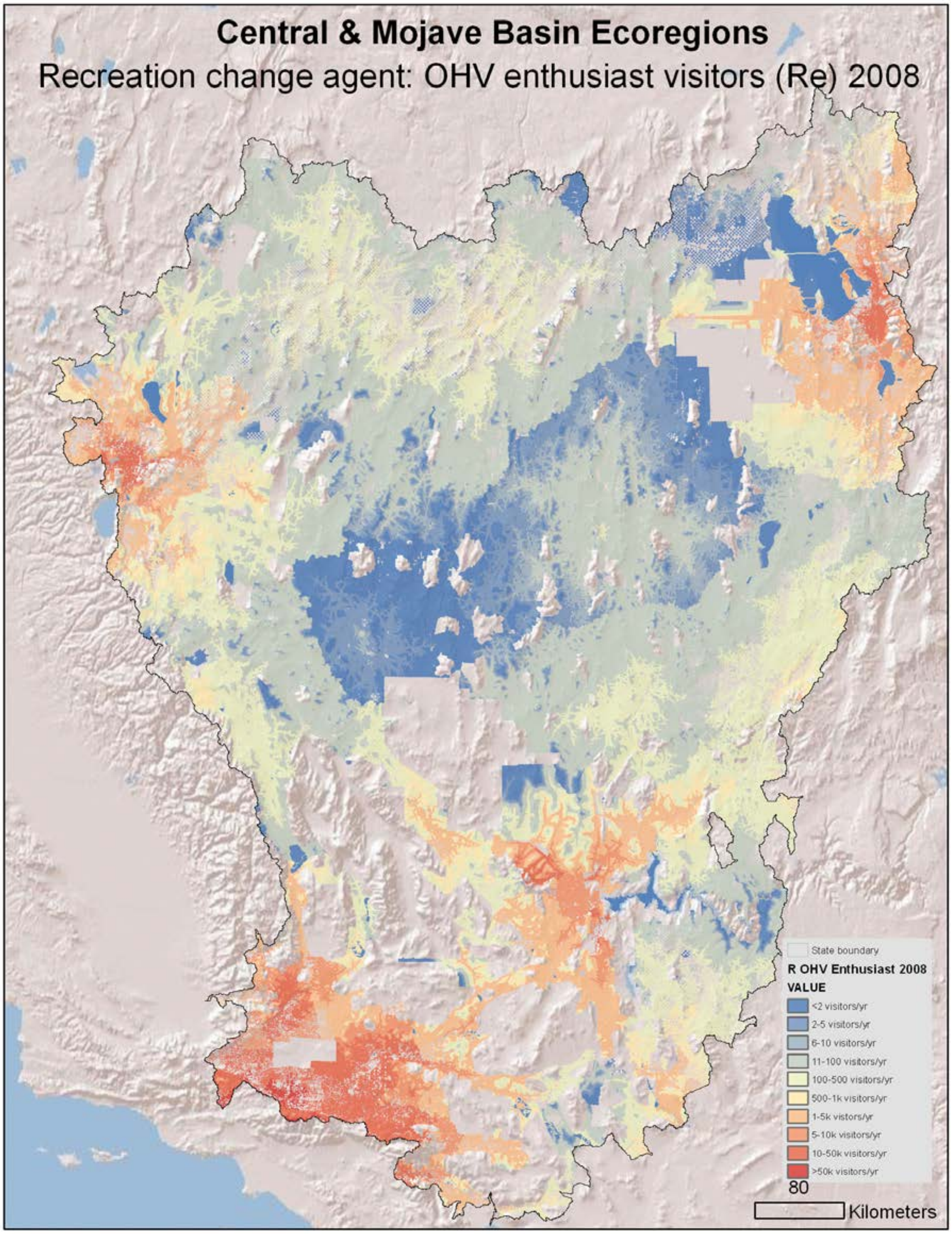

Figure A - 26 OHV enthusiast visitors in 2008

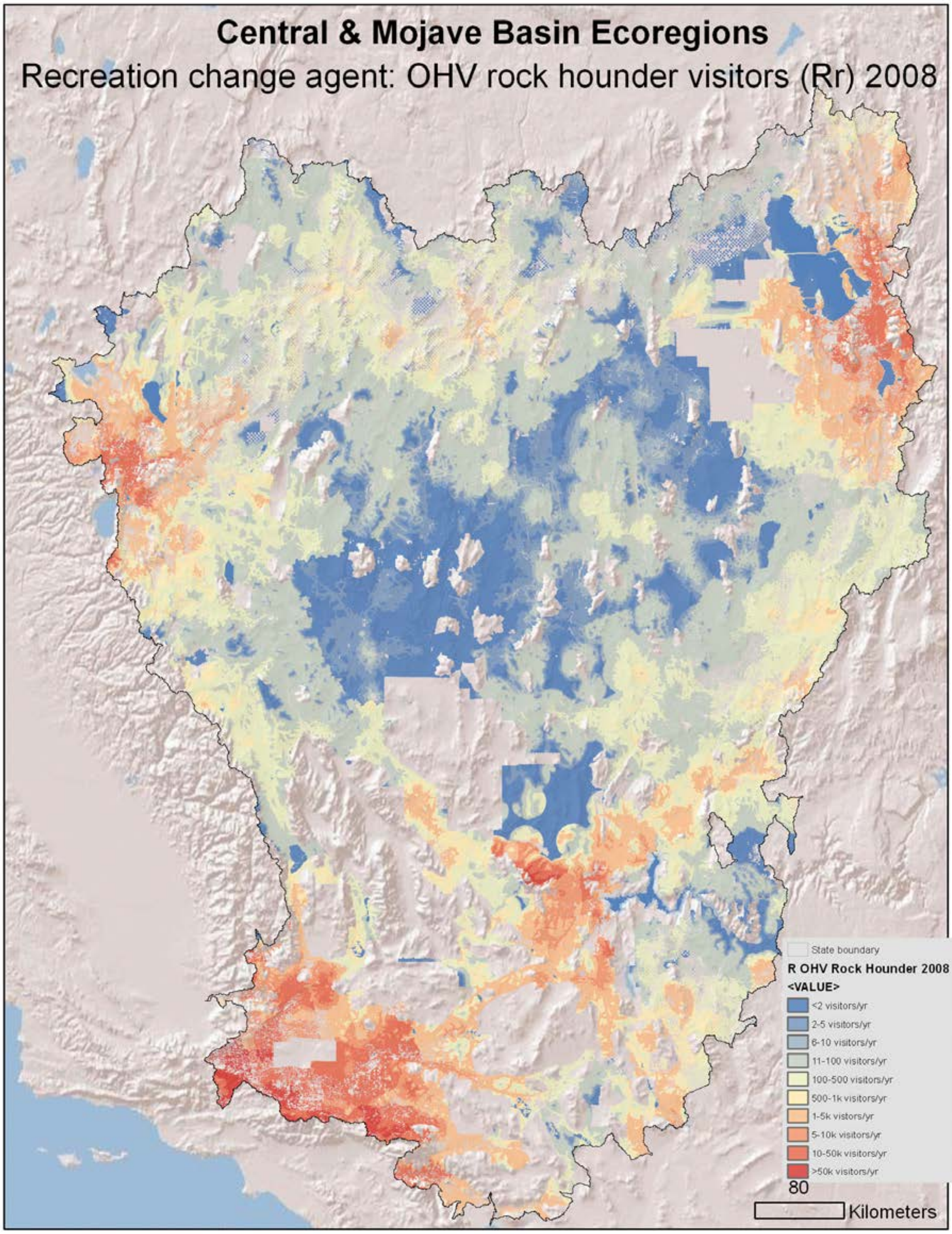

Figure A - 27 OHV Rock hounder visitors in 2008

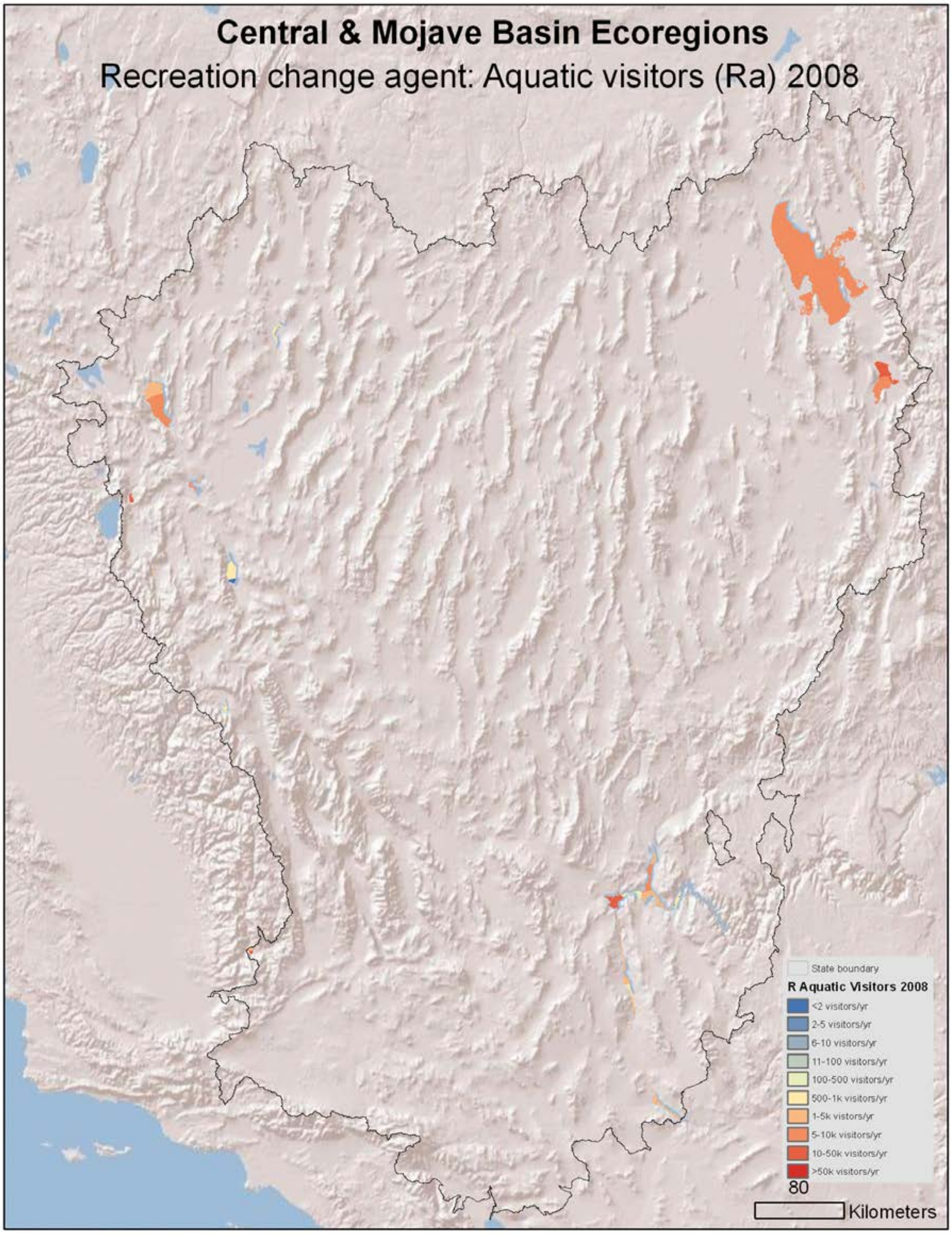

Figure A - 28 Aquatic recreation visitors in 2008

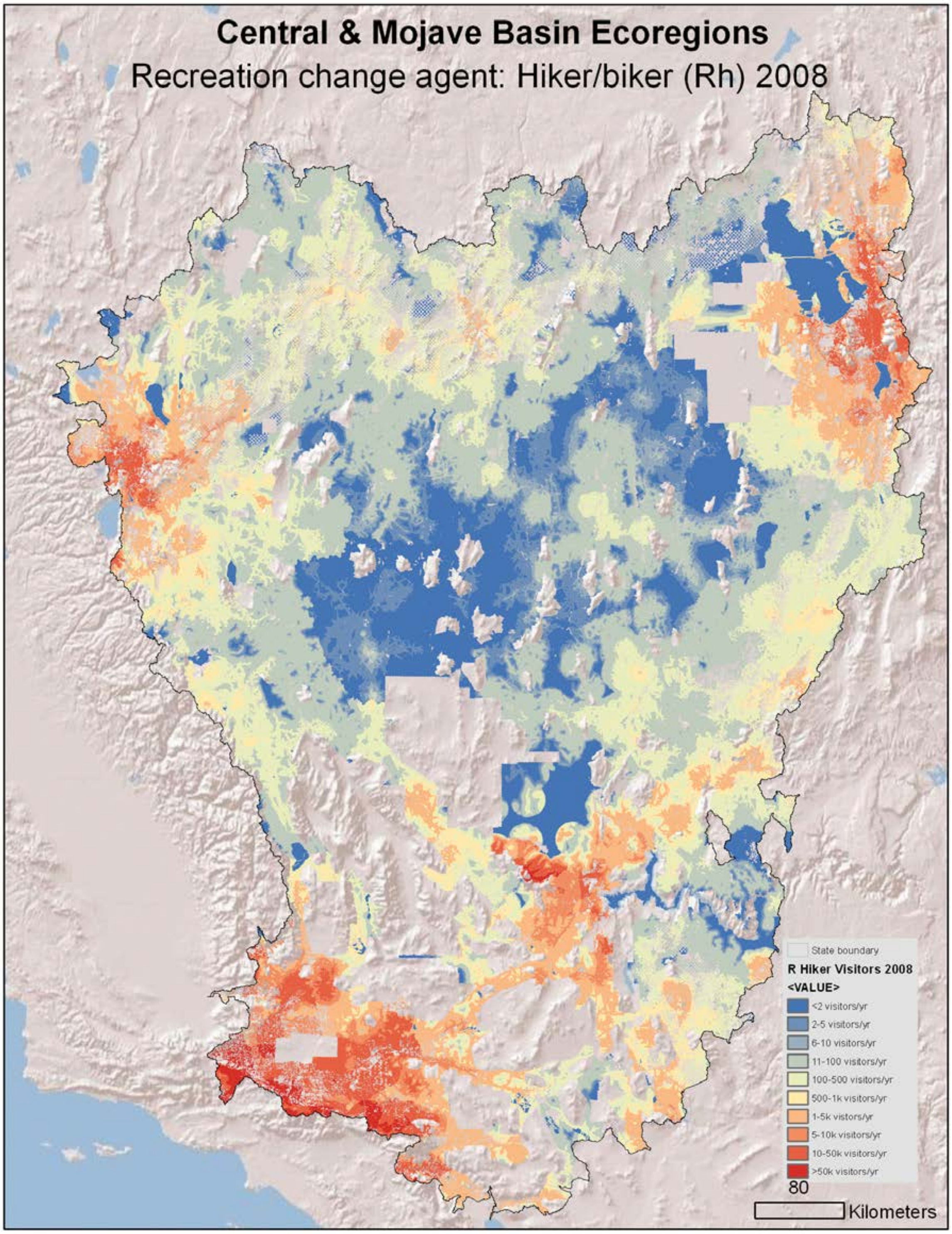

Figure A - 29 Hiker/biker recreation visitors in 2008

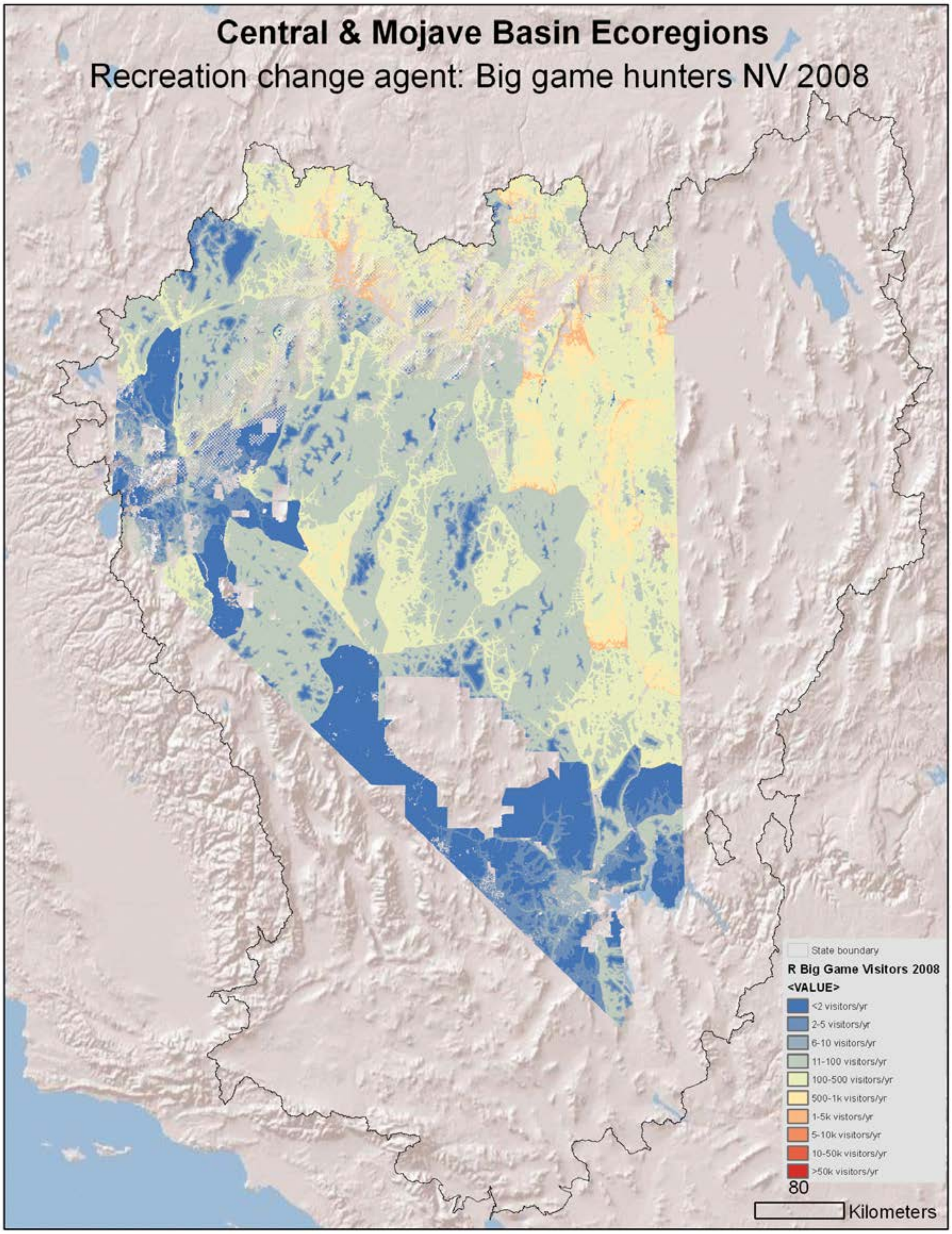

Figure A - 30 Big Game Hunters in 2008 (restricted to Nevada).

A-2.1.4 Invasives

A-2.1.4.1 Invasive Plants- Current

MQ44 - WHAT IS THE CURRENT DISTRIBUTION OF INVASIVE SPECIES INCLUDED AS CAS?

Detailed analyses of the location and abundance of invasive plants, segmented into categories of annual grasses, annual and biennial forbs, and riparian woody species, are provided in this section. Each is described within the context of the amount of the watershed affected by the change agent.

Invasive Annual Grasses

Table A - 24 provides an initial summary of five distinct spatial models aimed at depicting vulnerability to invasive annual grass infestation, at varying levels of percent cover, by 5th level watershed. Annual grass location and abundance was modeled using field observations and environmental data. Field records indicated both presence and percent cover of annual grass species in the sample. Spatial models therefore depict a probability that invasive annual grasses could be present at a given abundance, as measured by percent cover. For example, the top row of Table A - 24 indicates that of the 315 watersheds in the MBR, 8 of those (3%) are predicted to support just 5% aerial extent of annual grasses in 'trace' amounts (1-5% cover). This is significant in that, even at relative trace amounts, the presence of annual grasses has been shown to effectively introduce a fire regime into warm desert scrub communities that have historically never experienced significant natural wildfire (Brooks and Chambers 2011). As indicated in the table - and of much greater concern - 110 watershed (35% of the ecoregion) are vulnerable to having 50% of their extent with these trace abundances of annual grasses. Another 34% of the ecoregion's watersheds are vulnerable to having 75%, and even 100%, effected by trace amounts of annual grass (Table A - 24).

