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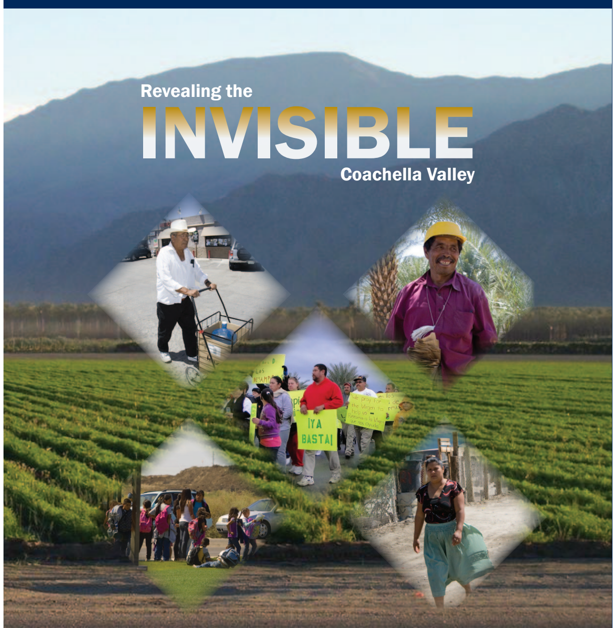

Technical Appendix:

Revealing the Invisible Coachella Valley

Putting Cumulative Environmental Vulnerabilities on the Map

Teri Greenfield, M. Ed.
Jonathan London, Ph. D.
Morgan Beryl, B.S.
Center for Regional Change, UC Davis

Center for Regional Change
University of California, Davis
One Shields Ave, 152 Hunt Hall
Davis, CA 95616
530.751.8799
http://regionalchange.ucdavis.edu

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CENTER FOR REGIONAL CHANGE

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University of California, Davis
One Shields Ave, 1309 Hart Hall
Davis, CA 95616
530.751.8799

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Summary

The Cumulative Environmental Vulnerability Assessment (CEVA) is intended to help policy makers, public agencies, advocates, businesses and other civic leaders identify the people and places facing the highest degrees of environmental hazards coupled with the lowest level of economic, political and social resources to mitigate these hazards.

The Center for Regional Change constructed the CEVA through two multi-indicator indices: the Cumulative Environmental Hazards Index (CEHI) and the Social Vulnerability Index (SVI). Both the CEHI and the SVI are relative measures that range in value from 1 to 5. The CEHI is a relative measure of key environmental hazards in and around each census tract. The higher the value, the more environmental hazards are within and/or around the census tract. The SVI is a relative measure of key factors associated with low levels of economic, political and social resources needed for community health protection. The higher the value, the greater concentration of people with high social vulnerability factors within each census tract.

The Cumulative Environmental Vulnerability Assessment (CEVA) is constructed by categorizing each census tract as either high, medium, or low on both the CEHI and the SVI. This creates a three by three table (Table 8, page 18) with nine possible combinations. The three categories that are high in both CEHI and SVI or high in one and medium in the other are considered Cumulative Environmental Vulnerability Action Zones (CEVAZ) and deserving of additional standards of protection, investment, and engagement.

The datasets used in the CEHI and the SVI are summarized in Table 1. In all cases, we used the most recent and most reliable data available.

Table 1: Summary of CEVA Data Sources

Index	Measure	Indicator	Source
Environmental Vulnerability	Agricultural pesticide application	Weighted average of active ingredient pesticide application, agricultural only. Included high priority chemicals based on amount applied, toxicology and transport/fate. Chemicals selected drew from OEHHA's CalEnviroScreen, along with several additional pesticides identified by experts familiar with local agricultural practices.	Department of Pesticide Regulation, 2008-2010
	Point source pollution emission sites	Total score based on number, status and site activity. Types include cleanup sites, leaking underground storage tanks, Superfund Sites, hazardous waste sites, solid waste disposal, transfer and processing sites, permitted hazardous waste sites. We used a 250 meter buffer to join point sources to census tracts.	Department of Toxic Substances Control, CA State Water Resources Control Board, CalRecycle, CalEPA, US EPA.
	Risk-Screening Environmental Indicators (RSEI)	Three-year average of hazard-based impact scores for TRI facilities in Riverside county. We used a 250 meter buffer to join facilities to census tracts.	US EPA 2008, 2009, 2010
	Air Quality	Maximum 8-hour ozone concentrations for each day from March to October, averaged over three years (2008-2010). GIS was used to interpolate the means for tracts near measurement sites, up to a distance of 30 miles.	California Air Resources Board, 2008-2010
	Impaired Water Bodies	Summed pollutant counts for tracts and scored tracts based on the number of individual pollutants that fell within or bordered the tract.	CA EPA State Water Resources Control Board, 2010
	Water Quality Assessment	Calculated a six-year average concentration by well for arsenic, lead, nitrates, chromium 6, perchlorates.	CDPH: PICME and WQI/WQM Data systems, 2006 through June 2011.
Social Vulnerability	Sensitivity of receptors	Percent of people younger than 5 or older than 65 in a census tract	Census 2010
	Availability of social/economic resources	Percent living below 200% FPL	ACS 2007-2011
		Percent of population of color	Census 2010
		Percent of population older than 25 with no HS diploma	ACS 2007-2011
		Percent who speak English "not very well"	ACS 2007-2011
		Foster care entry rates	Child Welfare Services, 2011
		Percent of population unemployed who are 16 or older, civilian only	ACS 2007-2011
		Percentage of renter and owner occupied units paying more than .5 of household income in housing costs	ACS 2007-2011
		Percentage of owner and renter-occupied housing units with 1.01 or more occupants per room.	ACS 2007-2011
	Health Condition	Low birth weight rate	CA Dept of Public Health, 2010
		Emergency department visits due to asthma	CA Office of Statewide Health Planning and Development and California Environmental Health Tracking Program, 2009

