Technical Report on Ozone Exposure, Risk, and Impact Assessments for Vegetation

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Technical Report on Ozone Exposure, Risk, and Impact Assessments for Vegetation

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Introduction

During the last review of the secondary ozone (O_3) NAAQS, as part of the development of the 1996 O_3 Staff Paper (SP), EPA conducted analyses that assessed national O_3 air quality, vegetation exposures and risk, and impacts to economic benefits. At the time of the last review, large rural sections of the country had little or no monitor coverage, including important growing regions for agricultural crops and forested ecosystems. Since O_3 monitor coverage in agricultural and rural/remote sites has changed little since the last review, EPA must again rely on generated O_3 air quality information in non-monitored areas to provide national O_3 exposure coverage. Given a number of recent air quality related developments, EPA has decided to use a different method to generate a national exposure surface in this review.

In this report we present analyses of national O_3 air quality, vegetation exposures and risk, and impact to economic benefits that incorporates improved methods for estimating O_3 at unmonitored locations. We present quantitative evaluations of these new methods and an application of several such methods to improve upon the results of the 1996 analysis. Ultimately, our purpose is to evaluate the economic benefits associated with several alternative O_3 standards currently under consideration.

The organization of the report is as follows:

Section 1 defines the O_3 metrics used in this report

Section 2 describes the data used to produce this analysis

Section 3 describes the methods considered for estimating O_3 at unmonitored locations; presents an evaluation of these methods; and describes the generation of the Potential O_3 Exposure Surface (POES) under a method chosen from the options considered.

Section 4 presents the methods and results of the “rollback” procedure, which estimates hypothetical air quality under several air quality standards that are currently being considered. It presents descriptive statistics for all air quality scenarios (alternative scenarios as well as current air quality as given by the POES).

Section 5 presents the methods and results of crop yield and tree seedling biomass loss estimates under each air quality scenario.

Section 6 presents the methods and results of the evaluation of impacts to economic benefits.

Section 7 discusses the impacts on mature tree growth of just meeting various alternative O_3 standards.

1. Definition of O_3 Metrics

To quantify the overall O_3 levels for a given time period, we used three O_3 metrics, namely maximum 8-hour average, 12-hour SUM06, and 12-hour W126. These can be calculated on the daily-level (e.g. "daily maximum 8-hour average") as well as on the yearly-level (e.g. "annual 4th highest daily maximum 8-hour average").

We define each of these metrics below. Since O_3 monitor data often contains missing values, criteria are given to determine if sufficient data exists to generate a valid metric. In certain cases, a valid metric can be generated, but its value must be adjusted to compensate for missing values.

1.1 Daily SUM06 and Annual Maximum 3-Month SUM06

The daily SUM06 metric is the sum of all O_3 values greater than or equal to 0.06 parts per million (ppm) observed from 8am-8pm. In order for a day to have a valid SUM06 value, 75 percent of the hours from 8am-8pm must be valid. To adjust for missing hourly O_3 values, we scale SUM06 by the ratio of (number of possible hourly O_3 values) / (number of valid hourly O_3 values)[c].

The yearly SUM06 metric is the "annual maximum 3-month SUM06." To compute it, we calculate the sum of all daily SUM06 values over all possible 3-month periods. To adjust for missing days, we scale each monthly SUM06 value by the ratio of (number of days in the month) / (number of valid days)[d]. The greatest of these 3-month SUM06 values is the annual maximum 3-month SUM06. In order for a 3-month period to have a valid "3-month SUM06" value, each month in the 3-month period must have at least 75 percent valid days. In order for a year to have a valid yearly SUM06 value (annual maximum 3-month SUM06), it must have at least one 3-month period with a valid 3-month SUM06 value.

1.2 Daily Maximum 8-hour Average and Annual 4th Highest Daily Maximum 8-hour Average

The daily maximum 8-hour average is calculated from rolling 8-hour averages of hourly O_3 data, where a valid 8-hour average must have 75 percent of a potential of eight hours in any given 8-hour period (i.e., at least six hours out of eight)[e]. The daily maximum 8-hour average is the greatest of the day's 8-hour averages. For a daily maximum 8-hour average to be considered valid, the day must have at least 75 percent of the potential 8-hour averages (i.e., 18 out of a potential of 24)[f].

The yearly metric associated with the 8-hour maximum is the annual 4th highest daily maximum 8-hour average. This is defined to be the 4th highest value amongst all of the valid daily 8-hour maximums throughout the year. The value is truncated at the ppb level. Thus if the 4th highest value is 84.378 ppb, the official value of the annual metric is actually 84 ppb.

1.3 Daily W126 and Annual Maximum 3-month 12-hour W126

The daily W126 metric is a *weighted* sum of all O_3 values observed from 8am-8pm. More formally, daily W126 is defined as:

$$W126 = \sum_{i=8AM}^{i<8PM} w_{C_i} C_i, \qquad \textbf{eq. (1)}$$

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[c] To simplify calculations for the annual SUM06 metric, we have in certain cases waited until the monthly level to make this adjustment.

[d] If the appropriate scaling factor was not applied at the daily level, we would scale by (number of possible hourly O_3 values in the month) / (number of valid hourly O_3 values in the month). See previous footnote for details.

[e] When there are six or seven hours in any given 8-hour period, we sum the available hourly measurements and then divide by the number of available measurements (as opposed to always dividing by eight).

[f] There are 24 possible 8-hour measurements in a day, starting with 12:00 midnight to 7:59 am, and going through 11:00 pm to 6:59pm. This allows 8-hour measurements to straddle days, following the approach in the Federal Register (40 CFR, Part 58). We consider an 8-hour measurement to be part of a day if it starts during that day. So 11pm[day1]-6am[day2] is part of day1.

$$where\ C_i = hourly\ ozone\ concentration\ at\ hour\ i, \quad and\ w_{C_i} = \frac{1}{1+4403e^{-126C_i}}$$

The following figure shows the relationship between O_3 concentration and weighting under W126, and the equivalent weighting scheme for SUM06. Note that while SUM06 uses an all-or-nothing threshold, W126 gradually increases the weight of O_3 values as they grow in magnitude:

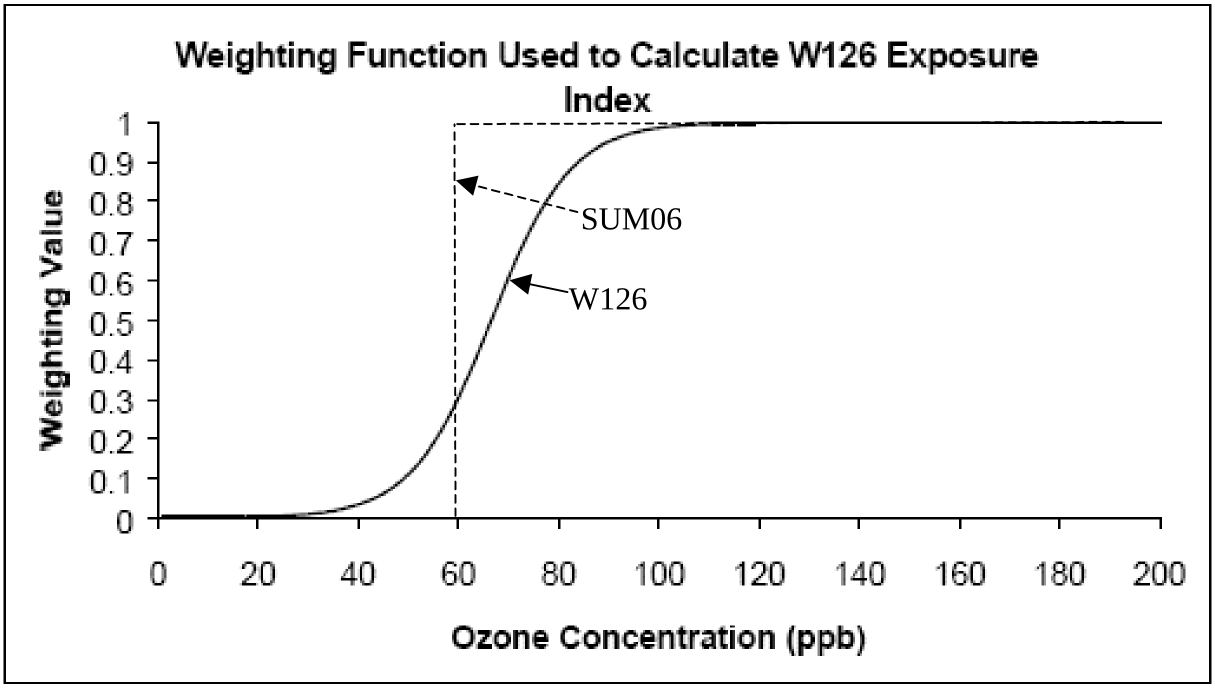

Figure 1-1: Weighting Function Used to Calculate W126 Exposure Index (SUM06 weighting shown in dotted line)[g]

In order for a day to have a valid W126 value, 75 percent of the hours from 8am-8pm must be valid. Daily W126 values are scaled to account for missing observations in the same fashion as daily SUM06 values.

Annual Maximum 3-month W126 is defined similarly to Annual Maximum 3-month SUM06. Namely it is the sum of daily W126 values from the 3-month period which yields the highest such sum. Validity criteria and scaling procedures for missing values are the same as those given for SUM06.

1.4 Terminology

To simplify the discussions that follow, we will use the generic term for a given metric (e.g. SUM06) to refer to the annual statistic (e.g. Annual maximum 3-month 12-hour SUM06). When referring to daily statistics, we will always preface the generic name with the word “daily” (e.g. daily SUM06, etc.).

[g] Lefohn A. S., J.A. Laurence, and R.J. Kohut. 1988. A comparison of indices that describe the relationship between exposure to O_3 and reduction in the yield of agricultural crops. Atmospheric Environment 22:1229-1240.

2. Input Data

2.1 Monitor Data

The monitor data used in this analysis was taken from the Air Quality System (AQS) and Clean Air Status and Trends Network (CASTNet) for the year 2001. AQS O_3 data was taken from the file *RD_501_44201_2001.zip*, and information on the monitors was taken from the file *AMP500_1994_FEB05.zip*. Both are available at http://www.epa.gov/ttn/airs/airsaqs/detaildata/downloadaqsdata.htm .

CASTNet O_3 data was taken from http://ww.epa.gov/camdis01/prepack/ozone_2001.zip , and information on CASTNet monitors can be found at http://cfpub.epa.gov/gdm/index.cfm .

Our initial monitor data set was comprised of hourly readings from 1194 monitors distributed across the US.

Completeness Criteria

Data from a given monitor was used only if the monitor was deemed "complete," i.e., if it had valid O_3 values for at least 50 percent[h] of the hours during its region's O_3 season. Note that O_3 seasons vary by geography and range from year-round (in California) to periods as short as June-September (Montana). In all states except Texas, O_3 regions follow state boundaries. Texas is unique in that it contains parts of 2 different O_3 regions, each with its own O_3 season. To simplify matters, we have applied the shorter of these seasons to the entirety of Texas. Out of an initial set of 1194 monitors, 1192 qualify as complete. At the recommendation of the EPA Work Assignment Contracting Officer's Representative (WACOR), an additional 77 downtown urban monitors were not included in the analysis to minimize the impact of inner-city O_3 depletion caused by NOx scavenging.[i]. Several additional exclusions were made for computational purposes[j].

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[h] For example, if the O_3 season were May-September, then a valid monitor would have to have at least 1,836 hourly observations out of a potential total of 3762 (= 153 days x 24 hours). Out of 1,194 monitors, all but two of them have at least 50 percent valid readings during their O_3 season. We considered raising this threshold to 75 percent. This would eliminate an additional 79 monitors, leaving about 93 percent of the original monitors remaining. In the end, we chose to keep the threshold at 50% to maximize the number of useable monitors.

[i] The following urban monitors were eliminated (given by monitor id = statecode, countycode, siteid, POC): 550790041, 550790026, 515100009, 510130020, 484391002, 483550025, 482011037, 482011035, 482011034, 482010075, 482010070, 481410055, 481410044, 481410037, 481130069, 470370011, 420450002, 420030010, 410052002, 390610040, 360810124, 360810098, 360810097, 360610063, 360610010, 360050083, 350010023, 340170006, 340130016, 320310016, 320032002, 320030021, 320030016, 295100072, 261630016, 250250042, 220330009, 220330003, 201730010, 180970057, 180890022, 170311003, 170310072, 170310042, 170310032, 110010043, 110010041, 110010025, 060950004, 060850004, 060831008, 060750005, 060731007, 060670010, 060591003, 060410001, 060375001, 060374002, 060371301, 060371103, 060371002, 060370113, 060370030, 060290014, 060290010, 060170020, 060133001, 060131003, 060090001, 060010005, 051190007, 040190002, 040139997, 040134005, 040134003, 040133002, 010730023.

[j]Three monitors were excluded because they were co-located with other monitors (i.e., had identical latitude and longitude values). The monitors kept were those with the highest POC codes. While this is not ideal, we believe the effect in a pool of over 1000 monitors to be negligible. Additionally, changes had to be made to account for single monitors whose data was used in both AQS and CASTNet databases (under different identifiers). For the sake of evaluating O_3 prediction approaches (see p 3-4), we eliminated AQS data from drawn from the same monitors that supplied CASTNet data. (Leaving both "twin monitors" present would cause there to be nearly perfect predictions

2.2 Model Data

We used two CMAQ modeling datasets, one with a resolution of 12km x 12km, the other with a resolution of 36km x 36km. The 12-km CMAQ grid consists of 188 x 213 cells covering the Eastern U.S. (bounded approximately on the west by the 99 line of longitude) excluding the northernmost parts of Maine, Wisconsin, Minnesota, and South Dakota, and the southernmost parts of Florida and eastern Texas. The 36-km CMAQ grid consists of 112 x 148 cells covering the entire continental US. Each dataset gives hourly O_3 values for each cell[k].

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made for those monitors, skewing the analysis). These monitors were still used in generating the POES (See p. 3-1). While not ideal, their effect in generating the POES is not nearly as pernicious as their effect in the evaluation phase.

[k] All of the CMAQ data was provided by EPA in netCDF (Network Common Data Form) format. Steve Howard from EPA provided a program to convert from netCDF to text.

3. Generating a National Potential O_3 Exposure Surface (POES)

3.1 Composite CMAQ Grid

To generate a national Potential O_3 Exposure Surface (POES) we needed a set of geographical locations for which O_3 data would be generated. Ideally, these locations would be regularly spaced, cover the continental U.S., and be close enough to each other to provide a good spatial resolution. We chose to use the regularly spaced grid structure of the CMAQ data as a basis for these locations. Specifically, we generated O_3 values for the center of each grid cell in the 12km x 12km grid (which covers only the Eastern U.S.), and for those grid cells in the 36km x 36km grid whose centers fell within the boundaries of the continental U.S., but did not fall within a 12km x 12km grid cell. In this fashion, we produced the densest possible grid of CMAQ grid cell centers which provides non-redundant coverage of the continental U.S.

3.2 Interpolation Approaches

A number of approaches for generating the POES were considered and evaluated. All were variations on two techniques –Voronoi Neighbor Averaging (VNA) and Enhanced Voronoi Neighbor Averaging (eVNA). The former is based only on monitor data, and the latter uses both monitoring and CMAQ modeling data.

We examined 8 variants of eVNA, as well as 2 standard VNA approaches and several eVNA / VNA blends. Based on their relative strengths in predicting known O_3 values, we chose to use a VNA interpolation approach in the East, and a blend of VNA and eVNA in the West. The remainder of this section describes in detail all approaches considered. Section 3.3 presents a quantitative evaluation of these approaches.

3.2.1 Voronoi Neighbor Averaging (VNA)

VNA uses distance-weighted averages of neighboring monitor data to arrive at predictions for a pre-determined non-monitored site (in our case, the center of a CMAQ modeling grid cell). VNA identifies neighboring monitors for each such site using a Voronoi Neighbor Algorithm (see Appendix C), and takes an inverse-distance-weighted average of each neighbor's value for the data point in question (hourly O_3 value, daily metric, etc) to arrive at a prediction for that data point corresponding to the non-monitored site in question.

3.2.2 Enhanced Voronoi Neighbor Averaging (eVNA)

The eVNA approach attempts to improve the accuracy of VNA predictions by taking into consideration modeling predictions for the areas involved. To illustrate the rationale behind eVNA, we consider a simple fictional example.

Suppose we wish to predict the O_3 level at a hypothetical monitor at location X for a given hour. Location X has two equidistant neighboring monitors, monitor A and monitor B. Monitor A reports 32 ppb, and monitor B reports 20 ppb. A simple VNA approach would calculate the O_3 at location X to be 26 ppb (the average of 32 and 20, with equal weights given to the two equidistant neighbors).
Suppose, however, that CMAQ modeling data shows O_3 levels at location X to be about twice that of O_3 levels at either location A or location B. For example, suppose the average CMAQ O_3 values for locations

A and B are 15 ppb, whereas average CMAQ O_3 values for location X are 30 ppb. If CMAQ accurately captures the relationship between locations A, B, and X, then we would expect the O_3 value to be twice as high at X, compared to A and B. That is we would expect a value closer to 52 ppb - the weighted-distance average of 2*32 ppb and 2*20 ppb. The eVNA technique formalizes this technique over large and more complicated sets of data.

Unlike VNA, which averages the "raw" monitor predictions, eVNA first "adjusts" the individual monitor predictions, multiplying by an adjustment factor that reflects the relationship between the neighbor's and the hypothetical monitor location's O_3 levels, as determined by modeling data. For example, if the modeling data suggested that O_3 levels at neighbor A were generally twice as high as at location X, and that O_3 levels at neighbor B were generally half as high as at location X, we would multiply neighbor A's O_3 value by 0.5 and multiply neighbor B's O_3 value by 2 before proceeding to take a distance weighted average over the two neighbors.

3.2.3 Four Types of Condition-Specific Adjustment Factors

The eVNA approach, as we have described it thus far, is imperfect in that it assumes the O_3-level relationship between two locations to be constant throughout the year. In fact, the relationship may vary with the season, or with the time of day, or with numerous other factors. To take this into account, we have added an additional layer of complexity. Rather than condensing a year's worth of model data into a single relationship between the O_3 levels of two locations (and thus a single adjustment factor for each neighbor-"grid cell center" pair), we determine the relationship for a number of different conditions. This allows us to tailor our adjustments to the conditions at hand; if we are adjusting a monitor value in January, we can use an adjustment factor that specifically reflects the modeled relationship between the locations at hand *during the month of January*. Similarly, if we are adjusting an O_3 value that is particularly high, we can use an adjustment factor that describes the general modeled relationship between the locations in question *when O_3 levels are high*.

One can imagine many such ways to divide the data into subsets that reflect the particular conditions of the data in question. We have chosen four such divisions, herein referred to as "conditions", which we outline below. Each condition represents a separate and distinct effort to generate an O_3 surface; i.e. each of these four conditions can each be applied separately to the data to yield a different set of O_3 predictions.

Month-Decile

We first sort CMAQ modeled hourly values into 12 groups by month. In each month-group we split evenly the ordered hourly values into ten rank-ordered deciles. This gives us 120 groups of hourly O_3 values (for every CMAQ grid cell). We calculate the average of the hourly values in each gridcell-month-decile combination, and use this average as the "representative value" of that CMAQ grid cell for that month-decile. In order to adjust a neighboring monitor value to reflect the modeled relationship to the unmonitored or dropout site (a "dropout site" is monitored location for which we compute predictions based on neighboring monitors so as to compare predicted data to actual data), the appropriate month-decile adjustment factor must be used. For example, to adjust a monitor value that falls into the 10^{th} decile of January monitor values, we multiply by the ratio of [the representative value of the dropout's gridcell for the 10^{th} decile of January] over [the representative value of the neighbor's gridcell for the 10^{th} decile of January].

adjusted monitor value =

$$monitor\_value_{neighbor} * \frac{representativeCMAQ_{dropout\_gridcell,month,decile}}{representativeCMAQ_{neighbor\_gridcell,month,decile}} \quad \textbf{eq. (2)}$$

Season-Decile

We first sort CMAQ modeled hourly values into four groups by season (Jan-Mar, Apr-Jun, July-Sep, Oct-Dec). In each season-group we split evenly the ordered hourly values into ten rank-ordered deciles. This gives us 40 groups of hourly O_3 values (for every CMAQ grid cell). We calculate the average of the hourly values in each gridcell-season-decile combination, and use this average as the representative value of that CMAQ gridcell for that season-decile. In order to adjust a neighboring monitor value to reflect the modeled relationship to the unmonitored or dropout site, the appropriate season-decile adjustment factor must be used. For example, to adjust a monitor value that falls into the 10^{th} decile of the Jan-Mar monitor values, we multiply by the ratio of [the representative value of the dropout's modeled O_3 data for the 10^{th} decile of Jan-Mar] over [the representative value of the neighbor's modeled O_3 data for the 10^{th} decile of Jan-March].

Month-Hour

We first sort CMAQ modeled hourly values into 12 groups by month. In each month-group we split evenly the ordered hourly values into 24 groups by time of day. This gives us 288 groups of hourly O_3 values (for every CMAQ grid cell). We calculate the average of the hourly values in each gridcell-month-hour combination, and use this average as the representative value of that CMAQ grid cell for that month-hour. In order to adjust a neighboring monitor value to reflect the modeled relationship to the unmonitored or dropout site, the appropriate month-hour adjustment factor must be used. For example, to adjust a monitor value from 9am in the month of January, we multiply by the ratio of [the representative value of the dropout's gridcell for the 9am hour in January] over [the representative value of the neighbor's gridcell for the 9am hour in January].

Season-Hour

We first sort CMAQ modeled hourly values into four groups by season. In each season-group we split evenly the ordered hourly values into 24 groups by time of day. This gives us 96 groups of hourly O_3 values (for every CMAQ grid cell). We calculate the average of the hourly values in each gridcell-season-hour combination, and use this average as the representative value of that CMAQ grid cell for that month-hour. In order to adjust a neighboring monitor value to reflect the modeled relationship to the unmonitored or dropout site, the appropriate season-hour adjustment factor must be used. For example, to adjust a monitor value from 9am in the Jan-Mar season, we multiply by the ratio of [the representative value of the dropout's gridcell for the 9am hour in the Jan-Mar season] over [the representative value of the neighbor's gridcell for the 9am hour in the Jan-Mar season].

3.2.4 Interpolating Hourly Data vs. Metrics

So far we have been speaking only of interpolating *hourly* O_3 values from neighbor sites to a dropout location. In principle, the exact same techniques can be used to interpolate daily (or even annual) metrics from neighbors to dropout.

For example, suppose we had a day's worth of hourly O_3 values for monitor A and monitor B. We wanted to predict the daily SUM06 value for location X, situated at the midpoint between monitors A and B. We have two options. We can use eVNA to generate *hourly* O_3 predictions for location X, then calculate the daily SUM06 from these hourly predictions. Alternately, we can calculate daily SUM06 at each of the neighbor sites, and then interpolate *daily* SUM06 values using eVNA.
We examine both of these methods. For each of the four eVNA conditions outlined above, we generate a set of predictions based on interpolating hourly O_3 values, and a set of predictions based on interpolating daily metrics.

To interpolate daily metrics, we class hourly data according to some condition (month-decile, month-hour, season-decile, season-hour). As with hourly-techniques, we adjust neighboring monitor values at the hourly level (scale by a ratio of representative CMAQ values). However, before taking a distance-weighted average over the set of neighbors, we compute daily metrics (SUM06 and 8-hour maximum average) from the adjusted hourly neighbor data. These metrics are then distance-weight averaged to produce daily metric predictions at the dropout site.

3.2.5 Summary of Approaches

The variations listed above make up the following 10 interpolation approaches for consideration:

Table 3-1: Interpolation Approaches Considered

	Traits		
Name	Technique: VNA or eVNA	Condition?	What gets interpolated?
1. Hour-VNA	VNA	N/A	Hour
2. Metric-VNA			Metric
3. Hour-Month-Decile	eVNA	Month-Decile	Hour
4. Metric-Month-Decile			Metric
5. Hour-Month-Hour		Month-Hour	Hour
6. Metric-Month-Hour			Metric
7. Hour-Season-Decile		Season-Decile	Hour
8. Metric-Season-Decile			Metric
9. Hour-Season-Hour		Season-Hour	Hour
10. Metric-Season-Hour			Metric

For the sake of comparison, we also examine the performance of the CMAQ modeling data.

3.3 Evaluation of Interpolation Approaches

A previous investigation tested the predictive power of these ten approaches by comparing predictions for 53 monitored U.S. sites (referred to as “dropouts”; data from these sites were not used in the generation of predictions) to the actual O_3 data from those sites. These data were split into an Eastern and Western region approximately at the -99th line of longitude[1]. This split was made to capture the effects of the West’s sparse monitor coverage. The following results were generated:

Table 3-2: Results from Previous Investigation: Eastern U.S. (41 locations)

Adjustment Method	What gets interpolated	SUM06 Bias	SUM06 Error	8-Hour Bias	8-Hour Error
model-predictions		37.59	69.22	-6.72	9.26
VNA (no adjustment)	Hour	4.18	32.61	-2.42	6.23
VNA (no adjustment)	Metric	116.69	118.89	-1.37	5.86
month-decile	Hour	-4.67	27.60	-3.09	6.09
month-hour	Hour	10.31	36.31	-0.64	6.17
season-decile	Hour	-5.09	27.02	-3.14	5.92
season-hour	Hour	14.33	39.05	-0.70	6.30
month-decile	Metric	108.47	111.35	-1.96	5.80
month-hour	Metric	115.06	117.02	1.33	7.02
season-decile	Metric	109.30	111.98	-1.86	5.73

[1] The Eastern region ends at the edge of the 12km x 12km CMAQ grid. The Western region begins at longitude –99.503. Since the 12km x 12km CMAQ grid is not exactly parallel to lines of longitude, there is a small wedge of overlap between these two regions. The entire continental US is covered either by the Western grid, by the Eastern grid, or in a few cases by both.

season-hour	Metric	115.11	117.08	1.18	6.93

Table 3-3: Results from Previous Investigation: Western U.S. (12 locations)

Adjustment Method	What gets interpolated	SUM06 Bias	SUM06 Error	8-hour Bias	8-hour Error
model-predictions		143.03	149.98	22.23	22.81
VNA (no adjustments)	Hour	-10.91	83.23	3.00	12.68
VNA (no adjustments)	Metric	203.76	203.76	4.77	12.65
month-decile	Hour	-18.97	73.49	1.95	11.78
month-hour	Hour	-17.11	73.40	4.50	13.47
season-decile	Hour	-19.50	71.62	1.69	12.03
season-hour	Hour	-15.53	71.64	3.83	13.10
month-decile	Metric	163.44	163.44	3.92	13.03
month-hour	Metric	161.56	164.58	7.87	13.98
season-decile	Metric	154.73	155.54	3.64	12.49
season-hour	Metric	160.90	162.65	7.44	13.86

In these tables, bias and error refer to normalized mean bias and normalized mean error, which are defined as follows:

$$SUM06\ normalized\ \ mean\ bias = average_{i \in dropouts}(100 * \frac{predictedSUM06_i - actualSUM06_i}{actualSUM06_i}) \quad \textbf{eq. (3)}$$

$$SUM06\ normalized\ \ mean\ error = average_{i \in dropouts}(100 * \frac{\left|predictedSUM06_i - actualSUM06_i\right|}{actualSUM06_i}) \quad \textbf{eq. (4)}$$

and likewise for the 8-hour statistic. The greater the error, the less accurate the approach is on average. The bias indicates whether there is a tendency to overpredict or underpredict and if so by how much. A negative bias indicates underprediction and a positive bias indicates overprediction.

The full memorandum describing this previous work was delivered to U.S. EPA by Abt Associates on April 12th 2006 and can be found in Appendix K. Based on these results, we chose to examine the hour-month-decile and hour-month-hour approaches in more detail.

As in the previous investigation, we divided the country into an Eastern region and a Western region. This time, however, we examined the performance of these approaches at predicting the values of *all* of the O_3 monitors within the region in question. We also analyzed performance in terms of the W126 metric, which had not been examined in the previous investigation.

In addition to evaluating the hour-month-decile and hour-month-hour approaches, we evaluated several VNA – eVNA blends. These approaches adjust monitor values according to the eVNA technique for distant neighbors but leave nearby neighbor values unadjusted. The technique is based on the observation that VNA outperforms eVNA at close range, but eVNA outperforms VNA at longer ranges (see Appendix K for full details of the investigation).

The following results were generated[m]:

Table 3-4: Results from Current Investigation: Eastern US: 8-hour Maximum (approx 800 locations)

Interpolation	*Measure*	*Count*	*Mean*	*Median*	*Min*	*Max*	*Range*	*STD*
CMAQ	Bias	790	-7.22	-7.19	-37.61	19.09	45.83	7.74
	Error	790	8.75	7.79	0.08	37.61	37.54	5.96
	Norm. Bias	790	-8.0%	-8.9%	-34.0%	36.9%	66.4%	9.0%
	Norm. Error	790	10.2%	9.6%	0.1%	36.9%	36.8%	6.4%
HMD	Bias	790	-2.53	-2.71	-25.80	32.77	54.96	6.19
	Error	790	5.05	3.96	0.01	32.77	32.75	4.39
	Norm. Bias	790	-2.7%	-3.2%	-27.5%	52.6%	77.1%	7.6%
	Norm. Error	790	6.0%	4.7%	0.0%	52.6%	52.6%	5.3%
HMD_VNA_100	Bias	790	-2.88	-2.90	-26.82	28.09	46.41	5.62
	Error	790	4.91	4.04	0.03	28.09	28.05	3.97
	Norm. Bias	790	-3.1%	-3.5%	-24.8%	47.8%	67.9%	6.8%
	Norm. Error	790	5.8%	4.8%	0.0%	47.8%	47.7%	4.7%
HMD_VNA_50	Bias	790	-2.82	-2.88	-26.82	28.09	46.41	5.67
	Error	790	4.88	4.00	0.01	28.09	28.05	4.03
	Norm. Bias	790	-3.0%	-3.5%	-24.8%	49.5%	69.6%	6.9%
	Norm. Error	790	5.8%	4.8%	0.0%	49.5%	49.4%	4.8%
HMH	Bias	790	-1.58	-1.78	-29.34	58.13	81.22	7.54
	Error	790	5.46	3.93	0.00	58.13	58.13	5.44
	Norm. Bias	790	-1.5%	-2.1%	-34.7%	69.3%	94.7%	9.2%
	Norm. Error	790	6.6%	4.8%	0.0%	69.3%	69.3%	6.6%
HMH_VNA_100	Bias	790	-2.79	-2.85	-26.72	28.09	46.41	5.66
	Error	790	4.89	4.04	0.02	28.09	28.05	4.00
	Norm. Bias	790	-3.0%	-3.5%	-24.7%	47.3%	67.5%	6.9%
	Norm. Error	790	5.8%	4.8%	0.0%	47.3%	47.3%	4.8%
HMH_VNA_50	Bias	790	-2.57	-2.73	-26.72	28.09	46.41	5.84
	Error	790	4.88	4.01	0.00	28.09	28.09	4.11
	Norm. Bias	790	-2.7%	-3.3%	-25.9%	47.7%	67.9%	7.1%
	Norm. Error	790	5.8%	4.8%	0.0%	47.7%	47.7%	4.9%
VNA	Bias	790	-2.91	-3.00	-18.32	28.09	46.41	5.71
	Error	790	4.95	4.02	0.04	28.09	28.05	4.07
	Norm. Bias	790	-3.1%	-3.6%	-20.2%	47.3%	67.4%	6.9%
	Norm. Error	790	5.9%	4.8%	0.0%	47.3%	47.2%	4.8%

[m] These results are slightly different than in previous drafts of this report. This is due to the removal of "twin monitors" – see footnote j on page 2-1.