Table A - 24. Estimated location and abundance of invasive annual grasses by 5th level watershed within the MBR ecoregion.

Model prediction at X% cover	Aerial percentage of watershed effected	Number of Watersheds	% of watersheds (n=315)
1 to 5% cover	5%	8	3%
n=311	10%	16	5%
	25%	70	22%
	50%	**110**	**35%**
	75%	**86**	27%
	100%	**21**	7%
5 to 15% cover	5%	**65**	**21%**
n=89	10%	18	6%
	25%	6	2%
	50%		
	75%		
	100%		
15 to 25% cover	5%	**47**	15%
n=66	10%	17	5%
	25%	2	1%
	50%		
	75%		
	100%		

Model prediction at X% cover	Aerial percentage of watershed effected	Number of Watersheds	% of watersheds (n=315)
25 to 45% cover	5%	**67**	**21%**
n=113	10%	**26**	8%
	25%	**19**	6%
	50%	1	0%
	75%		
	100%		
>45% cover	5%	**37**	**12%**
n=79	10%	**14**	4%
	25%	**14**	4%
	50%	9	3%
	75%	5	2%
	100%		

Worse yet, some 21% of watersheds are vulnerable to having 5-15% cover of annual invasives over 5% of their extent. Some 15% of watersheds are vulnerable to having 15-25% cover of annual invasives over 5% of their extent, and some 21% of watersheds are vulnerable to having 25-45% cover of annual invasives over 5% of their extent.

In the most extreme of cases indicated by the model, where >45% cover of invasive annuals is predicted to occur, fully 12% of watersheds are predicted to have at least 5% of their extent with dense annual grass cover. Eight percent, or 28 watersheds in total, concentrated on the northern and eastern end the ecoregion, could have 10% or 25% aerial coverage of dense invasive annual grasses (Figure A - 31).

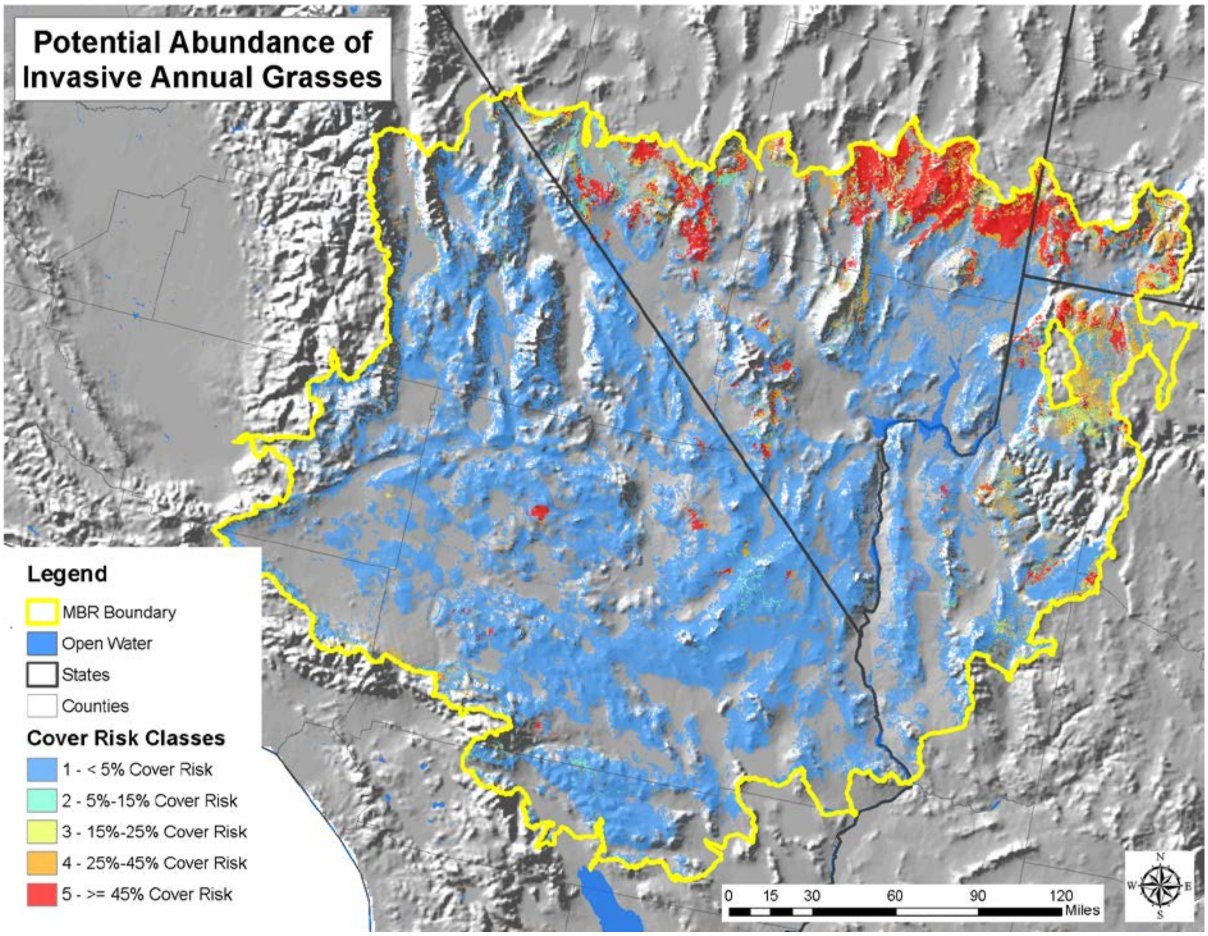

Figure A - 31. Invasive annual grass potential abundance for the MBR. Red color corresponds to possibility of >45% cover of invasive annual grasses.

Noxious Forbs

Figure A - 32 show the final spatial model aimed at depicting vulnerability to noxious forbs infestation. As with annual grass, the location was modeled using field observations and environmental data. Unlike annual grass, no abundance values were modeled, all observations were treated a presence/absence only.

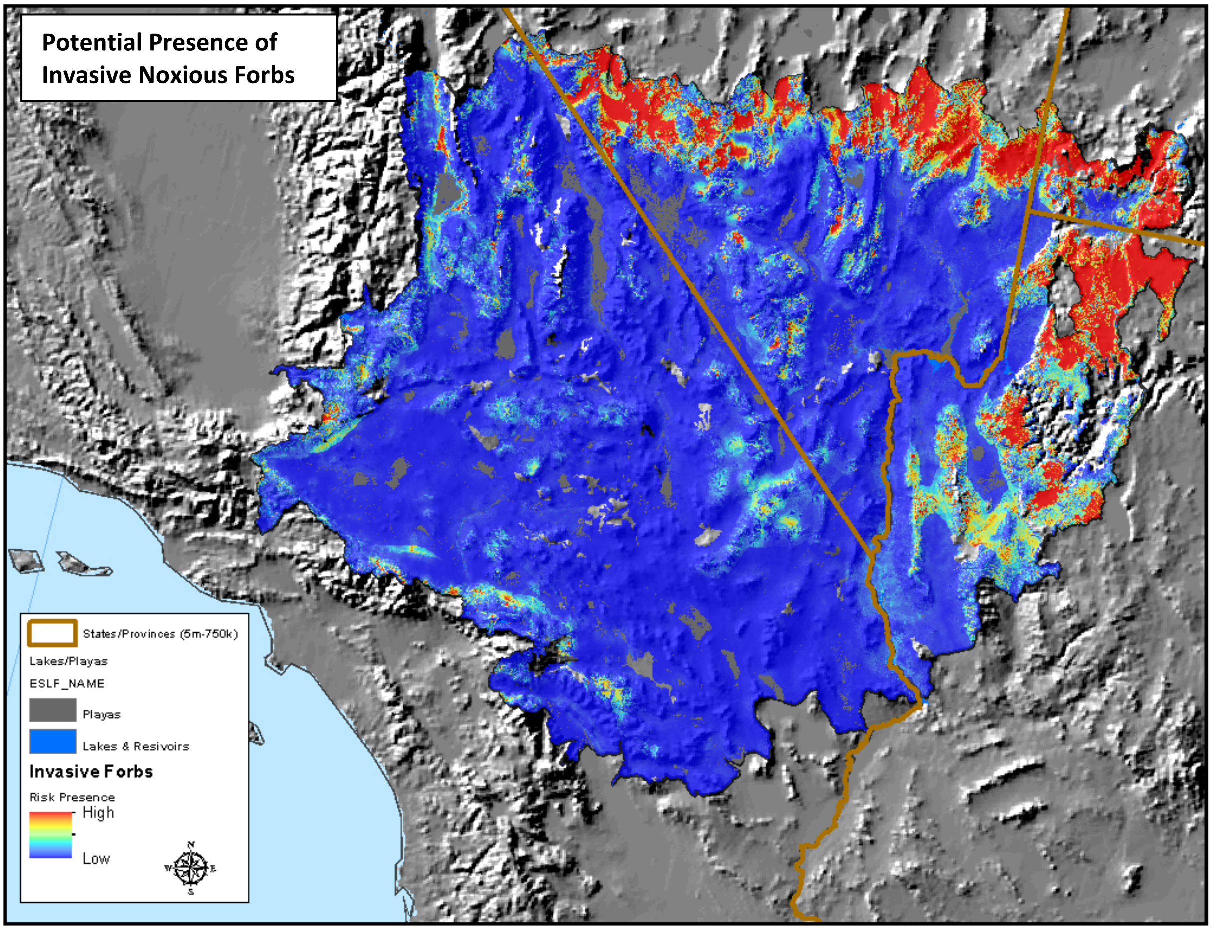

Figure A - 32. Final modeled distribution of invasive noxious forbs in the MBR, showing potential abundance. Red indicates high probability of invasive forbs present.