US Census Data Sources

This report used the census tract as the unit of analysis. Census tract is the smallest geographic unit for which statistically robust estimates can be calculated for our study area and Riverside County. According to American Community Survey 2007-2011, Riverside County has 453 census tracts. Two of these tracts did not have data for every indicator and were excluded from the analysis. More information on cartographic boundary files descriptions and Metadata for census tracts can be found on the website of the US Census Bureau. http://www.census.gov/.

We used Census 2010 data for percent of population of color and percent of people younger than 5 or older than 65 in a census tract. We used American Community Survey (ACS) 2007-2011 for percent below 200% poverty level, percent of population older than 25 with no HS diploma, percent who speak English "not very well", percent of population unemployed, percentage of renter and owner occupied units pay more than 50% of household income in housing costs, percentage of owner and renter occupied housing units with 1.01 or more occupants per room. ACS data is considered the best available data source, but for reasons such as sampling, averaging over five years, and weighting, these data are not as reliable in small geographic areas such as our study area.

Environmental Hazards

Pesticide Applications

Why it is important: There are many studies suggesting that exposure to pesticides can be harmful to one's health; and, residing and working in agricultural areas with extensive pesticide applications may increase that risk. Pesticide drift is a main source of these effects[i] A recent study also found that illness rates due to exposure for women workers are twofold that of males.[ii] Agricultural practices in the Coachella Valley involve significant applications of pesticides.

How we measured it: We obtained the data from the Department of Pesticide Regulation. We developed an indicator for total pounds of pesticides applied per census tract over a three-year period (2008-2010). The pesticides were selected based on their levels of human toxicity, amount applied, and their tendency to come into contact with humans. We consulted with the Office of Environmental Health Hazard Assessment and US EPA in the selection of pesticides and referred to http://www.pesticideinfo.org/Docs/ref_toxicity7.html to classify chemicals and to select locally-relevant chemicals. The final list of pesticides is in Table 2. More information and databases on agricultural pesticide use can be found at http://www.cdpr.ca.gov/docs/pur/purmain.htm.

Table 2. Pesticides included in the CEVA Pesticides Indicator

1,3-DICHLOROPROPENE	PHOSPHINE
2,2-DIBROMO-3-NITRILO-PROPIONAMIDE	POTASSIUM N-METHYL-DITHIOCARBAMATE (METAM-POTASSIUM)
ACEPHATE	PROPETAMPHOS
ACROLEIN	PROPOXUR
ALDICARB	PROPYLENE OXIDE
AZINPHOS-METHYL	PYRIMETHANIL MANEB*
BENSULIDE*	MALATHION
BROMOXYNIL HEPTANOATE	MANCOZEB*
BROMOXYNIL OCTANOATE	METALAXYL
BUPROFEZIN	METAM-SODIUM
CARBARYL	METHAMIDOPHOS
CARBOFURAN	METHIDATHION
CHLOROPICRIN	METHOMYL
CHLOROTHALONIL	METHYL BROMIDE
CHLORPYRIFOS	METHYL ISOTHIOCYANATE
CHLORTHAL-DIMETHYL	METHYL PARATHION
CLOMAZONE	MOLINATE
CYCLOATE	MYCLOBUTANIL
CYPRODINIL	NALED
DAZOMET	OXYDEMETON-METHYL
DDVP	PARAQUAT*
DIAZINON	PCNB
DICLORAN	ROTENONE*
DIMETHOATE	S,S,S-TRIBUTYL PHOSPHORO-TRITHIOATE (DEF)
ENDOSULFAN	SODIUM CYANIDE
EPTC	SODIUM TETRATHIOCARBONATE
ETHALFLURALIN	SULFUR DIOXIDE
ETHOPROP	SULFURYL FLUORIDE
FENAMIPHOS	THIRAM
FENPROPATHRIN	TRICLOPYR, BUTOXYETHYL ESTER
FENTHION	TRICLOPYR, TRIETHYLAMINE SALT
FLUDIOXONIL	TRIFLUMIZOLE
FLUMIOXAZIN	TRIFLURALIN
HYDROGEN CYANAMIDE	ZIRAM
IMAZALIL	
LINURON	

*Added based on consultation with CRLAF, US EPA and other expert sources.

Using ArcGIS 10, we calculated a spatially weighted average of the pounds of chemicals applied per tract. Pesticide application data is based on the public land survey system, which divides land into sections with an approximate 1-square mile area. We spatially joined sections to tracts and determined the percentage of the area of each tract that intersected each section. Some tracts intersected multiple sections, and large tracts had many intersections. To account for this, we used this formula:

*Define Pounds per Tract Intersection as: (Percent of tract intersected by section * pounds applied in the entire section)*

Calculate Pesticide Indicator as: (Sum of all "Pounds per Tract Intersection")/Number of intersections.