Table 3-5: Results from Current Investigation: Eastern US: SUM06 (approx 800 locations)

Interpolation	*Measure*	*Count*	*Mean*	*Median*	*Min*	*Max*	*Range*	*STD*
CMAQ	Bias	786	-1.70	-1.99	-26.70	26.18	48.90	6.99
	Error	786	5.66	4.83	0.00	26.70	26.70	4.44
	Norm. Bias	786	15.7%	-9.6%	-90.5%	4396.0%	4486.5%	193.8%
	Norm. Error	786	45.4%	23.4%	0.0%	4396.0%	4396.0%	189.1%
HMD	Bias	786	-1.46	-1.40	-24.00	23.56	45.50	5.91
	Error	786	4.61	3.68	0.00	24.00	23.99	3.97
	Norm. Bias	786	1.2%	-7.4%	-92.2%	1199.7%	1277.0%	63.0%
	Norm. Error	786	28.6%	19.0%	0.0%	1199.7%	1199.7%	56.2%
HMD_VNA_100	Bias	786	-1.85	-1.66	-22.58	23.05	40.27	5.09
	Error	786	4.14	3.21	0.00	23.05	23.05	3.49
	Norm. Bias	786	-1.3%	-8.6%	-92.2%	1252.8%	1325.2%	59.7%
	Norm. Error	786	25.2%	17.7%	0.0%	1252.8%	1252.8%	54.1%
HMD_VNA_50	Bias	786	-1.82	-1.64	-22.58	23.05	41.36	5.20
	Error	786	4.21	3.42	0.00	23.05	23.05	3.55
	Norm. Bias	786	-1.1%	-8.8%	-92.2%	1267.9%	1343.1%	60.8%
	Norm. Error	786	25.7%	17.6%	0.0%	1267.9%	1267.8%	55.2%
HMH	Bias	786	-0.75	-0.86	-22.22	25.53	47.59	6.42
	Error	786	4.84	3.66	0.04	25.53	25.49	4.28
	Norm. Bias	786	5.9%	-4.1%	-93.2%	1234.3%	1312.1%	68.6%
	Norm. Error	786	31.2%	18.7%	0.2%	1234.3%	1234.1%	61.4%
HMH_VNA_100	Bias	786	-1.76	-1.58	-20.91	23.05	40.66	5.09
	Error	786	4.12	3.23	0.00	23.05	23.05	3.47
	Norm. Bias	786	-0.7%	-8.4%	-92.0%	1247.2%	1319.5%	59.9%
	Norm. Error	786	25.1%	17.3%	0.0%	1247.2%	1247.2%	54.4%
HMH_VNA_50	Bias	786	-1.58	-1.50	-20.91	23.05	41.73	5.28
	Error	786	4.23	3.45	0.00	23.05	23.05	3.53
	Norm. Bias	786	0.6%	-6.9%	-92.0%	1257.8%	1334.5%	62.5%
	Norm. Error	786	26.2%	17.2%	0.0%	1257.8%	1257.7%	56.7%
VNA	Bias	786	-1.83	-1.69	-18.60	23.05	41.65	5.05
	Error	786	4.09	3.21	0.00	23.05	23.05	3.48
	Norm. Bias	786	0.0%	-8.4%	-73.7%	1243.5%	1317.2%	66.9%
	Norm. Error	786	25.8%	16.9%	0.0%	1243.5%	1243.5%	61.7%

Table 3-6: Results from Current Investigation: Eastern US: W126 (approx 800 locations)

Interpolation	*Measure*	*Count*	*Mean*	*Median*	*Min*	*Max*	*Range*	*STD*
CMAQ	Bias	786	-1.25	-1.28	-17.11	19.83	36.05	5.03
	Error	786	4.07	3.43	0.01	19.83	19.81	3.21
	Norm. Bias	786	4.6%	-8.2%	-81.7%	646.0%	727.7%	62.5%
	Norm. Error	786	31.8%	21.1%	0.0%	646.0%	646.0%	54.0%
HMD	Bias	786	-0.84	-0.87	-18.09	16.69	34.78	4.35
	Error	786	3.40	2.68	0.00	18.09	18.09	2.84
	Norm. Bias	786	1.3%	-5.6%	-78.1%	521.9%	600.0%	43.3%
	Norm. Error	786	25.3%	18.3%	0.0%	521.9%	521.9%	35.1%
HMD_VNA_100	Bias	786	-1.19	-1.13	-14.58	18.33	32.91	3.75
	Error	786	3.00	2.34	0.01	18.33	18.32	2.54
	Norm. Bias	786	-1.4%	-7.0%	-65.7%	547.0%	609.9%	38.7%
	Norm. Error	786	21.8%	16.3%	0.0%	547.0%	546.9%	32.1%
HMD_VNA_50	Bias	786	-1.14	-1.04	-14.58	18.33	32.91	3.82
	Error	786	3.07	2.48	0.01	18.33	18.32	2.55
	Norm. Bias	786	-1.1%	-6.6%	-72.2%	558.1%	622.0%	39.5%
	Norm. Error	786	22.3%	16.3%	0.1%	558.1%	558.1%	32.6%
HMH	Bias	786	-0.32	-0.45	-18.16	19.94	38.09	4.81
	Error	786	3.61	2.69	0.00	19.94	19.93	3.19
	Norm. Bias	786	5.2%	-2.5%	-83.3%	541.8%	620.2%	47.5%
	Norm. Error	786	27.5%	18.4%	0.0%	541.8%	541.8%	39.1%
HMH_VNA_100	Bias	786	-1.14	-1.05	-14.58	18.33	32.91	3.76
	Error	786	3.00	2.32	0.00	18.33	18.32	2.54
	Norm. Bias	786	-1.0%	-6.6%	-65.7%	543.8%	606.7%	39.0%
	Norm. Error	786	21.8%	16.0%	0.0%	543.8%	543.7%	32.3%
HMH_VNA_50	Bias	786	-0.99	-0.90	-14.58	18.33	32.91	3.89
	Error	786	3.08	2.44	0.00	18.33	18.32	2.56
	Norm. Bias	786	0.1%	-5.4%	-75.7%	548.5%	613.9%	40.2%
	Norm. Error	786	22.7%	16.0%	0.0%	548.5%	548.4%	33.2%
VNA	Bias	786	-1.21	-1.05	-14.58	18.33	32.91	3.75
	Error	786	2.99	2.30	0.01	18.33	18.32	2.56
	Norm. Bias	786	-1.1%	-6.8%	-62.9%	544.0%	607.0%	40.6%
	Norm. Error	786	21.9%	16.1%	0.1%	544.0%	544.0%	34.2%

Table 3-7: Results from Current Investigation: Western US: 8-hour Maximum (approx. 300 locations)

Interpolation	*Measure*	*Count*	*Mean*	*Median*	*Min*	*Max*	*Range*	*STD*
CMAQ	Bias	287	4.63	5.94	-45.13	36.29	81.41	13.48
	Error	287	11.27	9.94	0.05	45.13	45.08	8.72
	Norm. Bias	287	9.2%	8.0%	-37.6%	85.0%	122.6%	18.7%
	Norm. Error	287	15.8%	13.5%	0.0%	85.0%	85.0%	13.6%
HMD	Bias	287	-2.89	-2.59	-41.10	21.76	62.86	7.90
	Error	287	6.38	4.81	0.03	41.10	41.07	5.48
	Norm. Bias	287	-3.0%	-3.5%	-34.2%	53.8%	88.1%	10.6%
	Norm. Error	287	8.4%	7.1%	0.0%	53.8%	53.8%	7.1%
HMD_VNA_100	Bias	287	-3.19	-2.66	-25.34	19.65	44.99	7.62
	Error	287	6.33	4.99	0.01	25.34	25.33	5.31
	Norm. Bias	287	-3.1%	-3.7%	-32.5%	51.5%	84.0%	10.4%
	Norm. Error	287	8.3%	7.0%	0.0%	51.5%	51.5%	7.0%
HMD_VNA_50	Bias	287	-3.16	-2.83	-24.81	20.05	44.86	7.51
	Error	287	6.29	5.08	0.04	24.81	24.77	5.17
	Norm. Bias	287	-3.1%	-3.9%	-32.5%	53.8%	86.3%	10.2%
	Norm. Error	287	8.2%	6.9%	0.1%	53.8%	53.7%	6.8%
HMH	Bias	287	-1.98	-2.14	-40.01	24.83	64.83	8.11
	Error	287	6.34	4.85	0.00	40.01	40.00	5.43
	Norm. Bias	287	-1.8%	-2.8%	-33.3%	53.4%	86.7%	10.9%
	Norm. Error	287	8.4%	6.7%	0.0%	53.4%	53.4%	7.1%
HMH_VNA_100	Bias	287	-3.08	-2.63	-24.64	19.33	43.96	7.59
	Error	287	6.30	4.85	0.02	24.64	24.62	5.24
	Norm. Bias	287	-3.0%	-3.5%	-29.8%	51.9%	81.7%	10.2%
	Norm. Error	287	8.2%	6.7%	0.0%	51.9%	51.9%	6.8%
HMH_VNA_50	Bias	287	-2.84	-2.75	-24.60	19.89	44.48	7.54
	Error	287	6.26	5.05	0.00	24.60	24.60	5.08
	Norm. Bias	287	-2.7%	-3.6%	-29.8%	53.4%	83.2%	10.2%
	Norm. Error	287	8.2%	6.9%	0.0%	53.4%	53.4%	6.6%
VNA	Bias	287	-3.16	-2.63	-26.55	22.65	49.20	7.67
	Error	287	6.37	5.17	0.02	26.55	26.53	5.31
	Norm. Bias	287	-3.0%	-3.6%	-27.6%	60.8%	88.4%	10.5%
	Norm. Error	287	8.3%	7.1%	0.0%	60.8%	60.8%	7.0%

Table 3-8: Results from Current Investigation: Western US: SUM06 (approx. 300 locations)

Interpolation	*Measure*	*Count*	*Mean*	*Median*	*Min*	*Max*	*Range*	*STD*
CMAQ	Bias	286	3.77	3.98	-44.93	41.02	85.95	13.81
	Error	286	10.90	9.01	0.00	44.93	44.93	9.28
	Norm. Bias	279	298.6%	32.1%	-100.0%	29019.0%	29119.0%	1852.5%
	Norm. Error	279	317.1%	43.3%	0.0%	29019.0%	29019.0%	1849.4%
HMD	Bias	286	-1.93	-1.12	-32.15	44.64	76.80	9.76
	Error	286	6.76	4.50	0.00	44.64	44.64	7.30
	Norm. Bias	279	15.6%	-10.9%	-100.0%	3246.8%	3346.8%	210.8%
	Norm. Error	279	63.4%	36.6%	0.2%	3246.8%	3246.6%	201.7%
HMD_VNA_100	Bias	286	-2.96	-1.53	-33.75	41.26	75.01	9.62
	Error	286	6.84	4.80	0.00	41.26	41.26	7.38
	Norm. Bias	279	13.8%	-14.8%	-100.0%	2531.7%	2631.7%	178.9%
	Norm. Error	279	61.2%	31.7%	0.1%	2531.7%	2531.7%	168.7%
HMD_VNA_50	Bias	286	-2.69	-1.37	-31.81	44.64	76.45	9.54
	Error	286	6.68	4.56	0.00	44.64	44.64	7.32
	Norm. Bias	279	14.0%	-13.2%	-100.0%	2978.2%	3078.2%	196.6%
	Norm. Error	279	60.7%	31.5%	0.1%	2978.2%	2978.1%	187.5%
HMH	Bias	286	-1.77	-0.89	-30.79	40.58	71.37	9.72
	Error	286	6.76	4.37	0.00	40.58	40.58	7.21
	Norm. Bias	279	18.3%	-8.9%	-100.0%	3211.1%	3311.1%	211.3%
	Norm. Error	279	65.0%	33.4%	0.2%	3211.1%	3210.9%	201.9%
HMH_VNA_100	Bias	286	-2.90	-1.42	-33.81	40.15	73.97	9.50
	Error	286	6.82	4.94	0.00	40.15	40.15	7.22
	Norm. Bias	279	15.2%	-14.5%	-100.0%	2752.4%	2852.4%	191.8%
	Norm. Error	279	62.4%	32.8%	0.0%	2752.4%	2752.4%	182.0%
HMH_VNA_50	Bias	286	-2.62	-1.23	-32.27	39.65	71.91	9.39
	Error	286	6.68	4.55	0.00	39.65	39.65	7.10
	Norm. Bias	279	16.0%	-12.2%	-100.0%	3376.8%	3476.8%	219.1%
	Norm. Error	279	62.1%	29.9%	0.1%	3376.8%	3376.8%	210.7%
VNA	Bias	286	-2.93	-1.47	-34.39	41.06	75.45	9.53
	Error	286	6.82	5.06	0.00	41.06	41.06	7.27
	Norm. Bias	279	18.0%	-13.9%	-100.0%	2619.1%	2719.1%	189.6%
	Norm. Error	279	63.7%	32.8%	0.1%	2619.1%	2619.1%	179.5%

Table 3-9: Results from Current Investigation: Western US: W126 (approx. 300 locations)

Interpolation	*Measure*	*Count*	*Mean*	*Median*	*Min*	*Max*	*Range*	*STD*
CMAQ	Bias	286	2.53	3.50	-41.98	26.57	68.54	10.66
	Error	286	8.18	6.67	0.03	41.98	41.95	7.28
	Norm. Bias	286	112.9%	38.3%	-68.4%	5993.6%	6062.0%	389.2%
	Norm. Error	286	128.1%	49.3%	0.2%	5993.6%	5993.3%	384.5%
HMD	Bias	286	-1.08	-0.64	-26.39	27.84	54.23	6.95
	Error	286	4.68	2.86	0.02	27.84	27.82	5.25
	Norm. Bias	286	15.8%	-5.0%	-89.3%	2810.1%	2899.4%	176.2%
	Norm. Error	286	48.6%	26.0%	0.2%	2810.1%	2809.9%	170.1%
HMD_VNA_100	Bias	286	-1.76	-0.68	-29.36	28.41	57.77	6.95
	Error	286	4.77	3.14	0.01	29.36	29.34	5.34
	Norm. Bias	286	13.9%	-8.3%	-89.3%	2401.1%	2490.4%	154.1%
	Norm. Error	286	47.3%	25.7%	0.0%	2401.1%	2401.0%	147.3%
HMD_VNA_50	Bias	286	-1.59	-0.72	-28.32	28.80	57.12	6.88
	Error	286	4.70	2.90	0.01	28.80	28.79	5.26
	Norm. Bias	286	15.2%	-8.5%	-89.3%	2810.1%	2899.4%	176.3%
	Norm. Error	286	48.3%	25.6%	0.0%	2810.1%	2810.1%	170.2%
HMH	Bias	286	-0.84	-0.47	-27.12	28.57	55.69	7.07
	Error	286	4.75	2.91	0.00	28.57	28.57	5.29
	Norm. Bias	286	16.8%	-3.9%	-90.2%	2641.7%	2731.9%	167.0%
	Norm. Error	286	48.6%	24.8%	0.1%	2641.7%	2641.6%	160.7%
HMH_VNA_100	Bias	286	-1.72	-0.68	-29.59	28.07	57.66	6.93
	Error	286	4.79	3.23	0.00	29.59	29.58	5.30
	Norm. Bias	286	14.4%	-7.1%	-90.2%	2548.5%	2638.7%	161.8%
	Norm. Error	286	47.7%	25.7%	0.0%	2548.5%	2548.5%	155.3%
HMH_VNA_50	Bias	286	-1.50	-0.71	-28.59	28.22	56.82	6.86
	Error	286	4.75	3.09	0.00	28.59	28.59	5.18
	Norm. Bias	286	14.9%	-7.7%	-90.2%	2641.7%	2731.9%	166.6%
	Norm. Error	286	47.7%	25.4%	0.0%	2641.7%	2641.7%	160.3%
VNA	Bias	286	-1.77	-0.79	-29.80	28.58	58.37	7.01
	Error	286	4.84	3.07	0.00	29.80	29.80	5.38
	Norm. Bias	286	18.8%	-7.8%	-76.2%	3636.8%	3713.0%	223.0%
	Norm. Error	286	52.5%	27.7%	0.0%	3636.8%	3636.7%	217.6%

Here bias, normalized bias, and normalized error are defined as follows: For monitor i with actual value a_i and predicted value c_i:

$Bias_i = c_i - a_i$
Normalized $bias_i = bias_i / a_i$
Normalized $error_i = | bias_i | / a_i$

Bias, normalized bias, and normalized error are computed for each monitor, and the count, mean, median, max, min, range, and STD of these three values over the relevant set of monitors (East or West) is shown above. (Note: In the previous investigation, p 3-4 – 3-5, only mean normalized bias and mean normalized error were shown)

Appendix A presents more detailed results for the West. Based on our results we offer the following observations:

- Compared to other approaches examined, the CMAQ model data is a poor predictor of O_3 levels.

- Overall, VNA and eVNA perform similarly, though in certain circumstances one will outperform the other.
- Blends of VNA and eVNA techniques can produce better results than pure applications of either VNA or eVNA, especially in the Western U.S. (where monitor coverage is sparser).

3.4 Generation of the National Potential O_3 Exposure Surface

Based on the empirical strengths of these techniques, as well as logistical and methodological concerns, we chose the following approach to generate the POES:

- For monitors in the Eastern U.S., the VNA interpolation was used. Though several VNA-eVNA blends matched VNA's performance, none offered significantly more predictive power. Ultimately, the largest factor separating VNA from VNA-eVNA blends was VNA's simplicity, and the fact that it CMAQ data wasn't required to perform the interpolation, thus leaving open the possibility of adding other monitor years.

- For monitors in the Western U.S., we used a blend of eVNA and VNA techniques: For neighbors less than 50 km from the site of interpolation, VNA techniques were used. For neighbors of distance greater than 50 km, the Hour-month-hour eVNA approach was used. In the West, blends proved more successful than either pure VNA or eVNA techniques. The 50km threshold was chosen for consistency with previous studies that used a 50km threshold[n].

Using the chosen approach in each region, we interpolated O_3 values for each gridcell center in the "composite CMAQ grid" (This does not necessarily mean that we used data from the CMAQ model – indeed in the East we did not. This simply means that we used the same coordinate system that the CMAQ model uses – see section 3.1 for more detail). In the West, our predictions were made entirely on the 36km grid, (the only grid which covers the Western U.S.). The East was primarily covered by the 12km CMAQ grid, but relied on the 36 km grid point for the parts of Maine, Minnesota, Florida and Texas that were not covered by the 12km grid. The resulting surface gives hourly O_3 values for 44432 regularly spaced locations throughout the U.S.

A description of the resulting O_3 data will be postponed until the following section, where it can be discussed with a similar description of four alternate O_3 surfaces that correspond to four alternative standards currently being considered.

[n] For example: U.S. EPA. 1999. The Benefits and Costs of the Clean Air Act: 1990 to 2010: EPA Report to Congress. U.S. EPA, Office of Air and Radiation, Office of Policy. Washington, DC. EPA 410-R-99-001.

4. Rollback

To estimate the crop yield and tree seedling biomass changes due to meeting a hypothetical standard, we must first generate a hypothetical 2001 O_3 surface that replicates O_3 levels just meeting the standard. This procedure is referred to as a "rollback".

4.1 Scenarios

Hypothetical O_3 surfaces were generated for the following six hypothetical scenarios:

- Ozone levels which just meet an 84 ppb 4th highest 8-hour maximum standard (in this case, we performed a rollback to 84.999 ppb, since the 4th highest 8-hour maximum standard truncates decimals)
- Ozone levels which just meet a 70 ppb 4th highest 8-hour maximum standard (actually 70.999 for the reasons above)
- Ozone levels which just meet a 25ppm-h 3-month 12-hour SUM06 standard
- Ozone levels which just meet a 15ppm-h 3-month 12-hour SUM06 standard.
- Ozone levels which just meet a 21ppm-h 3-month 12-hour W126 standard.
- Ozone levels which just meet a 13ppm-h 3-month 12-hour W126 standard.

We shall refer to these respective scenarios as "the 84 ppb rollback", "the 70 ppb rollback", "the 25ppm-h rollback", the "15ppm-h rollback", the "21ppm-h rollback", and the "13ppm-h rollback". Together with the "as is" scenario (i.e. the POES generated in Section 3), these comprise the five scenarios for which we evaluate crop yield and tree seedling biomass loss, and the associated economic benefits.

4.2 Rollback Methodologies

The quadratic rollback reduces all hourly O_3 values at a given location $\{c_i \mid 1 < i < 8760\}$ according to the formula:

$$c_i^{rollback} = vc_i - bc_i^2 \quad \textbf{eq. (5)}$$

Where v and b are constants chosen such that the set of $\{c_i \mid 1 < i < 8760\}$ just meets the given standard. The procedure for determining the appropriate values for v and b is discussed below. We first describe the process for meeting a 4th highest maximum 8-hour average standard. We then describe the modifications to this approach necessary to rollback to a SUM06 or W126 standard.

4.2.1 8-hour Maximum Quadratic Rollback

A brief outline of the mathematical basis for the 4th highest 8-hour maximum quadratic rollback is given here. Full details can be found in Appendix B.

For a given location, we wish to choose v and b such that:

$$4^{th}\underset{j=1}{\overset{8752}{highest}}\max\left(\frac{\sum_{i=j}^{j+7} vc_i - bc_i^2}{8}\right) = S \quad \textbf{eq. (6)}$$

where:
c_i is the O_3 value at hour i and
S is the standard to be met.

In other words, we want to choose the v and b that will cause the new 8-hour-maximum period to have an average value equal to the standard. There generally exists more than one choice of v and b that will satisfy this condition. We follow the approach used previously by EPA to select a v and b which satisfy the above equation; namely, v=1 if and only if such a choice yields a strictly monotonic rollback function. Otherwise, v is chosen such that the domain of the function (hourly O_3 values) is identical to the maximum domain over which the rollback is strictly monotonic.

For a full account of the computations underlying this rollback, see the relevant Memo in Appendix B.

4.2.2 SUM06 Rollback

The SUM06 rollback is achieved through iterative 8-hour maximum rollbacks: We choose an "8-hour maximum target" and perform a rollback to meet this "target". We evaluate the SUM06 value of the resulting data; if it is below the standard we wish to be meeting, we increase the "8-hour maximum target"; if the SUM06 is above the standard we wish to be meeting, we decrease the "8-hour maximum target." We continue performing rollbacks and adjusting target values until the SUM06 value has sufficiently (see below) approached the standard we wish to be meeting.

As the 8-hour maximum target is incrementally increased, SUM06 will occasionally exhibit discrete jumps of magnitude. This occurs when an hourly value that was previously slightly less than .06 ppm (and thus contributed nothing to the SUM06 total) was increased to .06 ppm or greater (and thus contributes its full value). Because of these irregular jumps, one cannot always find an "8-hour maximum target" which yields a SUM06 exactly equal to the standard.

In performing the SUM06 rollbacks, we terminated the iterative process once the SUM06 value fell below and within .06 ppm-h of the standard (we will refer to this as "the approach condition"). For the purposes of this study, we considered the effect of a .06ppm-h error in SUM06 to be negligible. Additionally, iteration was terminated if the approach condition was not met after 25 iterations. The vast majority of locations met the approach condition before reaching 25 iterations[o].

4.2.3 W126 Rollback

The W126 rollback is performed in a similar fashion to the SUM06 rollback. We perform successive rollbacks to meet 8-hour maximum targets, varying the target such that the W126 value of the ensuing O_3 surface approaches the W126 standard we wish to meet.

The W126 metric is continuous with respect to variation in the target 8-hour maximum value – unlike the SUM06 metric, there are no discrete jumps in W126 value and so there is no theoretical limit to how closely one can approach the standard through continued iteration. For practical purposes, we continued iteration until a surface was generated whose W126 value fell within .005ppm-h of the standard.

[o] In the 25ppm-h rollback, only 3 out of over 40,000 locations did not meet the approach condition. All results still fell within the range of 24.88-25.03 ppm-hr. In the 15ppm-h rollback, only 4 out of over 40,000 locations did not meet the approach condition. All results fell within the range of 14.90-15.06 ppm-hr.

4.3 Aggregate Results

For each rollback scenario we compute maximum 3-month SUM06 values, 4^{th} highest maximum 8-hour average values, and maximum 3-month W126 values. The tables below give mean, median, maximum, and minimum O_3 levels in terms of these three O_3 metrics.

Table 4-1 Rollback Scenarios Described in Terms of Mean, Median, Maximum, and Minimum 8-Hour Maximum Values

8-hour	as_is	8-hour rollback 84	8-hour rollback 70	SUM06 rollback 25	SUM06 rollback 15	W126 rollback 21	W126 rollback 13
Mean	73.01635703	72.63478249	68.20098977	72.78260827	70.7770449	72.91678111	71.40617229
Median	73.62485235	73.62485235	70.99999904	73.54231589	71.57599665	73.61090821	72.55692302
Max	118.3070998	84.99999924	70.99999924	105.1970365	100.6138143	105.1970365	101.2226691
Min	39.83235804	39.83235804	39.83235804	39.83235804	39.83235804	39.83235804	39.83235804

Table 4-2 Rollback Scenarios Described in Terms of Mean, Median, Maximum, and Minimum SUM06 Values

SUM06	as_is	8-hour rollback 84	8-hour rollback 70	SUM06 rollback 25	SUM06 rollback 15	W126 rollback 21	W126 rollback 13
Mean	12.50749036	12.26495298	8.719191633	12.24571169	10.23400932	12.40493551	10.8833816
Median	11.83841584	11.75921953	8.539042804	11.83841584	11.83841584	11.83841584	11.80423751
Max	76.03335358	59.0338992	35.79732406	25.02971601	15.052334	33.97458015	19.54925481
Min	0	0	0	0	0	0	0

Table 4-3 Rollback Scenarios Described in Terms of Mean, Median, Maximum, and Minimum W126 Values

W126	as_is	8-hour rollback 84	8-hour rollback 70	SUM06 rollback 25	SUM06 rollback 15	W126 rollback 21	W126 rollback 13
Mean	10.5704409	10.3593442	7.80108448	10.3685444	8.97140437	10.4861036	9.39789481
Median	9.93151599	9.88411229	7.56656303	9.93151599	9.93151599	9.93151599	9.93151599
Max	61.8103728	40.9327805	22.5694254	21.2697139	14.9021518	20.9999942	12.9999982
Min	0.28970418	0.28970418	0.28970418	0.28970418	0.28970418	0.28970418	0.28970418

4.4 Air Quality Maps For Alternative Ozone Standards

In Appendix D, we present O_3 air quality maps under the six rollback scenarios described above, and under “as is” conditions as described by the POES. Ozone levels are shows in terms of the Maximum 3-month 12-hour W126 metric. The maps show the entire continental U.S. as a whole, even though the data for the East and Western U.S. were generated separately according to slightly different interpolation methods.

5. Crop and Tree Exposure

A direct consequence of elevated O_3 levels is a reduction in agricultural output, which translates into higher commodity prices, and a loss in economic welfare. To assess the benefits of attaining alternate air quality standards, we need to quantify the relationship between air quality and crop yield, and then incorporate the resulting yield effects into an agricultural economic model. This section documents the methodology and data used to quantify the impact of reaching the alternate air quality standards on crop yield and tree seedling biomass. In the next section we will present the resulting economic benefits.

Fifteen commodities, including eight field crops and seven fruits and vegetables, as well as ten tree species were retained in the analysis[p]. Based on USDA National Agricultural Statistics Service (NASS) estimates, these fifteen commodities accounted for a yearly market value of $53 billion in 2001.

Field crops (8 crops)
- Cotton
- Field Corn
- Grain Sorghum
- Peanuts
- Potatoes
- Rice
- Soybean
- Winter Wheat

Fruits and vegetables (7 crops)
- Cantaloupes
- Grapes
- Kidney Bean
- Lettuce
- Onions
- Tomatoes Processing
- Valencia Oranges

Tree Species (10 species)
- Quaking Aspen
- Black Cherry
- Douglas Fir
- Eastern White Pine
- Ponderosa Pine
- Red Alder
- Red Maple
- Sugar Maple
- Tulip Poplar
- Virginia Pine

The relative shares of market value for the selected commodities are illustrated in Figure 5-1 below.

To estimate crop yield loss under a hypothetical O_3 standard, we must first generate a hypothetical 2001 O_3 surface that replicates O_3 levels just meeting the standard. This procedure is referred to as a “rollback”. The various air quality scenarios considered are described in Chapter 4 above.

The baseline is the year 2001 O_3 surface. The 2001 surface and each rollback scenario were reported using both monthly SUM06 and monthly W126 metrics for field crops (including potatoes, lettuce, and kidney beans) and tree seedlings. A comparison of results between SUM06 and W126 is presented subsequently. For other fruits and vegetables, we used monthly 7-hour-average and monthly 12-hour-average metrics to calculate yield changes, as SUM06 and W126 functions were not available.

[p] Barley and Lemon were removed from the analysis for lack of consistent SUM06 and W126 concentration-response functions.

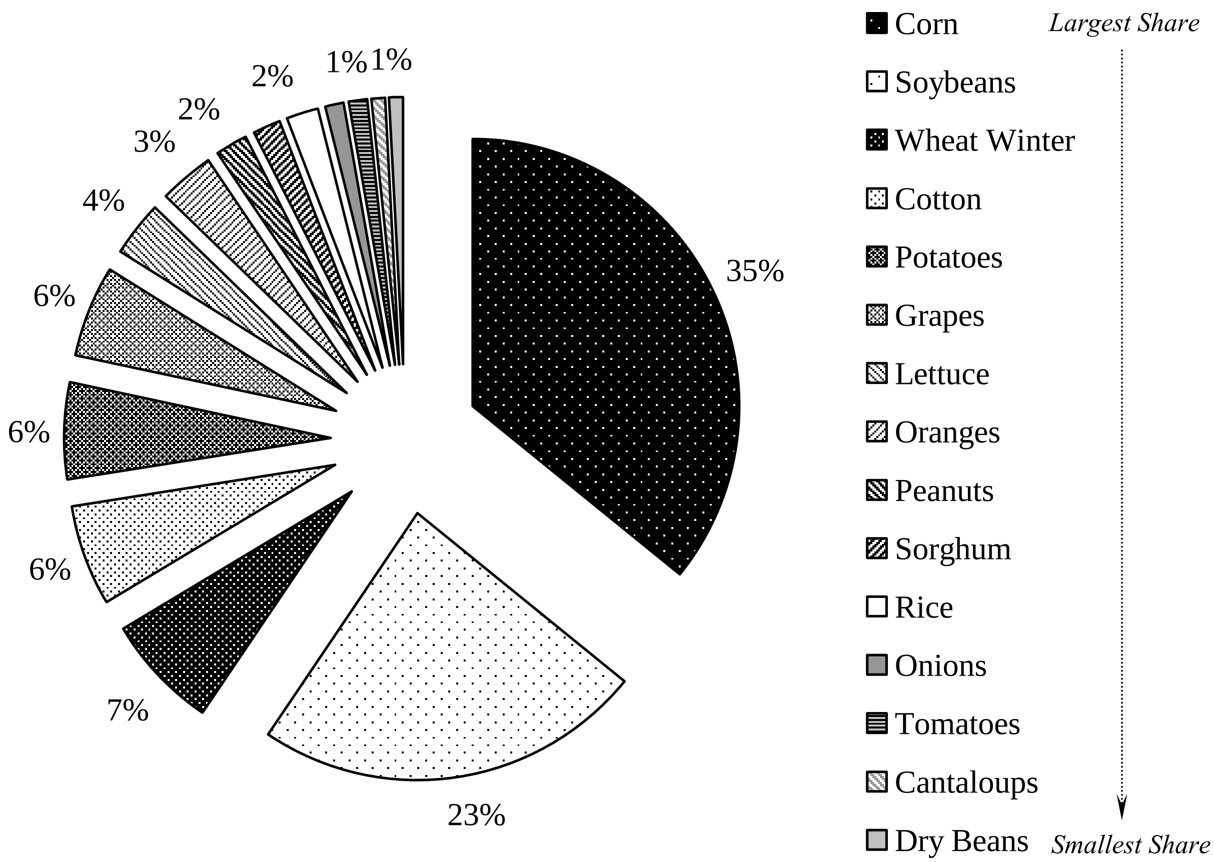

Figure 5-1: Shares of Value of Production for Selected Crops, Fruits, and Vegetables (2001, total value is $53 billion). Source: NASS[q]

The steps involved in generating yield and biomass changes are summarized below.

Step 1. *Collect* O_3 *concentration-response (C-R) functions for all crops, fruits, vegetables, and tree seedlings and adjust C-R parameters to the appropriate air quality metric (SUM06, W126, 12-hour-average, and 7-hour-average depending on the C-R function)*. C-R functions and parameters were derived from previous studies by Olszyk and Thompson (1988), Lee and Hogsett (1996), and Abt Associates (1995).

Step 2. *Identify areas of the country where each crop is cultivated.* This requires getting growing range boundaries for all crops, fruits, and vegetable. We relied on NASS 2001 Crop County Data for all major field crops, and on the 2002 Census of Agriculture for field crops, fruits and vegetables.

Step 3. *Identify areas of the country where specific tree species grow.* This requires getting growing range boundaries for all tree species. We used the USGS tree species range maps (Little, 1978) available in ArcGIS Shapefile format.

[q] The value of production for *All Dry Edible Beans* was used for kidney beans since NASS does not provide a breakdown by bean species. Other edible bean species include navy bean, pinto bean, and black bean.

Step 4. *Obtain usual harvest dates for all crops, fruits and vegetables to link crop growing season and O_3 exposure*. The USDA reports usual planting and harvesting seasons for major crops at the state level. Missing data was sourced from published crop profiles from the Integrated Pest Management (IPM) centers.