Species Invasive to Riparian Areas

Figure A - 33 shows the final spatial model aimed at depicting vulnerability to invasive riparian species infestation. As with annual grass, the location was modeled using field observations and environmental data. Similarly to noxious forbs, no abundance values were modeled, all observation were treated a presence/absence only.

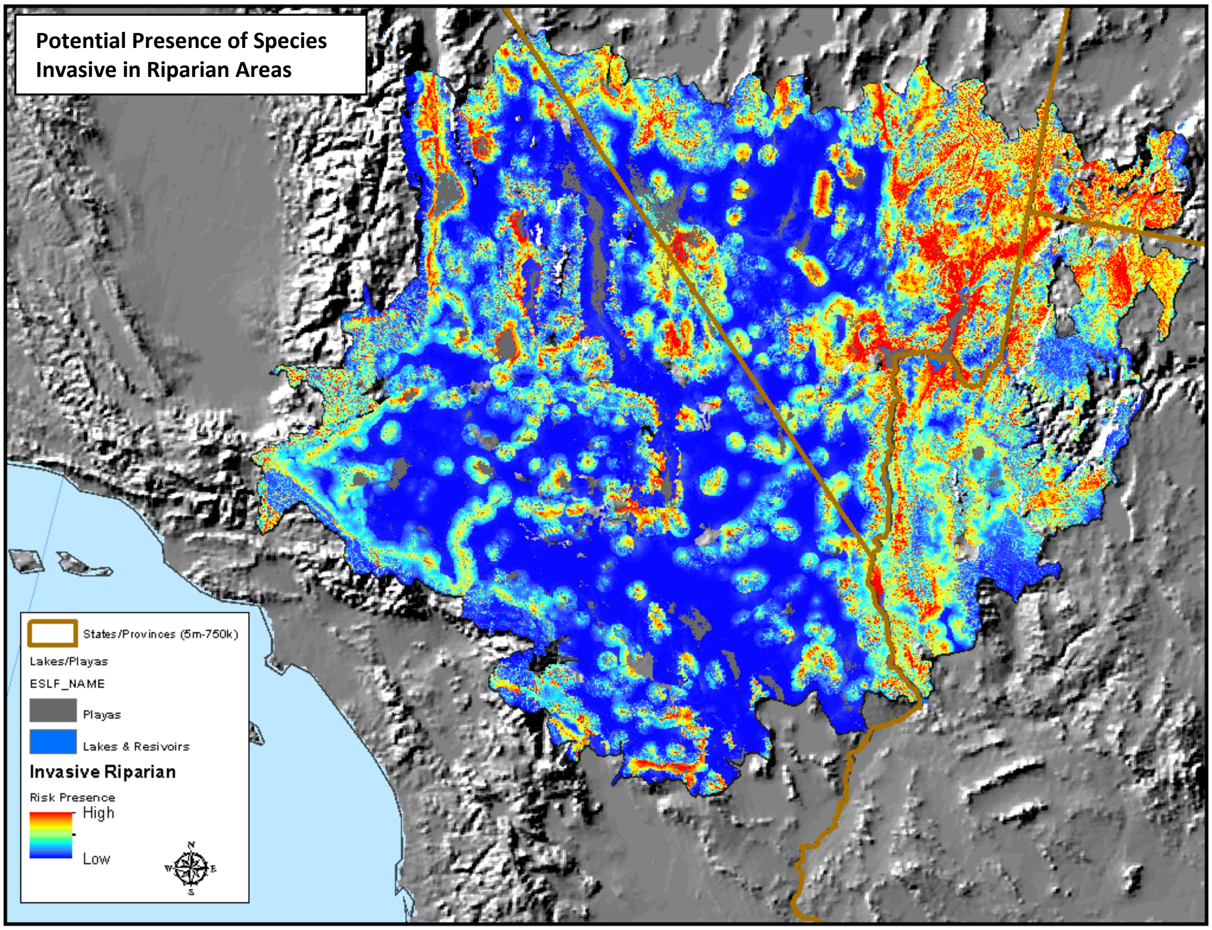

Figure A - 33. . Final modeled distribution of plants invasive to riparian areas (tamarisk & russian olive primarily) in the MBR, showing potential abundance. Red indicates high probability of invasive woody species, such as tamarisk or russian olive, present.

A-2.1.4.2 Aquatics Current

MQ44 - WHAT IS THE CURRENT DISTRIBUTION OF INVASIVE SPECIES INCLUDED AS CAS?

Aquatic Invasive Species -- There are limited databases containing surveyed locations including sites that were surveyed but no taxa were found and rapidly increasing number of novel introductions and establishment of aquatic invasive species. A majority of the CEs within HUCs had no reported invasive taxa in the available databases. This could have been a result of surveys that did not find any invasives or HUCs where no surveys occurred (i.e. no data). Therefore, any CE within a HUC that did not have an invasive reported was rated as 'no data' = Undetermined. The Mojave Desert has 16 watersheds reporting on invasive taxa (Figure A - 34). One watershed has 7 records, two watersheds have 4 records, three with 2 records, two with 2 records and eight with only 1 record each.

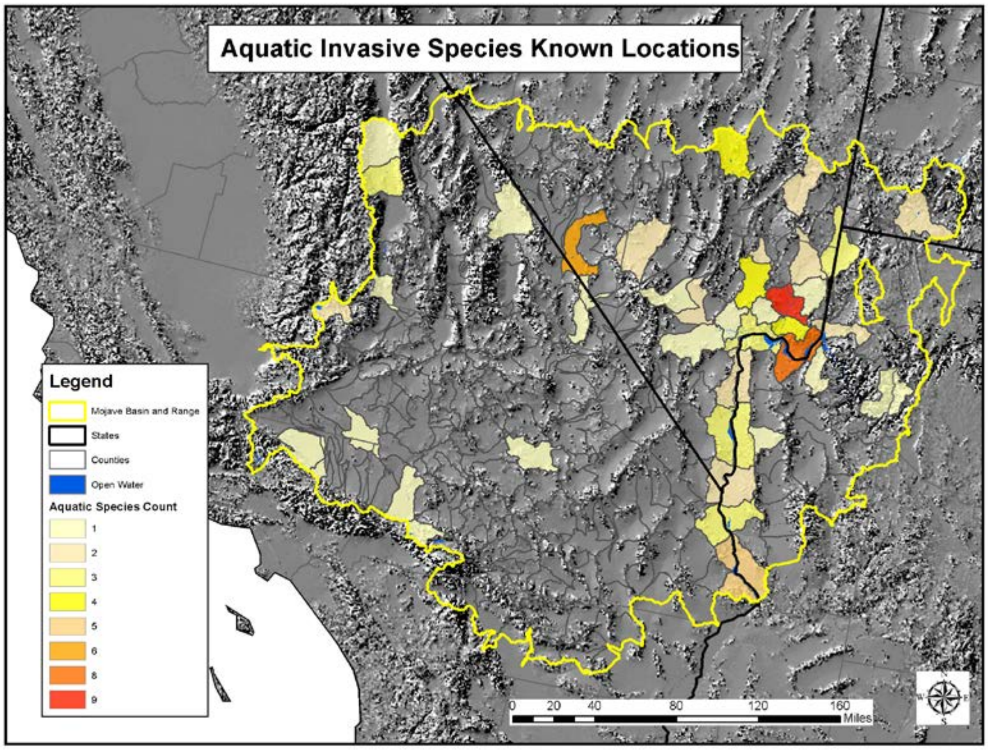

Figure A - 34. Documented watersheds with between 1 and 9 aquatic invasive species (primarily fish and mollusks) present within the ecoregion.

A-2.1.5 Fire

A-2.1.5.1 Extent of fire perimeter

MQ40 - WHERE HAVE FIRES GREATER THAN 1000 ACRES OCCURRED?

Since 1980, a total of 2,307,068 acres have burned at least once by a fire >1,000 acres across the MBR. Approximately half of all MBR watersheds included fires of >1,000 acres since 1980, with concentrations occurring throughout the eastern and northeastern portion, and along the western fringe of the ecoregion within California (Figure A - 35). One half of these watersheds included burn area greater than 3,875 acres in size. Nearly 40 watersheds included burned area between 17,800 and nearly 132,000 acres. Four watersheds included burned area between 50,000 and 75,000 acres, and six watersheds included burned area between 75,000 and 100,000 acres. Again, this analysis did not include measurement of fire occurrences < 1,000 acres in size, or overlapping fire events from multiple years, so overall area experiencing fire in recent decades can only be higher than these reported numbers.

Table A - 25 includes summary statistics for burned area for the 157 watersheds with recorded fires, segmented by quartile. That is, the 25% of watersheds with smallest area burned, followed by those within the 26-50% range, 51-75% range, and 76-100% range, in burnt area.

Table A - 25. Burned area by watershed, for 157 watersheds with recorded fires > 1,000 acres

Quartile of Area Burned	Number of Watersheds	Range of Burned Area (acres)
>75	39	17,812 to 131,570

51-75	40	3,876 to 17,717
26-50	39	1,901 to 3,739
1-25	39	1 to 1,867

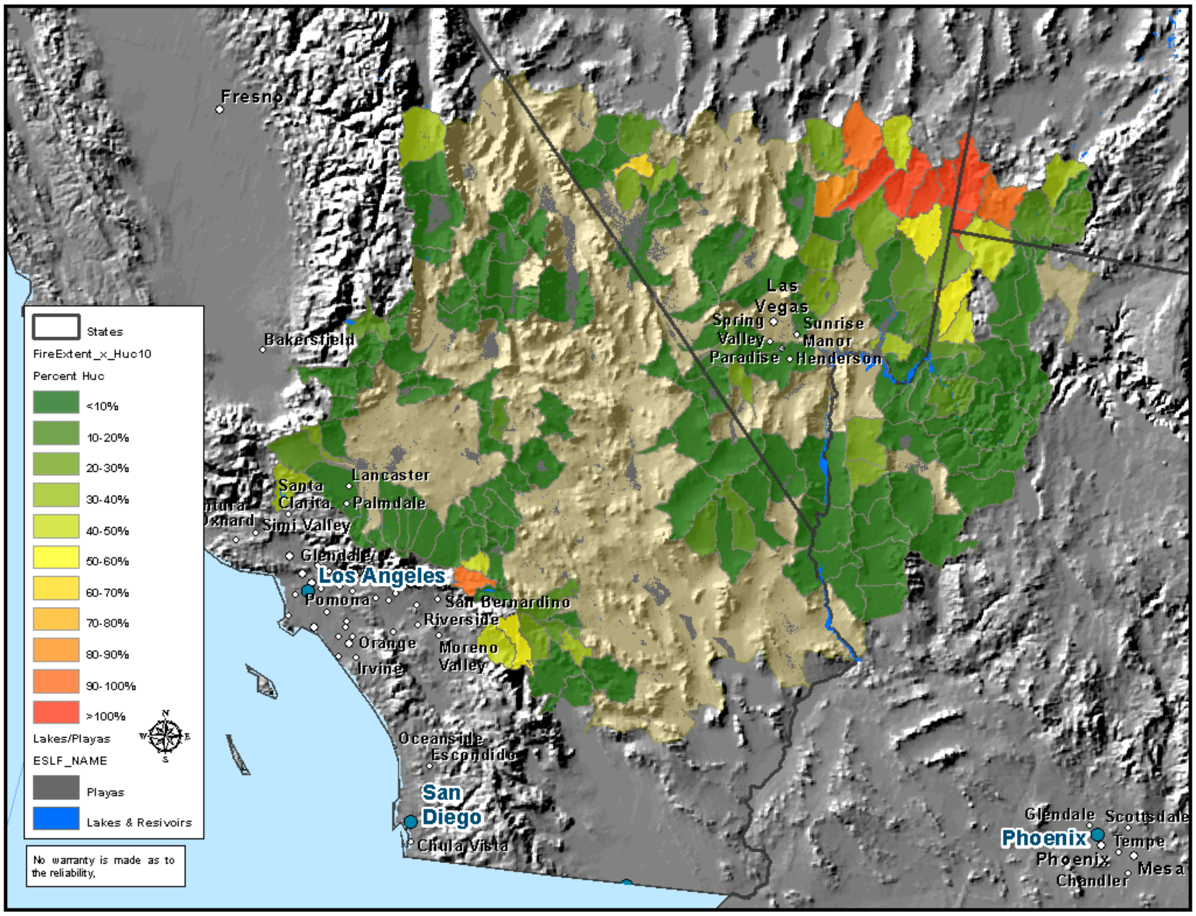

Figure A - 35. Area burned since 1980 within and across 5th level watersheds in the MBR ecoregion.