Limitations: It is important to note that the pesticide application indicator is only a measure of the pounds of chemicals applied. It is not an indicator of exposure or harm, but it is an indicator of potential exposure and possible environmental damage.

Pollution Point Sources

Why it is important: People who live near leaking underground storage tanks, facilities that process hazardous waste, and sites classified as "hazardous waste clean-up sites" may suffer adverse health effects such as low child birth rate[iii], increased risk of liver disease[iv], and increased hospitalization for diabetes[v] and coronary heart disease.[vi] These health impacts are largely due to contaminated air and water. There is also evidence of indirect harm to local economic vitality such as property value loss.[vii] There are many regulations governing facilities that pollute the environment, and this data is publically available.

Table 3. Types of Pollution Point Sources

Types of Pollution Point Sources
Cleanup Sites http://www.envirostor.dtsc.ca.gov/public/Envirostor%20Glossary.pdf
Leaking Underground Storage Tanks http://geotracker.waterboards.ca.gov/data_download.asp
Solid Waste Sites and Facilities http://www.calrecycle.ca.gov/SWFacilities/Directory/Search.aspx#DOWNLOAD
EPA Cleanup Sites http://www.epa.gov/enviro/geo_data.html

How we measured it:

1. Cleanup Sites. Source: Envirostor, Department of Toxic Substances Control.
We combined and cleaned the dataset and eliminated duplicates. We excluded site types including school investigations, border zone/hazardous waste evaluations and referrals. The remaining sites were scored on the basis of site type and status, according to the criteria developed by CalEnviroScreen, being developed by CalEPA/OEHHA (see Table 4 below). Site locations were mapped in ArcMap and missing site locations were geocoded. A 250 meter buffer was drawn around each site, and these buffers were joined to census tracts. This sized buffer is a reasonable, and likely conservative, approximation of the human exposure pathway. A tract-level file was created by aggregating all the sites into one tract, and summing the scores for all of the sites that intersected that tract.

Table 4. Weighting Matrix for Cleanup Sites from DTSC's Envirostor Database

Site Type	Low: -Certified -Completed -No Further Action -De-listed -Inactive -Inactive-Withdrawn -Refer (multiple)	Medium -Inactive-Needs Eval. -Certified O&M	High -Active -Backlog -Inactive-Action Required
Low: Evaluation, Military Evaluation, Historical.	2	4	6
Medium: Corrective Action, School Cleanup, Voluntary Cleanup	5	7	9
High: State Response, Superfund	8	10	12

2. Leaking Underground Storage Tanks. Source: GeoTracker, State Water Resources Control Board.

We cleaned the dataset and eliminated duplicates and closed cases. The remaining sites were scored on the basis of site type and status, according to the criteria developed by CalEnviro-Screen, being developed by CalEPA/OEHHA (see Table 5 below). Site locations were mapped in ArcMap and missing site locations were geocoded. A 250 meter buffer was drawn around each site, and these buffers were joined to census tracts. A tract-level file was created by aggregating all the sites into one tract, and summing the scores for all of the sites that intersected that tract.

Table 5. Weighting Matrix for Leaking Underground Storage Tanks from CA State Water Resources Control Board's GeoTracker Database

	Status	
Site Type	Low -Inactive Open -Verification Monitoring -Open: Eligible for Closure	High -Remediation -Reopen -Site Assessment -Site Assessment and Remedial Action
Low: LUST Cleanup Program, Military UST	3	5
Medium: Land Disposal Site	6	10
High: Cleanup Program Site, Military Privatized Site, Military Cleanup Site	9	15

3. Solid Waste Sites and Facilities and Hazardous Waste Facilities: Source: Cal Recycle's Solid Waste Information System (SWIS) and Envirostor Hazardous Waste Facilities Database.
We cleaned the datasets and eliminated duplicates and closed cases. The remaining sites were scored on the basis of site type and status, according to the criteria developed by CalEnviro-Screen, being developed by CalEPA/OEHHA (see Table 6 below). Site locations were mapped in ArcMap and missing site locations were geocoded. A 250 meter buffer was drawn around each site, and these buffers were joined to census tracts. A tract-level file was created by aggregating all the sites into one tract, and summing the scores for all of the sites that intersected that tract.

Table 6. Weighting Matrix for Solid Waste Sites and Facilities and Hazardous Waste Facilities: Source: Cal Recycle's Solid Waste Information System (SWIS) and Envirostor Hazardous Waste Facilities Database.