Step 5. *When appropriate, adjust all hourly* O_3 *values down by 10%* to account for the height differential between monitoring stations and crop foliage, and compute monthly O_3 metrics. Yield changes and economic benefits were obtained for both reduced and unreduced metrics. A comparison between the two approaches is available in Appendix L.

Step 6. *Generate seasonal* O_3 *indices for all commodities*. Concentration-response functions are calibrated for specific experimental exposure durations, so it was necessary to compute O_3 indices over the corresponding period. Seasonal SUM06, W126, 7-hour-average, and 12-hour-average O_3 indices were derived from the monthly metrics estimated in Step 5 for all air quality scenarios. For example, the concentration-response function for winter wheat is calibrated for a 58-day growing season, so we identified typical harvest dates for winter wheat by state, and calculated O_3 exposure for the 58 days previous to harvest time.

Step 7. *Generate relative crop yield and tree seedling biomass loss at the CMAQ grid level*. The seasonal O_3 indices generated above were plugged into the C-R functions to generate relative yield and biomass losses over each crop and tree growing range.

Step 8. *Aggregate yield and biomass losses from gridcell to county to production regions (as defined by the USDA Economic Research Service)*. To serve as input into the AGSIM© model, yield losses at the gridcell level had to be combined into nine production regions according to USDA Economic Research Service (ERS) classification. We used planted acreages reported in NASS 2001 County Crop Data to generate weighted-average yield changes across ERS region. We also relied on the U.S. Census Cartographic Boundaries for an administrative map of U.S. counties.

The schematic below describes the process of combining all primary data sources and monthly O_3 estimates to generate yield and biomass changes. Tables are presented with an indicative list of variables.

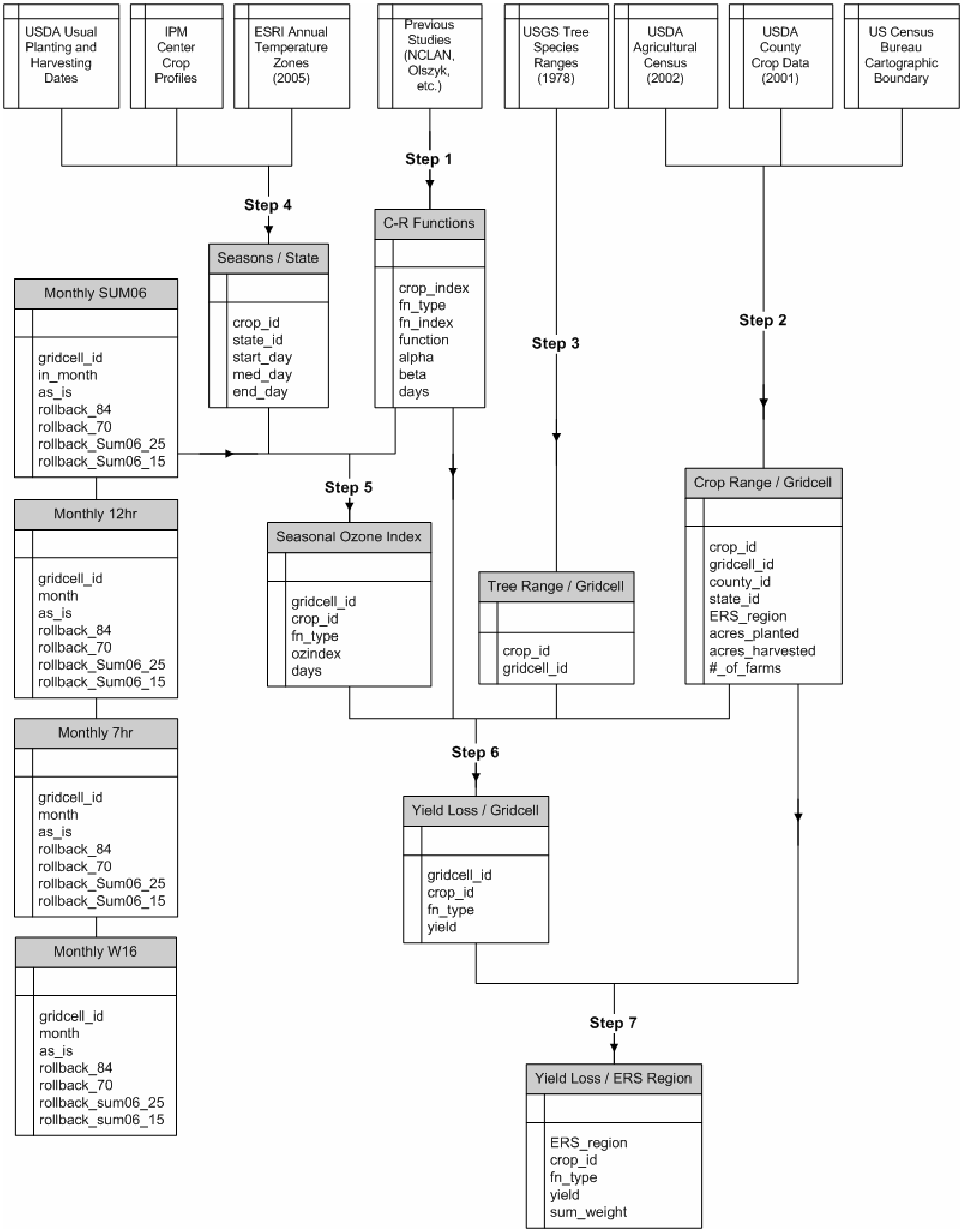

Figure 5-2: Estimation of Yield and Biomass Losses – Data Sources and Data Flow

5.1 Ozone Concentration-Response Functions

Ozone concentration-response functions estimate the relationship between elevated O_3 exposure and plant yields. The data necessary to estimate these functions can come from tests in open fields, open-top chambers, or econometric methods. The present crop assessment was built upon National Crop Loss Assessment Network (NCLAN) O_3 concentration-response functions. These functions come from tests in open-top chambers, in which O_3 is injected into the chamber through an inlet to replicate various O_3 exposures. Typically, the experimental test data is fit to a Weibull function. Its general form is as follows (Lesser et al., 1990):

$$Y = A.\exp^{-\left(ozone/\gamma\right)^{\lambda}} \qquad \textbf{eq. (7)}$$

Where Y is the estimated mean yield, *ozone* is the O_3 exposure index, A the theoretical yield at zero O_3 concentration, γ the scale parameter for O_3 exposure that reflects the dose at which the expected response is reduced to $0.37A$, and λ the shape parameter affecting the change in the predicted rate of loss. Because the response of crop yield to O_3 exposure in the NCLAN study varies by cultivar and experimental location, we used estimated median C-R functions. Minimum and maximum C-R functions are also presented in Table 5-1and Table 5-2.

Relative yield losses (RYL) are defined as:

$$RYL = 1 - Y/Y_{base} \qquad \textbf{eq. (8)}$$

Where Y_{base} is the estimated mean yield at the reference exposure index ("clean air" in the charcoal-filtered air treatment). We rely on the original sources of the exposure-response functions for the reference levels for different indices. The reference level is 27 ppb for 7-hour-average, 25 ppb for 12-Hout-average, and 0 ppm/h for SUM06 and W126 (Olszyk, 1988).

Functions for field crops and tree seedlings were adjusted to a seasonal 12-Hour SUM06 and W126 O_3 index, 12-hour-average index for fruits, and 7-hour-average index for rice and cantaloupes. All crop and fruit/vegetable functions are calibrated for an experimental O_3 exposure duration, typically corresponding to the duration of each crop growing season.

A summary of all relative yield loss (RYL) functions and O_3 indices is presented in tables below. Figure 5-3 and Figure 5-4 below provide a comparison of W126 median C-R function schedules for all major crops and trees.

Table 5-1: Composite SUM06 Relative Yield Loss Functions for Major Crops, Beans, Lettuce, and Potatoes

Crop	RYL	Index	Response	γ (ppm)	λ	days
			Max	78	1.311	119
Cotton	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	SUM06	Median	105.9	1.655	114
			Min	116.8	1.523	119
			Max	92.4	2.816	83
Field Corn	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	SUM06	Median	96.9	3.194	83
			Min	94.2	4.307	83
			Max	27.2	1.000	58
Winter Wheat	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	SUM06	Median	53.3	2.766	58
			Min	72.1	2.353	58
			Max	131.4	1.000	104
Soybeans	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	SUM06	Median	109.7	1.567	93
			Min	299.7	1.547	104
			Min	79.3	1.654	62
Potatoes	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	SUM06	Median	86.2	1.274	66
			Max	93.8	1.000	70
Grain Sorghum	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	SUM06	--	177.8	2.329	85
Peanuts	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	SUM06	--	99.8	2.219	112
Lettuce	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	SUM06	--	54.9	5.512	53
Kidney Beans	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	SUM06	--	42.9	2.537	57

Source: Lee and Hogsett (1996) table 10.2 for crops. Abt Associates Inc (1995) exhibit 11 for fruits and vegetables. Note: Peanuts, Grain Sorghum, Lettuce, and Kidney Beans, only have one C-R function and therefore do not have a Median, Max, and Min.

Table 5-2: Composite W126 Relative Yield Loss Functions for Major Crops, Beans, Lettuce, and Potatoes

Crop	RYL	Index	Response	γ (ppm)	λ	days
			Max	74.7	1.0700	119
Cotton	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	W126	Min	113.5	1.4100	119
			Median	94.4	1.5720	114
			Max	92.9	2.5940	83
Field Corn	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	W126	Min	94.5	4.1900	83
			Median	98.3	2.9730	83
			Median	53.7	2.3910	58
Winter Wheat	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	W126	Max	25.0	1.0000	58
			Min	76.1	2.1000	58
			Max	130.3	1.0000	104
Soybeans	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	W126	Min	470.2	1.1283	104
			Median	110.0	1.3670	93
			Median	99.5	1.2420	66
Potatoes	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	W126	Max	96.3	1.0000	70
			Min	113.8	1.2990	62
Grain Sorghum	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	W126	--	205.9	1.9630	85
Peanuts	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	W126	--	97.4	1.9050	112
Lettuce	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	W126	--	54.6	4.9210	53
Kidney Beans	$1\text{-}exp[-(ozone/\gamma)^{\lambda}]$	W126	--	44.2	2.3530	57

Source: Lee and Hogsett (1996) table 10.2 for crops. Abt Associates Inc (1995) exhibit 11 for fruits and vegetables adjusted between SUM06 and W126.

Table 5-3: Composite 12-hour-average and 7-hour-average Relative Yield Loss Functions for Fruits and Other Vegetables

Crop	RYL	Index	Response	γ (ppm)	λ	days
Grapes	1-[γ -(λ*ozone)] / [γ-(λ*base12)]	12-Hour	Min	1.1210	6.630	152
			Median	357.2540	2300.000	166
			Max	9315.0000	64700.000	138
Tomatoes Processing	1-[γ -(λ*ozone)] / [γ-(λ*base12)]	12-Hour	Max	8590.0000	41277.000	76
			Median	9055.0000	32367.000	76
			Min	6315.0000	21070.000	76
Onions	1-[γ -(λ*ozone)] / [γ-(λ*base12)]	12-Hour	--	5034.0000	10941.000	105
V. Oranges	1-[γ -(λ*ozone)] / [γ-(λ*base12)]	12-Hour	--	53.7000	261.100	214
Cantaloupes	1-[γ -(λ*ozone)] / [γ-(λ*base7)]	7-Hour	--	35.8000	280.800	77
Rice	1-exp[-(ozone/γ)$^{\lambda}$] /exp[-(base7/γ)$^{\lambda}$]	7-Hour	--	0.2016	2.474	69

Source: Abt Associates Inc (1995) exhibit 11.
Note: Onions, Rice, Oranges, and Cantaloupes only have one C-R function and therefore do not have a Max and Min. base7 = 27 ppb and base12 = 25 ppb which are equal to the O_3 concentrations in the charcoal-filtered treatments.

Table 5-4: Median SUM06 Relative Yield Loss Functions for Tree Seedlings

Tree Species	RYL	Index	γ (ppm)	λ
Aspen	1-exp[-(ozone/γ)$^{\lambda}$]	SUM06	131.92	1.134
Black Cherry	1-exp[-(ozone/γ)$^{\lambda}$]	SUM06	40.15	1.084
Douglas Fir	1-exp[-(ozone/γ)$^{\lambda}$]	SUM06	124.82	6.702
Eastern White Pine	1-exp[-(ozone/γ)$^{\lambda}$]	SUM06	57.69	1.875
Ponderosa Pine	1-exp[-(ozone/γ)$^{\lambda}$]	SUM06	202.33	1.008
Red Alder	1-exp[-(ozone/γ)$^{\lambda}$]	SUM06	183.46	1.317
Red Maple	1-exp[-(ozone/γ)$^{\lambda}$]	SUM06	269.64	1.700
Sugar Maple	1-exp[-(ozone/γ)$^{\lambda}$]	SUM06	34.91	6.395
Tulip Poplar	1-exp[-(ozone/γ)$^{\lambda}$]	SUM06	40.77	2.609
Virginia Pine	1-exp[-(ozone/γ)$^{\lambda}$]	SUM06	1815.43	1.000

Source: Lee and Hogsett (1996) table 14. Individual exposure-response curves are reported using the 12hr-SUM06 index adjusted to a 92-day exposure duration.

Table 5-5: Median W126 Relative Yield Loss Functions for Tree Seedlings

Tree Species	RYL	Index	γ (ppm)	λ
Aspen	1-exp[-(ozone/γ)$^{\lambda}$]	W126	109.81	1.2198
Black Cherry	1-exp[-(ozone/γ)$^{\lambda}$]	W126	38.92	0.9921
Douglas Fir	1-exp[-(ozone/γ)$^{\lambda}$]	W126	106.83	5.9631
Eastern White Pine	1-exp[-(ozone/γ)$^{\lambda}$]	W126	63.23	1.6582
Ponderosa Pine	1-exp[-(ozone/γ)$^{\lambda}$]	W126	159.63	1.1900
Red Alder	1-exp[-(ozone/γ)$^{\lambda}$]	W126	179.06	1.2377
Red Maple	1-exp[-(ozone/γ)$^{\lambda}$]	W126	318.12	1.3756
Sugar Maple	1-exp[-(ozone/γ)$^{\lambda}$]	W126	36.35	5.7785
Tulip Poplar	1-exp[-(ozone/γ)$^{\lambda}$]	W126	51.38	2.0889
Virginia Pine	1-exp[-(ozone/γ)$^{\lambda}$]	W126	1714.64	1.0000

Source: Adjusted parameters from Lee and Hogsett (1996) table 14.

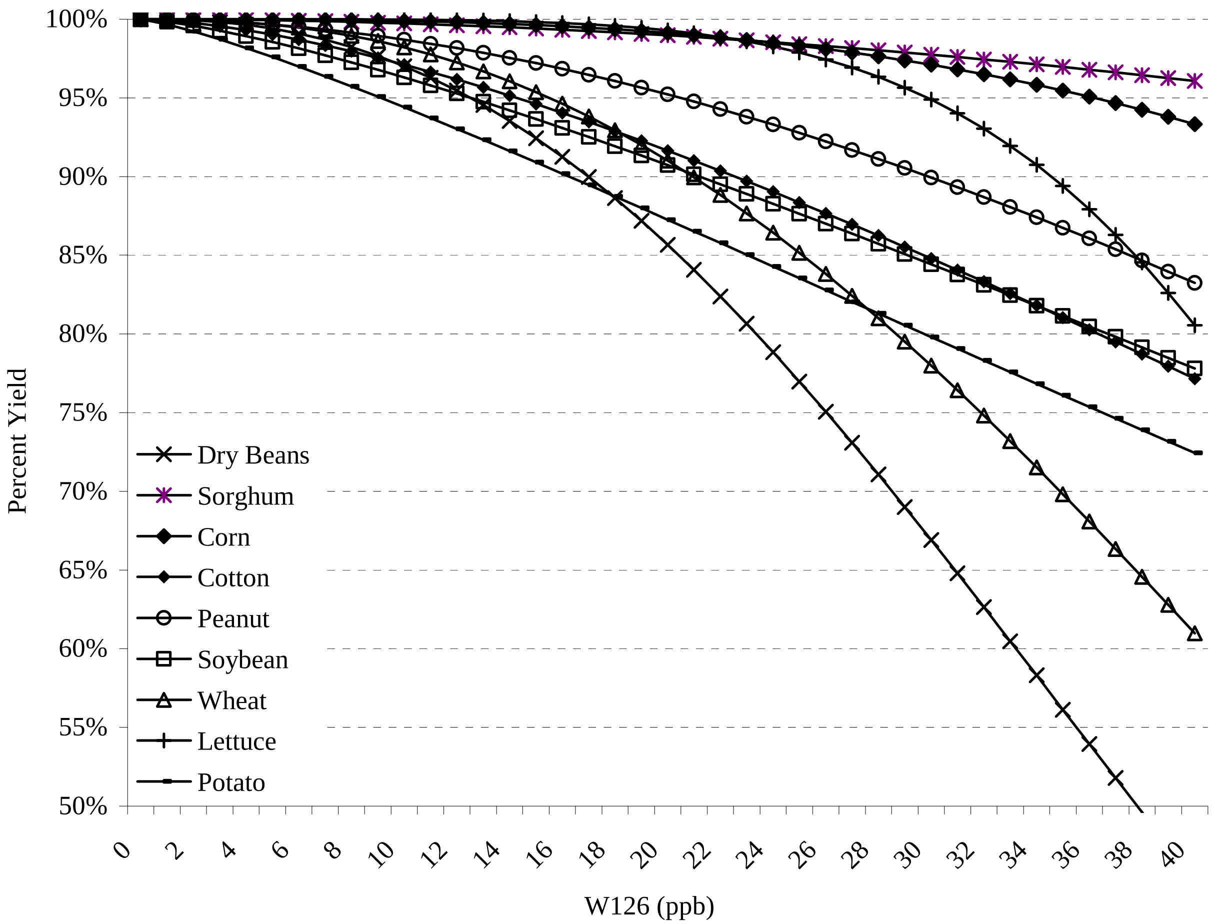

Figure 5-3: Relative W126 Concentration-Response Curves for Major Crops (percent yield loss/ppb). Curves were created with median functions if more than one function was available

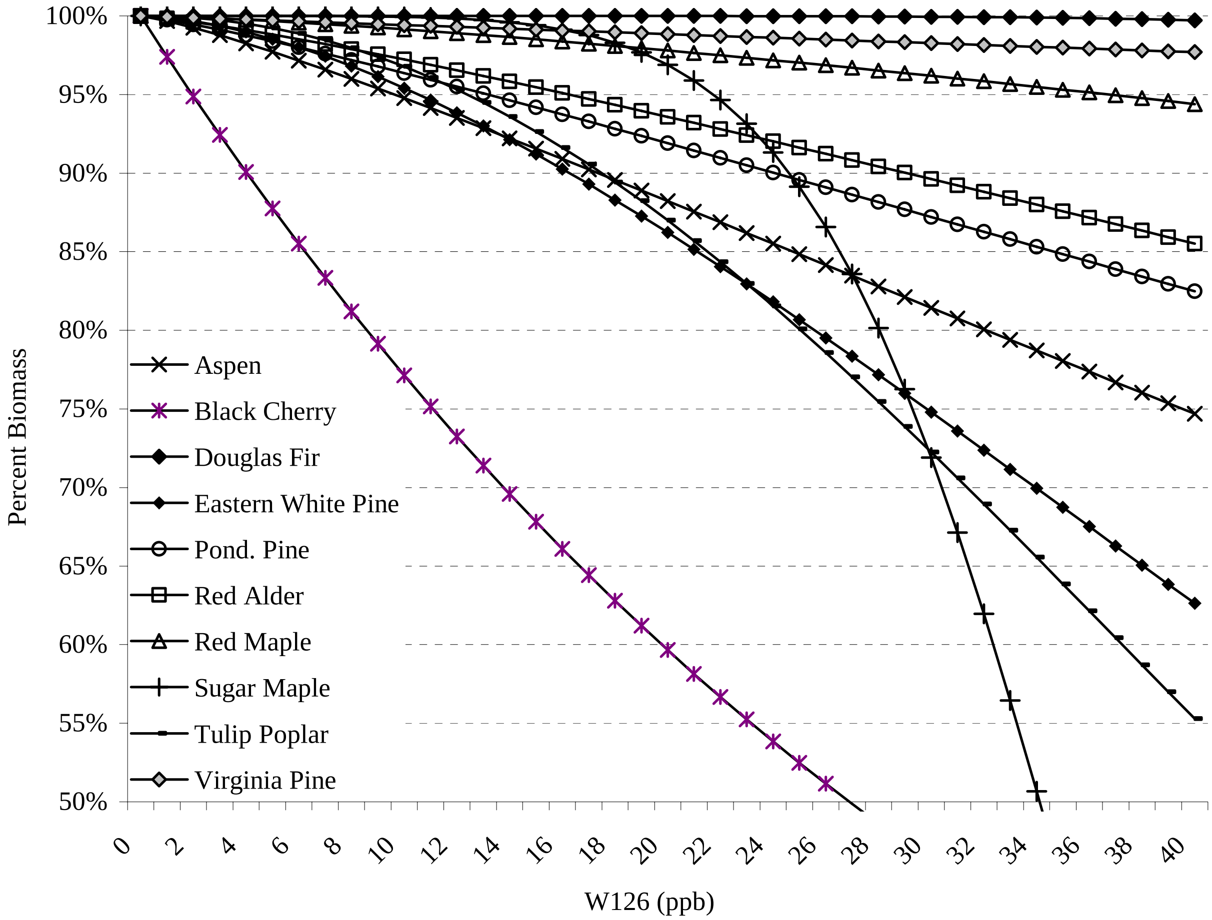

Figure 5-4: Relative W126 Concentration-Response Curves for Selected Tree Species (percent biomass loss/ppb). Curves were created with median functions if more than one function was available

5.2 Derivation of Seasonal Ozone Indices for Crop and Tree Species

Ozone indices were generated at the CMAQ grid level (12 km x 12 km resolution for the Eastern U.S. and 36 km x 36 km resolution for the Western U.S. or 44,432 gridcells). All SUM06, W126, 12-Hour and 7-Hour O_3 values were derived from monthly average O_3 estimates based on hourly values adjusted down by 10% to reflect a height differential between monitoring stations and crop foliage. For comparison we also derived monthly O_3 estimates without a 10% adjustment. The results of those analyses can be found in Appendix G2.2 and H2.2. All results presented in Chapter 5 used estimated O_3 exposure metrics with a 10% reduction of hourly values. Throughout the document we will refer to results with 10% reduction of hourly values as "reduced" and results without 10% reduction of hourly values as "unreduced".

5.2.1 Ten Percent Adjustment

In response to direction provided by the EPA WAM, we applied a 10% reduction to the hourly O_3 values in each of the rollback scenarios whenever those data were used to predict crop yield loss. This was done to compensate for the height difference between crops and O_3 monitors (which may be placed significantly higher than crop level). It should be noted that this 10% reduction has a magnified effect on the values of metrics such as SUM06 and W126.

In the case of SUM06, O_3 values between 60-66 ppb which previously contributed their full values to SUM06 do not contribute at all to SUM06, because after a 10% reduction, they fall below the 60 ppb threshold; O_3 values greater than 66 do contribute to SUM06, but their contribution is reduced by 10%.

In the case of W126, not only are hourly O_3 values reduced, but the weight assigned to them in the W126 sum is also reduced. In the "As is" scenario, we observe a 53% overall reduction in SUM06 levels and a 42% overall reduction in W126 values[r].

5.2.2 Characterization of Crop and Tree Growing Seasons

To generate seasonal SUM06 and W126 O_3 indices used in the crop C-R functions, we chose to have the last day of the experimental duration coincide with a mid-point harvest day. Since harvest dates tend to vary across geographical regions, we relied on USDA tables (USDA, 1997) and crop profiles published by the Integrated Pest Management Centers (IPM Centers, various).

When data were available in the 1997 USDA "Usual Planting and Harvesting Dates" then an early and late harvest dates were recorded as well as the mid-point day of the most active harvesting season. When data were collected from the IPM Centers, we used the mid-point of each state harvesting season as anchor.

Harvest dates are not reported at the county level, so state-level approximations were used instead. When harvest dates could not be found, we extrapolated a mid-point harvest date based on states situated in the same climatic zone. States were grouped into four climatic zones based on yearly high temperatures as reported in ESRI Annual World Temperature Zones (2005). The climatic classification used is presented in Map E-1 and

Map **E-2** in Appendix E. Experimental durations for crops typically range between 2 and 3 months, so it is reasonable to assume that a difference of a few days in the anchor harvest date has no significant effect on yield change estimates. Growing seasons are shown in Figure F-1 through Figure F-4.

In the case of field crops we used a scaled sum of monthly W126 (and SUM06) indices over the reference duration starting from a mid-point harvest day and moving back in time:

$$SUM06_{crop} = \sum_{i=1}^{crop.\exp.duration} SUM06_i \left({d_i}/{D_i} \right) \qquad \textbf{eq. (9)}$$

Where d_i is the number of O_3 exposure days in month i, D_i is the total number of days in month i, and $SUM06_i$ is the estimated 12-Hour SUM06 O_3 index in month i.

Lettuce and potatoes are grown throughout the year, so we used the highest monthly rolling SUM06 (W126) adjusted for each crop exposure duration (53 days for lettuce and 62/66/70 days for potatoes):

$$SUM06_{crop} = \underset{m=Jan}{\overset{Dec}{MAX}} \left(\sum_{i=1}^{crop.\exp.duration} SUM06_i \left({d_i}/{D_i} \right) \right) \qquad \textbf{eq. (10)}$$

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[r] These percentages compare the sum of all SUM06 values (there are 44,432 such values for each location in the POES) in the unreduced POES with the sum of all SUM06 values in the 10% reduced POES (similarly for the W126 metric).

For rice and cantaloupe, we used a weighted average of monthly 7-hour-average indices over the reference duration starting from a mid-point harvest day and moving back in time:

$$7hr_{crop} = \sum_{i=1}^{crop.\exp.duration} 7hr_i . d_i \Big/ \sum_{i=1}^{crop.\exp.duration} D_i \qquad \textbf{eq. (11)}$$

Onions and tomatoes are also grown throughout the year, so we used the highest monthly rolling 12-hour-average weighted average adjusted for each crop exposure duration (105 days for onions and 76 days for tomatoes):

$$12hr_{crop} = \underset{m=Jan}{\overset{Dec}{MAX}} \left(\sum_{i=1}^{crop.\exp.duration} 12hr_i . d_i \Big/ \sum_{i=1}^{crop.\exp.duration} D_i \right) \qquad \textbf{eq. (12)}$$

For fruit trees, we assumed an April-October growing season and derived a 12-hour-average weighted average index over this period:

$$12hr_{crop} = \sum_{i=Apr}^{Oct} 12hr_i . d_i \Big/ \sum_{i=Apr}^{Oct} D_i \qquad \textbf{eq. (13)}$$

For tree seedlings we used the highest 3-month 12-Hour SUM06 (W126) index for the months of April through October:

$$SUM06_{tree} = \underset{i=Apr}{\overset{Oct}{MAX}} \left(SUM06_i \right) \qquad \textbf{eq. (14)}$$

5.3 Characterization of Crop and Tree Species Growing Ranges

Growing ranges for crops, fruits, and vegetables were derived from the 2002 Census of Agriculture and from NASS 2001 County Crop Data. The 2002 Agricultural Census is based on farm surveys and we assumed that any county having at least one farm growing a particular crop would be part of the growing range for that crop. NASS County Crop Data on the other hand reports actual acreage planted and harvested on a yearly basis. In other words, data from the 2002 Agricultural Census can be regarded as a potential growing range, while NASS data is an actual growing range for a particular year. Table 5-6 shows the differences between the two data sources. In all cases, the 2002 Census data translates into much larger growing ranges, and we therefore used the 2002 Census to convey average yield responses in the maps and summary tables.

Since O_3 levels and yield responses are computed at the CMAQ grid level, we then relied on spatial interpolation techniques to relate the CMAQ grid to each crop growing range. A similar technique was used to relate the USGS tree species maps to the CMAQ grid.

Table 5-6: Growing Ranges Reported in 2002 Census of Agriculture vs. 2001 Crop County Data for Major Crops

Crop	'02 Census of Agriculture		NASS '01 Crop County Data		Not Covered in '01	
	Counties	*States*	*Counties*	*States*	*Counties*	*States*
Barley	1247	42	446	22	801	20
Corn	2587	48	1994	41	593	7
Cotton	662	17	181	17	481	0
Dry Beans	580	40	171	11	409	29
Peanut	406	16	191	9	215	7
Potatoes	1575	49	129	13	1446	36
Rice	150	10	101	6	49	4
Sorghum	1316	39	597	18	719	21
Soybean	2080	40	1619	31	461	9
Winter Wheat	2516	48	1666	41	850	7

5.4 Estimation of Crop Yield and Tree Seedling Biomass Loss

Yield and biomass responses were estimated for four air quality scenarios using the 2001 surface as baseline, or "as-is" scenario. For major field crops and trees, we computed yield changes based on both monthly SUM06 and monthly W126 metrics. In the case of fruits and vegetables, O_3 levels were expressed in terms of the 12-hour-average and 7-hour-average metrics.

Results are summarized below as yield and biomass gains from the 2001 baseline. The box plots show low and high quartiles, and minimum and maximum responses based on the monthly W126 metric Note that the results presented here are based on *simple county-level averages*. No weights have been applied, contrary to the regional statistics used in AGSIM©. The summary tables show median, mean, minimum, and maximum responses based on the W126 metric. See Appendices G and I for additional tables and maps based on the SUM06 metric.

5.4.1 Yield Impact on Cotton and Soybean

The box plots (Figures 5-5 and 5-6) and tables (5-7 to 5-11) below present *unweighted* yield responses over the continental U.S. at the *county level*. The crop ranges used to compute national estimates are the ones reported in the 2002 Census of Agriculture. The first box plot shows percent yield loss at the baseline exposure level. The subsequent plots show percent yield gain from the baseline situation. The shaded boxes represent the lowest and highest quartiles; the low and high bars show minimum and maximum values. Exact numbers are presented in Table 5-7 through Table 5-12. Note that the minimums and maximums reported on the maps will differ from the summary results presented in the tables because the maps are based on individual gridcell results whereas the results in the tables and box plots have been averaged across counties.