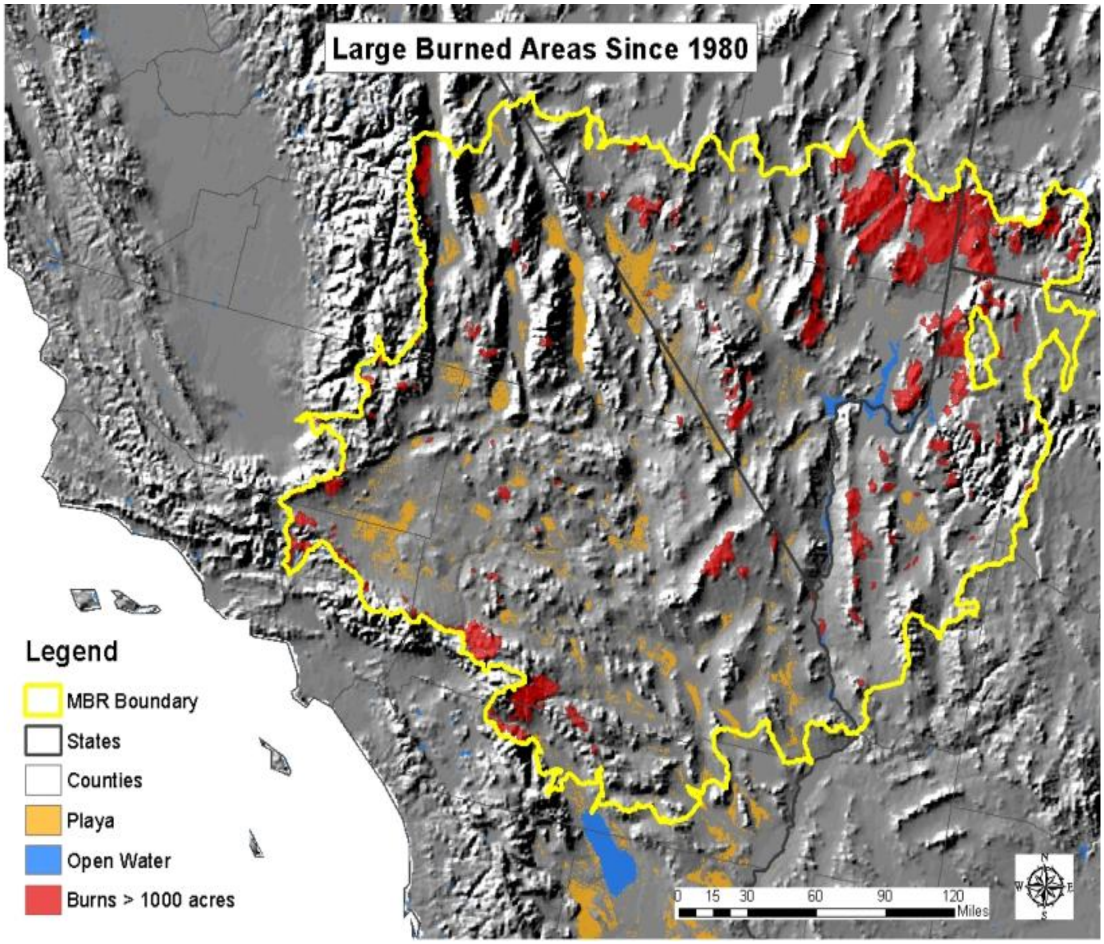

Figure A - 36. Mapped perimeters of fires >1000 acres, since 1980.

These patterns indicate the association of larger fires with vegetation where sufficient biomass accumulation has historically supported a natural fire regime. However, throughout much of the ecoregion, where desert scrub is the overwhelming dominant vegetation, large fire patches are much more likely to lead to the introduction of invasive plant species, and the initiation of a fire regime where no natural fires previously occurred.

A-2.1.5.2 Extent of each SClass

MQ42 - WHAT AREAS NOW HAVE UNPRECEDENTED FUELS COMPOSITION (INVASIVE PLANTS), AND ARE THEREFORE AT HIGH POTENTIAL FOR FIRE?

The results of this modeling of effort are provided in two ways, as the departure outputs from each model, and as a summary by HUC. The latter are provided as part of the Database of Conceptual Models for Conservation and Elements. The departure by HUC was calculated as an area-based weighted mean of the departure for each CE found within a HUC. This gives priority to those CEs that are most abundant within each watershed, and provides some insights into the overall departure within ecoregion.

When examining the departure by CE is informative to examine both the departure score and the proportion of the CE's spatial extent that these in an uncharacteristic state. CEs can exhibit departure either because their disturbance regime has changed relative to NRV or because native vegetation is being replaced by exotic or native invaders. Interpretation of the magnitude of departure requires that one examines both these variables and interpolates the interaction of the two. Table A - 26 through Table A - 36 show both the departure scores and the percent of each CE within uncharacteristic states for every CE group modeled. The tables also present the departure as departure class rather than the actual value. Because these are stochastic models there is variation among runs, these departure classes or likely more accurate, albeit less precise, indicators of the condition of each CE. Each table presents these variables for the initial starting conditions, predicted conditions in 2025, and predicted conditions in 2060.

Table A - 26. Fire regime departure scores for Great Basin Pinyon-Juniper Woodland: This CE is moderately common in the Ecoregion with 95 HUCs modeled. The model results for this CE are confused with some groups showing an improvement in ED over the next 50 years while other show a relatively little change. During the past several decades this CE has been impacted by a reduction in the frequency of moderate intensity fires and an increase in servere intensity fires resulting in a paucity of the oldest stands and an overabundance of young and mid-aged stands. An increase in the frequency of moderate (non-stand replacing) fires will result in an increase in the abundance of these oldest classes, reducing ED. Class 5 shows a continued loss in class B resulting in an increase in ED over the next 50 years.

Group	Departure _initial	Departure _2025	Departure _2060	%Uncharacter-istic_Initial	%Uncharacter-istic_2025	%Uncharacter-istic_2060
1	30%	39%	53%	13%	3%	7%
2	30%	31%	37%	13%	6%	9%
3	34%	30%	32%	4%	13%	15%
4	54%	59%	63%	15%	6%	9%
5	25%	39%	61%	29%	3%	6%

Table A - 27. Fire regime departure scores for Great Basin Xeric Mixed Sagebrush Shrubland: This CE is relatively uncommon, appearing in 98 HUCs, but with only 32 HUCs having a sufficient spatial extent to be included in the modeling. The models are confused with some groups showing worsening ED and others indicating an improvement. However, all models indicate an increase in uncharacteristic states associated with increasing abundance of annual grasses.

Group	Departure _initial	Departure _2025	Departure _2060	%Uncharacter-istic_Initial	%Uncharacter-istic_2025	%Uncharacter-istic_2060
1	75%	74%	62%	20%	26%	38%
2	51%	69%	63%	21%	26%	37%
3	40%	66%	65%	18%	23%	35%
4	49%	67%	58%	27%	32%	42%

Table A - 28. Fire regime departure scores for Inter-Mountain Basins Mixed Salt Desert Scrub: This is an uncommon CE, with only 13 HUCs having sufficient spatial extent to be modeled. Thus, it is not surprising that the models present a confused picture. Two groups exhibit an increase in ED and the third suggests in improvement. However, all models show an increase in the abundance of uncharacteristic states, suggesting a general decline in the condition of this CE. The uncharacteristic annual grassland class shows the most significant increase over the next 50 years.

Group	Departure_initial	Departure_2025	Departure_2060	%Uncharacter-istic_Initial	%Uncharacter-istic_2025	%Uncharacter-istic_2060
1	91%	76%	66%	8%	14%	28%
2	64%	55%	49%	36%	40%	48%
3	53%	80%	69%	2%	9%	23%

Table A - 29. Fire regime departure scores for Mogollon Chaparral: This CE is moderately common in the ecoregion occurring in 90 HUCs. Currently the CE shows moderate departure with an overabundance in the youngest stage class. The models suggest that, with infrequent high intensity fires this CE will recover as those systems age. However, invasion of annual grasses may prevent this from occurring.

Group	Departure_initial	Departure_2025	Departure_2060	%Uncharacter-istic_Initial	%Uncharacter-istic_2025	%Uncharacter-istic_2060
1	47%	100%	99%	N/A	N/A	N/A
2	65%	100%	100%	N/A	N/A	N/A
3	25%	100%	100%	N/A	N/A	N/A
4	50%	100%	100%	N/A	N/A	N/A

Table A - 30. Fire regime departure scores for Mojave Mid-Elevation Mixed Desert Scrub-Mesic: This is one of the most abundant CEs in the ecoregion, occurring in 206 HUCs. The models suggest little change in ED over the next 50 years. However, the models do suggest an increase in uncharacteristic states, with the presence of annual grasses having the most significant impact. All models indicate an increase in the spatial extent of annual grasslands over the next 50 years.

Group	Departure_initial	Departure_2025	Departure_2060	%Uncharacter-istic_Initial	%Uncharacter-istic_2025	%Uncharacter-istic_2060
1	62%	64%	66%	9%	16%	31%
2	42%	41%	36%	58%	59%	64%
3	62%	62%	61%	16%	22%	36%
4	71%	67%	55%	27%	33%	45%

Table A - 31. Fire regime departure scores for Mojave Mid-Elevation Mixed Desert Scrub-Thermic: This is the most common CE in the ecoregion, occurring in 266 HUCs. Ninety percent of these HUCs had sufficient spatial extent to be included in the modeling. This CE is currently highly departed, and the models do not suggest any change in this condition. NRV suggests that this CE should be dominated by the oldest stage. Currently it is dominated by young-growth and uncharacteristic states dominated by annual grasses and bare ground.

Group	Departure_initial	Departure_2025	Departure_2060	%Uncharacter-istic_Initial	%Uncharacter-istic_2025	%Uncharacter-istic_2060
1	6%	8%	13%	10%	18%	34%
2	5%	6%	8%	66%	69%	75%
3	9%	11%	15%	8%	16%	32%
4	5%	8%	11%	22%	28%	42%
5	5%	8%	12%	12%	20%	35%

Table A - 32. Fire regime departure scores for Sonora-Mojave Creosotebush-White Bursage Desert Scrub: This is an abundant CE in the ecoregion, occurring in 270 HUCs. Ninety percent of those HUCs have a sufficient spatial extent to be included in the modeling. Currently this CE is highly departed and dominated by annual grasses or by the youngest age classes. The apparent reduction in CE is, unfortunately, and artifact of the almost complete lack of the older stages in the current vegetation. Thus, any small increase in the abundance of this class is reflected in a decline in ED. The predicted increase in annual-grass dominated uncharacteristic states suggests that this CE will remain highly departed over the next half century.

Group	Departure_initial	Departure_2025	Departure_2060	%Uncharacter-istic_Initial	%Uncharacter-istic_2025	%Uncharacter-istic_2060
1	10%	68%	65%	12%	20%	35%
2	9%	8%	7%	91%	92%	93%
3	10%	58%	54%	28%	34%	46%
4	12%	69%	65%	12%	19%	35%
5	10%	44%	39%	48%	53%	61%

Table A - 33. Fire regime departure scores for Sonora-Mojave Mixed Salt Desert Scrub: This CE is moderately common, occurring in 133 HUCs. However only 50% of those HUCs had a sufficient spatial extent to be included in the models. NRV for this CE suggests that it should be dominated by mid-aged classes. With the exception of group 2, which is entirely dominated by annual grasses, current vegetation is largely dominated by the earliest age class to the exclusion of the mid- and late-age classes. The apparent improvement in ED is a result of some of these youngest classes "maturing" into this mid-age class. However, there is no evidence of a re-emergence of the oldest age-class. The models suggest that in those occurrence where annual grasses are not well established there might be an improvement over time as these earliest age-classes mature. However, in those occurrence where annual grasses are already abundant, they will continue to replace the native vegetation.

Group	Departure _initial	Departure _2025	Departure _2060	%Uncharacter-istic_Initial	%Uncharacter-istic_2025	%Uncharacter-istic_2060
1	20%	75%	65%	8%	14%	28%
2	7%	6%	5%	93%	94%	95%
3	44%	76%	65%	6%	13%	27%
4	22%	51%	45%	41%	45%	54%
5	33%	62%	55%	27%	32%	41%

Table A - 34. Fire regime departure scores for Sonora-Mojave Semi-Desert Chaparral: Chaparral is an uncommon CE in the ecoregion, occurring in only 56 HUCs. This CE's departure is driven almost entirely by the relative abundance of uncharacteristic states. Those groups that have a small initial extent of uncharacteristic states are only slightly departed and show little departure over the next 50 years. In contract, those with the largest extent of uncharacteristic vegetation are currently highly departed and will continue to be so. Groups 1 and 2 are currently dominated by the youngest stage, whereas NRV suggests that the Chaparral should be dominated by the oldest stage. The reduction in ED is a reflection of these youngest stages maturing into the older stages. Increased fire frequency, resulting from fires carried into the CE by annual grasses might reverse this apparent improvement, causing the CE to remain highly departed.

Group	Departure _initial	Departure _2025	Departure _2060	%Uncharacter-istic_Initial	%Uncharacter-istic_2025	%Uncharacter-istic_2060
1	20%	93%	93%	7%	7%	7%
2	51%	63%	62%	37%	37%	38%
3	2%	2%	2%	98%	98%	98%
4	21%	90%	90%	10%	10%	10%

Table A - 35. Fire regime departure scores for Sonoran Mid-Elevation Desert Scrub-Mesic: This is an uncommon CE, occurring in only 35 HUCs within the ecoregion. NRV for this CE suggests a fairly uniform distribution among the 3 SClasses. Current vegetation is highly dominated by the mid-aged SClass. Thus, increased fire frequency, as a result of the increased abundance of annual grasses results in a reduction of ED, as some patches transition into younger SClasses. However, this improvement in ED is off-set by the increased abundance of uncharacteristic states. Thus, while the departure scores indicate little change over the next 50 years, the increase in uncharacteristic states will result in a significant transformation of this CE.