Category	Criteria	Site or Facility Type
Solid Waste Landfill or Construction, Demolition and Inert (CDI) Debris Waste Disposal	Tonnage	8 (> 10,000 tpd) 7 (> 3,000 to < 10,000 tpd) 6 (> 1,000 to < 30,000 tpd) 5 (> 100 to < 10,000 ptd) 4 (< 100 tpd)
Solid Waste Disposal Site (closed, closing, inactive)	Tonnage	1 (All)
Inert Debris: Engineered Fill	Regulatory Tier	Notification
Inert Debris: Type A Disposal	Regulatory Tier	Permitted
Composting	Regulatory Tier	
Transfer/Processing	Regulatory Tier	
Closed, Illegal, or Abandoned Site	Priority Code	6 (Priority Code A) 4 (Priority Code B) 2 (Priority Code C) 1 (Priority Code D)
Waste Tire	Regulatory Tier	4 (Major) 2 (Minor)
Permitted Hazardous Waste Facilities	Permit Type: 1 (Large facilities) 1 (Non-RCRA facilities) 2 (RCRA facilities)	10 (Landfill) 7 (Treatment) 4 (Storage) 2 (Post-closure)

4. EPA cleanup sites: Source: EPA Geospatial Data Access Project.

We obtained a shapefile from the US EPA. We excluded Superfund sites that were included in the Envirostor database. We located, verified through online searches and included several sites that were identified by project partners. A 250 meter buffer was drawn around the remaining sites, and these buffers were joined to census tracts. A tract-level file was created by aggregating all the sites into one tract and summing the total number of sites that intersected that tract. We did not employ a scoring system for these sites because there we did not have enough information to differentiate between sites in terms of status and impact on the environment.

Limitations: Although we attempted to be as thorough as possible, it is possible that some pollution sources were not included the analysis, or were not scored or weighted appropriately. We also attempted to avoid double-counting of sites between datasets, but it may still have occurred due to different pollution source coding systems.

TRI (Toxic Release Inventory) and RSEI (Risk Screening Environmental Indicators Model)

Why it is important: People who live near facilities that emit toxic substances to air, water, and/or land may suffer adverse health effects due to contaminated air and water, with youth especially at risk.[viii] A recent study has also found TRI facilities are predominately located and disproportionally affect people of color.[ix] The impacts of location and pollution emitted from such facilities has also been found to have indirect harm on local economic vitality, degrading attractiveness to incoming businesses, and overall quality of life.[x] There are many regulations governing facilities that pollute the environment, such as the Toxic Release Inventory, and this data is publically available.

How we measured it: Manufacturers must report annually to the EPA the amounts of chemicals released into the environment as part of the federal Toxic Release Inventory. The Risk Screening Environmental Indicators Model (RSEI) uses reported quantities of TRI releases and transfers of chemicals to estimate the impacts associated with each type of air and water release or transfer by every TRI facility. The hazard-related impacts potentially posed by a chemical release are a function of chemical toxicity, the fate and transport of the chemical in the environment after it is released, the pathway of human exposure. We incorporated the RSEI score into the index because it combines reported quantities of TRI releases and transfers of chemicals and the risk-related impacts potentially posed by a chemical release.

We used the RSEI model to produce a three-year average score for each facility in the county. Site locations were mapped in ArcMap and a 250 meter buffer was drawn around each site. These buffers were joined to census tracts. A tract-level file was created by aggregating all the sites into one tract, and summing the scores for all of the sites that intersected that tract.

Air Quality (Ozone)

Why it is important: High levels of ozone have been linked to respiratory problems such as asthma and reduced lung function by causing toxicity to lung tissue.[xi] Recent and historical studies have found that long-term and short-term exposure to ozone air pollution also increases incidences of hospital admissions, cardiac deaths and a variety of respiratory illnesses.[xii] In some cases, high ozone levels have been shown to create chronic and acute damage in plant species, further weakening their ability to react successfully to other stressors.[xiii]

How we measured it: To develop the ozone indicator, we obtained maximum daily 8-hour ozone average from the California Air Resources Board, Air Monitoring Network Database, for 2008, 2009 and 2010. If fewer than 11 hours were measured during the 13 hour period, the data for that day was not used (based on input from CARB staff). We calculated an average for the three year period, using observations from May to end of October, which are the hottest and worst air quality months of the year in the Coachella Valley. We used an Inverse Distance Weighted (IDW) ArcGIS model to interpolate the levels of ozone at the ozone detection stations to areas encompassing the county. This model uses the values at a particular location to estimate values in other areas based on their proximity to that location. In this case the ozone detection station point data layer was the basis for the interpolation. We calculated the mean of the values for each tract.

Limitations: It is important to note that air monitoring stations are not equally distributed throughout the county, particularly in our study area. The interpolation technique could over-estimate, or in some cases underestimate the actual ozone measurements. In addition, although we collected PM 2.5 data, we could not use it in the index because there were not enough monitoring stations in the eastern part of the county. Our IDW GIS model was not accurate beyond 53 km.

Impaired Water Bodies

Why it is important: Communities located near contaminated water sources face a range of health risks such as waterborne diseases and/or acute gastrointestinal illnesses.[xiv] The State Water Resources Control Board provides data on impaired water sources pursuant to The Clean Water Act Section 303(d)).[xv]

How we measured it: We obtained GIS data from the State Water Resources Control Board http://www.waterboards.ca.gov/water_issues/programs/tmdl/integrated2010.shtml. We counted the tracts that intersected a stream, river or other water body, and then counted the number of pollutants in those impaired water bodies. The pollutant counts were summed for each tract. The census tract was scored based on the sum of the number of individual pollutants that fell within or bordered the tract. This method produced an indicator that is a measure of the quantity of chemicals in a body of water, but it does not account for the varying toxicity or volatility of the chemicals, or whether the water is causing harm to humans, animals, plants or all three.