Results for all field crops, fruits and vegetables are shown in Appendix G. The results for exposures without the 10% reduction can be found in Appendix G2.2

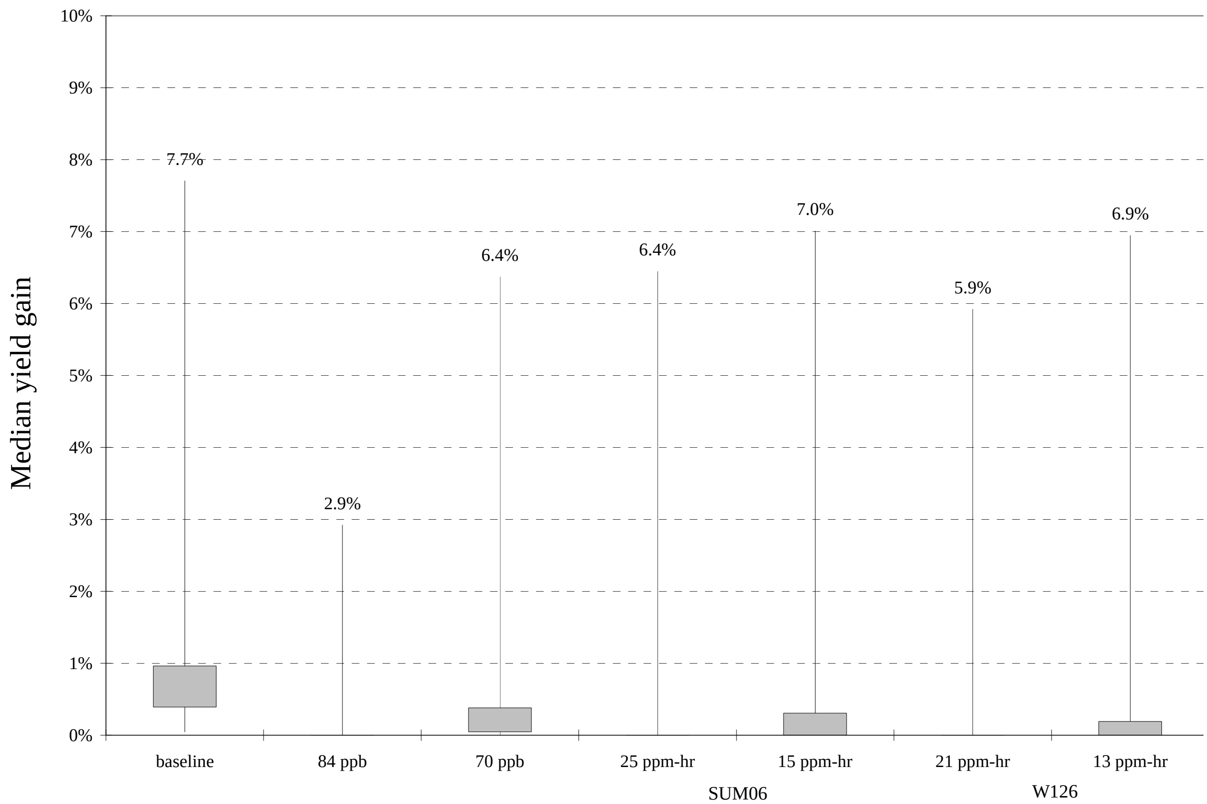


Figure 5-5: Median Yield Gain from Baseline for Cotton (reduced W126)

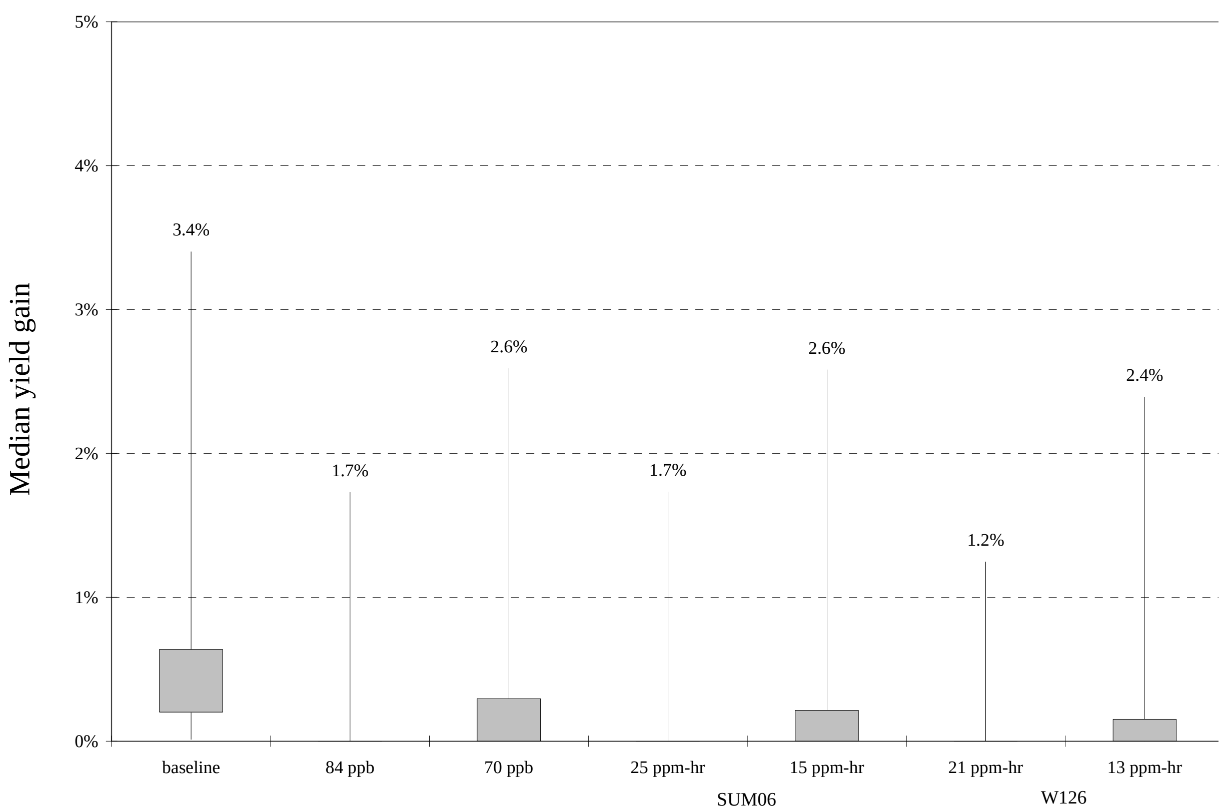


Figure 5-6: Median Yield Gain from Baseline for Soybean (reduced W126)

The following tables show mean, maximum, minimum, median, and standard deviation in yield responses for soybean and cotton for the six alternate air quality scenarios presented in Section 4. These are based on straight average yield responses at the county-level (no production weights were applied). Median, maximum and minimum C-R responses are included.

Table 5-7: Median Yield Gain from Baseline for Cotton (reduced W126)

Scenario	*Max*	*Min*	*Mean*	*Median*	*STD*
Baseline	7.71%	0.04%	0.78%	0.65%	0.69%
84 ppb	2.92%	0.00%	0.03%	0.00%	0.23%
70 ppb	6.37%	0.00%	0.32%	0.21%	0.55%
SUM06 25 ppm-hr	6.44%	0.00%	0.07%	0.00%	0.45%
SUM06 15 ppm-hr	7.01%	0.00%	0.26%	0.05%	0.59%
W126 21 ppm-hr	5.92%	0.00%	0.05%	0.00%	0.39%
W126 13 ppm-hr	6.94%	0.00%	0.19%	0.00%	0.56%

Table 5-8: Maximum Yield Gain from Baseline for Cotton (reduced W126)

Scenario	*Max*	*Min*	*Mean*	*Median*	*STD*
Baseline	28.19%	0.86%	5.63%	5.14%	2.92%
84 ppb	7.39%	0.00%	0.10%	0.00%	0.62%
70 ppb	18.50%	0.00%	1.65%	1.20%	1.99%
SUM06 25 ppm-hr	18.79%	0.00%	0.26%	0.00%	1.38%
SUM06 15 ppm-hr	21.81%	0.00%	1.34%	0.32%	2.21%
W126 21 ppm-hr	16.44%	0.00%	0.15%	0.00%	1.12%
W126 13 ppm-hr	21.44%	0.00%	0.95%	0.00%	2.00%

Table 5-9: Minimum Yield Gain from Baseline for Cotton (reduced W126)

Scenario	*Max*	*Min*	*Mean*	*Median*	*STD*
Baseline	12.49%	0.11%	1.38%	1.14%	1.09%
84 ppb	4.31%	0.00%	0.05%	0.00%	0.33%
70 ppb	9.78%	0.00%	0.54%	0.33%	0.84%
SUM06 25 ppm-hr	9.90%	0.00%	0.12%	0.00%	0.68%
SUM06 15 ppm-hr	10.96%	0.00%	0.47%	0.09%	0.92%
W126 21 ppm-hr	8.97%	0.00%	0.07%	0.00%	0.59%
W126 13 ppm-hr	10.84%	0.00%	0.35%	0.00%	0.87%

Table 5-10: Median Yield Gain from Baseline for Soybean (reduced W126)

Scenario	*Max*	*Min*	*Mean*	*Median*	*STD*
Baseline	3.40%	0.01%	0.52%	0.40%	0.47%
84 ppb	1.73%	0.00%	0.03%	0.00%	0.15%
70 ppb	2.59%	0.00%	0.24%	0.11%	0.37%
SUM06 25 ppm-hr	1.73%	0.00%	0.03%	0.00%	0.13%
SUM06 15 ppm-hr	2.58%	0.00%	0.18%	0.04%	0.32%
W126 21 ppm-hr	1.25%	0.00%	0.01%	0.00%	0.09%
W126 13 ppm-hr	2.39%	0.00%	0.14%	0.01%	0.29%

Table 5-11: Maximum Yield Gain from Baseline for Soybean (reduced W126)

Scenario	*Max*	*Min*	*Mean*	*Median*	*STD*
Baseline	8.21%	0.26%	2.41%	2.24%	1.38%
84 ppb	2.90%	0.00%	0.07%	0.00%	0.28%
70 ppb	5.61%	0.00%	0.78%	0.48%	0.90%
SUM06 25 ppm-hr	2.78%	0.00%	0.08%	0.00%	0.29%
SUM06 15 ppm-hr	5.03%	0.00%	0.61%	0.19%	0.82%
W126 21 ppm-hr	1.98%	0.00%	0.03%	0.00%	0.16%
W126 13 ppm-hr	4.56%	0.00%	0.45%	0.03%	0.70%

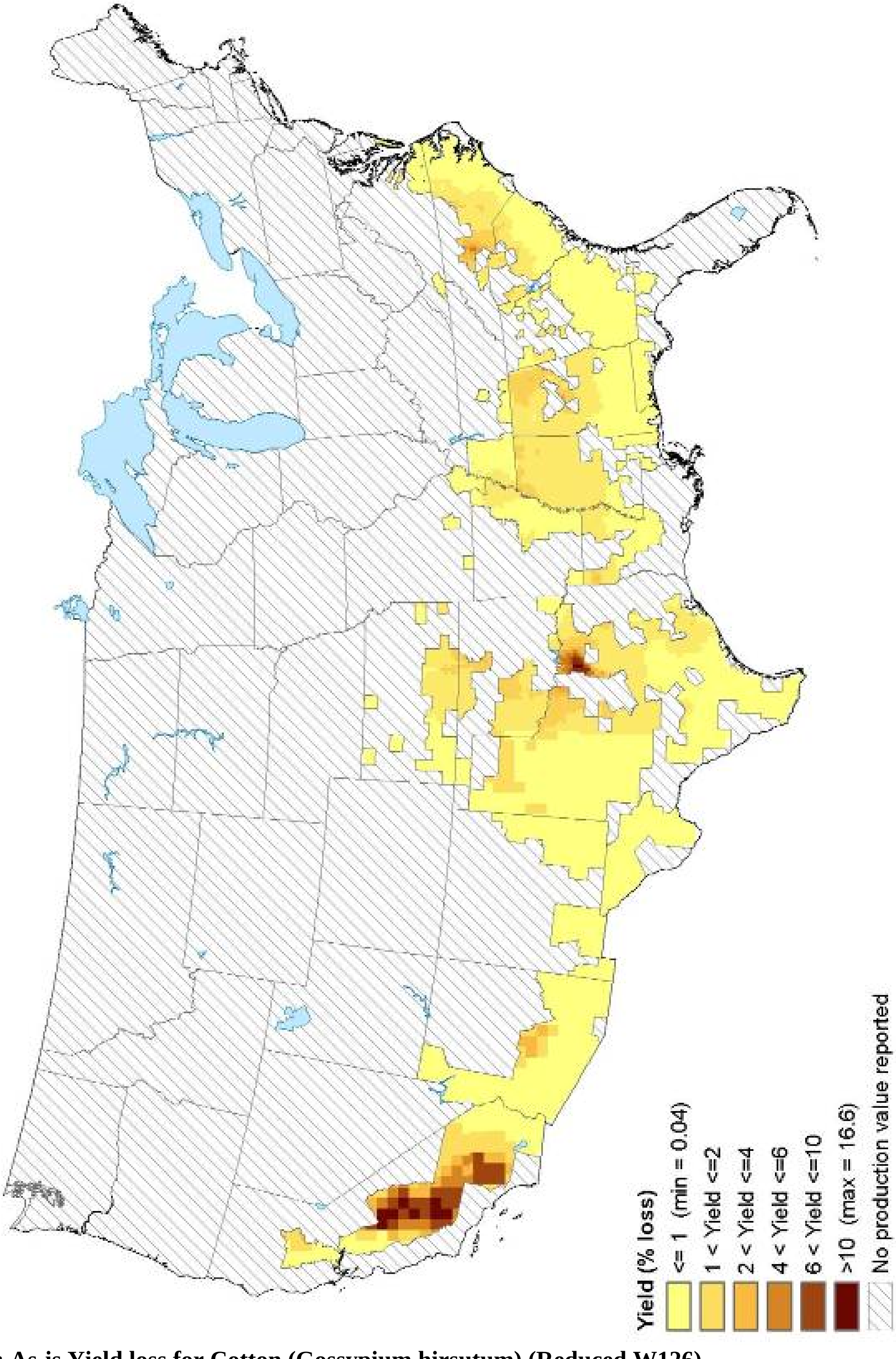
Table 5-12: Minimum Yield Gain from Baseline for Soybean (reduced W126)

Scenario	*Max*	*Min*	*Mean*	*Median*	*STD*
Baseline	1.46%	0.03%	0.37%	0.33%	0.24%
84 ppb	0.55%	0.00%	0.01%	0.00%	0.05%
70 ppb	1.07%	0.00%	0.13%	0.08%	0.16%
SUM06 25 ppm-hr	0.54%	0.00%	0.01%	0.00%	0.05%
SUM06 15 ppm-hr	0.97%	0.00%	0.11%	0.03%	0.15%
W126 21 ppm-hr	0.38%	0.00%	0.01%	0.00%	0.03%
W126 13 ppm-hr	0.89%	0.00%	0.08%	0.01%	0.13%

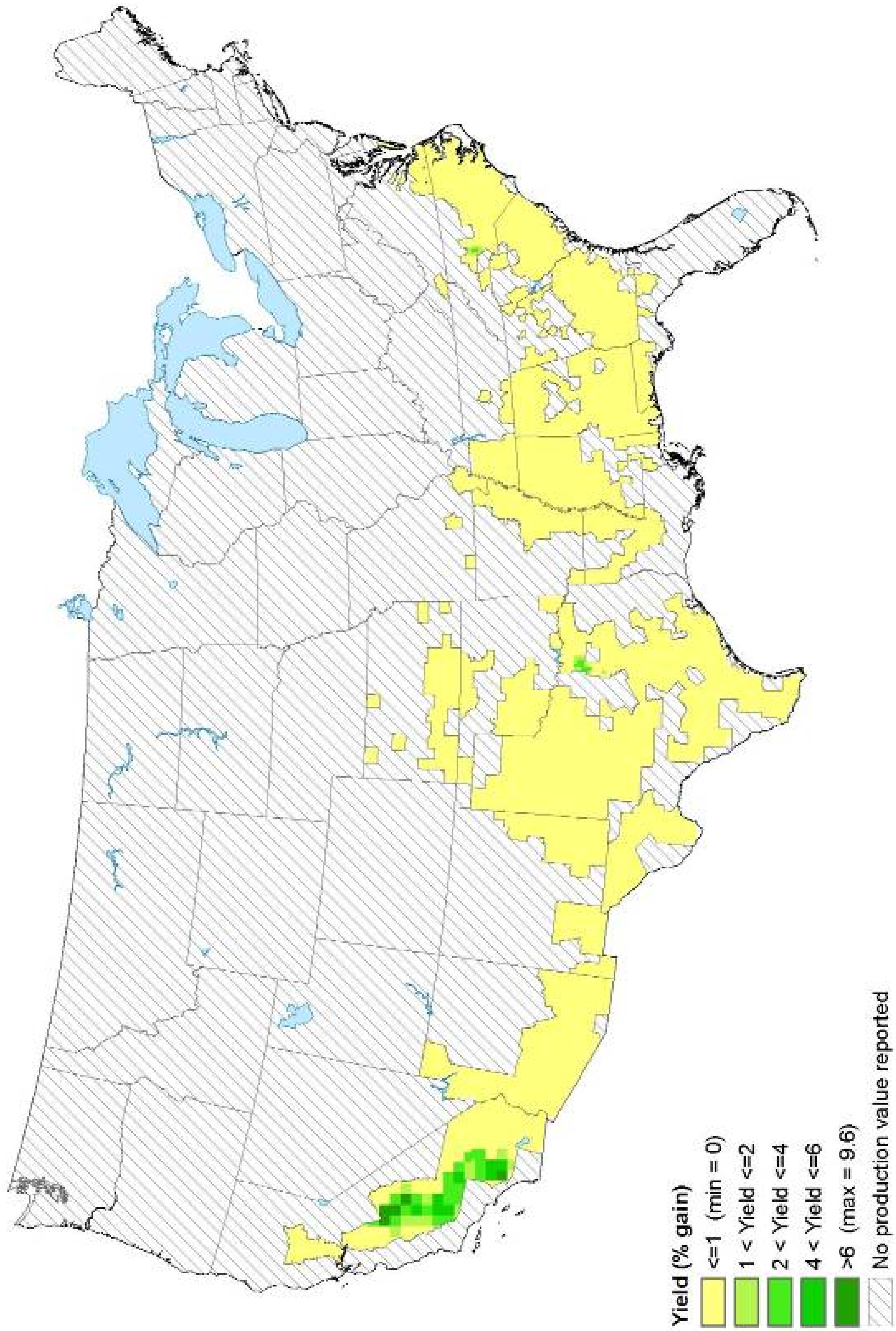
5.4.2 Yield Response Maps for Cotton and Soybean

Contrary to the above tables, the maps below were generated at the gridcell level. No weighting was applied. The minimum and maximum statistics in the legends correspond to yield responses for individual gridcells, and thus they tend to display more extreme yield responses than the statistic reported in the previous tables (additional crop maps can be found in Appendix G). Once again, these maps report results from 12-hr W126 exposures that have been calculated from 10% reduced hourly values. To compare with results from unreduced exposures, see Appendix G2.2.

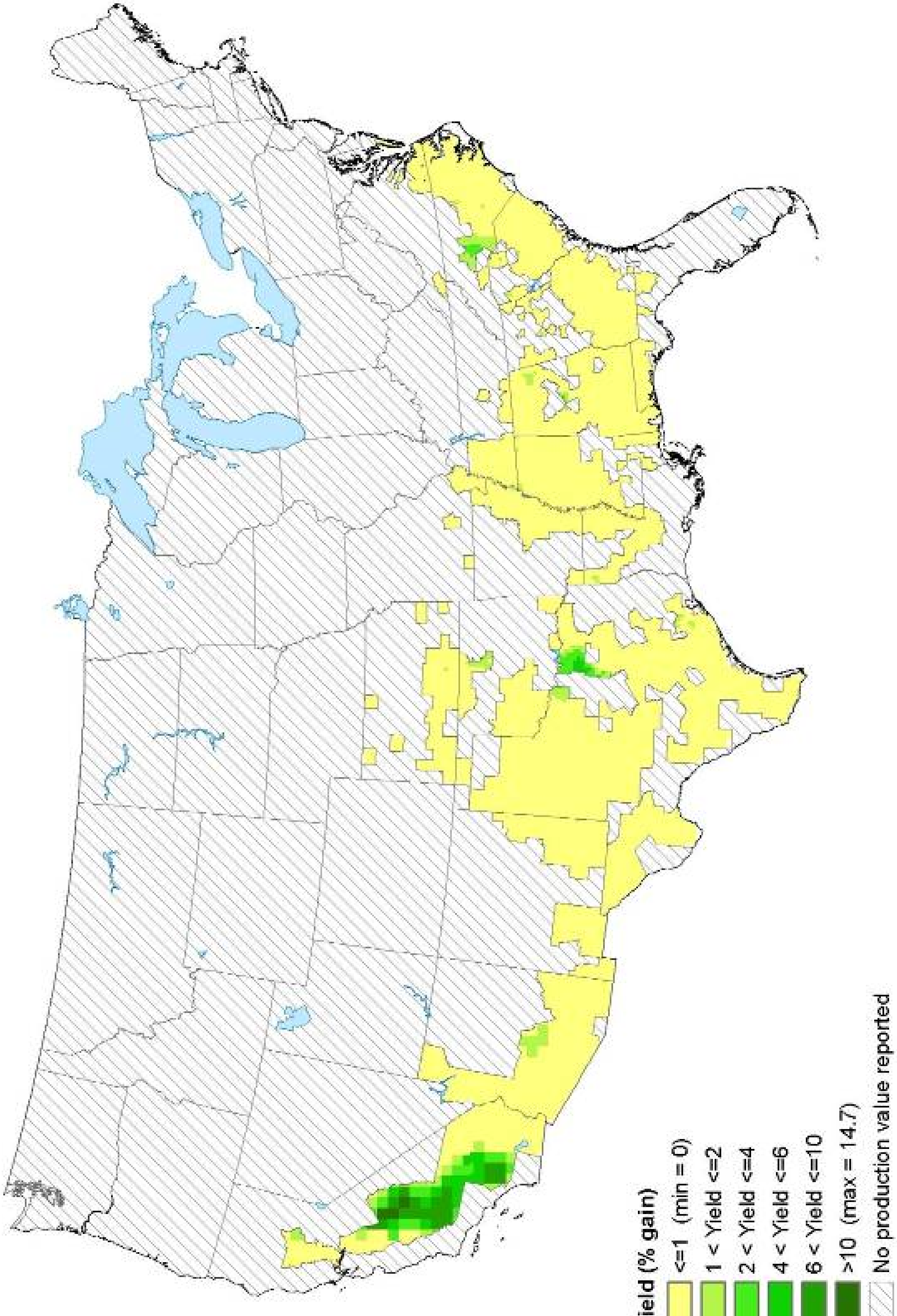
Cotton Response Maps



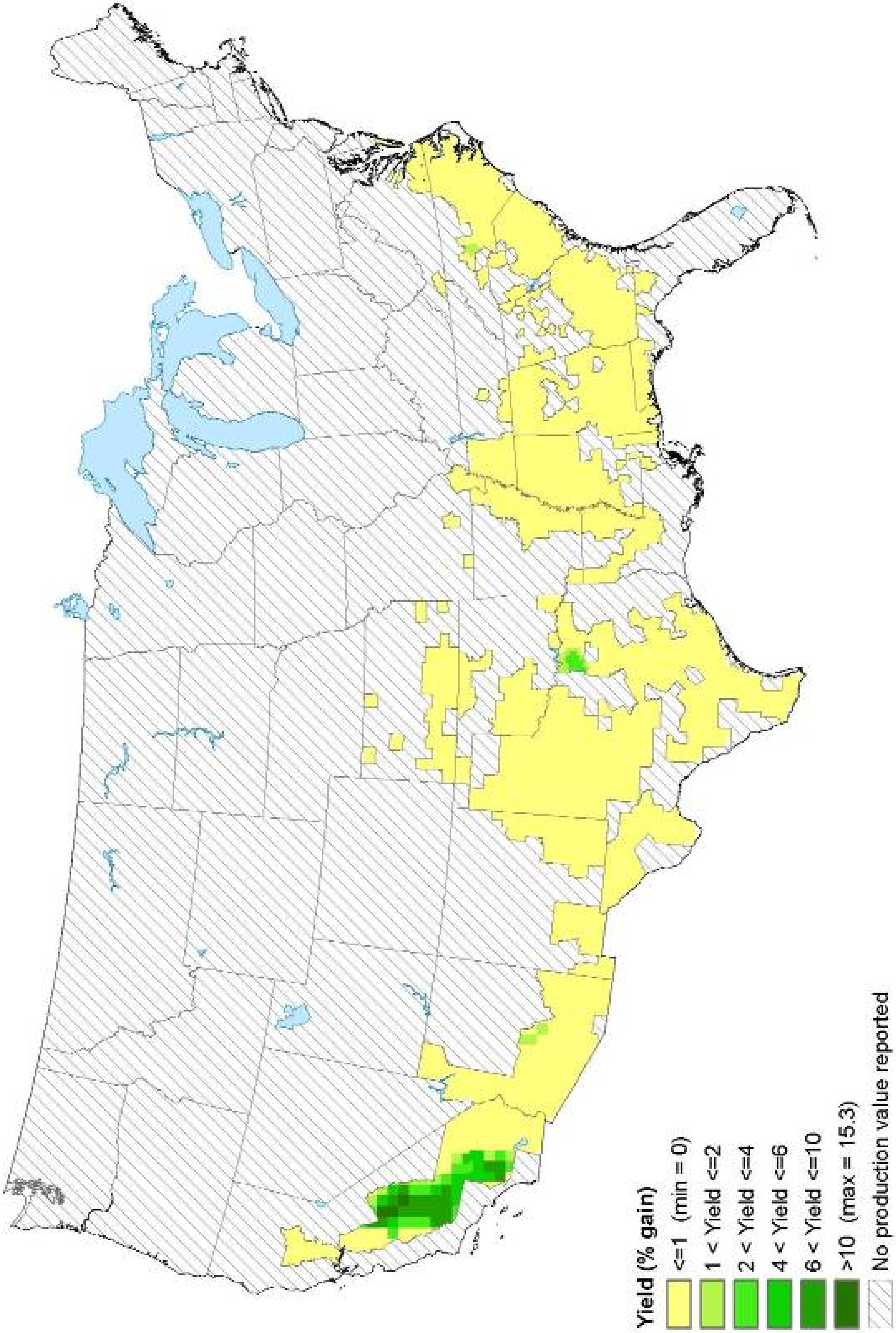
Map 5-1: As-is Yield loss for Cotton (Gossypium hirsutum) (Reduced W126).



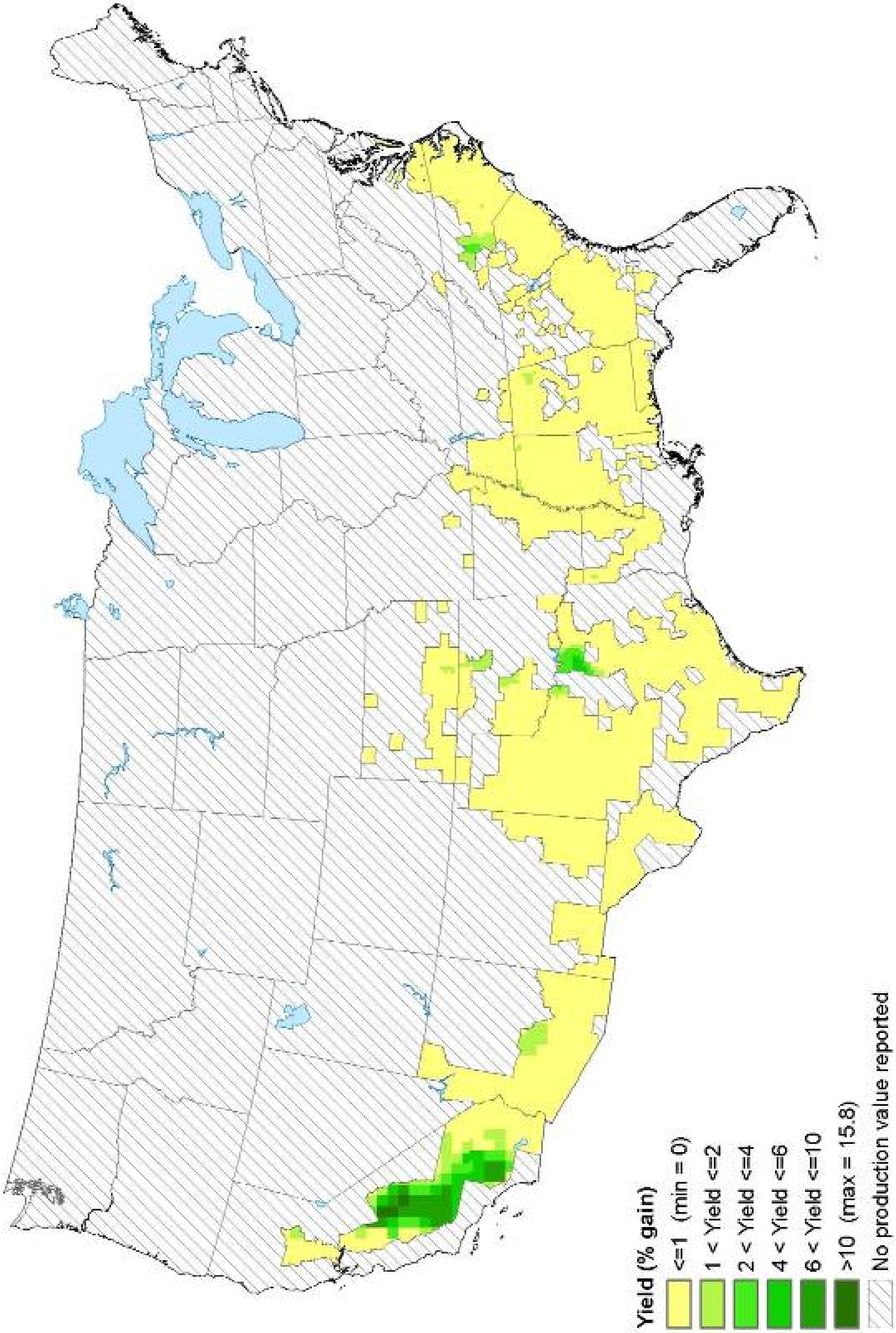
Map 5-2: Yield Gain from Baseline for Cotton (Gossypium hirsutum). Quadratic Rollback 4th Highest 8-hour Maximum to 84 ppb. (Reduced W126)



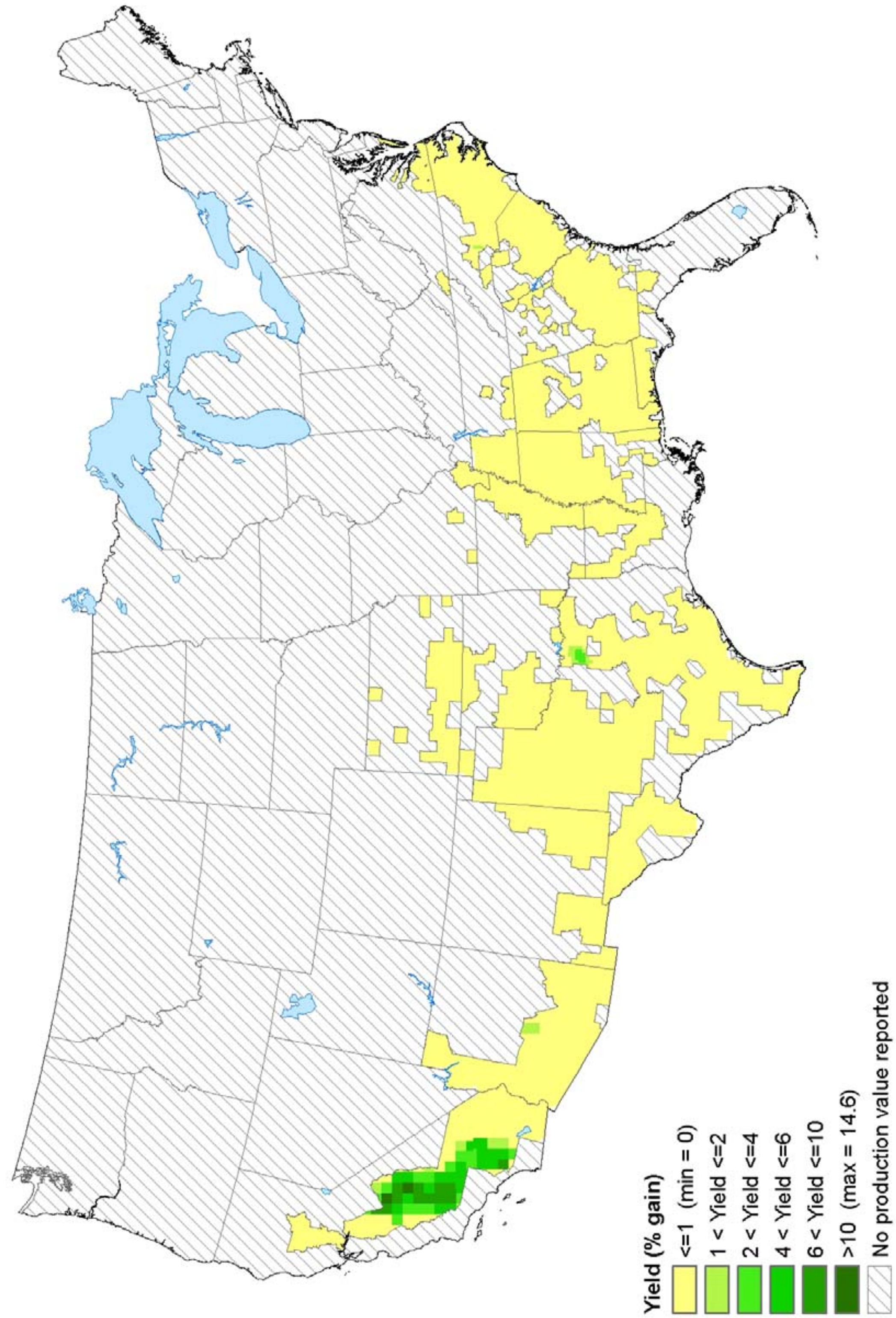
Map 5-3: Yield Gain from Baseline for Cotton (Gossypium hirsutum). Quadratic Rollback 4th Highest 8-hour Maximum to 70 ppb. (Reduced W126)