Group	Departure_initial	Departure_2025	Departure_2060	%Uncharacter-istic_Initial	%Uncharacter-istic_2025	%Uncharacter-istic_2060
1	53%	57%	64%	2%	11%	26%
2	48%	51%	48%	22%	45%	52%
3	30%	30%	28%	36%	70%	72%
4	54%	67%	55%	2%	33%	45%

Table A - 36. Fire regime departure scores for Sonoran Mid-Elevation Desert Scrub-Thermic: This CE is uncommon in the ecoregion, occurring in only 24 HUCs. NRV models suggest that historically this CE was dominated by the older SClass, with over 90% of the CE in this SClass. Current vegetation is completely dominated by the young SClass, with about 90% dominance in this state. The models suggest little, if any improvement in this condition over the next 50 years. Any improvement in ED as a result of younger vegetation “maturing” into the older SClass is off-set by the increased abundance of uncharacteristic states dominated by annual grasses.

Group	Departure_initial	Departure_2025	Departure_2060	%Uncharacter-istic_Initial	%Uncharacter-istic_2025	%Uncharacter-istic_2060
1	12%	13%	17%	3%	11%	28%
2	10%	11%	15%	11%	19%	35%
3	5%	8%	12%	4%	13%	30%

A-2.2 2025 Change Agents: Invasives and Climate

A-2.2.1 Future Invasive Species

MQ47 - GIVEN CURRENT PATTERNS OF OCCURRENCE AND EXPANSION OF THE INVASIVE SPECIES INCLUDED AS CAS, WHAT IS THE POTENTIAL FUTURE DISTRIBUTION OF THESE INVASIVE SPECIES?

A-2.2.1.1 Terrestrial Plants- Future

The footprint of two invasive species are denoted by models from Bradley (2008). Both Cheatgrass (*Bromus tectorum*) and Tamarisk (*Tamarix* spp.) are represented by AOGCM models that represent the future time frame of 2100.

Potential climate shifts in cheatgrass in the MBR is limited to contractions along the northern periphery of the ecoregion (Figure A - 37). Unlike cheatgrass, future climatic models show the MBR completely inclusive of tamarisk (Figure A - 38) with limited expansion along the western elevation gradient along the Sierra (Figure A - 39).

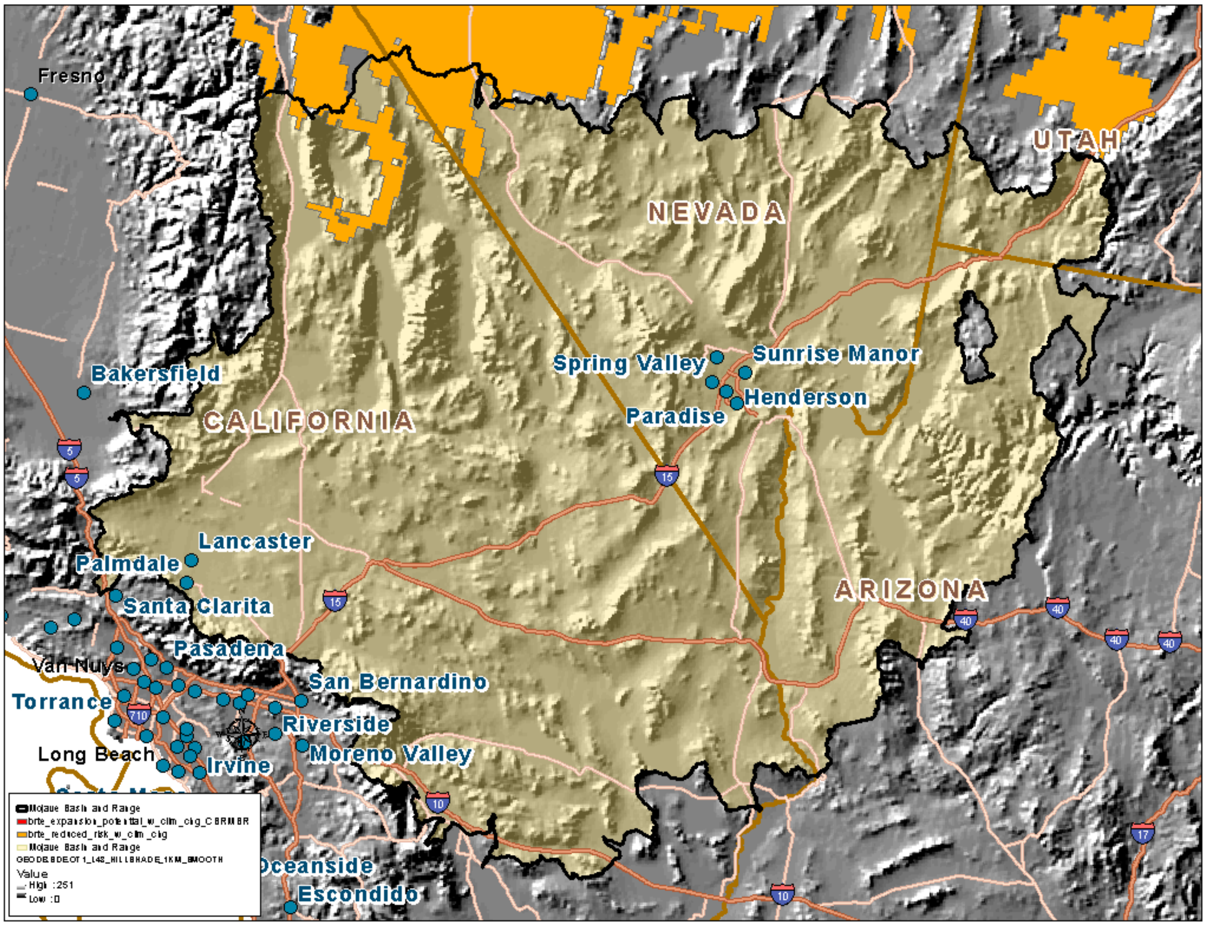

Figure A - 37. Areas of climatic contraction (orange) of cheatgrass predicted in Bradley (2008).

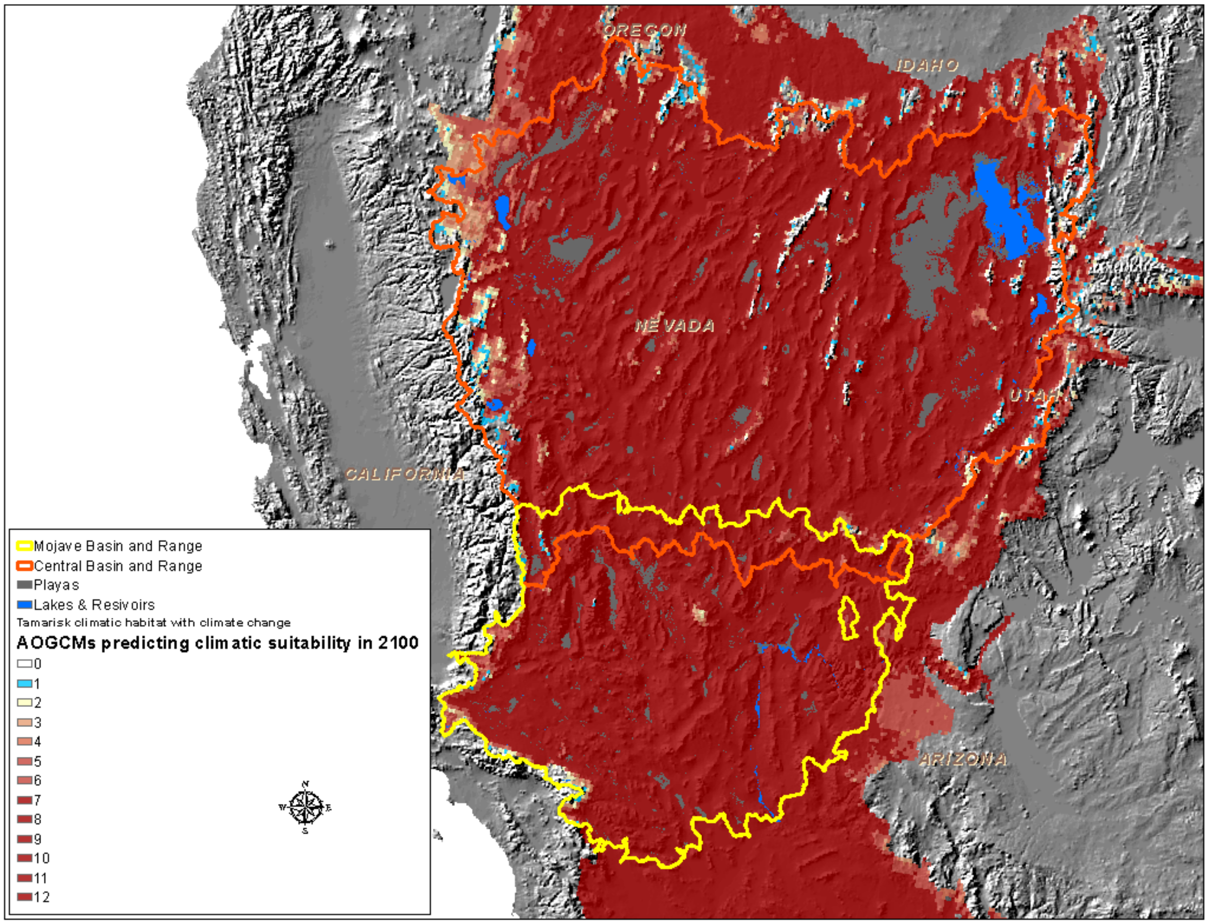

Figure A - 38. Tamarisk habitat distribution under future climate conditions (Bradley 2008). Darker red indicates more models are in agreement.

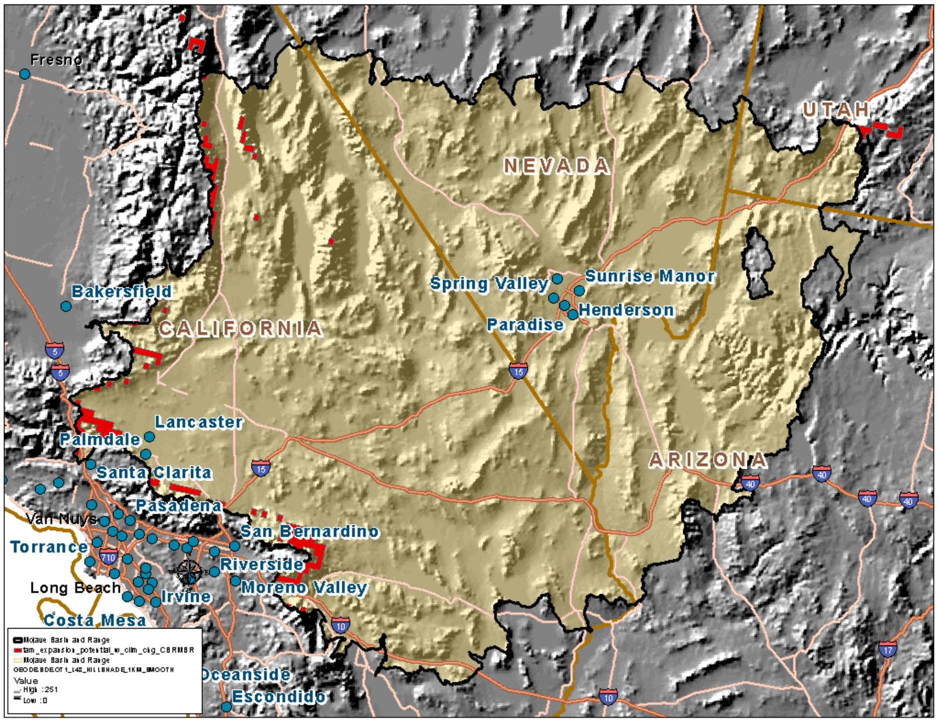

Figure A - 39. Tamarisk habitat expansion (in red) under future climate conditions (Bradley 2008).

A-2.2.1.2 Future Aquatic Invasive Species

The modeled extent of riparian invasive plant species is the potential future distribution of these species (see Figure A - 34 above).

Future Aquatic Invasives Impact Index 2025

No CE or HUC is an island and invasion potential is strongly related to conditions in surrounding watersheds. Invasion potential is strongly correlated with distance from nearest invaded location and distance is considered to be one of the most important factors in invasion theory (Shigesada and Kawasaki 1997). Therefore, we included two metrics from surrounding 5th watershed within the same 4th level watershed for development of the Future Aquatic Invasives Impact Index: the Number of novel invasive taxa present in all CEs within 4th level watershed and the Number of novel trophic levels in all CEs within 4th watershed metrics (Table A - 37). Again, aquatic invasive species include exotic fish, mollusks and *Didymo*.

Upstream and downstream dispersal and connectivity strongly affects invasion potential in freshwater ecosystems with invasive taxa more prone to downstream dispersal than upstream dispersal in connected systems. Thus, the location of a HUC relative to other HUCs is important. We included an upstream/downstream/closed basin metric in the Future Aquatic Invasives Impact Index: the Upstream or downstream from other 5th level watershed metric (Table A - 37). This metric was based on whether a HUC8 was upstream, downstream, or in a closed basin regardless if any invasive species were reported in the other upstream or downstream 5th level watershed. We did this because of the very limited data on invasives available (i.e. it was unknown if invasive species already occurred in many of the surrounding HUCs) and because in general, unknown future aquatic invasives are also expected to disperse more readily downstream than upstream and less readily from closed basins.

Human economic activity, particularly recreational activity, is also a major factor for the spread of aquatic invasive species in the future. Recreational activities and economic conditions are directly related but their relationship is often complex and difficult to predict. We do not know if the number of recreational use sites and users will decrease or increase in the future given economic uncertainties, therefore the Use metric, the Number of Aquatic Recreational Use Sites within a 4TH LEVEL WATERSHED (Table A - 37), was based solely on the known number of recreation sites at the time of the index generation.

Table A - 37. Future Aquatic Invasive Species Impact Index 2025 scoring criteria for each CE within a 4th level watershed.