Water Quality

Why it is important: Communities located near contaminated drinking water wells are impacted by a range of health risks, including skin irritations, neurological effects, cardiovascular disease, and other morbidities.[xvi] Depending on the prevalence of specific contaminates, exposure to affected drinking water can also increase cancer risk.[xvii] While poor water quality directly affects human health, it can also negatively affect economic vitality, particularly in agricultural regions such as the Eastern Coachella Valley, where industry is dependent on high quality water.[xviii]

How we measured it: We developed a water quality indicator that provides an estimation of the presence of contaminated drinking water in a census tract. California's Drinking Water Source Assessment and Protection Program monitor chemicals and contaminants in drinking water. We obtained test results from the California Department of Public Health, WQM (Water Quality Management) and PICME (Permits, Inspections, Compliance Monitoring & Enforcement) databases, 2006 through June 2011. Point data for public drinking water sources and treatment plants was also obtained from the PICME database.

We selected active, untreated groundwater sources because these were most likely to expose people to contaminated drinking water.[xix] We selected five chemicals that have been shown to be prevalent in local drinking water for the indicator: arsenic, lead, nitrates, chromium 6 and perchlorates. Chemical findings were averaged over six years, separately for each chemical and each well. Using ArcGIS 10, we joined the wells to census tracts. We calculated an average for each chemical, for each tract. We sorted the tracts from highest to lowest and ranked the tracts from 5 (high) to low (1) for each chemical. For example, the tract containing the well with the highest six-year average for arsenic would be coded "5". We ranked the tracts for each chemical in the same manner, and computed an average of these rankings.

Limitations: We faced many challenges in developing this indicator. At the time of this study, we did not have water system boundaries for the entire county. Even if we had those, we would not know the direction of the water distribution system or where it ended. Also, a single finding above MCL does not indicate a well or water system is contaminated. Therefore, we developed an approach that would show the tracts in the county where there are wells that had higher findings for certain chemicals, over a six year period. This estimate should not be perceived as an average water quality for the entire tract.

Social Vulnerabilities

A. Sensitivity of Receptors

Percent of people younger than 5 or older than 65 in a census tract

Why it is important: This variable is also an indicator of sensitive receptors. Based on their developmental, physiological, and immunological profiles, young children and seniors[xx] can be more sensitive than the general population to environmental hazards such as air pollutants, pesticides, and poor drinking water.[xxi] A higher percentage of these age groups in a census tract is considered a measure of population sensitivity.

B. Availability of social/economic resources

Foster Care Entry Rates

Why it is important: Foster care entry rates are a proxy for family and community stability[xxii] and the presence of especially vulnerable young people. Children of foster care often lack a secure base, putting them at risk for a variety of behavioral and health risks, including incarceration, drug abuse, and academic failure.[xxiii]

How we measured it: Data were collected from the Child Welfare Dynamic Reporting System which is a California Department of Social Services / University of California at Berkeley collaboration. Their website is: http://cssr.berkeley.edu/ucb_childwelfare/GeoData.aspx. Of note, the foster care data for 2010 were collected based on year 2000 census tracts. In order to crosswalk the 2000 census tract data to 2010 boundaries, we used code developed for STATA statistical software (Stata/MP 12.0 for Windows, StataCorp LP, College Station, TX) by researchers at Brown University*. The code can be accessed at: http://www.s4.brown.edu/us2010/Researcher/LTBDDload/DataList.aspx. The use agreement for this code included non-redistribution of the data.

C. Health Conditions

Asthma Rates

Why it is important: Asthma is a disease that affects the respiratory system and makes it difficult to breathe. Asthma symptoms, asthma attacks and high medication use have been found to increase in areas associated with both indoor and outdoor air quality.[xxiv] Having asthma and other related health issues can increase the sensitivity of individuals to air pollution levels.[xxv]

How we measured it: Asthma emergency department (ED) visits represent people with severe poorly managed asthma who visit an ED because of their asthma. The dataset was obtained from the California Office of Statewide Health Planning and Development, 2009, http://www.ehib.org/page.jsp?page_key=124. The data is available by zip code, and we used ArcGIS to assign the rates into census tracts. We converted zip code data to zip code tabulation areas (ZCTAs), and we intersected the ZCTAs with census tracts.

Limitations: It is important to note that this method yields a best estimation of the actual locations, due to the spatial transformations involved in converting zip code data to census tracts. It is also important to note that asthma hospitalizations have many causes beyond outdoor air pollution and should not be a proxy for air quality. Instead, asthma can be understood as a factor that can increase vulnerability to ambient air pollution.

Low Birth weight Rate

Why it is important: There are many maternal risk factors that may contribute to low birth weight including young age, multiple pregnancies, previous LBW infants, poor nutrition, heart disease or hypertension, drug addiction, alcohol abuse, amoking, and insufficient prenatal care.[xxvi] Environmental risk factors include smoking, lead exposure, and other types of air pollution.[xxvii] We included this variable in the index because it is a proxy for the presence of especially sensitive and vulnerable populations.

How we measured it: The dataset was obtained from the California Department of Public Health. We obtained three years of data and calculated an average for the years 2008-2010.

Limitations: The data is only available by zip code, and we used ArcGIS 10 to convert the zip code data to census tracts. It is important to note that this method yields a best estimation of the actual locations, due to the spatial transformations involved in converting zip code data to census tracts.