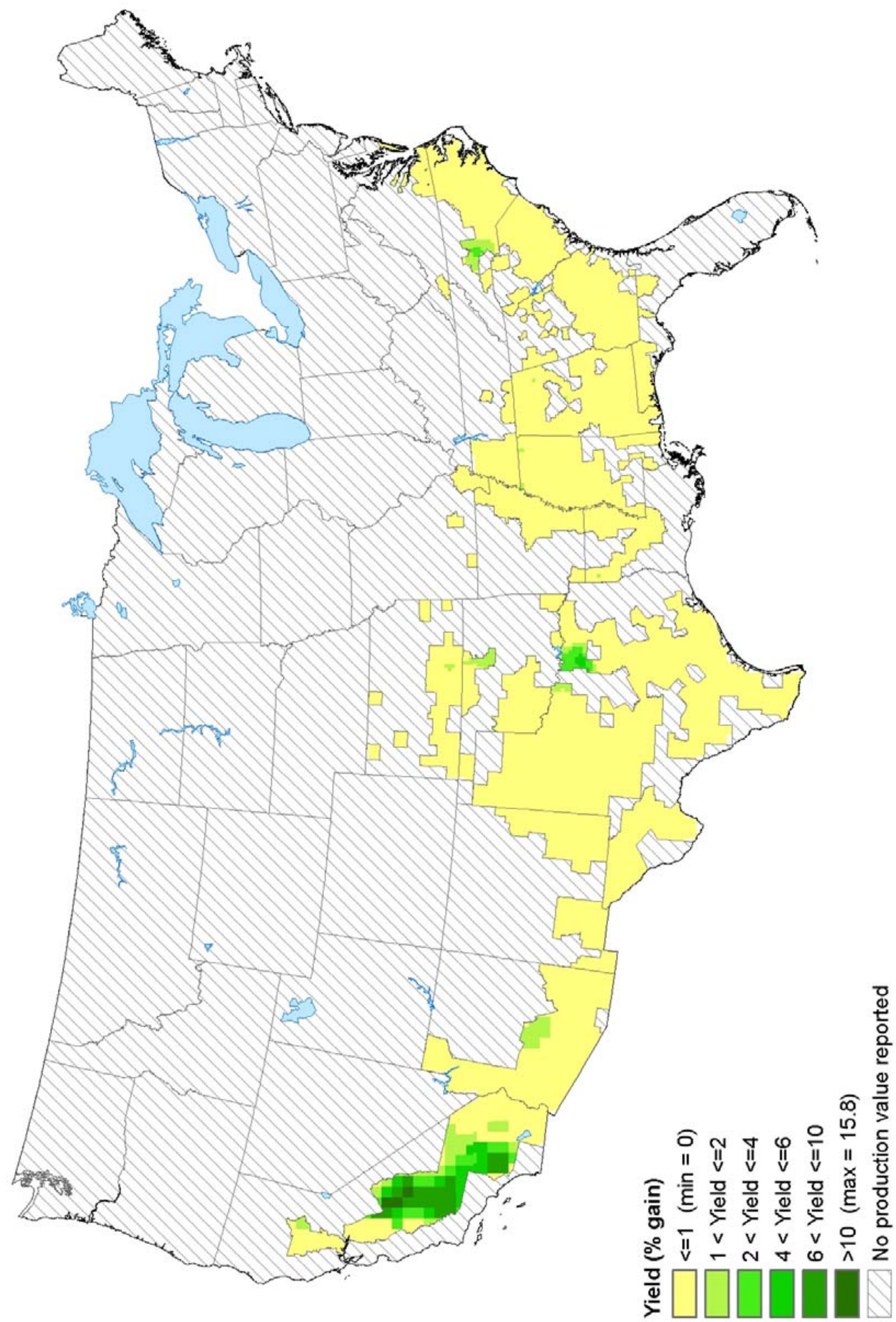
Map 5-4: Yield Gain from Baseline for Cotton (Gossypium hirsutum). Quadratic Rollback 3-month SUM06 to 25 ppm-hour. (Reduced W126)



Map 5-5: Yield Gain from Baseline for Cotton (Gossypium hirsutum). Quadratic Rollback 3-month SUM06 to 15 ppm-hour. (Reduced W126)

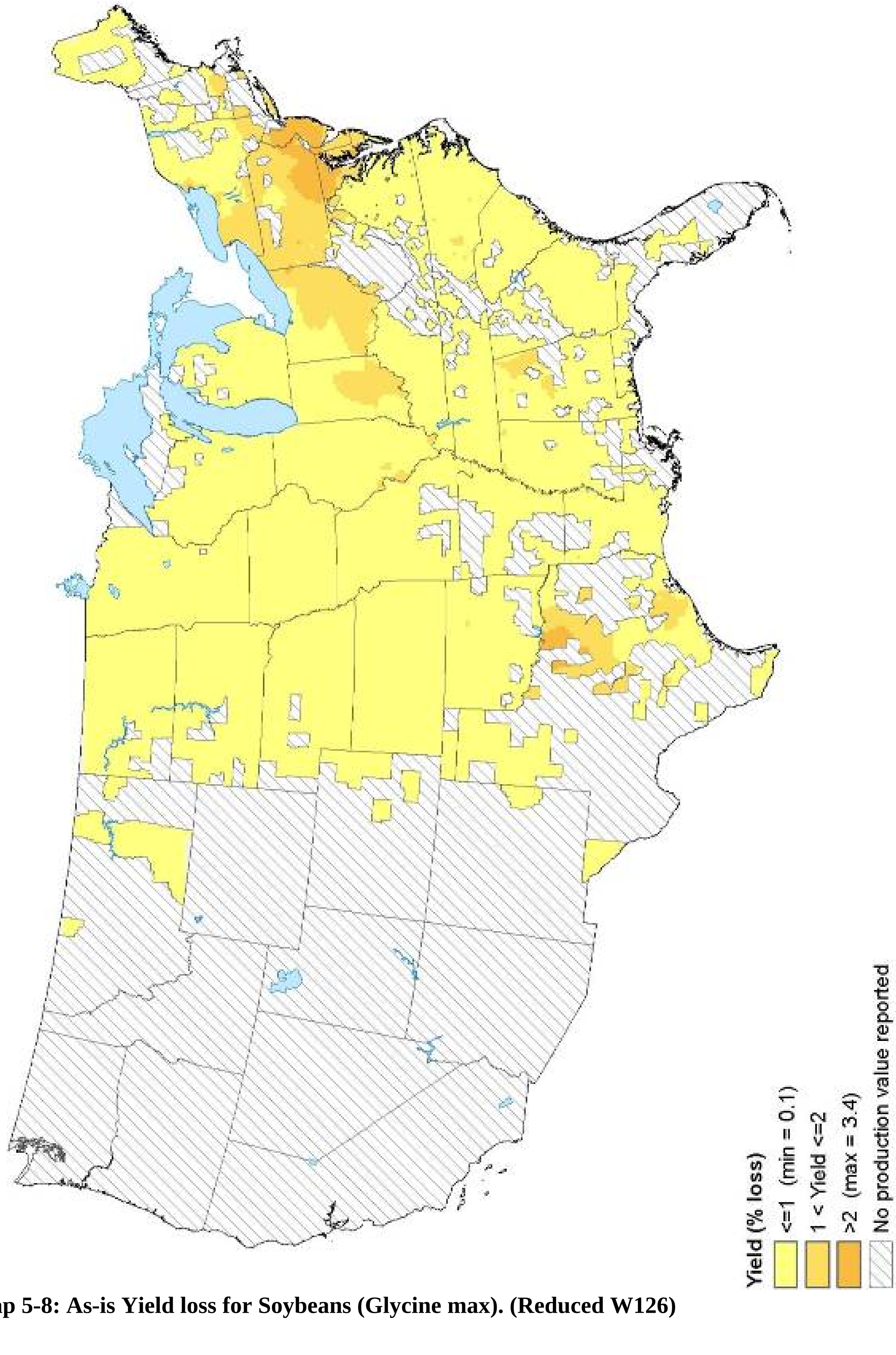


Map 5-6: Yield Gain from Baseline for Cotton (Gossypium hirsutum). Quadratic Rollback W126 to 21 ppm-hr (W126). (Reduced W126)

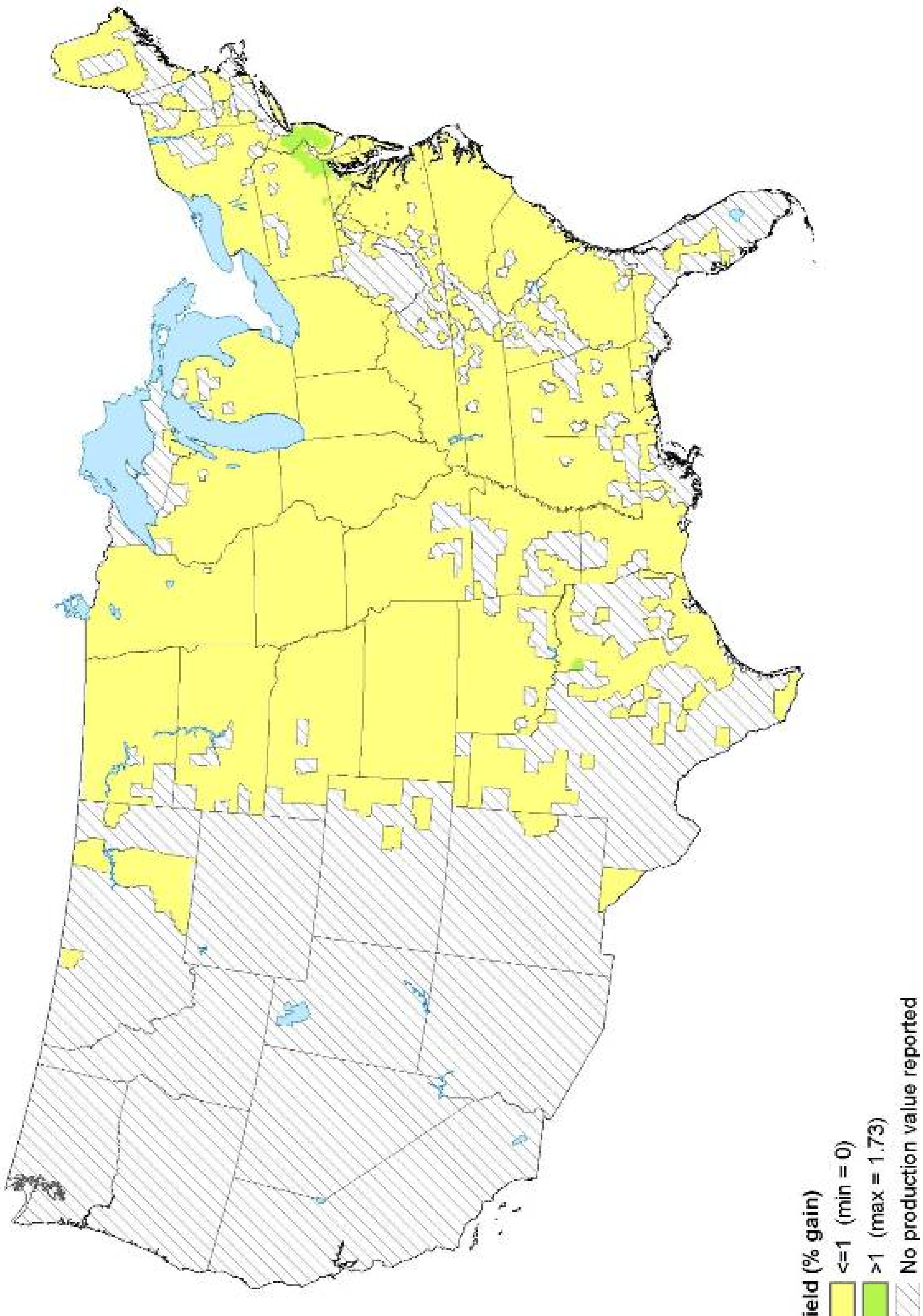


Map 5-7: Yield Gain from Baseline for Cotton (Gossypium hirsutum). Quadratic Rollback W126 to 13 ppm-hour (W126). (Reduced W126)

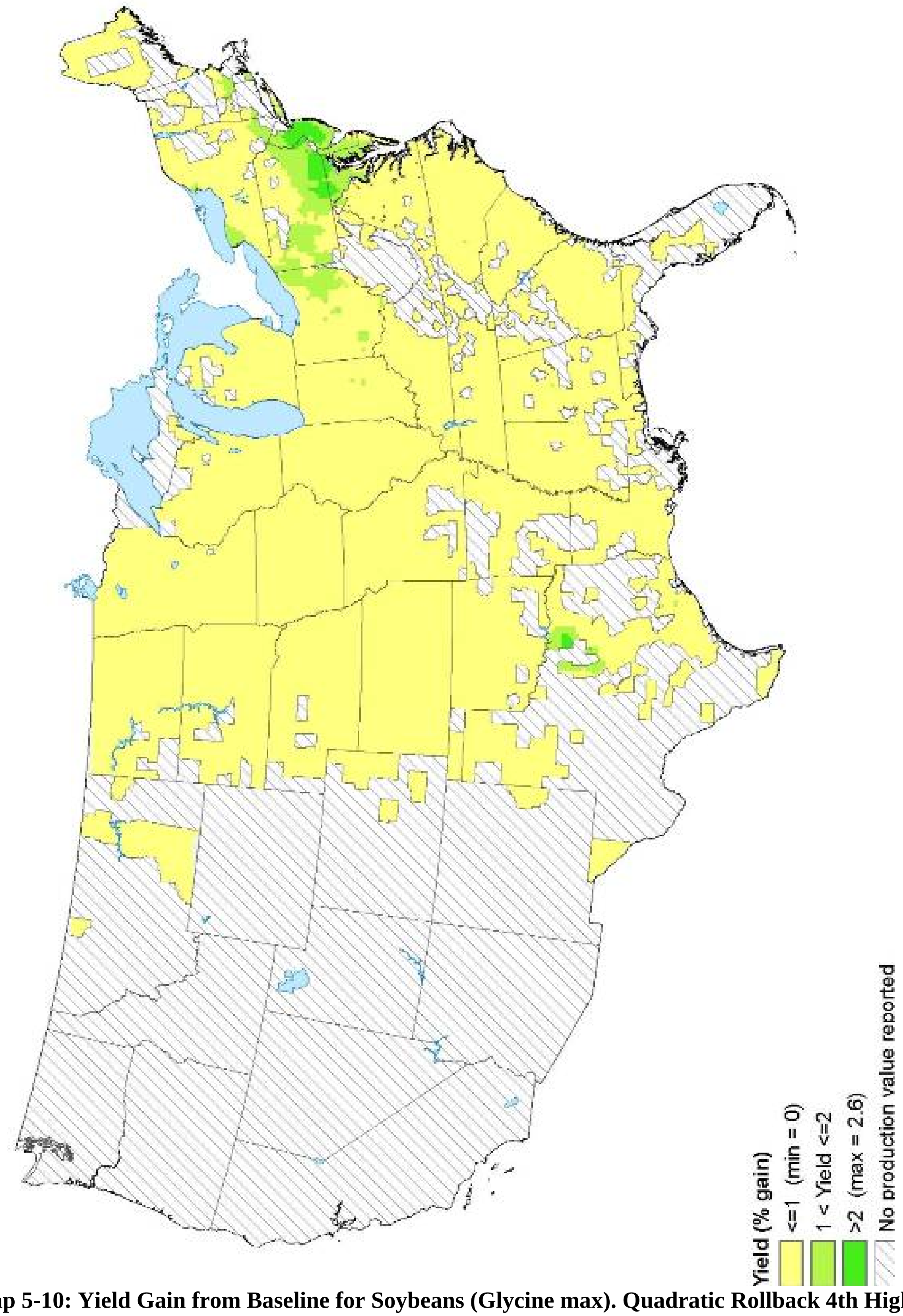
Soybean Response Maps



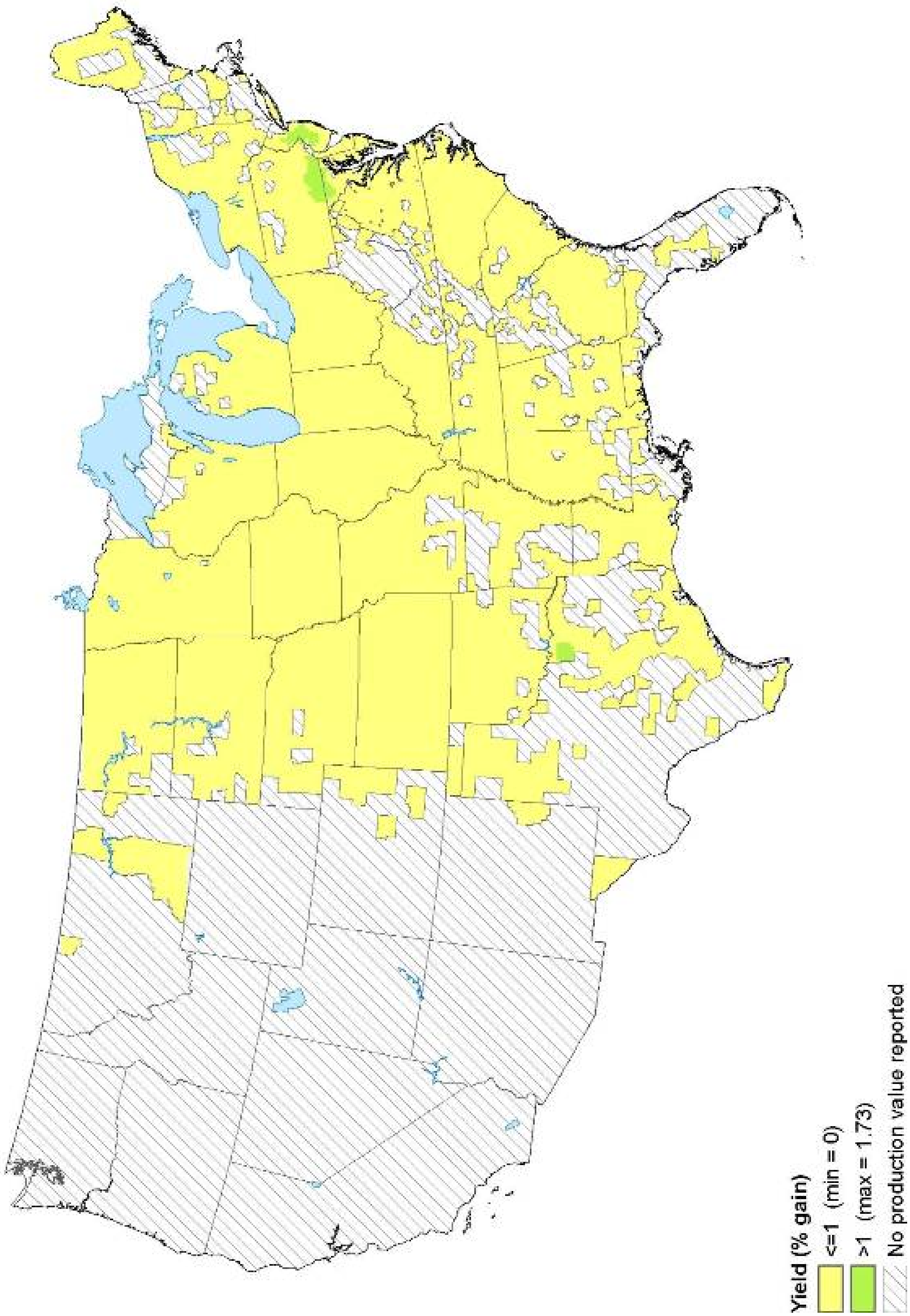
Map 5-8: As-is Yield loss for Soybeans (Glycine max). (Reduced W126)



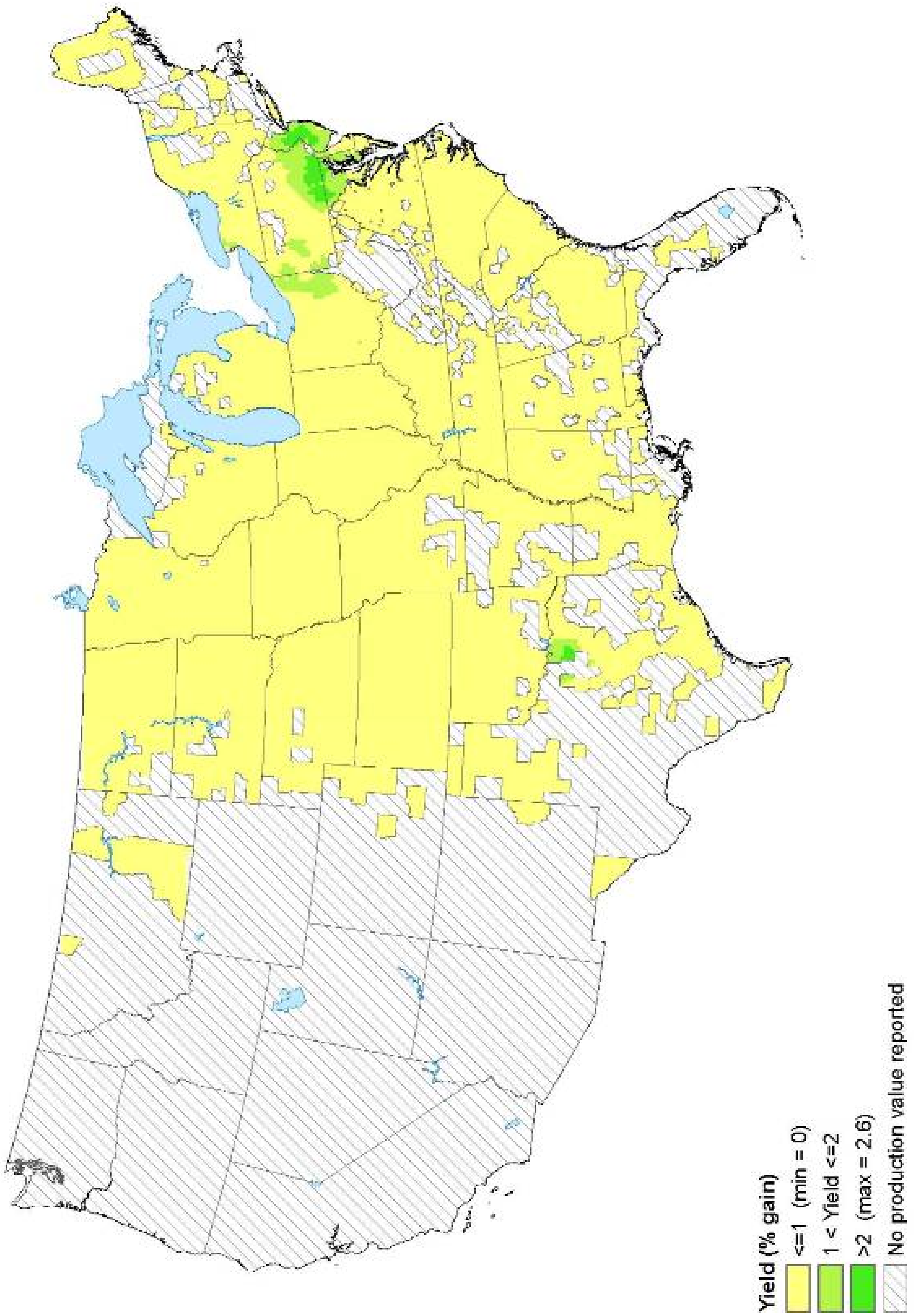
Map 5-9: Yield Gain from Baseline for Soybeans (Glycine max). Quadratic Rollback 4th Highest 8-hour Maximum to 84 ppb. (Reduced W126)



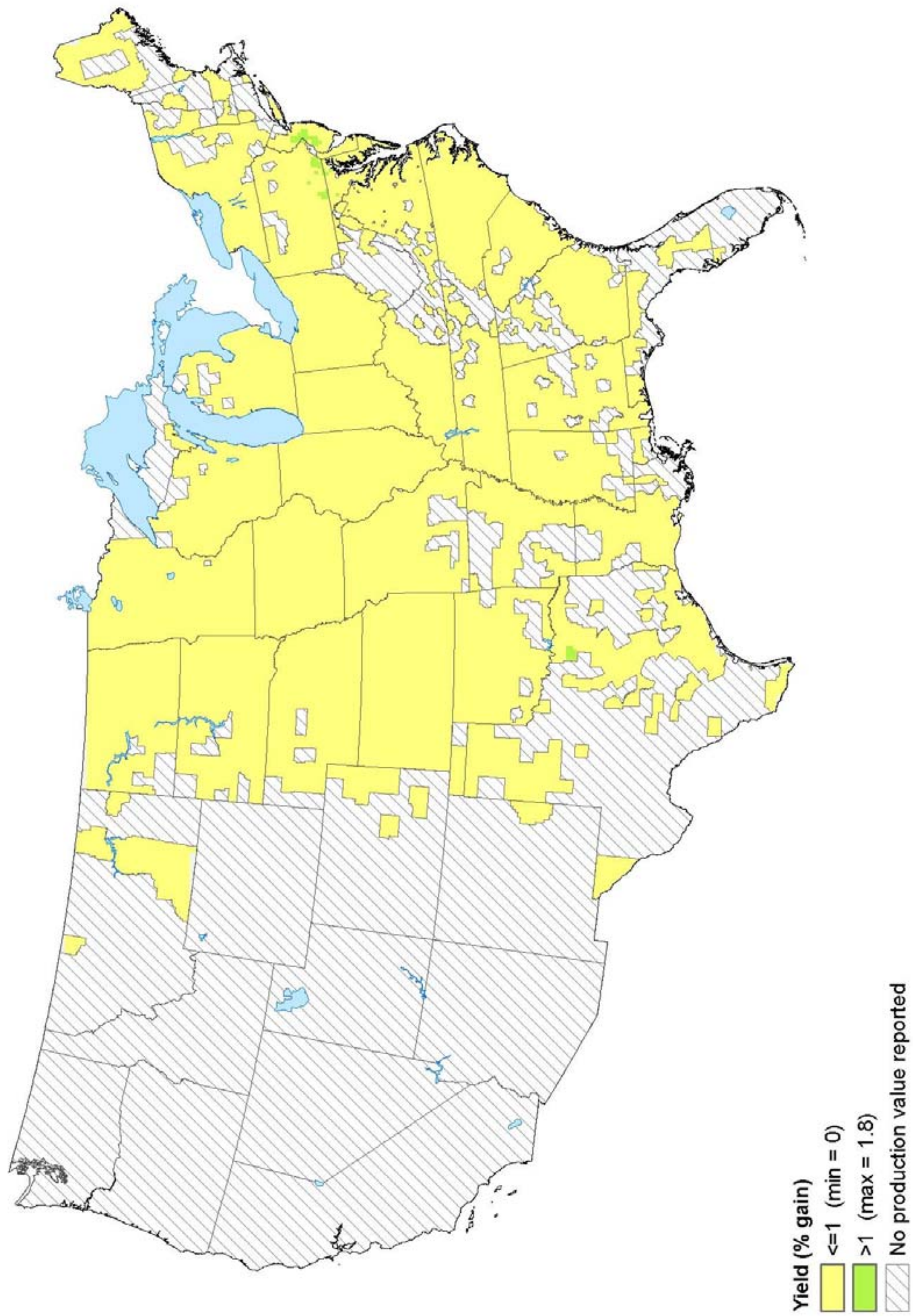
Map 5-10: Yield Gain from Baseline for Soybeans (Glycine max). Quadratic Rollback 4th Highest 8-hour Maximum to 70 ppb. (Reduced W126)



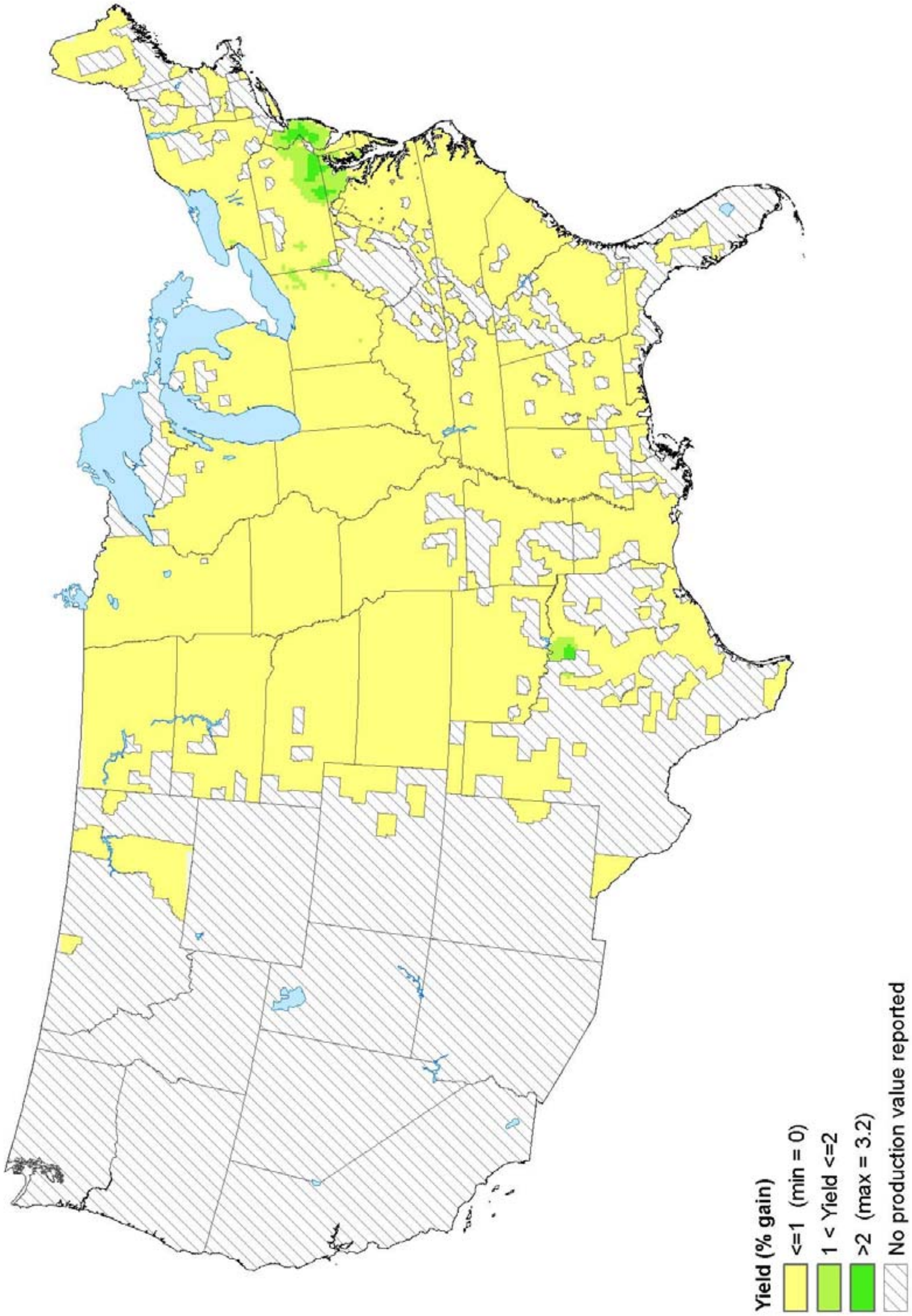
Map 5-11: Yield Gain from Baseline for Soybeans (Glycine max). Quadratic Rollback 3-month SUM06 to 25 ppm-hour. (Reduced W126)



Map 5-12: Yield Gain from Baseline for Soybeans (Glycine max). Quadratic Rollback 3-month SUM06 to 15 ppm-hour. (Reduced W126)



Map 5-13: Yield Gain from Baseline for Soybeans (Glycine max). Quadratic Rollback W126 to 21 ppm-hour. (Reduced W126)



Map 5-14: Yield Gain from Baseline for Soybeans (Glycine max). Quadratic Rollback W126 to 13 ppm-hour. (Reduced W126)

5.4.3 Biomass Impact on Tree Seedlings

The mean national response is a weighted average of gridcell-level results. Results in the western grid were *weighted by nine* to account for the difference in gridcell size between the eastern and western grid (1,296 km^2 vs. 144 km^2). Results for all tree species are included in Appendix H. All results presented in this section use estimated O_3 exposure metrics with a 10% reduction of hourly values. The results for exposures without the 10% reduction can be found in Appendix H2.2

The following tables show count, mean, maximum, minimum, median, and standard deviation statistics for Aspen, Black Cherry and Ponderosa Pine based on the six scenarios described in Chapter 4.