Future Aquatic Invasive Species Impact Index 2025					
Type of Indicator	**Metric category**	**Metric**	**Justification**	**Data Source**	**Evaluation and score**
Biotic	**Number of invasives**	5. Number of novel invasive taxa present in all CEs within 4TH LEVEL WATERSHED	The greater the number of invasive taxa there are in a HUC, the greater a CE is at risk	USGS NAS, USGS didymo database, Natural Heritage Programs attributed to specific CEs (~90% of the records). + Assignment of records in datasets that lack specific CE attributes (~ 10% of data) based on CE invasive potential (Appendix 1) and closest CE.	0 taxa = NA 1-2 taxa = 0.67 > 2 taxa = 0.33
	Trophic levels	6. Number of novel trophic levels in all CEs within 4th level watershed	The greater the number of trophic levels infested in the HUC, the greater the impairment	Based on data from Metric #1	0 taxa= NA=1.00 1 trophic level = 0.67 > 1 trophic level = 0.33
Physical	**Watershed Connectivity**	7. Upstream or downstream from other 4th level watersheds	Most invasive taxa are better able to disperse downstream (drift) than upstream	MSU Graphical Locator	Closed basin = 1.00 Upstream HUC = 1.00 Downstream HUC = 0.67
Landscape context	**Use**	8. Number of Aquatic Recreational Use Sites within a 4th level watershed	Access sites are invasion hotspots. The greater the number of access sites, the greater the impact	NLUD_AQUATIC data set	0 sites = 1.00 1-3 site = 0.67 > 3 site = 0.33

A-2.2.2 Climate Space Trends

MQ65 - WHERE WILL CHANGES IN CLIMATE BE GREATEST RELATIVE TO NORMAL CLIMATE VARIABILITY?

Climate Change Results with PRISM and EcoClim Dataset

The strength of the climate space trend analysis using the PRISM and EcoClim datasets is the ability to assess natural climatic variation over a relatively long baseline, in this case, 1900-1979. For each month and each variable, the standard deviation characterizing 80 years of climatic variability was calculated. Using an ensemble mean from 6 GCMs, every 4x4 km pixel in the MBR was analyzed to calculate if and when future climate change projected values that exceeded this measure of natural variability. Table A - 38 through Table A - 40 show percent of 4km^2 pixels within the MBR region that are either +1, -1, +2, or -2 STDEV from the mean baseline(1900-1978) for each variable, for each month of the two timeslices.

Results for precipitation suggest there is a trend toward increasing precipitation during July and August in the Mojave Basin. The areal extent predicted to experience increasing summer rains is not consistent across the two decadal time slices – about 45% of the Mojave is wetter in the 2020's, while only about 25% of the region is wetter in the 2050's. This result is likely associated with the time frame for future time slices. Decadal averages are a relatively short time frame for measuring trends in precipitation from climate model outputs. Any given climate model could produce a relatively wet decade or a relatively dry decade according to the future timing of predictions for large-scale regional phenomena that global models are trying to reproduce, such as the El Nino/Southern Oscillation, or in this case, the southwest monsoon. A next step in efforts to understand future precipitation patterns could analyze rolling thirty year averages (i.e.: 2010-2039, 2020-2049, 2030-2059…etc), as this approach can produce a clearer picture of modeled trends in precipitation. Outside this increase in summer monsoon, there was no signal of either increase or decrease in precipitation for any other month. Two factors likely contribute to this result. Natural variability in precipitation is high in this region, with the standard deviation often exceeding the average values for most months. Thus a dramatic increase or decrease in modeled future precipitation would be required to produce statistically significant forecasts of future precipitation changes. A second factor contributing to this result is the lack of consensus among climate models in future precipitation regimes. In a multimodel ensemble, climate models that project wetter futures are averaged with climate models that project drier futures, and the ensemble result produces a muted signal of precipitation changes – but reflecting the reality of the state of climate model science. Climate space trends could be run on individual climate models, particularly those that have been evaluated for their ability to reproduce patterns of 20th century observed climates for the basin and range ecoregion (Fordham et al 2011). This would provide an improved estimate of future precipitation projections for the MBR.

There are significant increases in maximum monthly temperatures forecast by climate models for the Mojave Basin, and these model projections have a strong seasonal distribution, with winter maximum temperatures increasing the least, and summer maximum temperatures increasing the most. For December, January, and February, between zero and 20% of the MBR area is projected to experience statistically significant increases in monthly maximum temperature by the 2020's. In contrast, for this same near future time slice, July, August and September may see significant maximum temperature increases over 85-95% of the MBR ecoregion. Spring and fall experience intermediate amounts of significant maximum temperature increases, with spring projected to be less severe than fall. By midcentury, the 6 GCM ensemble projects dramatic increases in maximum temperatures for all months, again with an emphasis on summer. For July and August, over 90% of the Mojave is projected to experience maximum temperatures two standard deviations beyond the values of the 20th century baseline. This statistic suggests models predict future summer maximum temperatures will exceed 95% of the values that occurred during the 1900-1979 baseline period. March and April are the only two months where less than 90% of the Mojave is projected to experience at least one standard deviation shift in monthly maximum temperatures. The number of months affected by statistically significant climate change, and the extent of the region projected to be affected, are both greater than the corresponding results for the Central Basin.

Of the 3 climate variables examined with the PRISM and EcoClim datasets, the 6 GCM average model projection suggests monthly minimum temperatures will experience the most significant changes both in rate and magnitude. Again, there is a strong seasonal signal to these projections. As early as the 2020's, July through October minimum temperature are predicted to exceed one standard deviation beyond the 20th century baseline for a approximately 90% of the area of the Mojave Basin. However, by the 2050's, the increases in monthly minimum temperature are pervasive and severe. For every month, 85-99% of the MBR is projected to exceed one standard deviation beyond the 20th century baseline. For midcentury summers – July thru October – models predict 85-95% of the region will experience monthly minimum temperatures two standard deviations beyond baseline values. There is no clear spatial pattern to the area that is not affected to experience these changes, although portions of southeastern MBR more frequently experience values within the range of historic climatic variability.

Table A - 38. Ecoclim Climate Space Trend summary: Precipitation

month	stdv+1_20	stdv+1_50	stdv-1_20	stdv-1_50	stdv+2_20	stdv+2_50	stdv-2_20	stdv-2_50
Jan	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Feb	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Mar	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Apr	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
May	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Jun	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Jul	44.73%	14.09%	0.00%	0.00%	10.52%	0.00%	0.00%	0.00%
Aug	43.16%	29.30%	0.00%	0.00%	2.89%	7.41%	0.00%	0.00%
Sep	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Oct	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Nov	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Dec	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Table A - 39. Ecoclim Climate Space Trend summary: Monthly maximum temperature (Tmax)

month	stdv+1_20	stdv+1_50	stdv-1_20	stdv-1_50	stdv+2_20	stdv+2_50	stdv-2_20	stdv-2_50
Jan	0.07%	96.23%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Feb	19.41%	76.16%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Mar	0.00%	65.07%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Apr	11.56%	94.90%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
May	1.28%	97.72%	0.00%	0.00%	0.00%	0.01%	0.00%	0.00%
Jun	34.14%	99.58%	0.00%	0.00%	0.00%	38.52%	0.00%	0.00%
Jul	87.58%	99.85%	0.00%	0.00%	0.00%	91.54%	0.00%	0.00%
Aug	94.61%	99.71%	0.00%	0.00%	0.02%	94.06%	0.00%	0.00%
Sep	74.00%	99.00%	0.00%	0.00%	0.00%	16.00%	0.00%	0.00%
Oct	48.78%	99.55%	0.00%	0.00%	0.00%	8.61%	0.00%	0.00%
Nov	0.20%	89.64%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Dec	94.21%	94.21%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Table A - 40. Ecoclim Climate Space Trend summary: Monthly minimum temperature (Tmin)

month	stdv+1_20	stdv+1_50	stdv-1_20	stdv-1_50	stdv+2_20	stdv+2_50	stdv-2_20	stdv-2_50
Jan	24.69%	97.93%	0.00%	0.00%	0.00%	2.46%	0.00%	0.00%
Feb	17.29%	93.46%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Mar	10.67%	87.48%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Apr	12.89%	89.64%	0.00%	0.00%	0.00%	0.07%	0.00%	0.00%
May	41.75%	98.09%	0.00%	0.00%	0.00%	10.74%	0.00%	0.00%
Jun	75.57%	99.83%	0.00%	0.00%	0.00%	57.53%	0.00%	0.00%
Jul	92.13%	99.66%	0.00%	0.00%	3.47%	94.31%	0.00%	0.00%
Aug	95.64%	99.80%	0.00%	0.00%	6.28%	95.33%	0.00%	0.00%
Sep	93.00%	99.00%	0.00%	0.00%	1.00%	90.00%	0.00%	0.00%
Oct	90.66%	99.87%	0.00%	0.00%	0.06%	82.49%	0.00%	0.00%
Nov	12.71%	89.26%	0.00%	0.00%	0.00%	5.82%	0.00%	0.00%
Dec	4.75%	94.68%	0.00%	0.00%	0.00%	0.92%	0.00%	0.00%

A-2.2.2.1 Climate Space Forecast Summary

Overall climate-space forecasts for 2060 can be summarized in the form found in Figure A - 40. This map displays a count for each pixel where up to 12 of the 36 monthly temperature variables (maximum and minimum temperature, each X 12 months) and total precipitation (x12) are forecasted to depart by at least 2 standard deviations from the 20th century baseline mean values. This analysis indicates the locations where concentrated change (or lack of change) in these monthly variables could occur; and provides an initial suggestion of areas where climate-change impacts might be more or less intense.

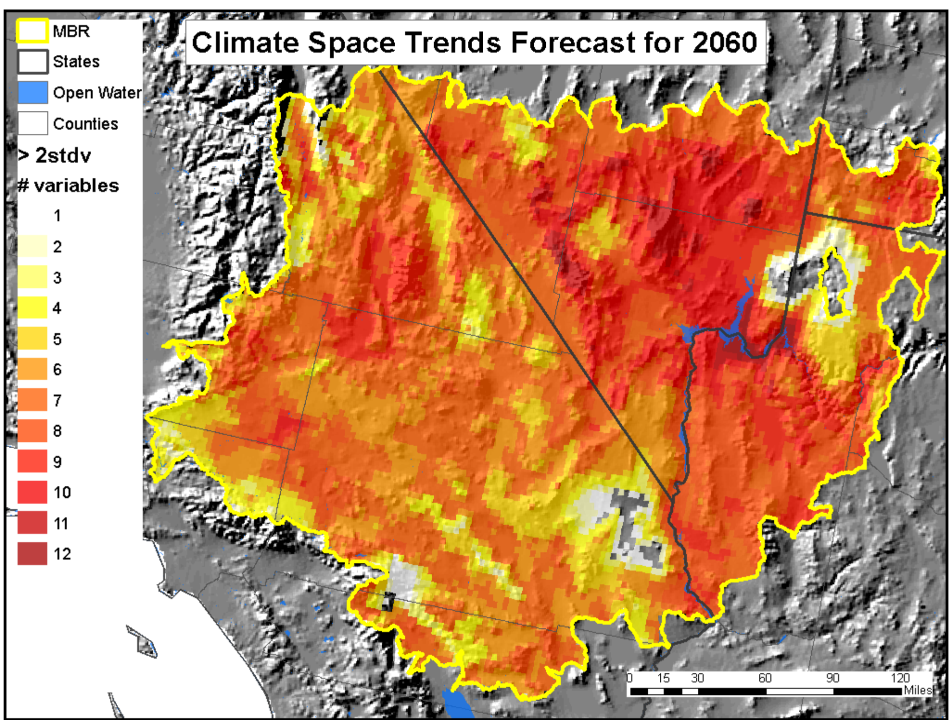

Figure A - 40. Composite 2060 forecast where climate variables depart by > 2 stdv

Among these monthly data, forecasts suggest there will be a trend toward increasing precipitation during July and August in the Mojave Desert (Figure A - 41). The areal extent predicted to experience increasing summer rains is not consistent across the two decadal time slices – about 45% of the Mojave is >1" wetter in the 2020s, while only about 25% of the region is >1"wetter in the 2050s; the latter concentrated in the West Mojave and Spring Mountains. Figure A - 41 indicates the range of predicted increase in August precipitation, reaching a high of nearly 3 inches at highest elevations.

Some caution is warranted in reviewing these results. This precipitation result could in part stem from the analysis time frame used for future time slices. Decadal averages are a relatively short time frame for measuring trends in precipitation from climate model outputs. Any given climate model could produce a relatively wet decade or a relatively dry decade according to the future timing of predictions for large-scale regional phenomena that global models are trying to reproduce, such as the El Nino/Southern Oscillation, or in this case, the southwest monsoon. A next step in efforts to understand future precipitation patterns could analyze rolling thirty year averages (i.e.: 2010-2039, 2020-2049, 2030-2059…etc), as this approach can produce a clearer picture of modeled trends in precipitation.

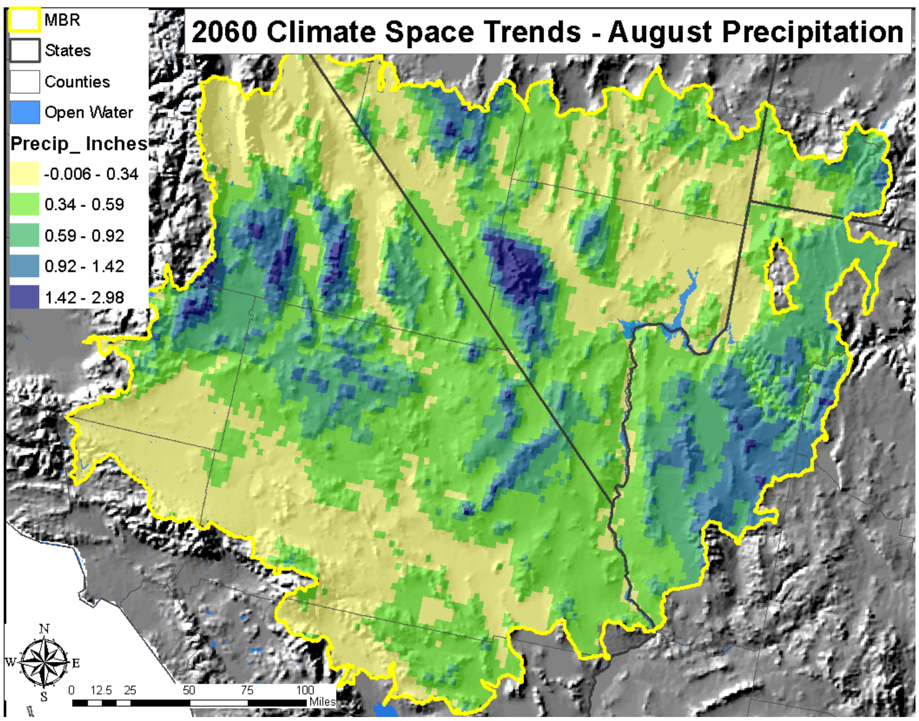

Figure A - 41. Forecasted increase of August precipitation by 2060 (inches) ; ensemble mean of 6 GCM forecasts, summarized by 4km2 grid

Outside of this increase in August precipitation, there was no signal of either increase or decrease in precipitation for any other month. Two factors likely contribute to this result. Natural variability in precipitation is high in this region, with the standard deviation often exceeding the average values for most months. Thus a dramatic increase or decrease in modeled future precipitation would be required to produce statistically significant forecasts of future precipitation changes. A second factor contributing to this result is the lack of consensus among climate models in future precipitation regimes. In a multi-model ensemble, climate models that project wetter futures are averaged with climate models that project drier futures, and the ensemble result produces a muted signal of precipitation changes – but reflecting the reality of the state of climate model science.