Constructing and Calculating the Indices

Cumulative Environmental Hazards Index (CEHI)

The CEHI is a relative measure of the environmental hazards in and around each census tract and scores each tract from 1 to 5. The higher the value, the more environmental hazards are within and/or around the census tract. The CEHI was calculated at the census tract level from the following six datasets: (1) pesticide application, (2) cumulative point-source pollution scores (3) Toxic Release Inventory sites from the RSEI model, (4) ozone, (5) impaired water bodies and (6) presence of contaminated drinking water. Each indicator was sorted and ranked from high (5) to low (1), roughly in quintiles. Census tracts that had no environmental hazards for that indicator were coded 1. We combined four pollution point sources into one indicator by ranking them separately, calculating a mean, and ranking them (1-5) across census tracts.

The formula for calculating CEHI is shown below. The CEHI is shown in Figure 1.

$$CEHI_i = \frac{\sum_{j=1}^{n} vij}{n}$$

Where $CEHI_i$ is the cumulative environmental hazard index score for census tract i;

vi_1 = Point Source Pollution Rank

vi_2 = Pesticides Rank

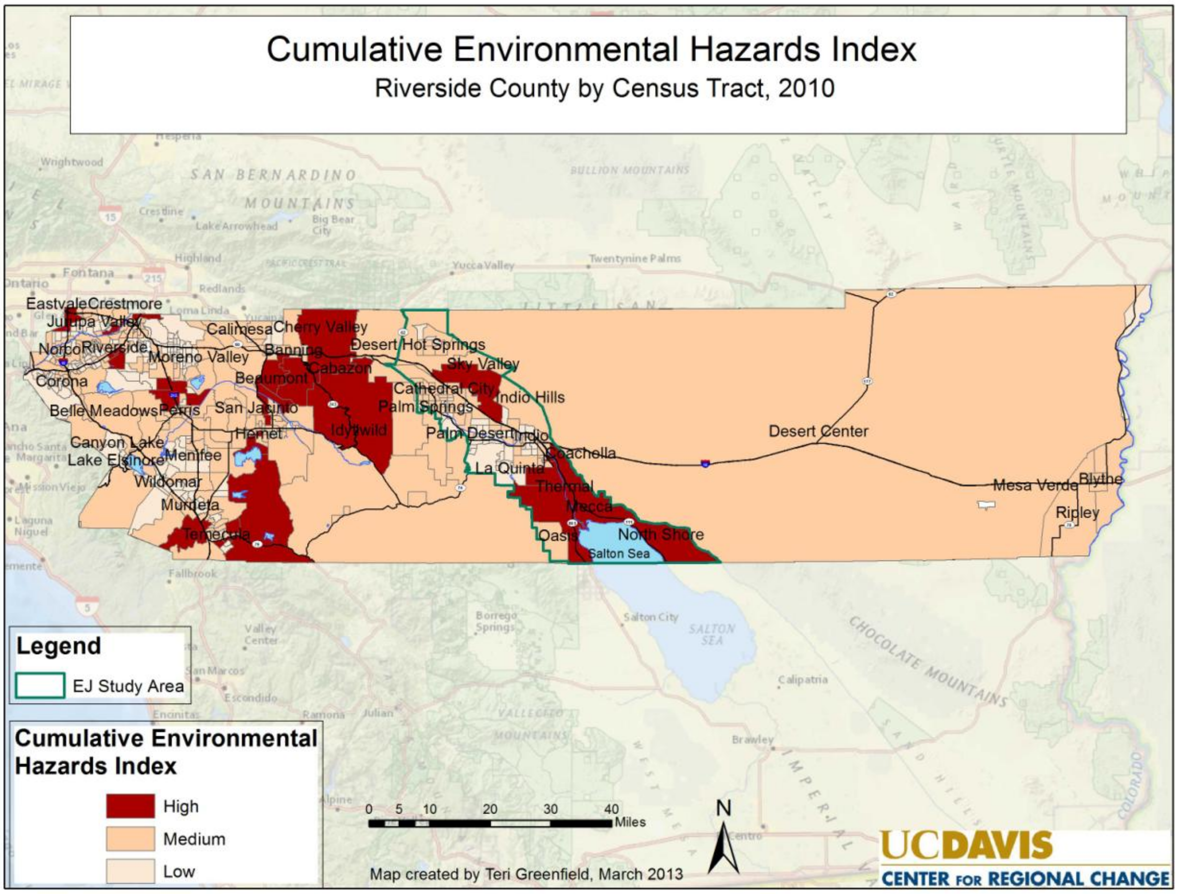
vi_3 = RSEI (Toxic Release Inventory Sites)

vi_4 = Ozone Rank

vi_5 = Impaired Water Body Rank

vi_6 = Presence of Water Contamination Rank

Figure 1: Riverside County Cumulative Environmental Hazards Index



Social Vulnerability Index (SVI)