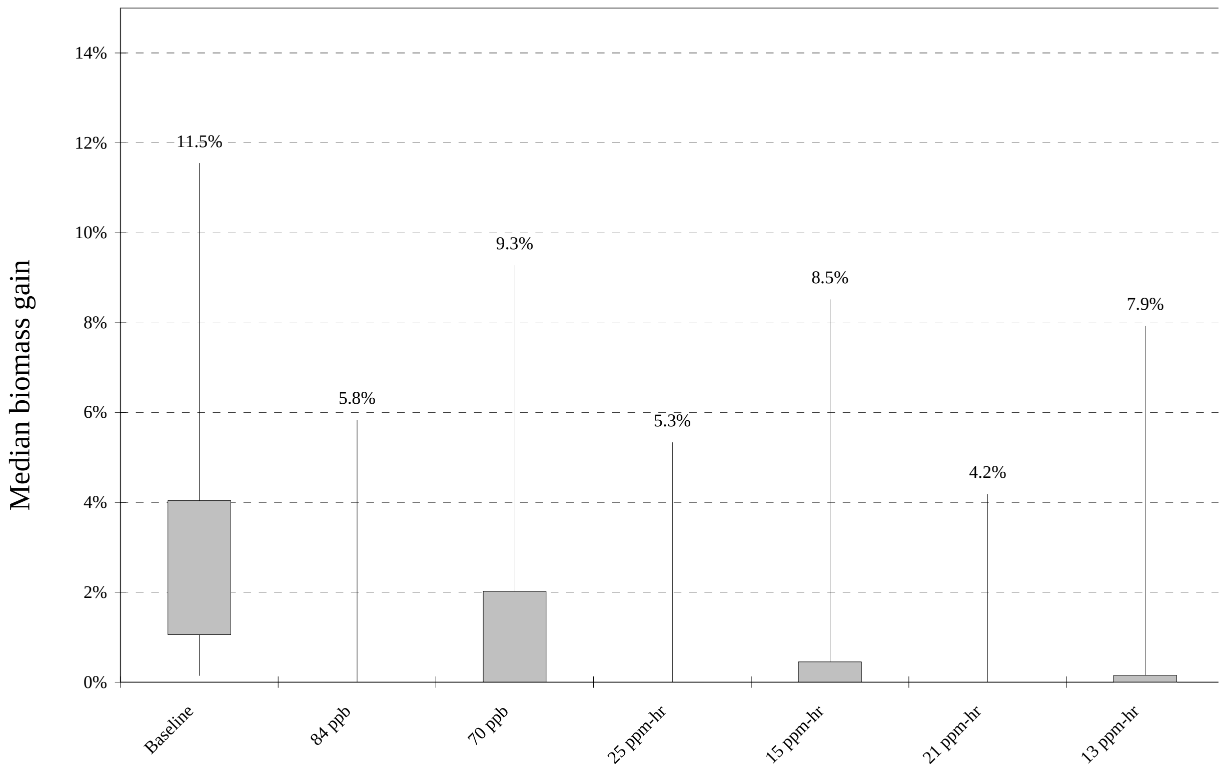


Figure 5-7: Median Biomass Gain from Baseline for Aspen (reduced W126)

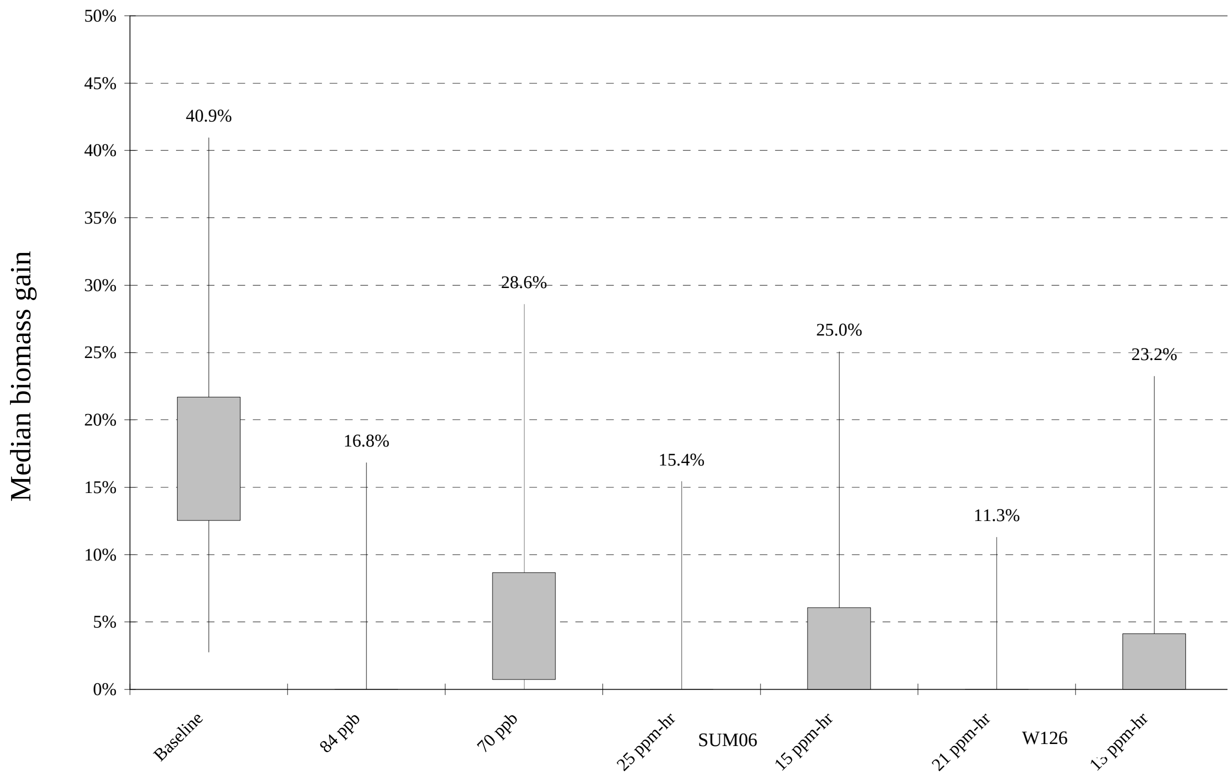


Figure 5-8: Median Biomass Gain from Baseline for BlackCherry (reduced W126)

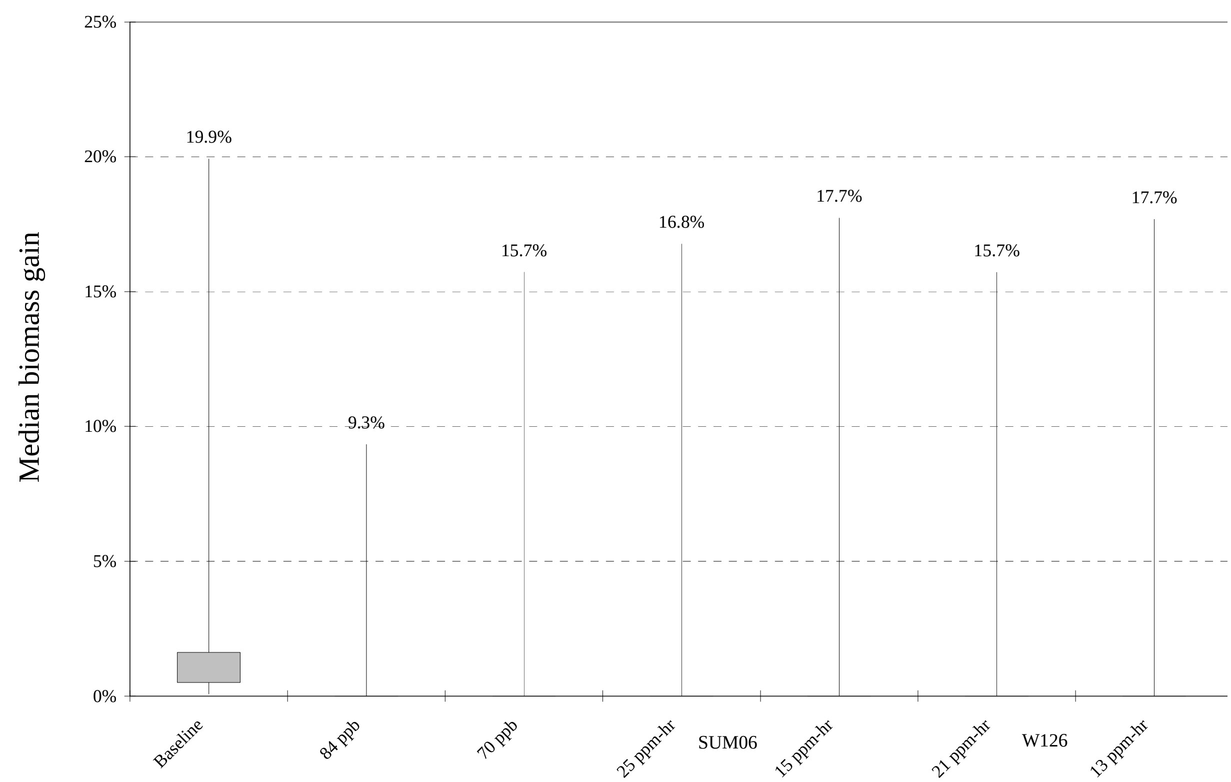


Figure 5-9: Median Biomass Gain from Baseline for Ponderosa Pine (reduced W126)

Table 5-13: Median Yield Gain from Baseline for Aspen (reduced W126)

Scenario	*Max*	*Min*	*Mean*	*Median*	*STD*
Baseline	11.5%	0.1%	2.7%	2.0%	2.5%
84 ppb	5.8%	0.0%	0.1%	0.0%	0.6%
70 ppb	9.3%	0.0%	1.1%	0.0%	1.9%
SUM06 25 ppm-hr	5.3%	0.0%	0.1%	0.0%	0.5%
SUM06 15 ppm-hr	8.5%	0.0%	0.6%	0.0%	1.5%
W126 21 ppm-hr	4.2%	0.0%	0.0%	0.0%	0.3%
W126 13 ppm-hr	7.9%	0.0%	0.5%	0.0%	1.3%

Table 5-14: Median Yield Gain from Baseline for Black Cherry (reduced W126)

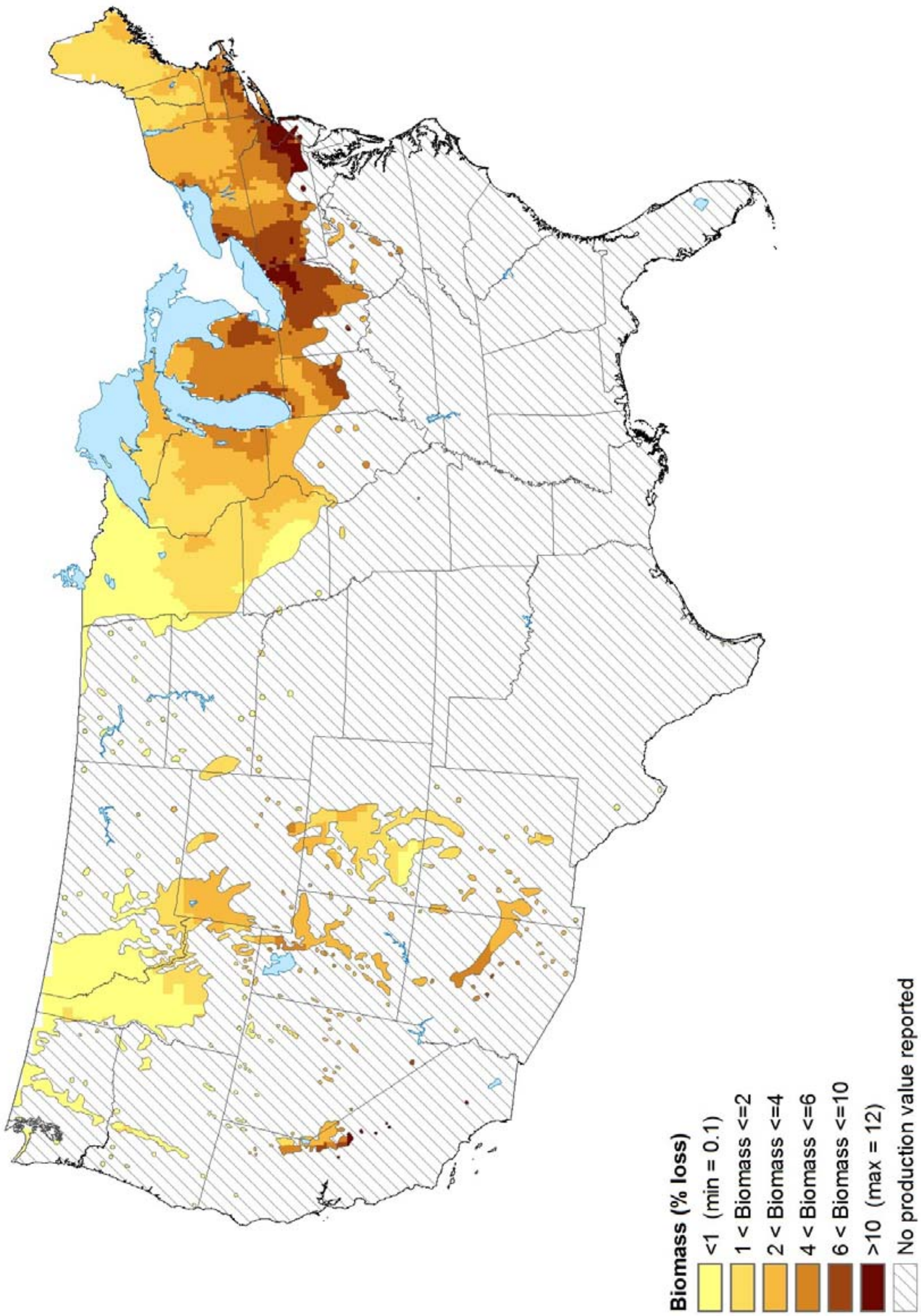
Scenario	*Max*	*Min*	*Mean*	*Median*	*STD*
Baseline	40.9%	2.8%	17.2%	16.8%	6.5%
84 ppb	16.8%	0.0%	0.4%	0.0%	1.6%
70 ppb	28.6%	0.0%	5.4%	4.0%	5.3%
SUM06 25 ppm-hr	15.4%	0.0%	0.3%	0.0%	1.4%
SUM06 15 ppm-hr	25.0%	0.0%	3.4%	0.9%	4.6%
W126 21 ppm-hr	11.3%	0.0%	0.1%	0.0%	0.8%
W126 13 ppm-hr	23.2%	0.0%	2.4%	0.0%	3.8%

Table 5-15: Minimum Yield Gain from Baseline for Ponderosa Pine (reduced W126)

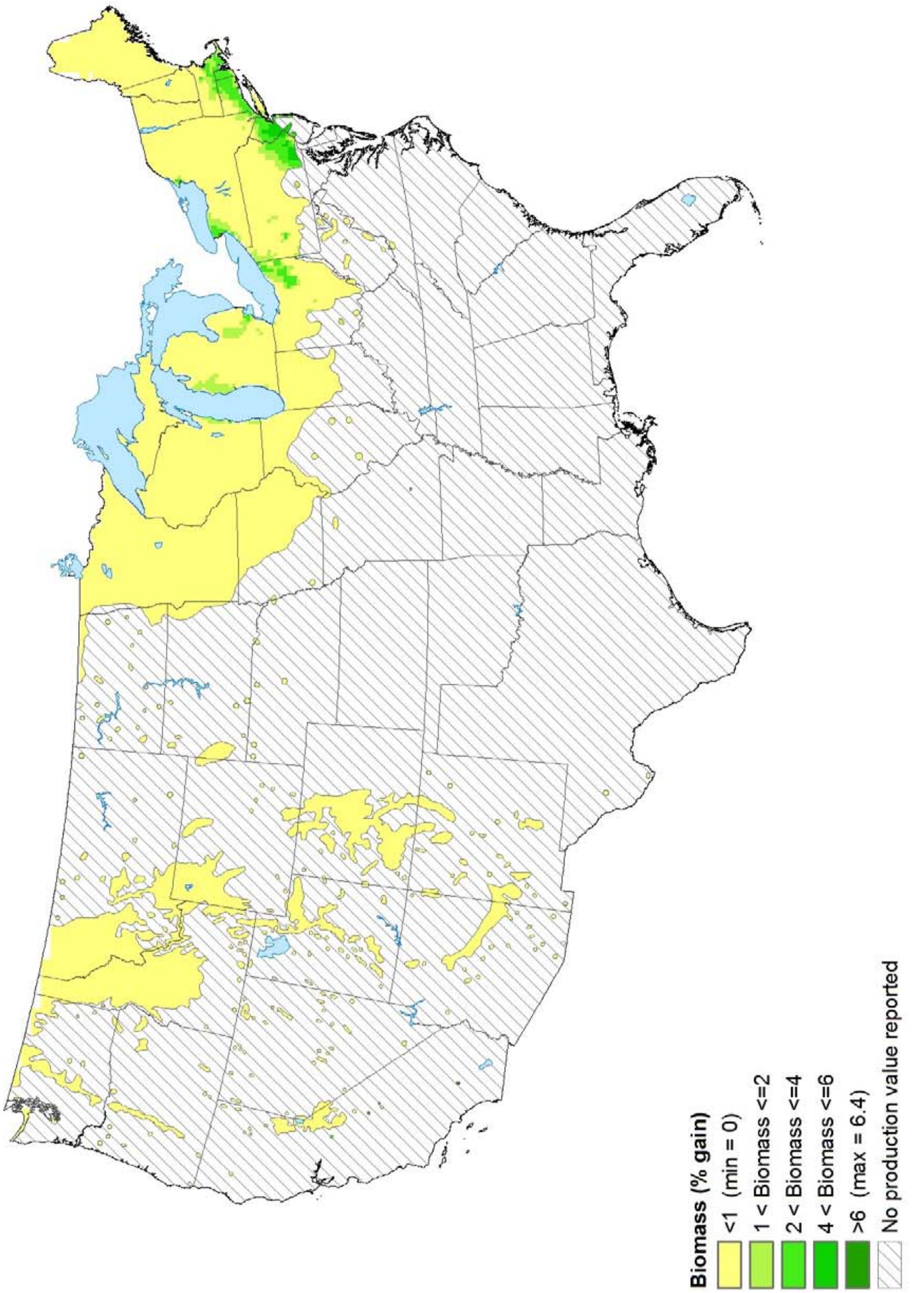
Scenario	*Max*	*Min*	*Mean*	*Median*	*STD*
Baseline	19.9%	0.1%	1.3%	0.8%	5.5%
84 ppb	9.3%	0.0%	0.1%	0.0%	2.1%
70 ppb	15.7%	0.0%	0.3%	0.0%	4.1%
SUM06 25 ppm-hr	16.8%	0.0%	0.2%	0.0%	3.8%
SUM06 15 ppm-hr	17.7%	0.0%	0.3%	0.0%	4.5%
W126 21 ppm-hr	15.7%	0.0%	0.2%	0.0%	3.4%
W126 13 ppm-hr	17.7%	0.0%	0.3%	0.0%	4.4%

5.4.4 Seedling Biomass Response Maps for Selected Tree Species

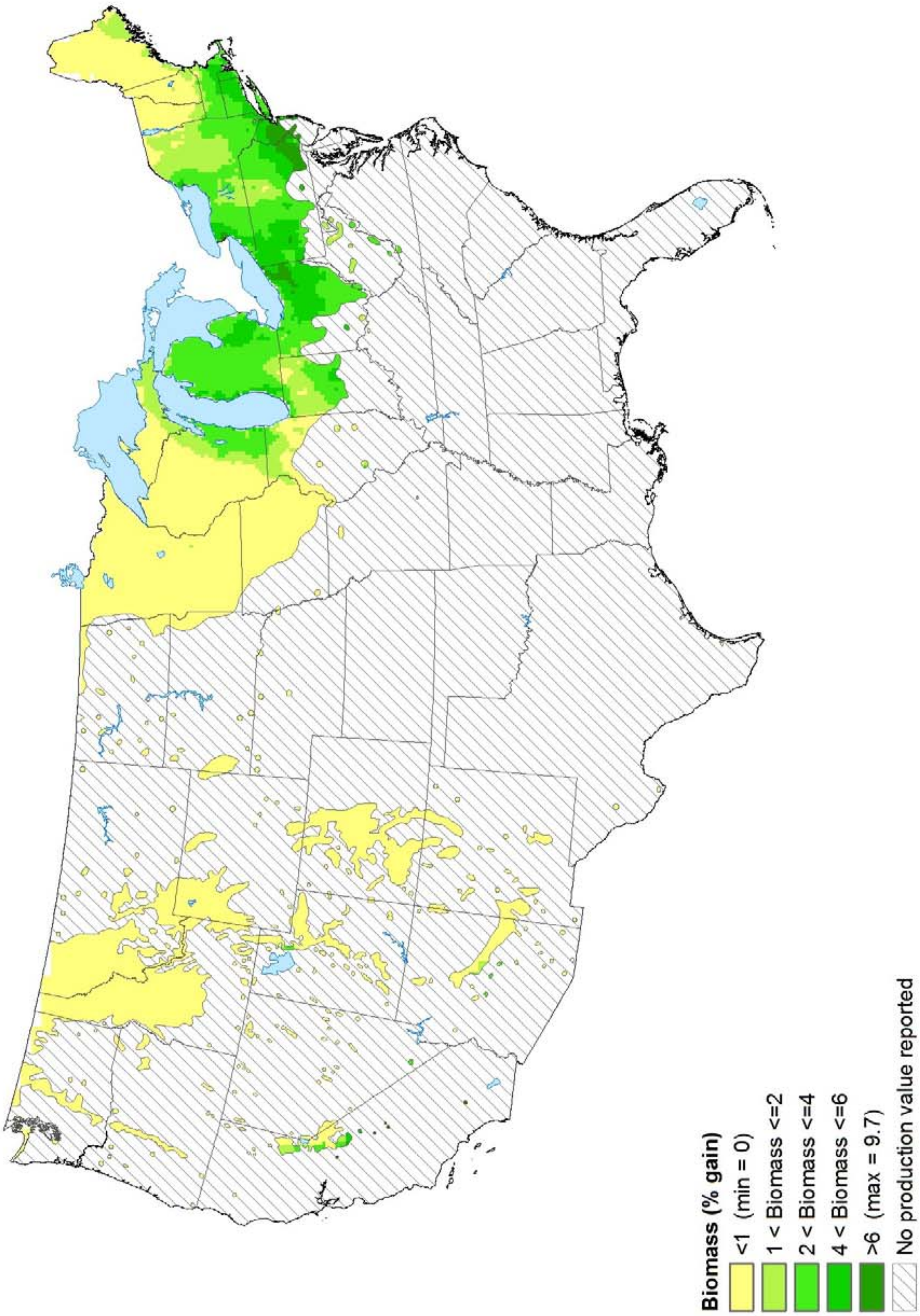
Aspen Response Maps



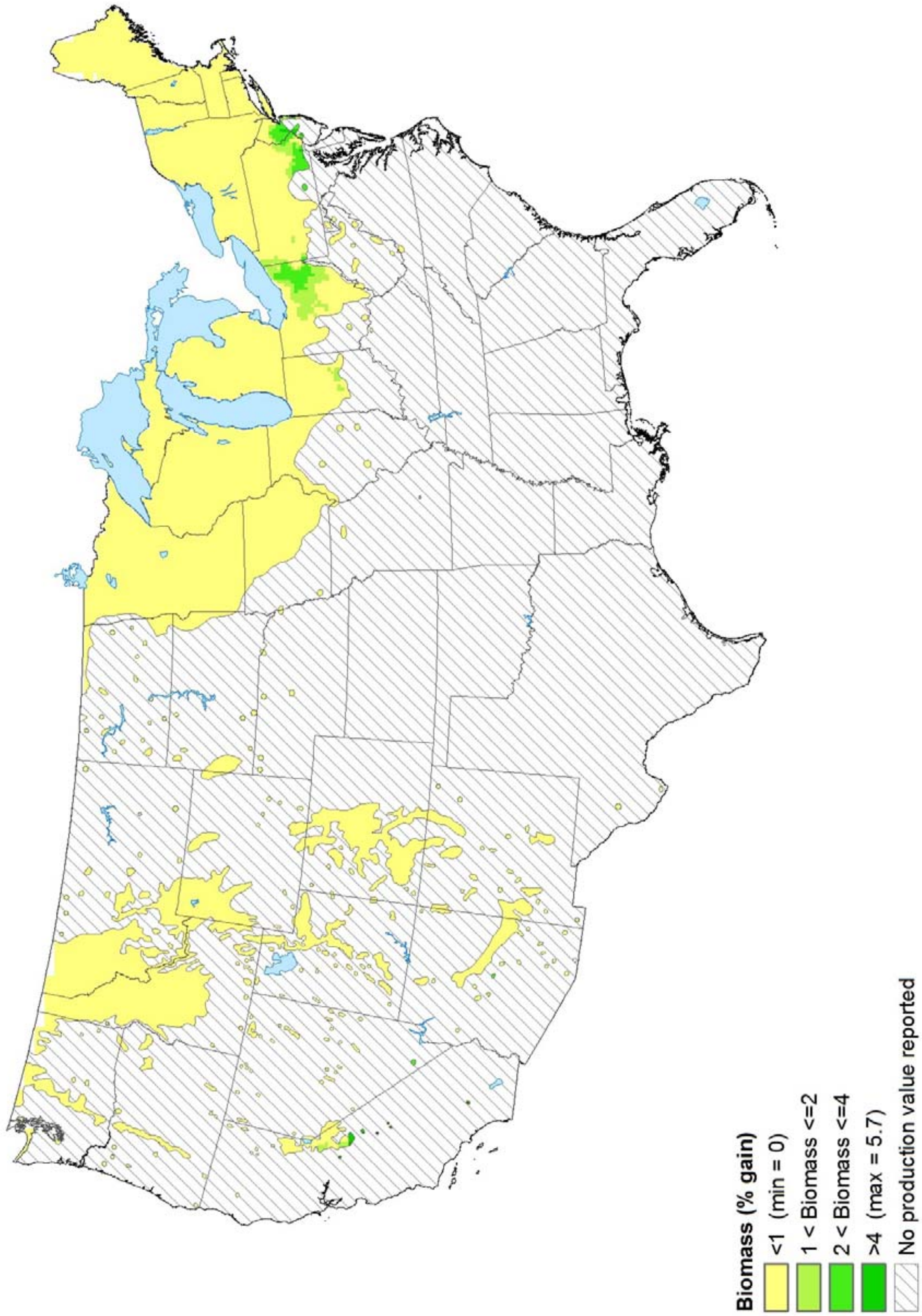
Map 5-15: As-is Biomass Loss for Aspen (Reduced W126)



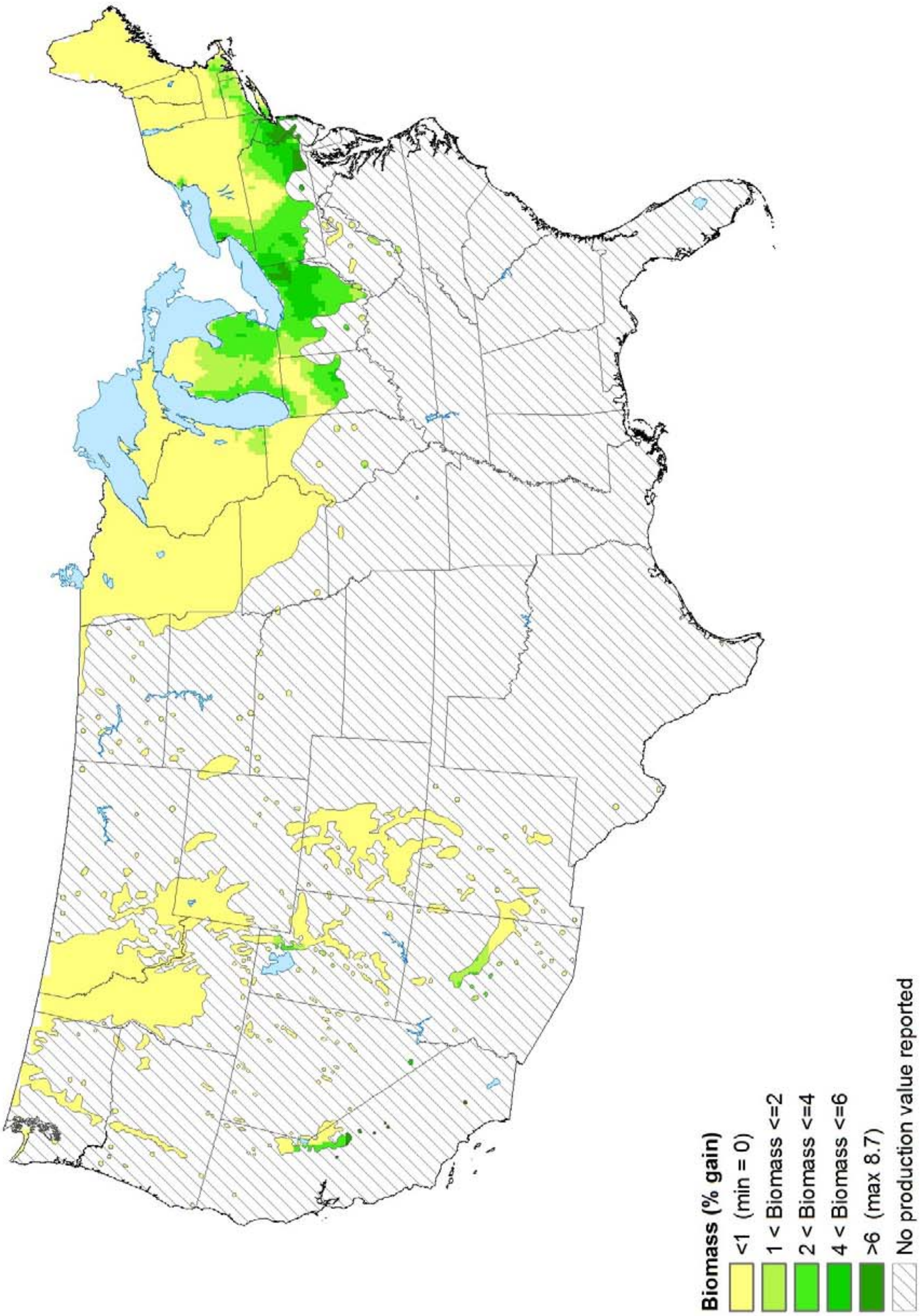
Map 5-16: Biomass Gain from Baseline for Aspen. Quadratic Rollback 4th Highest 8-hour Maximum to 84 ppb. (Reduced W126)



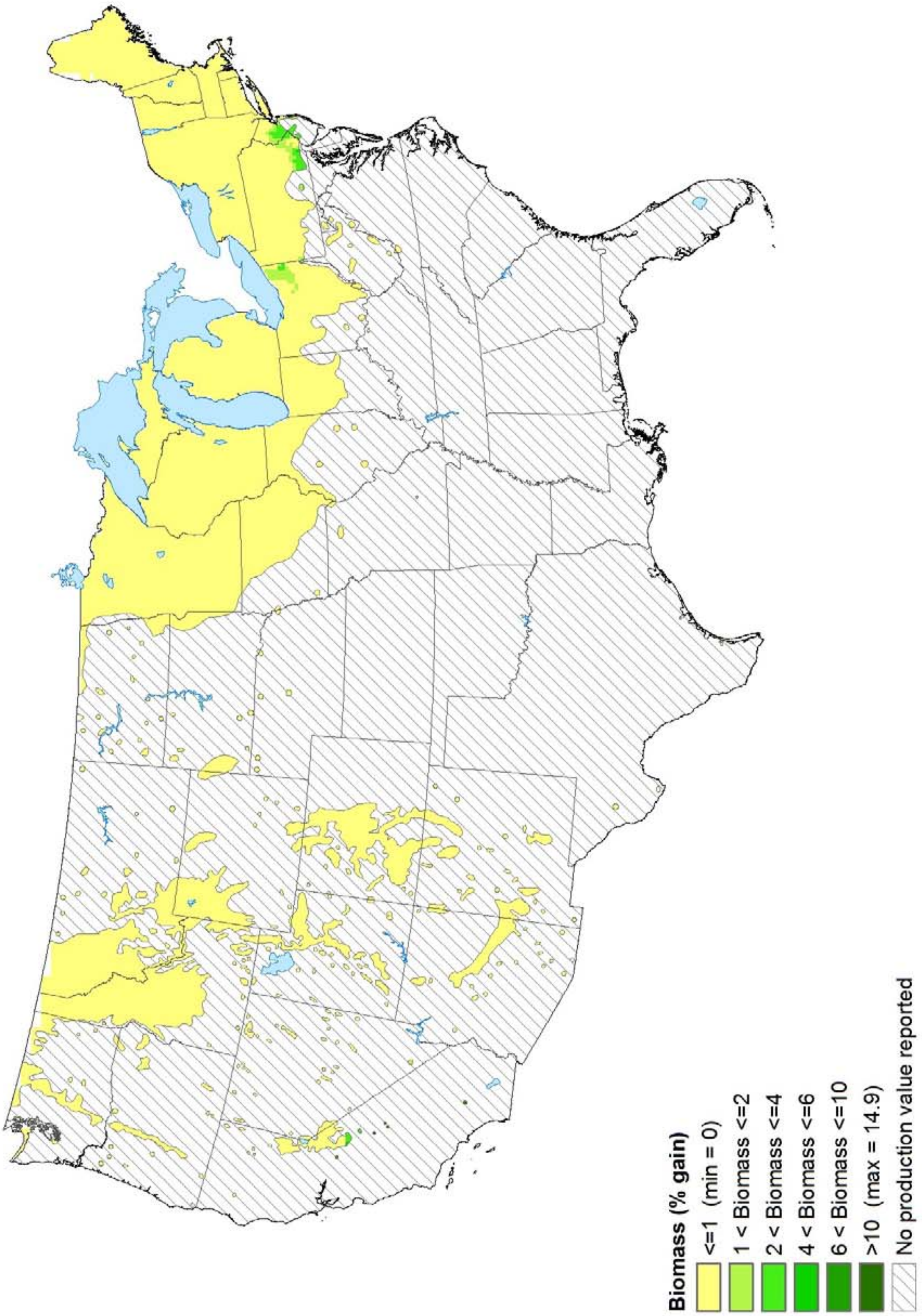
Map 5-17: Biomass Gain from Baseline for Aspen. Quadratic Rollback 4th Highest 8-hour Maximum to 70 ppb. (Reduced W126)