Of course, all forecasts regarding precipitation should be evaluated in light of temperature forecasts, as increasing temperatures can easily cancel out effects of increased precipitation due to increasing surface evaporation and evapo-transpiration of plants. Model forecasts for the 2020s and 2050s have a strong seasonal distribution, with winter maximum temperatures increasing the least, and summer maximum temperatures increasing the most. For December, January, and February, between zero and 20% of the MBR area is projected to experience statistically significant increases in monthly maximum temperature by the 2020s. In contrast, for this 2020s time period, July, August and September may see significant (1 stdv departure) maximum temperature increases over 85-95% of the MBR ecoregion (Table A - 39). Spring and fall experience intermediate amounts of significant maximum temperature increases, with spring projected to be less severe than fall.

There are much more significant increases in maximum monthly temperatures forecast by climate models for 2060. Figure A - 42 includes forecasts where, by 2060, monthly maximum (daytime) temperature variables (Tmax) are forecasted to increase at least 2 standard deviations above the 20th-century baseline values. As indicated in the figure, everywhere across the ecoregion is forecasted to experience at least one month with temperatures significantly exceeding baseline values; with concentrated increases up to 6 months forecasted on the northern and eastern portions of the ecoregion.

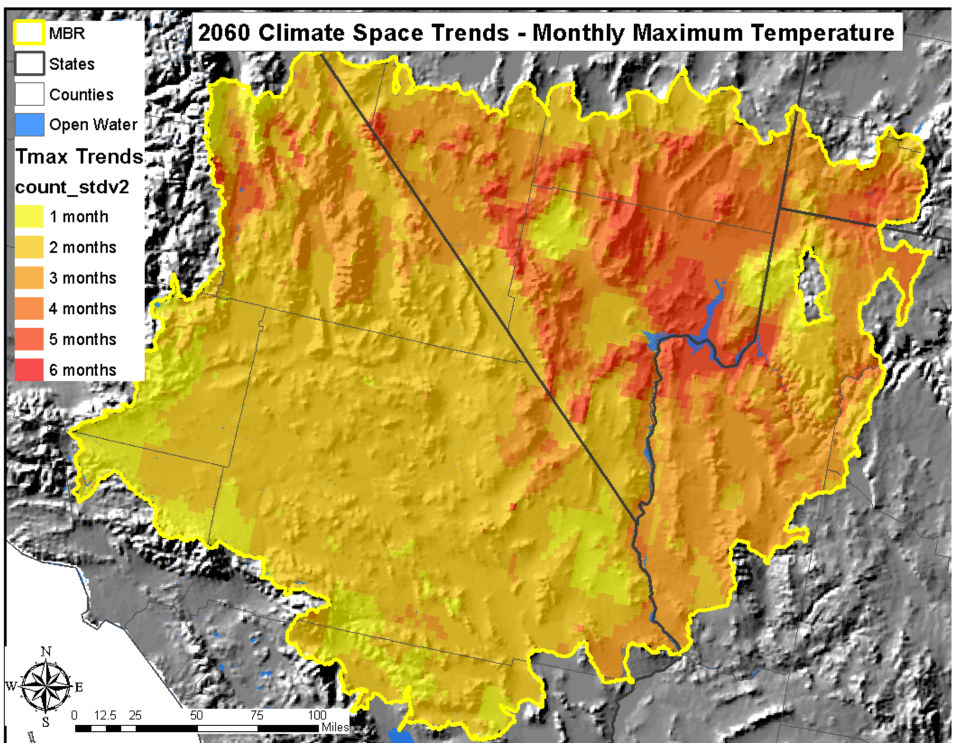

Figure A - 42. 2060 Climate space trends for monthly Tmax , indicating numbers of months with forecasted Tmax exceeding 20th century baseline mean by > 2 stdv; ensemble mean of 6 GCM forecasts, summarized by 4km2 grid

By midcentury models predict future summer maximum temperatures will exceed 95% of the values that occurred during the 1900-1979 baseline period. March and April are the only two months where less than 90% of the Mojave Desert is projected to experience at least one standard deviation shift in monthly maximum temperatures. Figure A - 43 includes 2060 change forecasts of July maximum temperatures indicating increases varying from less than 2 degrees to 8.6 degrees F. These patterns of extreme temperature are generally concentrated in the northern and eastern portions of the ecoregion.

The increases in monthly minimum temperature (i.e., night-time temperature) are also pervasive and severe. For every month, 85-99% of the MBR is projected to exceed one standard deviation beyond the 20th century baseline (Table A - 40). For midcentury summers – July thru October – models predict 85-95% of the region will experience monthly minimum temperatures two standard deviations beyond baseline values; with extremes reaching a 9.6 degree F increase (Figure A - 44). This may be related to cloud-cover associated with increased precipitation forecasts. Overall, there is no clear spatial pattern to the area that is not affected to experience these changes, although portions of southern MBR more frequently experience values closer to the range of historic climatic variability.

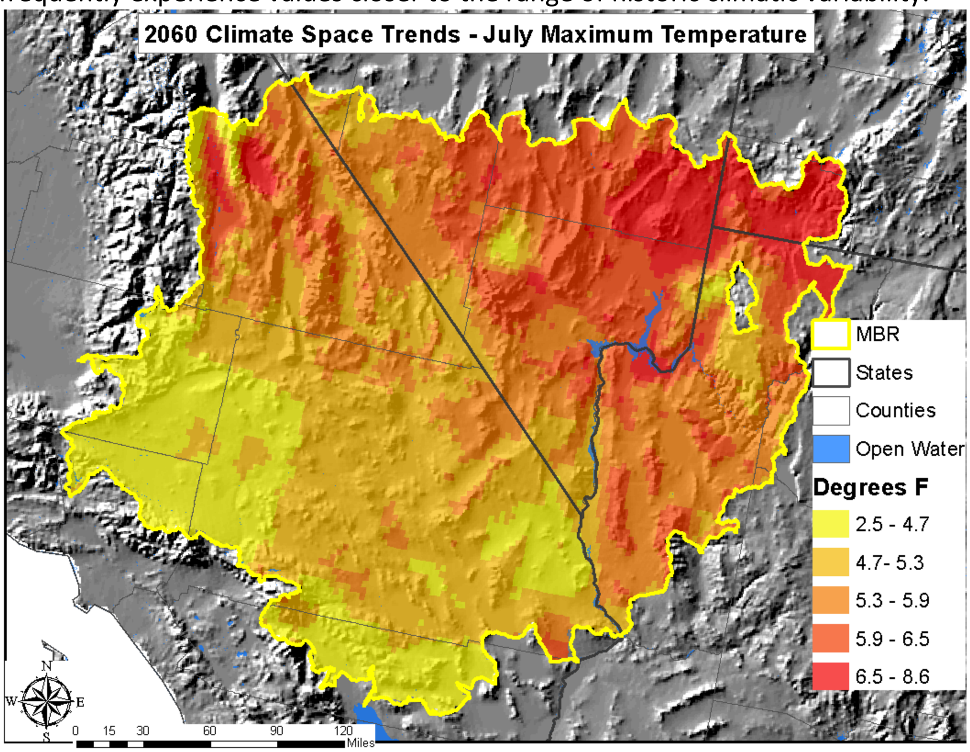

Figure A - 43. Forecasted increase in monthly maximum temperature for July in the MBR, in degrees F ; ensemble mean of 6 GCM forecasts, summarized by 4km2 grid

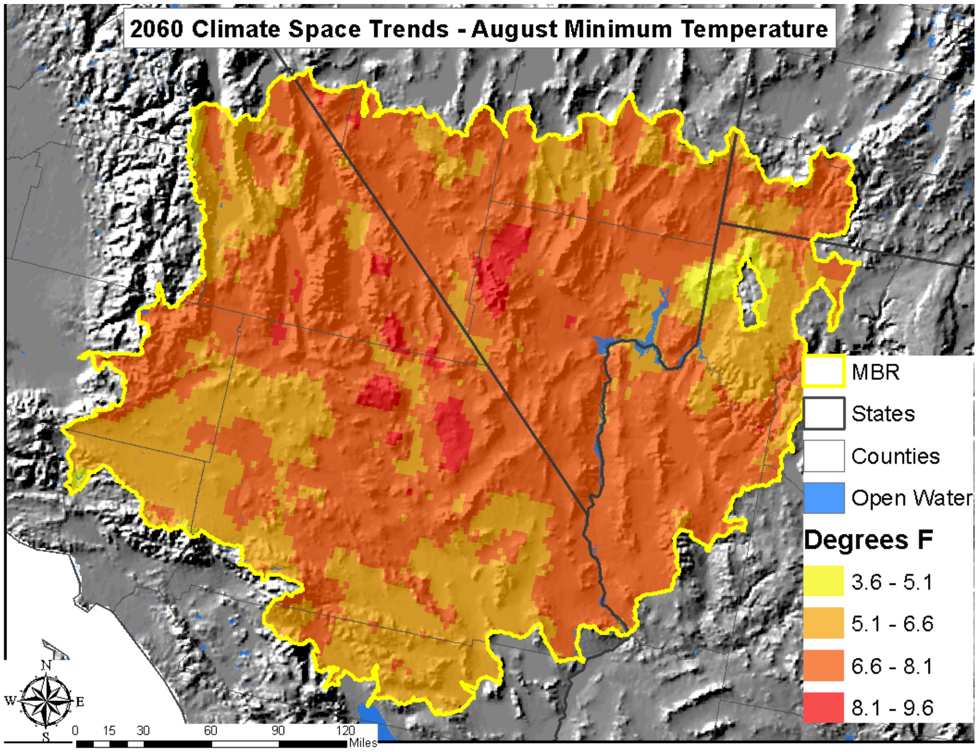

Figure A - 44. Forecasted increase in 2060 Minimum (night-time) temperature for August ; ensemble mean of 6 GCM forecasts, summarized by 4km2 grid

Climate Change Results with USGS/Hostetler Dataset

Table A - 41 through Table A - 46 below show the percent (%) of pixels within the MBR region with future projected values exceeding the values of the baseline and its standard deviations <-2, <-1, >+1, >+2, for each variable, for every month of the year. These tables are summarizing the degree of statistically significant climate change relative to the area of the MBR, as defined by our method using the ratio of the future projected values to the current values, the NCEP baseline, and its standard deviation. In discussing the geographic regions that are affected by the significant changes projected, it must be kept in mind that each pixel is $15km^2$, so the geography of climate change can only be interpreted at relatively coarse scale.

There is very little change in evapotranspiration (ET) projected for midcentury in the Mojave Basin and Range. Across most months, only 0 - 1% of pixels across the region are affected, with both increases and decreases of ET. In the spring months, there is a decrease in ET in the northwestern part of the MBR, and an increase in ET in the northeastern part of the MBR, but overall the amount of area predicted to change in either direction is minimal.

Highly significant changes in surface runoff (RNFS) are projected by midcentury, with an emphasis on major decreases in late spring. The magnitude of change in April and May is greater than -2 STDEV from the baseline for 34-43% of the MBR area in late Spring. The spatial pattern of this highly significant negative change in late spring runoff is concentrated in the northern part of MBR. Late summer and early fall are also decreasing significantly in the western side of MBR. However, surface runoff in June and September is increasing by >1 STDEV across 66% and 42% of the MBR region, respectively, with a concentration of these increases in southern areas MBR.

Top layer soil moisture (SMU) is projected to decrease in late spring by midcentury, concordant with the above late spring major decreases in soil runoff. The magnitude of projected change is not as extreme as the changes projected for surface runoff. In April and May, 33% and 14%, respectively, of the MBR area shows decreases of -1 STDEV, mainly in the northern and eastern mountainous areas around the edges of the MBR boundary. For all other months of the year, the projected changes are only between 0-3%, mostly towards slightly negative soil moisture, but a few areas have very slight (<1%) increases +1 STDEV in the months of February, May and June. The late spring soil moisture decreases in the northern and eastern edges of the MBR are the main significant results for projected future changes in soil moisture.

Dramatic decreases in snow water equivalent (SNOW) are also projected for November through May. From January through May, 47-83% of the MBR is projected to experience snow water equivalent that is -2 STDEV below the 1968-1999 baseline values. These projections translate to midcentury SNOW values that are lower than 95% of the values from 1968-1999. In February and March, almost 90% of the MBR is projected to experience -1 STDEV in snow water equivalent. Spatial patterns are not distinct; change is essentially across the entire region.

The above four variables are all reflections of the interaction of future temperature and precipitation that models predict for the MBR. Similar to the CBR, the projected changes in moisture variables such as soil runoff, soil moisture, and snow water equivalent are in relative contrast to projected changes in precipitation. The modeled values for monthly total precipitation in the MBR show very little projected significant change. Spring months show a decrease in precipitation in the small parts of the northwest (2-12% MBR), and summer months show a decrease in precipitation in the southwest (<2% MBR). No months have an increase in precipitation, except for June, with 5% of the region increasing by +1 STDEV mainly in the south of MBR. Similar to the results for CBR and the EcoClim 6 GCM ensemble, there are two possible reasons for this result, which are not mutually exclusive. Natural variability across the 1968-1999 baseline could be high, meaning that a large degree of change would need to be forecast for future precipitation in order to produce statistically significant change. Also, climate models are often opposed in the direction of their projections for future precipitation. If one model projects and increase and another projects a decrease, the ensemble average will predict little change. Both of these factors may be at play here. It is difficult to reconcile the highly significant decreases in moisture related variables such as soil runoff, soil moisture, and snow water equivalent with the forecasts for insignificant future precipitation changes. This result deserves further inquiry.