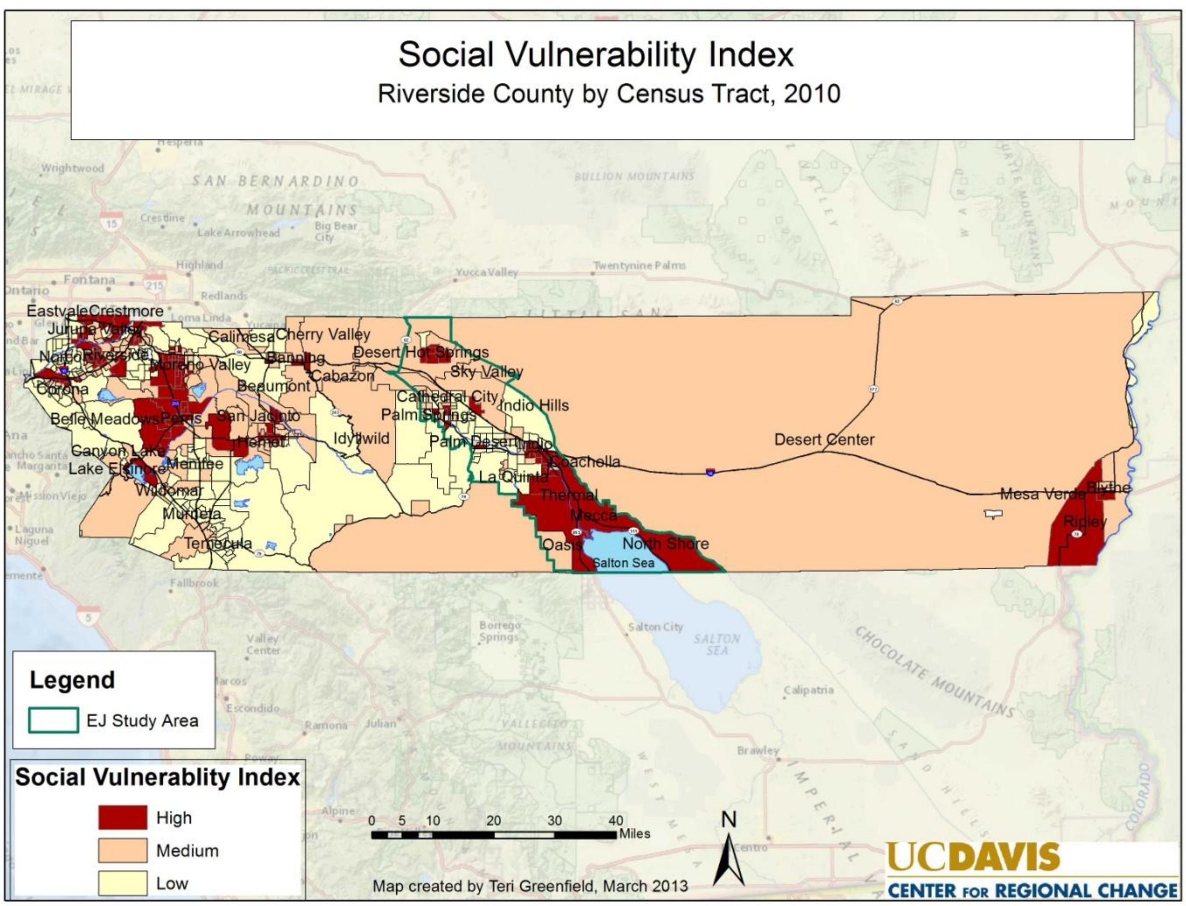
The SVI is a relative measure with values between 1 and 5. The higher the value, the more vulnerable the residents of a census tract are to environmental hazards. The Social Vulnerability Index (SVI) was calculated at the census tract level from the following datasets: (1) percent of people younger than 5 or older than 65 in a census tract, (2) percent living below 200% FPL, (3) percent of population of color, (4) percent of population older than 25 with no HS diploma, (5) percent who speak English “not very well”, (6) foster care entry rates, (7) percent of population unemployed who are 16 or older, civilian only, (8) percentage of renter and owner occupied units paying more than .5 of household income in housing costs, (9) percentage of owner and renter-occupied housing units with 1.01 or more occupants per room, and (10) a combined health index of low birth weight rate and age-adjusted asthma rates. Each indicator was sorted and ranked from high (5) to low (1), roughly in quintiles. We combined two pollution health indicators into one indicator by ranking them separately, calculating a mean, and ranking the means across census tracts.

The formula for calculating SVI is shown below. The SVI is shown in Figure 2.

$$SVI_i = \frac{\sum_{j=1}^{n} vij}{n}$$

Where SVI_i is the cumulative environmental hazard index score for census tract i;
vi_1 = ranking for percent of people younger than 5 or older than 65 in a census tract
vi_2 = ranking for percent living below 200% FPL rank
vi_3 = ranking for percent of population of color rank
vi_4 = ranking for percent of population older than 25 with no HS diploma rank
vi_5 = ranking for percent who speak English "not very well" rank
vi_6 = ranking for foster care entry rates rank
vi_7 = ranking for percent of population unemployed who are 16 or older, civilian only
vi_8 = ranking for percentage of renter and owner occupied units paying more than .5 of household income in housing costs
vi_9 = ranking for percentage of owner and renter-occupied housing units with 1.01 or more occupants per room
vi_{10} = ranking on a combined health index of low birth weight rate and age-adjusted asthma rates

Figure 2: Riverside County Cumulative Social Vulnerability Index



Calculating the CEVA

To create the CEVA, we used natural breaks to divide the CEHI and SVI into high, medium and low groups and determined the tracts that fell within each combination of SVI and CEHI. This resulted in 9 different combinations, such as "Low CEHI, Low SVI; Low CEHI, Medium SVI…" and so on. We gave each category a numeric value between 1 and 9. The CEVA map is based on these 9 values.