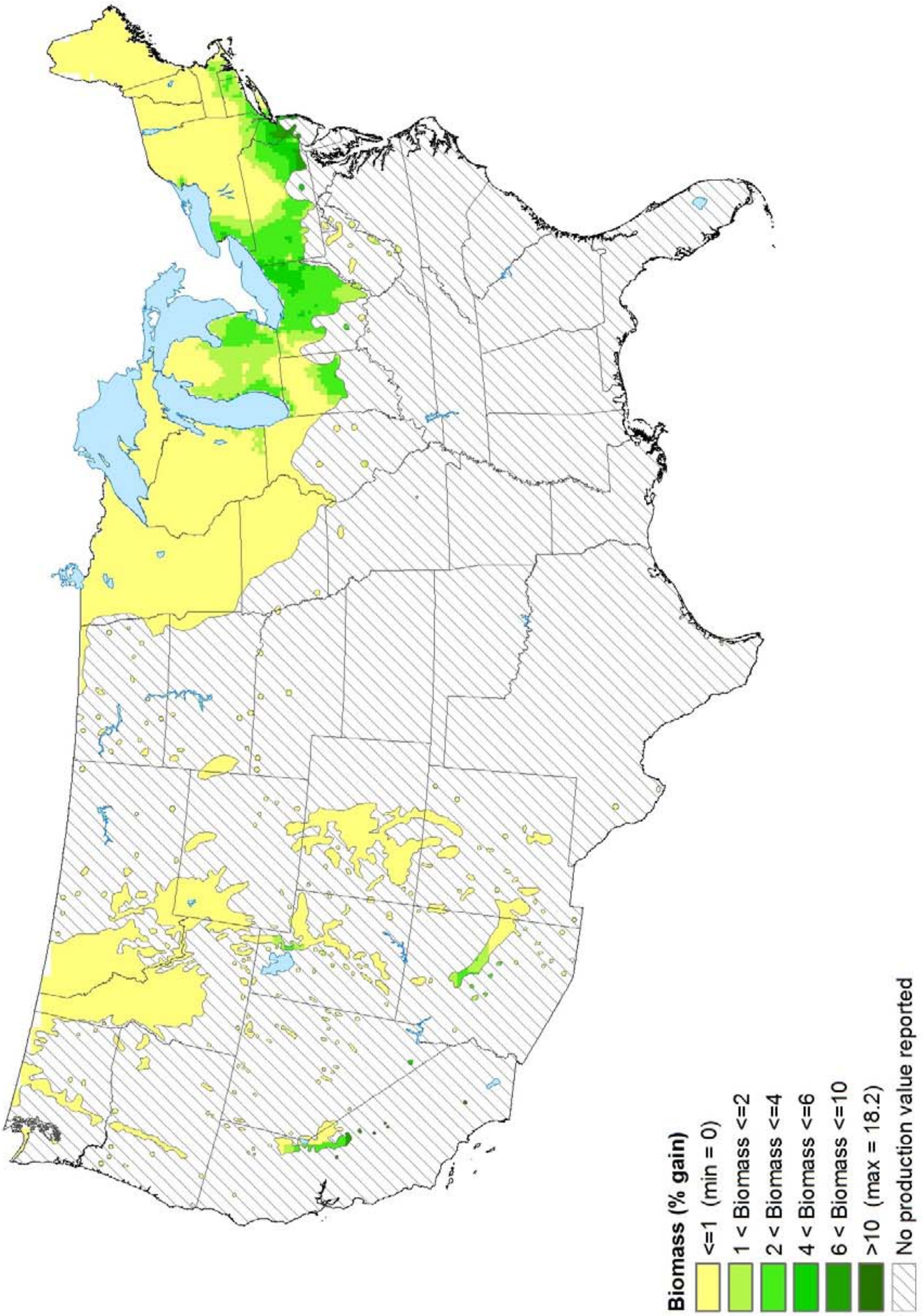
Map 5-18: Biomass Gain from Baseline for Aspen. Quadratic Rollback 3-month SUM06 to 25 ppm-hour. (Reduced W126)



Map 5-19: Biomass Gain from Baseline for Aspen. Quadratic Rollback 3-month SUM06 to 15 ppm-hour. (Reduced W126)

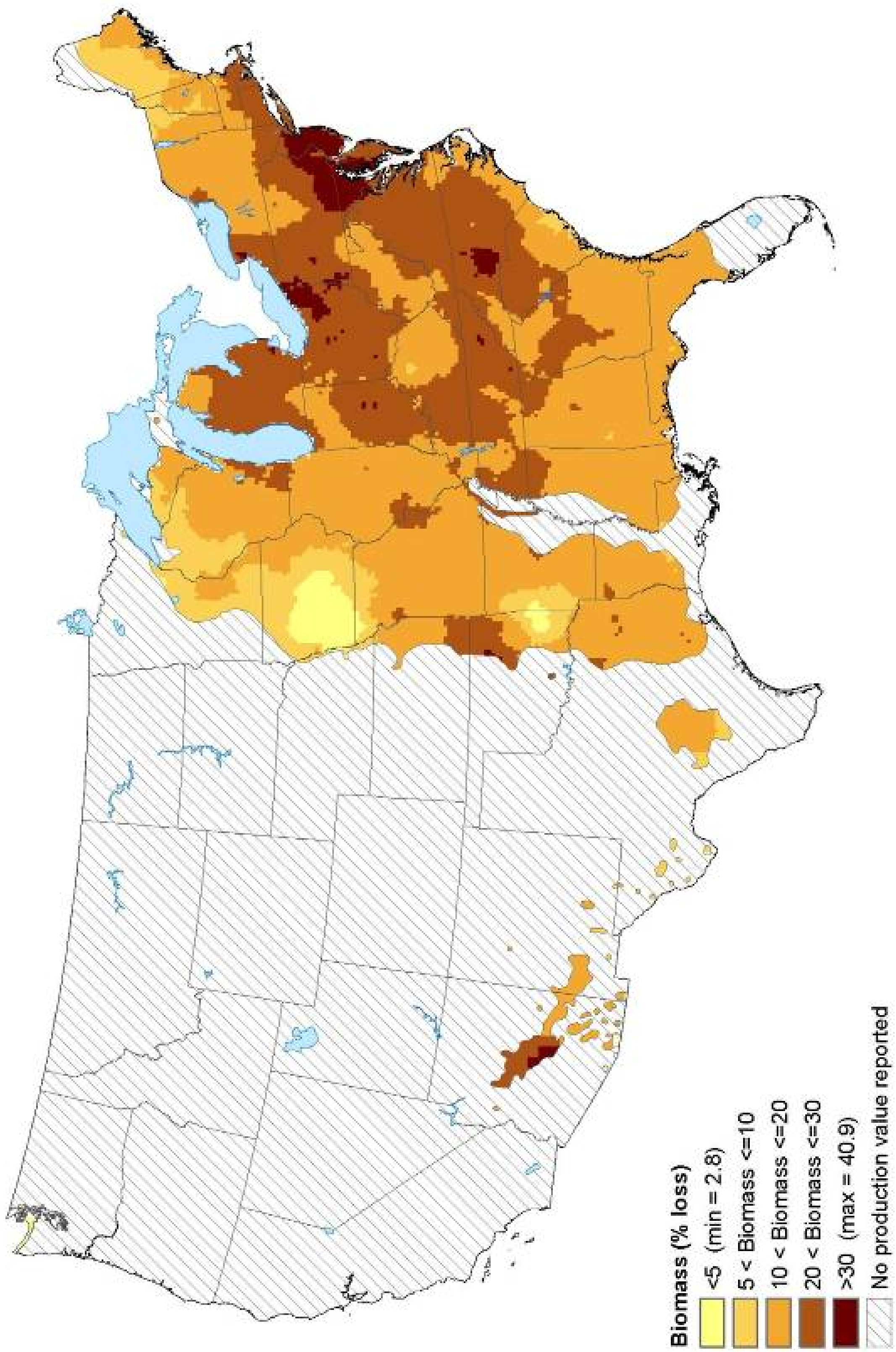


Map 5-20: Biomass Gain from Baseline for Aspen. Quadratic Rollback W126 to 21 ppm-hour. (Reduced W126)

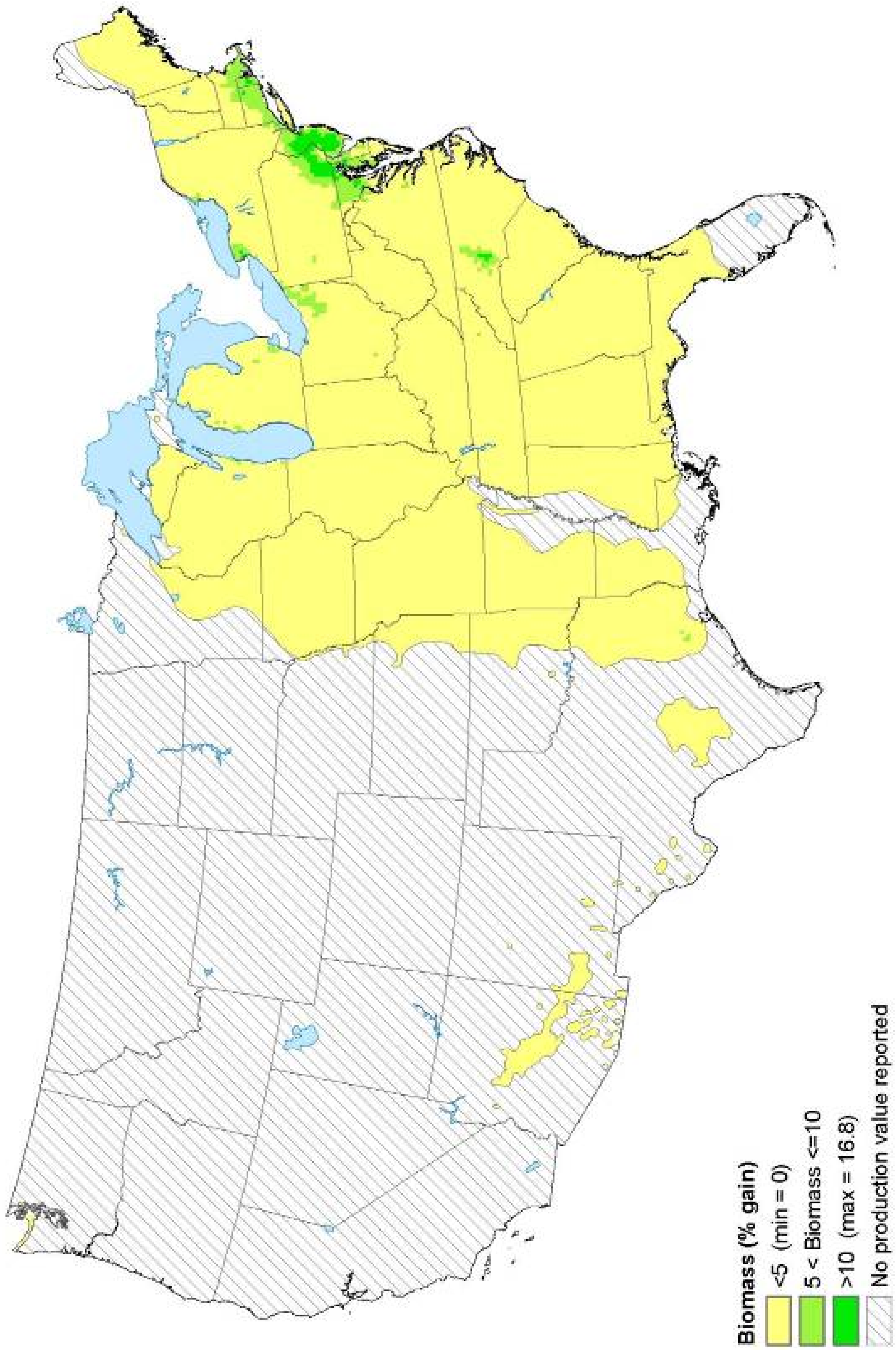


Map 5-21: Biomass Gain from Baseline for Aspen. Quadratic Rollback W126 to 13 ppm-hour. (Reduced W126)

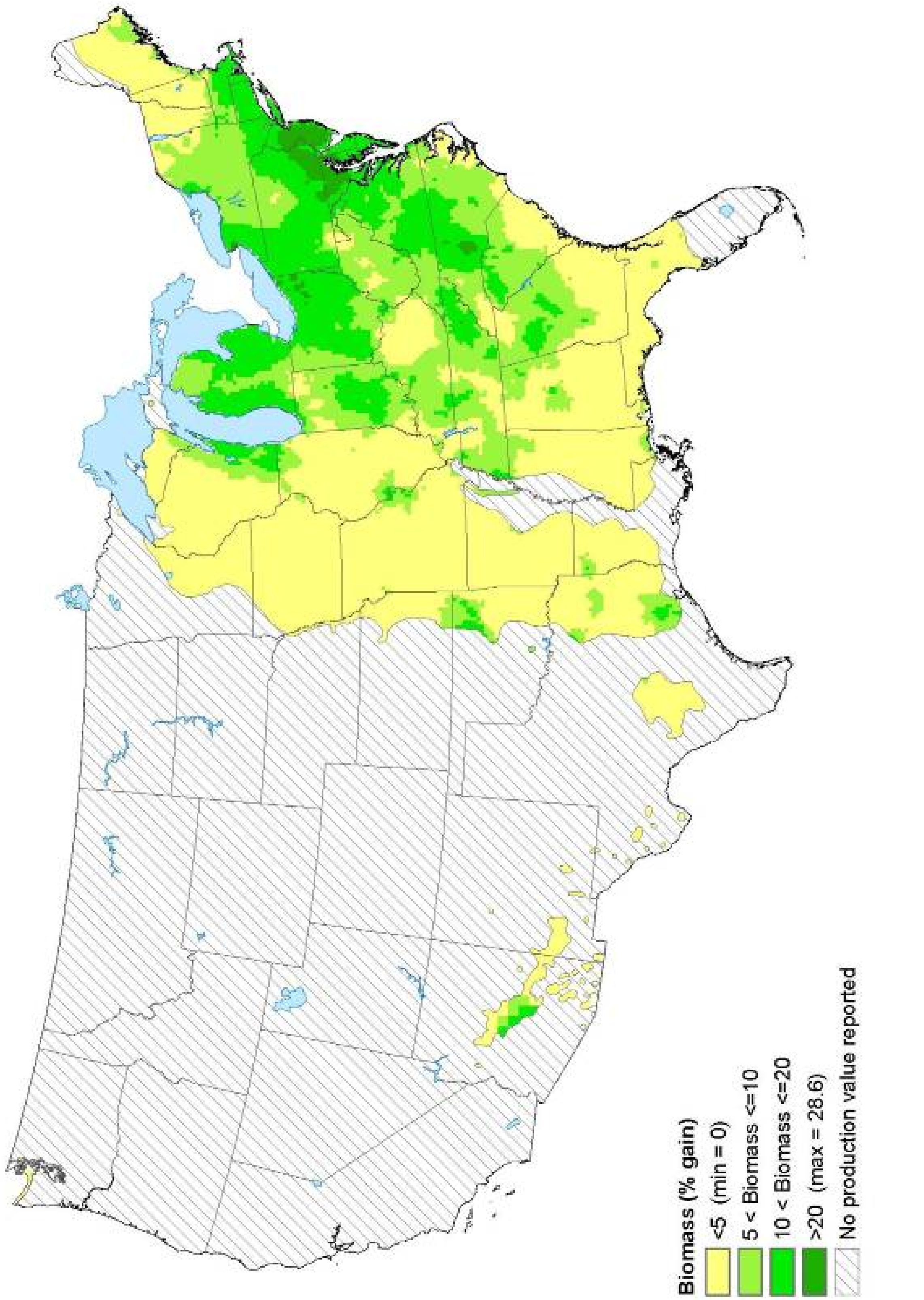
Black Cherry Response Maps



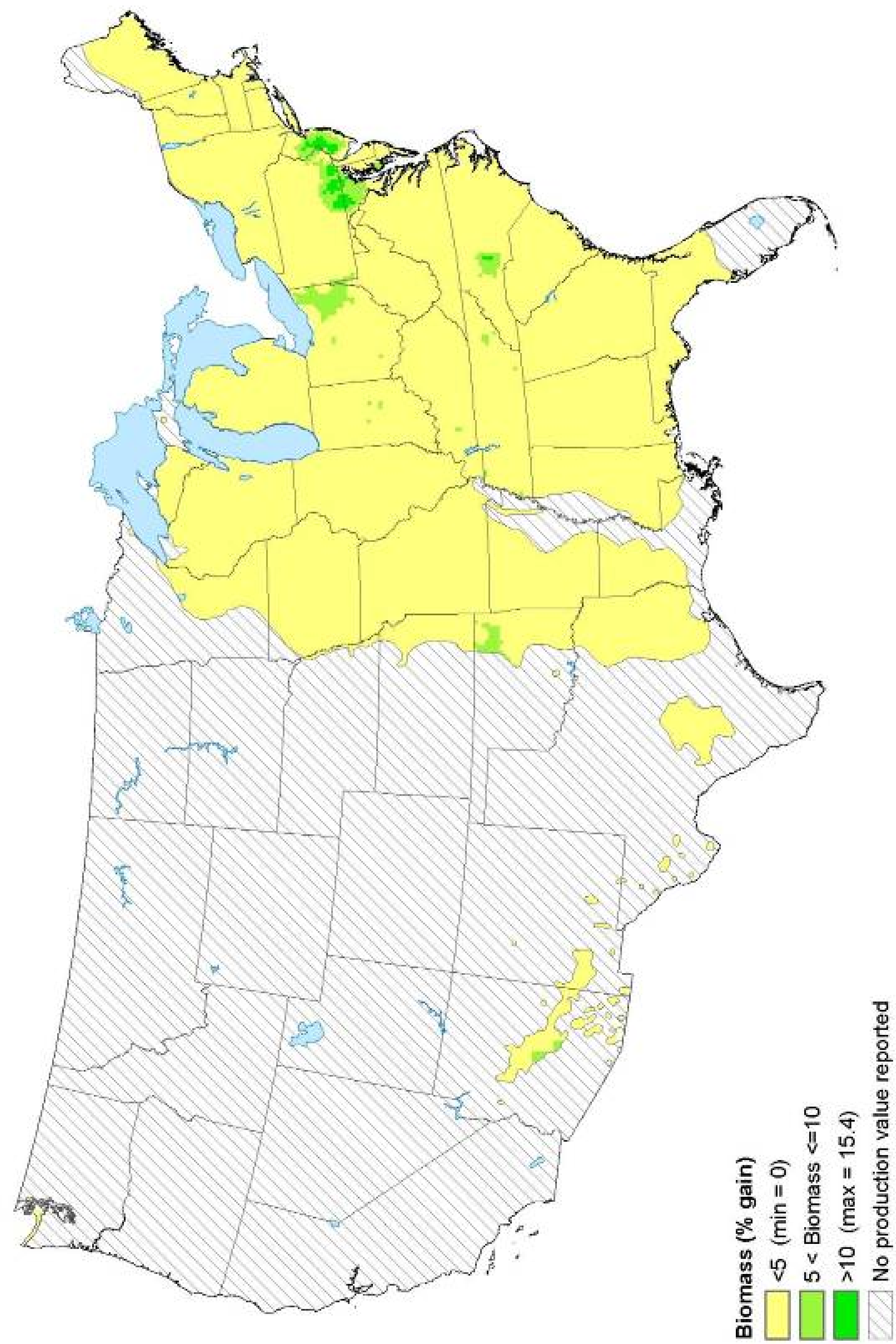
Map 5-22: As-is Biomass Loss for Black Cherry (Prunus serotina). (Reduced W126)



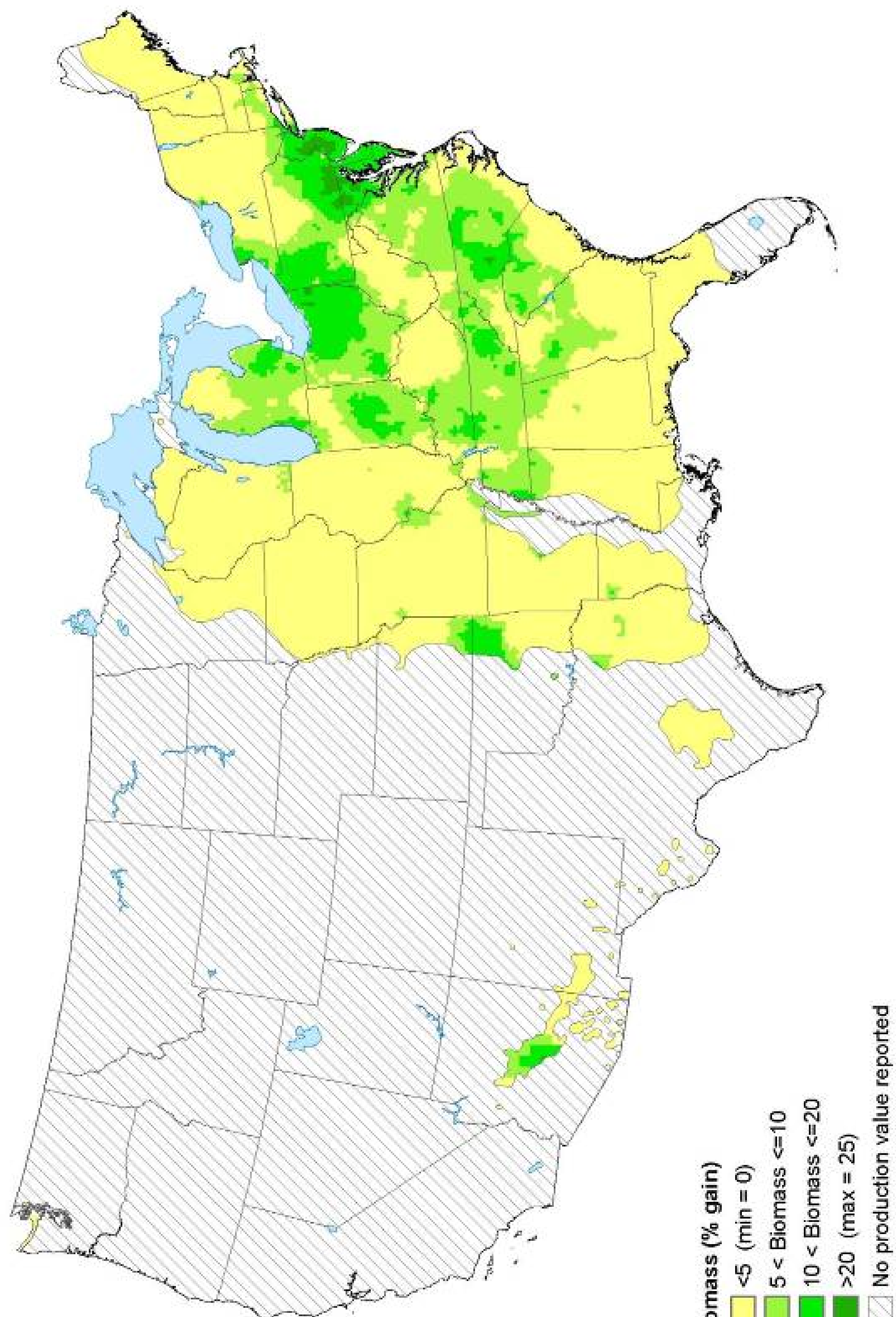
Map 5-23: Biomass Gain from Baseline for Black Cherry (Prunus serotina). Quadratic Rollback 4th Highest 8-hour Maximum to 84ppb. (Reduced W126)



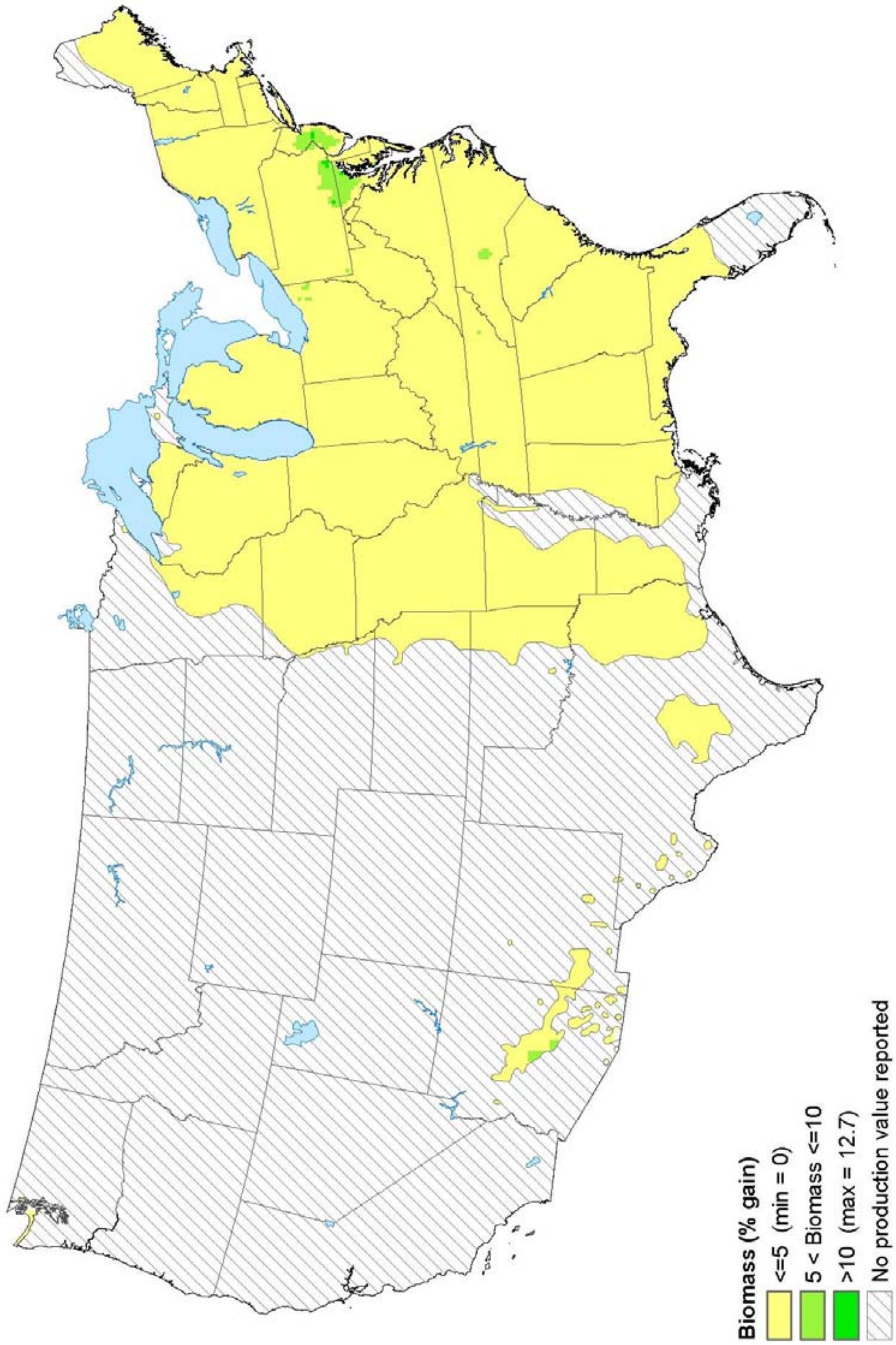
Map 5-24: Biomass Gain from Baseline for Black Cherry (Prunus serotina). Quadratic Rollback 4th Highest 8-hour Maximum to 70 ppb. (Reduced W126)



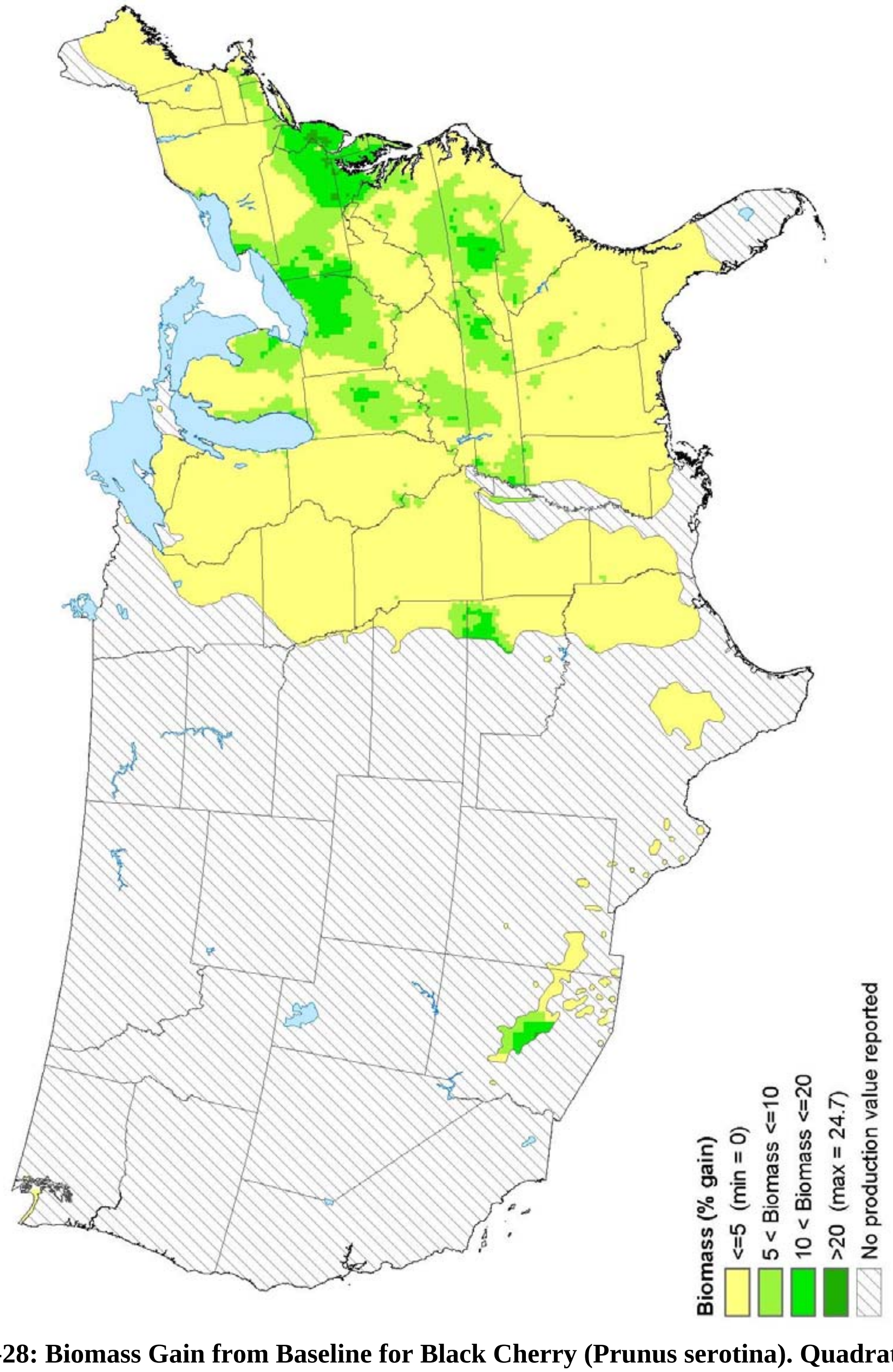
Map 5-25: Biomass Gain from Baseline for Black Cherry (Prunus serotina). Quadratic Rollback 3-month SUM06 to 25 ppm-hour. (Reduced W126)



Map 5-26: Biomass Gain from Baseline for Black Cherry (Prunus serotina). Quadratic Rollback 3-month SUM06 to 15 ppm-hour. (Reduced W126)