However, the extensive increases that models suggest for future temperatures could drive much of the decreases that are projected for soil moisture and snow water equivalent. Monthly maximum temperature (TAMAX) in the Mojave is projected to increase mainly in the summer and fall. Essentially the entire region (93-100%) is projected to experience an increase of +1 STDEV in May, June, July, and August. In the fall, 64-95% of the region is projected to experience the same magnitude of increase in maximum temperatures. In winter, increases vary from 0–54% of the MBR area, with the spatial pattern showing that increases are mainly concentrated in the south.

Similar to CBR, it is monthly minimum temperatures that are experiencing the most pervasive and extreme changes. From May to November, 99-100% of the MBR will experience minimum temperatures that are +1 STDEV higher than the 1968-1999 baseline. February – April are the only months that remain relatively unaffected by projected minimum temperature increases. July is the month that the highest magnitude of change is found, with 13% of the region exceeding +2 STDEV in minimum temperatures. This extreme change is concentrated along the eastern edge of the MBR boundary.

Table A - 41. Hostetler Climate Space Trend Summary: Evapotranspiration (ET)

month	-2 stdev	-1 stdev	+1 stdev	+2 stdev
Jan	0	0	0.142857	0
Feb	0	0	0.285714	0

month	-2 stdev	-1 stdev	+1 stdev	+2 stdev
Mar	0	0	2.57143	0
Apr	0	0.428571	2	0
May	0	2.57143	0.142857	0
Jun	0	0.714286	0.285714	0
Jul	0	0	0	0
Aug	0	0	0	0
Sep	0.285714	0.285714	0.285714	0
Oct	0.285714	0.428571	0.142857	0
Nov	0	0.285714	0.142857	0
Dec	0	0	0	0

Table A - 42. Hostetler Climate Space Trend Summary: Surface runoff (RNFS)

month	-2 stdev	-1 stdev	+1 stdev	+2 stdev
Jan	0	0	0	0
Feb	0.142857	2.85714	0	0
Mar	1.14286	17	0	0
Apr	43.1429	74.8571	0.285714	0.142857
May	34	53.8571	4.42857	1.71429
Jun	3.28571	5.57143	66.1429	51
Jul	2.71429	7.14286	3.85714	1.42857
Aug	14.8571	48.1429	0.142857	0
Sep	1.71429	3.42857	42.4286	22.1429
Oct	14.5714	37.8571	5.42857	0.428571
Nov	4.85714	42.8571	0	0
Dec	0	0	7.42857	0.571429

Table A - 43. Hostetler Climate Space Trend Summary: Top layer soil moisture (SMU)

month	-2 stdev	-1 stdev	+1 stdev	+2 stdev
Jan	0.142857	0.142857	0	0
Feb	0.142857	0.285714	0.285714	0
Mar	0	2.28571	0	0
Apr	2.57143	33.2857	0	0
May	0.857143	14.7143	0.142857	0
Jun	0	1	0.142857	0
Jul	0.142857	0.142857	0	0
Aug	0	0.142857	0	0
Sep	0	0.142857	0	0
Oct	0	0	0	0
Nov	0	0	0	0
Dec	0	0.142857	0	0

Table A - 44. Hostetler Climate Space Trend Summary: Future precipitation change (RT)

month	-2 stdev	-1 stdev	+1 stdev	+2 stdev
Jan	0	0	0	0

month	-2 stdev	-1 stdev	+1 stdev	+2 stdev
Feb	0	0	0	0
Mar	0.142857	0.571429	0	0
Apr	0.285714	2.14286	0	0
May	0.142857	12.5714	0	0
Jun	0	0	5.28571	1.57143
Jul	0	0.142857	0	0
Aug	0.428571	1.85714	0	0
Sep	0.285714	0.285714	5	1
Oct	0.714286	1.85714	0	0
Nov	0	0.142857	0	0
Dec	0	0	0	0

Table A - 45. Hostetler Climate Space Trend Summary: Monthly average maximum temperature (TAMAX)

month	-2 stdev	-1 stdev	+1 stdev	+2 stdev
Jan	0	0	54.1429	0
Feb	0	0	0	0
Mar	0	0	2.71429	0
Apr	0	0	72	0
May	0	0	93.8571	0
Jun	0	0	99.5714	0.142857
Jul	0	0	100	0
Aug	0	0	98.1429	0
Sep	0	0	64	0
Oct	0	0	94.5714	0
Nov	0	0	49.5714	0
Dec	0	0	54.1429	0

Table A - 46. Hostetler Climate Space Trend Summary: Monthly average minimum temperature (TAMIN)

month	-2 stdev	-1 stdev	+1 stdev	+2 stdev
Jan	0	0	100	0
Feb	0	0	9	0
Mar	0	0	2.28571	0
Apr	0	0	0.857143	0
May	0	0	99.2857	0
Jun	0	0	100	0.428571
Jul	0	0	99	13.1429
Aug	0	0	100	1.14286
Sep	0	0	100	0.142857
Oct	0	0	100	0
Nov	0	0	96.4286	0
Dec	0	0	39.8571	0

A-2.3 Use in Assessment: Overall Uncertainty, Limitations and Data Gaps

A-2.3.1 General Limitations

- Raster analyses with multiple inputs required resampling which affects areal calculations
- All models of distribution have inaccuracies and will have errors of omission and commission
- The age of some distribution maps may mean that there have been changes in the distribution since the maps were generated
- None of the input data were field validated for this application although all were submitted to BLM review teams for comments which in some cases resulted in revisions to the products.
- Forecasts of future distributions have high sensitivity to changes in factors that affect those distributions.
- Each CE or classes of CEs have different spatial representations based on source information and modeling methods. These differences resulted in variability in the precision of the spatial representation of the CEs and the spatial results using those data in combination with other data.

More specific limitations

- **Development change agent distribution** – Development patterns across the ecoregion appear to be reasonably well described with existing data sets. One weakness identified through the REA was the spatial representation from surface disturbances, such as from open-pit mines and gravel pits. Similarly, the ability to adequately represent motorized and non-motorized recreational usage was highlighted as a weakness in current data sets. Additional investments in these particular areas should yield useful outcomes for subsequent assessment and planning. Forecasts of some development trends may be vulnerable to poorly integrated information on infrastructure plans, such as those currently maintained as proprietary information by energy or mining companies and utilities.
- **Invasive species risk models** – Invasive plant models face similar constraints as many CE distribution models. Many field-based and georeferenced samples indicting the species and cover of these species is required to develop robust models. Additional time and effort is needed to integrate processed satellite imagery; ideally multi-date images capturing early spring green-up, in order to better predict invasive plant species abundance and risk of invasion. Freshwater aquatic species were very poorly represented in existing data sets for this ecoregion, so all results and conclusions related to these should be viewed as preliminary. Substantial investment in the inventory and monitoring of aquatic nuisance and invasive species is needed throughout this ecoregion.
- **Fire regime models** – While a substantial base existed for this REA, as a result of prior national and regional efforts, this area of both conceptual and spatial modeling remains in early stages. One could expect substantial benefits from regionally customized and field-validation of models for most vegetation types in the ecoregion. Similarly, there are likely substantial benefits to be gained by more rigorous characterization and mapping of

selected landscape species habitats; and for those with considerable fire regimes, the customized development of new fire regime models would be warranted.

- **Areas high potential hydrocarbon energy development** – Given the volatile nature of hydrocarbon markets and technologies for extraction, one should take care in the interpretation of these REA findings as they pertain to potential development zones in this sector.
- **Areas of most likely renewable energy development** (i.e., constrained by transmission access) – with some similarities to hydrocarbon development, the sensitivities of investors to factors such as the existing or planned placement of transmission corridors, or the rapid shifts in technology (e.g., heights of wind turbines), can have dramatic effect on the potential for renewable energy development. Our findings should be carefully considered in this light.
- **Climate Change Analyses** – as described previously, current climate data are limited in this area by a number of factors. Weather stations, forming the basis for characterizing our 1900-1980 'baseline' at 4km^2, have relatively low density with respect to the size of the MBR. For the 15km^2 analyses, the baseline is restricted to a shorter time period, 1961-1990, and the baseline climate values are model outputs, although strongly forced by observations. Our definition of significant climate change is based on the variability of climate over these two baseline periods. Given the observed high variability in this basin and range landscape, one should be careful to not over interpret our findings for climate space trends. These analyses are based not only on these 20th century baselines, but upon the rapidly developing science of climate forecasting.
- We made a concerted effort to produce climate change effects analyses that include a broad range of variables derived from a wide range of global and regional climate model outputs. Moving beyond monthly temperature and precipitation, our analysis includes variables such as evapo-transpiration and soil moisture that feed into our understanding of ecological features, such as future fire regimes and streamflow. The available data require a tradeoff between spatial resolution, number of climate model outputs, and climate variables analyzed.
- We believe our handling of these uncertainties has been appropriate for the task and constraints imposed by the REA process, but we also encourage that care be taken with interpretation of our findings. Future investment could further refine these REA results. Additional climate data sets, both improved global and regional climate models, as well as independent weather station data, are available to further test the hypotheses climate-induced change that we have identified for the upcoming decades.

A-2.3.2 Specific Data Gaps

- Lack of data on specific areas and intensities of exotic ungulate grazing precluded inclusion of that CA.
- Lack of data on planned, projected, or potential oil and gas development precluded inclusion in future scenarios.

<u>Limitations to the Aquatic Assessment</u>

The Aquatic Key Ecological Attribute, *Stressors to Biotic Condition*, has two indicators dealing with exotic invasive species, in order to answer the management question “What areas are significantly ecologically affected by invasive species”? Unfortunately these were the weakest indicators. The data available for known presence of invasive plant species (tamarisk, Russian olive, annual grasses) and aquatic invasive species), while available across the ecoregion, were sparsely distributed. As a result, these data give a false picture of reality on the ground. Early in the REA process, the assessment team considered using data on native species distributions and condition as indicators of biotic condition for aquatic CE types. For example, the distribution and condition of native trout species would provide information on the biotic condition of higher-elevation, coldwater streams. Unfortunately, this proved impossible within the limitations and criteria established for the REA. For example, it was decided not to use native fish species distribution data for four reasons: (1) maps of the historic or expected current geographic ranges of species were available but could not be used as substitutes for data on actual current distribution on a stream-by-stream basis; (2) data for the entire ecoregion were not available; (3) data on native fishes were available for Utah, but these data did not meet the ecoregion-wide criteria as stated in main assessment report Chapter 2, section 2.7.1.1 Limitations: Issues of Scale & Certainty; and (4) the location and status of native fish species were not the subjects of any management questions.

We also actively sought to use data on stream benthic macroinvertebrates, collected as parts of systematic studies of stream biotic condition for purposes of building multi-variate measures of stream biotic integrity. The Western Center for Monitoring and Assessment of Freshwater Ecosystems (WMC) and the National Aquatic Monitoring Center (NAMC) maintains a regional database of such data, from which we hoped to obtain multi-variate measures of stream biotic integrity. Scott Miller, Director of the BLM “Buglab” at the NAMC provided a copy of this dataset for review, clipped to the ecoregion. Unfortunately, the available data were spatially very sparse – and necessarily limited to perennial stream reaches only. The individual states within the ecoregion are all developing stream bioassessment programs based on common methods, and it was hoped that state data could be used to complement the data provided by the NAMC. However, only Utah had bioassessment data available beyond those contained in the regional database. Nevada is rapidly building its stream bioassessment metrics, and its data should be available soon – but not in time for this REA. California reports that it is the process of building a digital database for its bioassessment data, but that this database will not be functional for data extraction for some time. Further, the data available from the NAMC included both reference and impacted sites. We found it difficult to summarize this information on a watershed scale, as a single stream might have highly impacted (negative scores) and reaches of highest quality. Integrating sparsely collected, very-fine scale data into a regional assessment always raises such challenges. As a result, we determined that it would not be feasible to use the stream bioassessment data for this REA.

This aquatic invasive species impact index most certainly underestimated the full impacts that occurred within the CEs and HUCs. There were two major reasons for underestimation of impacts: 1) invasive species database gaps and 2) invasive species that were not considered in the models.

Database gaps included delayed reporting, non- reporting, or CEs and HUCs where no surveys were conducted. A problem with all invasive species databases is that there are often large lag times between when a private citizen, researcher, or manager observed an aquatic invasive species, when it was reported to the appropriate agency, and when it was verified and entered into a useable database. There are also large differences in observational and survey effort between water- body (CE) types. Invasive species are more likely to be reported and monitored in easily accessible or popular fisheries or in CEs that are more heavily managed (e.g. protected areas).

Many invasive taxa were intentionally not included in these indices. To keep this assessment rapid, we made a short list of invasives that focused on the most invasive taxa. These taxa were selected from a wide spectrum of phylogenies that included all trophic levels and what we considered representative of taxa that were included. We also ‘rolled up’ many taxa from species or genus to family level to be more consistent across phylogenies. Many invasive species (e.g. game fish) have been granted clemency by management agencies due to recreational and economic concerns, even though the ecological impacts of these species are well known and often very large. As a result of not including all of the invasive taxa in our ecoregions, CEs and HUCs that we rated as ‘undetermined’, ‘sustainable’ or ‘transitioning’ could very well be more impaired than our ratings suggest.

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Data Request Method

Rapid Ecoregional Assessments (REAs)—National Operations Center, CO

Individual REA data layers and some other products are still available but are no longer being published.

If you would like to obtain more information, including data and model zip files* (containing Esri ModelBuilder files for ArcGIS 10.x and relevant Python scripts), please email **BLM_OC_REA_Data_Portal_Feedback_Team@blm.gov**.
*Note that a few models require software that BLM does not provide such as R, Maxent, and TauDEM.

Models associated with individual REAs may require data links to be updated to function properly. REA reports, technical appendices, and model overviews (for some REAs) contain detailed information to determine what products are available and what datasets are necessary to run a certain model.

Please include the report name and any specific data information that you can provide with your request.

Other BLM data can be found on the Geospatial Business Platform Hub (https://gbp-blm-egis.hub.arcgis.com).