Table 7. Numeric values for each CEVA

7=High CEHI, Low SVI	8= High CEHI, Medium SVI	9= High CEHI, High SVI
4=Medium CEHI, Low SVI	5= Medium CEHI, Medium SVI	6= Medium CEHI, High SVI
1=Low CEHI, Low SVI	2=Low CEHI, Medium SVI	3=Low CEHI, High SVI

Each cell in Table 8 includes the mean of the CEHI and SVI, the 95% confidence intervals, and number of census tracts represented in each category. The CEVAZ are the three categories in the upper left set of cells: those with medium and/or high SVI and CEHI. These colors match those used to map the CEVAZ across the county.

Table 8. Descriptive Statistics for Cumulative Environmental Vulnerability Assessment

CEHI ↑			
	Low SVI/High CEHI Mean CEHI: 3.17 (2.93, 3.4) Mean SVI: 2.10 (1.85, 2.35) Census Tracts = 8	**Medium SVI /High CEHI** Mean CEHI: 3.19 (3.01, 3.56) Mean SVI: 3.18 (2.97, 3.39) Census Tracts = 10	**High SVI /High CEHI** Mean CEHI: 3.23 (3.05, 3.40) Mean SVI: 4.00 (3.82, 4.18) Census Tracts = 11
	Low SVI/Medium CEHI Mean CEHI: 2.30 (2.23, 2.34) Mean SVI: 2.16 (2.09, 2.23) Census Tracts = 61	**Medium SVI/Medium CEHI** Mean CEHI: 2.33 (2.27, 2.38) Mean SVI: 3.13 (3.07, 3.19) Census Tracts =89	**High SVI /Medium CEHI** Mean CEHI: 2.28 (2.21, 2.34) Mean SVI: 4.09 (4.02, 4.17) Census Tracts = 66
	Low SVI/Low CEHI Mean CEHI: 1.56 1.52 1.60) Mean SVI: 2.10 (2.04, 2.16) Census Tracts = 97	**Medium SVI/Low CEHI** Mean CEHI: 1.56 (1.51, 1.62) Mean SVI: 3.08 (3.00, 3.15) Census Tracts = 57	**High SVI /Low CEHI** Mean CEHI: 1.59 (1.54, 1.65) Mean SVI: 4.09 (4.01, 4.17) Census Tracts =52
	SVI →		

Scales for CEHI and SVI range from 0 to 5. Each cell includes the mean, 95% confidence interval in parentheses and number of census tracts represented in each category.

Limitations and Innovations

The Cumulative Environmental Vulnerability Index is not an assessment of actual exposures to pollution measures and it is not a health risk assessment. It should be understood to be a screening method, helping to identify places that have higher levels of vulnerability to environmental hazards. It also has many of the same limitations that other multi-indicator indices have.[xxviii]

First, it is only as accurate as the available datasets. We used publically available data that was available spatially, and wherever possible, at the scale we selected for our unit of analysis (census tract). However, each dataset has its own limitations, discussed earlier in this document. Second, as with any multi-indicator index, a composite score is created by combining multiple variables. A high score on one variable and low score on another variable could result in the same score as a tract with opposite scores on the same variables. To see the indicators mapped individually (forthcoming), please see http://mappingregionalchange.ucdavis.edu/ Third, it does not provide indicators for many outcomes related to health (such as premature death), due to the lack of quality data. A local survey to collect health data is planned, and will result in a more accurate representation of the health issues in the study area.

In this study, we built on many of the methods we first developed studying the San Joaquin Valley and presented in the 2011 report: Land of Risk, Land of Opportunity. See: http://regionalchange.ucdavis.edu/ourwork/projects/ceva-sjv.

With the addition of water quality data, the enhanced selection of pesticides and a system of scoring of pollution sources, we are moving toward a better assessment of environmental risk in California's communities. In this study, we were able to link chemical test results from the Water Quality Management System to the sources from which they were collected. Future studies are needed to accurately map the communities served by each water system. We will continue to refine our approach to water, but the results could be vastly improved when state and local municipalities can provide accurate spatial boundaries for water systems. This will be critical to understanding where the drinking water is actually flowing, how contaminated it is, and who is drinking it.

When developing the pesticides indicator, we recognized that it is important to address issues of toxicity and potential exposure, more than simply the quantities applied. We drew on promising practices from the field, such as the CalEnviroScreen being developed by CalEPA/ OEHHA and other experts in developing an indicator that includes only those most likely to cause harm to humans. We also used a method that assigns a spatially-weighted average to assign the pesticide data to census tracts based on what percentage of the tract was within the range of where the pesticides were applied. We believe this will result in a better representation of the potential exposures.

Pollution source data can now be obtained relatively easily, and interactive mapping sites are becoming common and accessible to the public. However, it is difficult sifting through the vast quantity of datasets that are often duplicated, and to determine the relative impact of each pollution source in a dataset. Our CEVA method contributes to addressing this difficulty by weighting the type of sources and the multiple occurrences of points in the same census tract and mapping these together with a robust measure of social vulnerability.

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