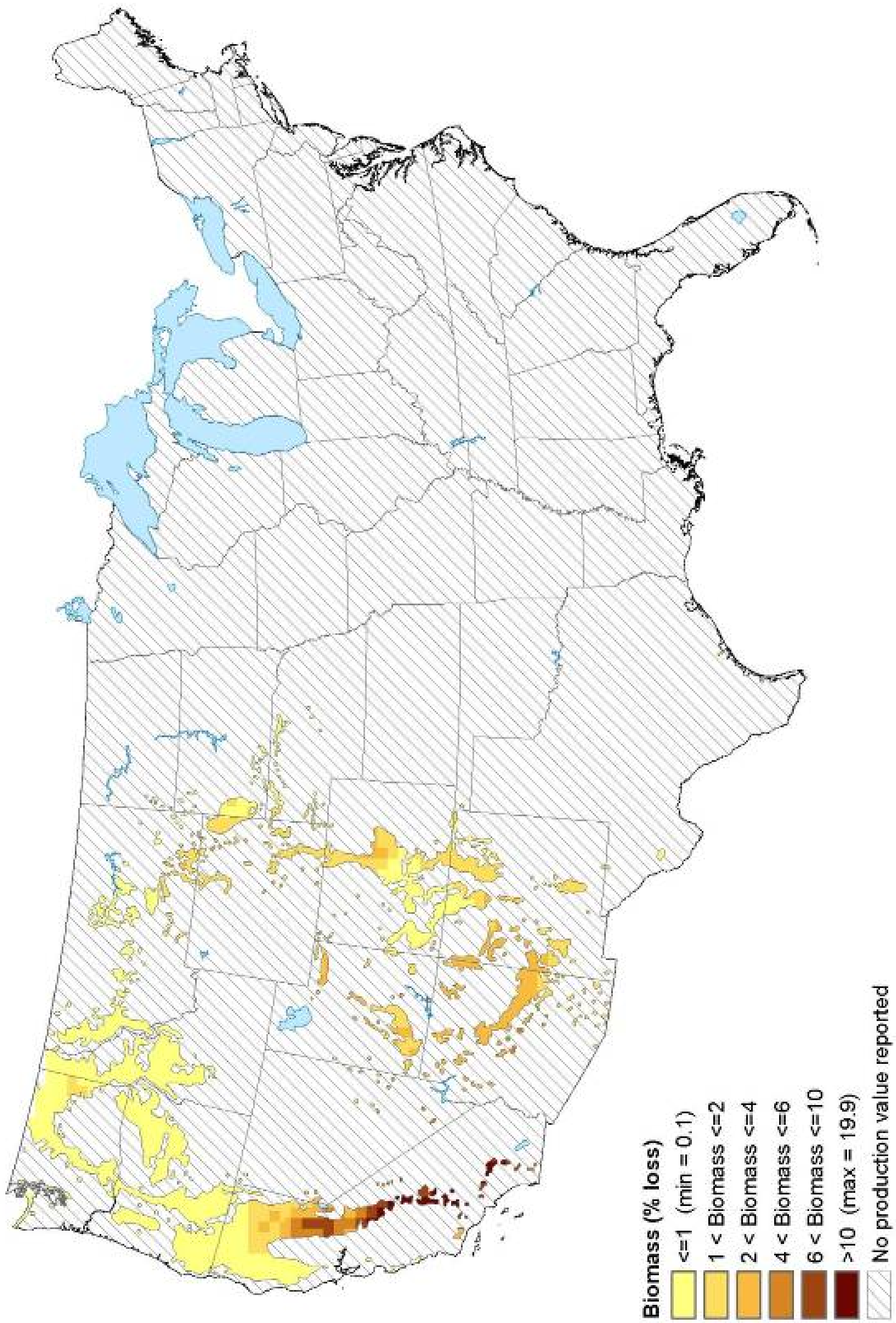


Map 5-27: Biomass Gain from Baseline for Black Cherry (Prunus serotina). Quadratic Rollback 3-month W126 to 21 ppm-hour. (Reduced W126)

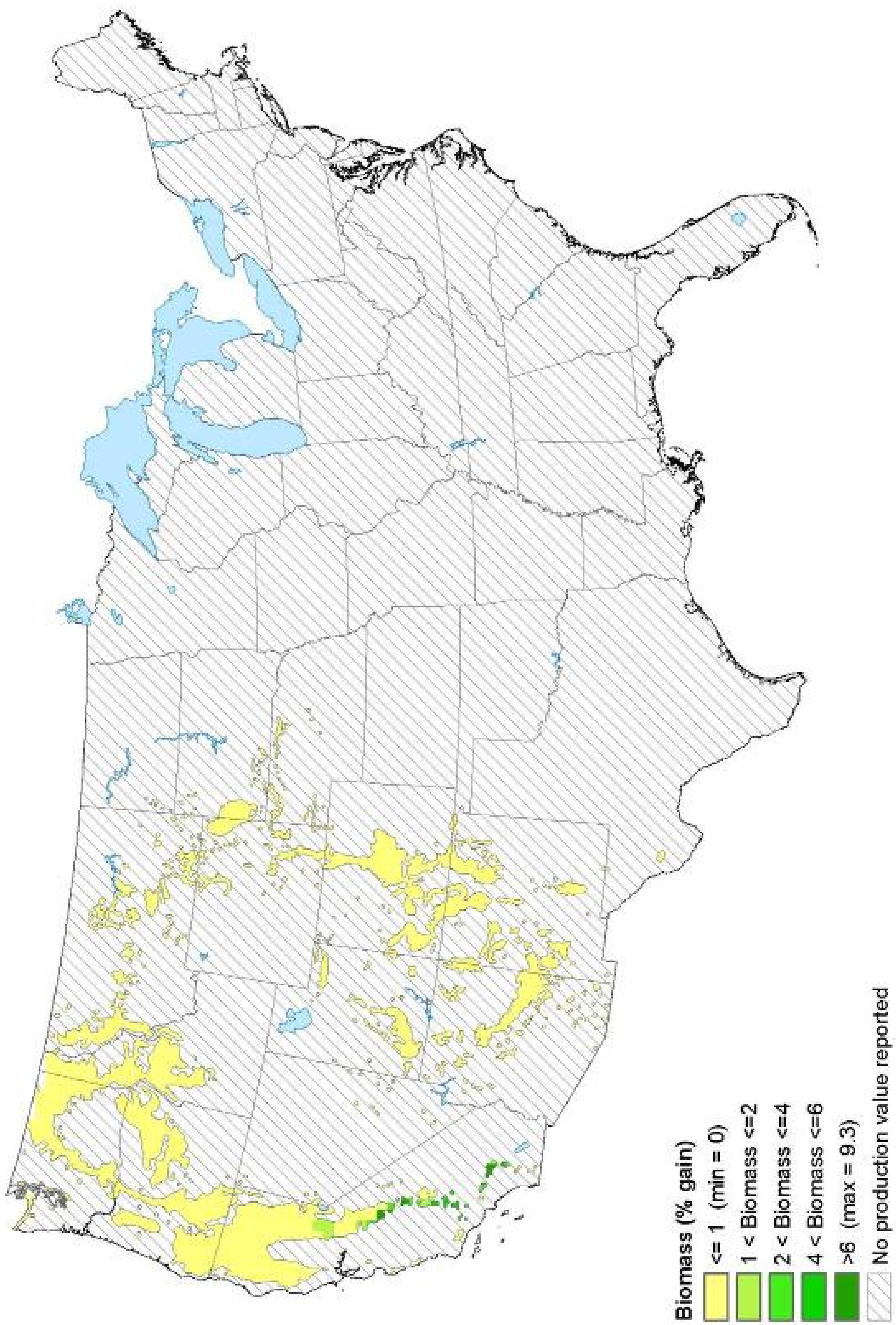


Map 5-28: Biomass Gain from Baseline for Black Cherry (Prunus serotina). Quadratic Rollback 3-month W126 to 13 ppm-hour. (Reduced W126)

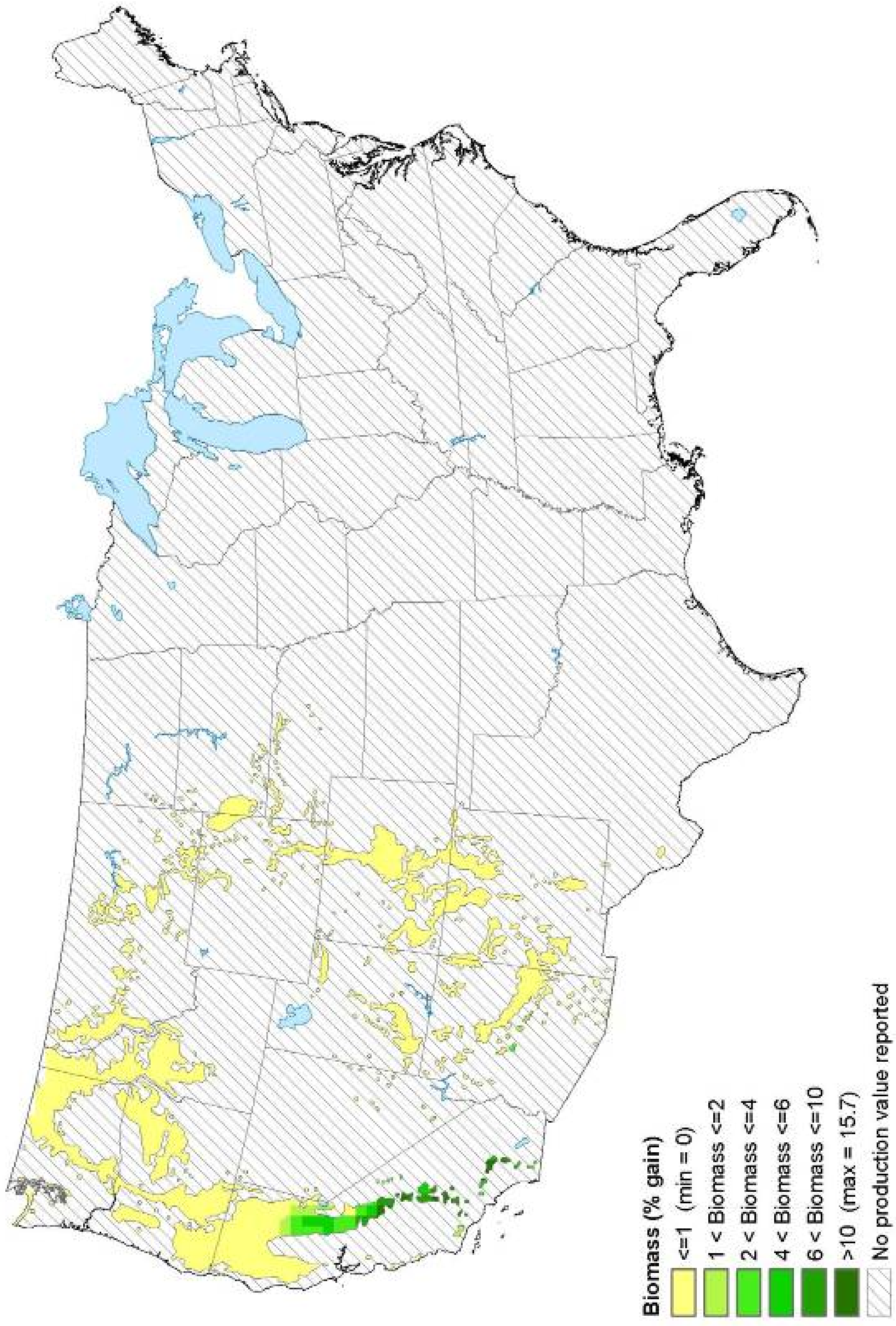
Ponderosa Pine Response Maps



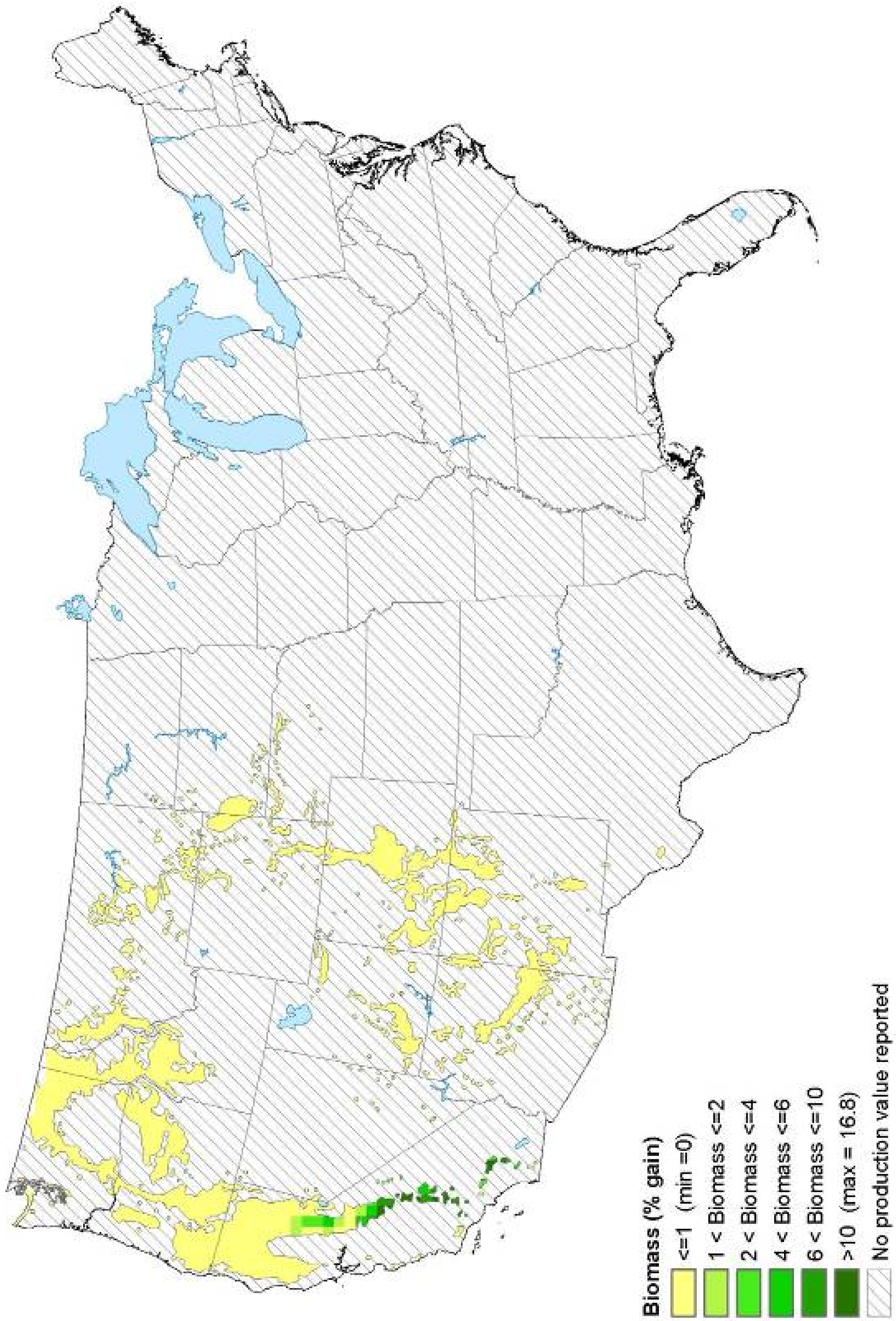
Map 5-29: As is Biomass Loss for Ponderosa Pine (Pinus ponderosa) seedlings. April – October SUM06. (Reduced W126)



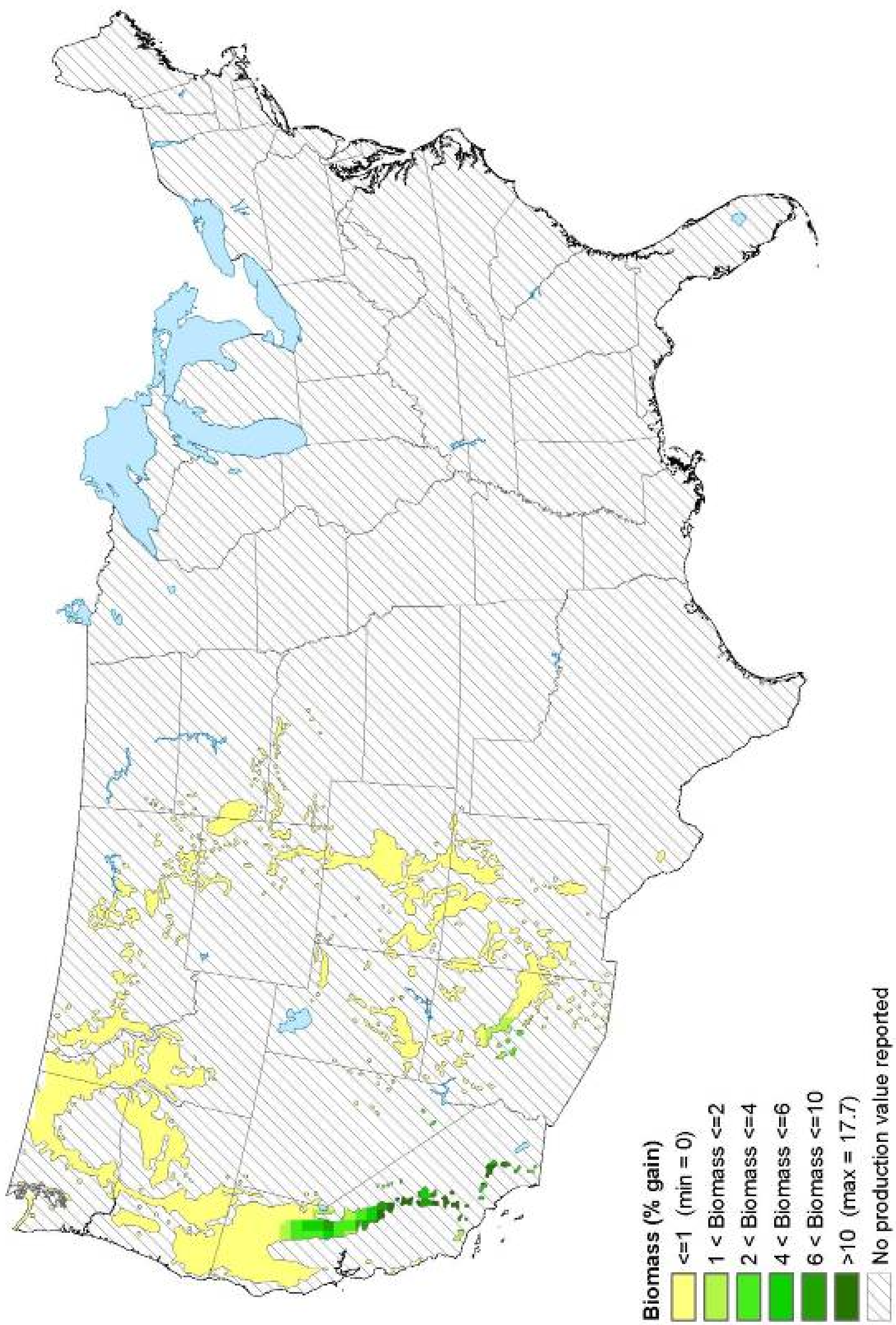
Map 5-30: Biomass Gain from Baseline for Ponderosa Pine (Pinus ponderosa). Quadratic Rollback 4th Highest 8-hour Maximum to 84 ppb. (Reduced W126)



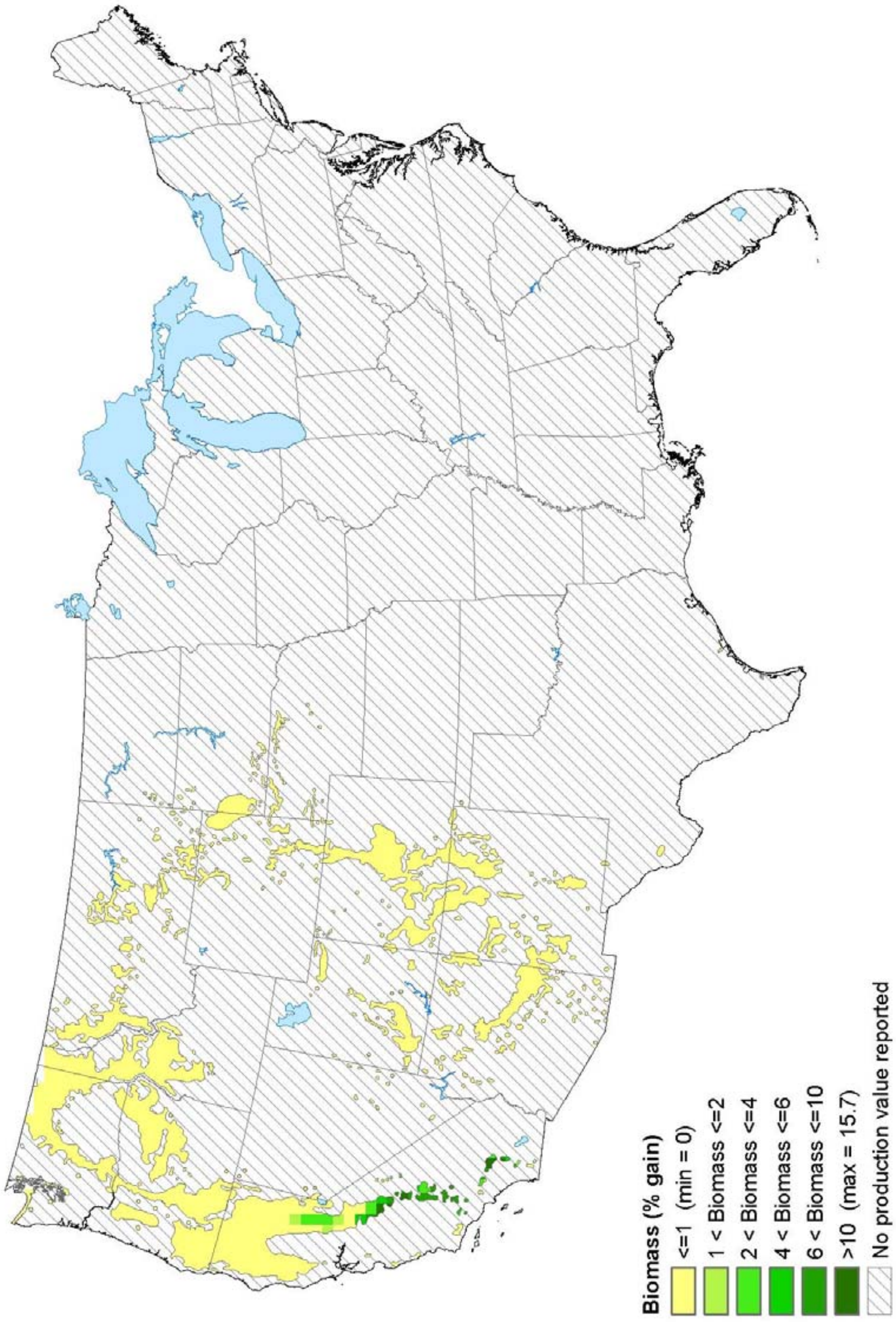
Map 5-31: Biomass Gain from Baseline for Ponderosa Pine (Pinus ponderosa). Quadratic Rollback 4th Highest 8-hour Maximum to 70 ppb. (Reduced W126)



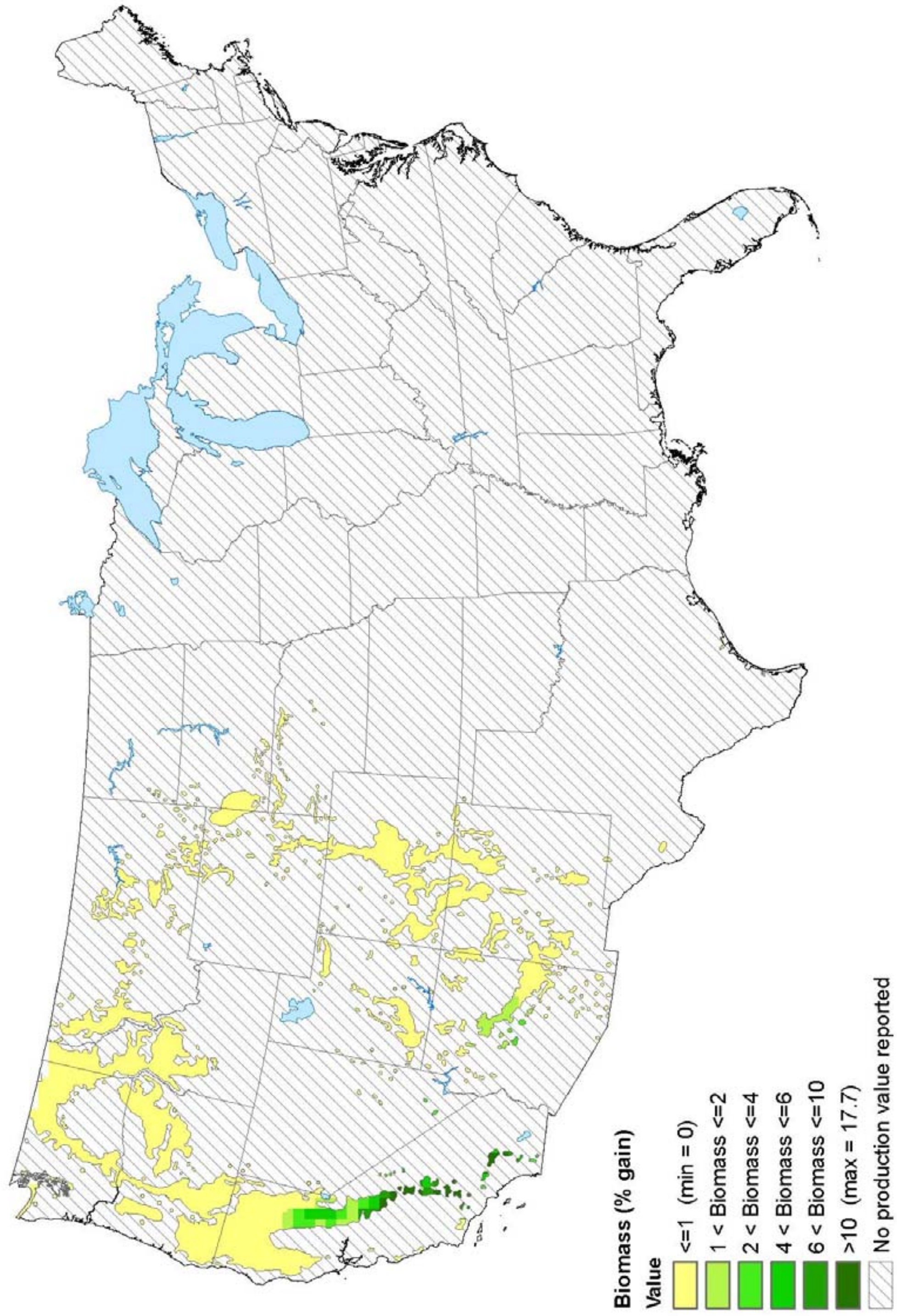
Map 5-32: Biomass Gain from Baseline for Ponderosa Pine (Pinus ponderosa). Quadratic Rollback 3-month SUM06 to 25 ppm-hour. (Reduced W126)



Map 5-33: Biomass Gain from Baseline for Ponderosa Pine (Pinus ponderosa). Quadratic Rollback 3-month SUM06 to 15 ppm-hour. (Reduced W126)



Map 5-34: Biomass Gain from Baseline for Ponderosa Pine (Pinus ponderosa). Quadratic Rollback W126 to 21 ppm-hour. (Reduced W126)



Map 5-35: Biomass Gain from Baseline for Ponderosa Pine (Pinus ponderosa). Quadratic Rollback W126 to 13 ppm-hour. (Reduced W126)

6. Economic Benefits

6.1 AGSIM©

AGSIM© is a large-scale econometric simulation model of regional crop and national livestock production in the United States. The model ties together econometrically estimated demand and supply equations and solves for the set of crop and livestock prices that simultaneously clears all markets in a given year for given exogenous factors. The model is capable of analyzing the economic effects of changes in farm programs and other relevant policies on 1) changes in regional per-acre crop yields, 2) changes in production costs, 3) changes in target prices and set-aside rates, 4) changes in paid land diversion by crop and region, and 5) acreage in the conservation reserve. The simulation model can provide a full welfare evaluation of 1) domestic consumers' surplus, 2) farm income, 3) government program payments, and foreign surplus. A complete description of the model is provided in Appendix I.

6.2 Methodology

AGSIM© was used to quantify the economic benefits resulting from meeting alternate O_3 standards as specified in Section 4. Crop yield changes generated in Section 5 were fed into the model, which then solved for the new level of supply and demand. No other exogenous shock was applied. Yield changes incorporated into AGSIM© were broken down by ERS region. The mean regional yield response is a weighted average of county-level results. Weights were derived from NASS 2001 County Crop Data (planted acreage) and when NASS data was not available for a particular crop, we used the 2002 Census of Agriculture instead (number of harvested farms). All negative values were zeroed out before averaging.

Five scenarios were considered based on the five rollback scenarios presented in Section 4. For each rollback, we measured the economic benefits incurred for median, minimum, and maximum yield responses, for a total of fifteen model runs. In addition a soybean-only scenario was considered, keeping all other crop yields constant.

A summary of simulation results is presented in the following section.

6.3 Results

Total benefits are summarized in Table 6-1 below. This table provides the overall change in producer and consumer surplus for field crops plus fruits and vegetables and field crops by themselves. The results for the soybean-only runs are separated in Table 6-2.

Leaving out farm payments, since they do not translate into increased welfare, total economic gains range from \$7 million under the 84 ppb rollback to \$199 million under the 70 ppb rollback (based on the median concentration-response levels). When fruits and vegetable yield changes are added, total gains range from \$75 to \$383 million.

Table 6-3 and Table 6-4 present similar results for the scenarios based on the non-adjusted metric (i.e. hourly O_3 values were not reduced by 10 percent).

Table 6-5 compares results from the scenarios based on the 10%-adjusted metric vs. the non-adjusted metric. In general, the results without the 10% reduction are 10 to 100% higher. The differences are somewhat greater for the "As Is Soybeans Only MEDIAN" and the "Roll 70 Soybeans Only MIN" scenarios.

Table 6-6 compares the results for the 25 vs. 21 scenarios and the 15 versus the 13 scenarios. The SUM06 scenarios (25 and 15) have greater benefits than the comparable W126 scenarios (21 and 13). The effect of the 10 percent reduction is reasonably similar across the different scenarios, with a somewhat more pronounced effect on the W126/13 scenario.

Table 6-1: Total Undiscounted Economic Surplus Effect, 2001/02 through 2014/15 (with 10% adjustment)

Scenario	C-R Level	Change in Total Economic Surplus ($ million)			
		Field crops and F&V Avg/year	*Field crops and F&V (less farm payments) Avg/year*	*Field crops only Avg/year*	*Field crops only (less farm payments) Avg/year*
AS-IS	all medians	$1,792	$1,669	$326	$203
	7 max, 9 median	$3,250	$2,365	$1,687	$802
	7 min, 9 median	$1,709	$1,586	$328	$205
roll_84	all medians	$80	$75	$11	$7
	7 max, 9 median	$114	$96	$40	$22
	7 min, 9 median	$75	$70	$12	$8
roll_70	all medians	$407	$383	$71	$46
	7 max, 9 median	$749	$564	$383	$199
	7 min, 9 median	$381	$356	$71	$46
roll_SUM06 25	all medians	$189	$181	$22	$14
	7 max, 9 median	$269	$230	$89	$50
	7 min, 9 median	$182	$172	$28	$18
roll_SUM06 15	all medians	$400	$367	$90	$56
	7 max, 9 median	$710	$532	$373	$195
	7 min, 9 median	$379	$345	$93	$58
roll_W126 21	all medians	$144	$10	$149	$16
	7 max, 9 median	$179	$35	$204	$60
	7 min, 9 median	$137	$14	$145	$21
roll_W126 13	all medians	$310	$29	$326	$45
	7 max, 9 median	$440	$136	$562	$258
	7 min, 9 median	$291	$32	$308	$49

Source: AGSIM© model simulation results.

Table 6-2: Total Undiscounted Economic Surplus Effect of Soybean Yield Response, 2001/02 through 2014/15 (with 10% adjustment)

Scenario	C-R Level	Change in Total Economic Surplus ($ million)	
		Avg/year	*(farm payments excl.) Avg/year*
AS-IS	all medians	$74	$52
	7 max, 9 median	$310	$216
	7 min, 9 median	$46	$32
roll_84	all medians	$3	$2
	7 max, 9 median	$6	$4
	7 min, 9 median	$1	$1
roll_70	all medians	$28	$20
	7 max, 9 median	$79	$55
	7 min, 9 median	$28	$5
roll_SUM06 25	all medians	$3	$2
	7 max, 9 median	$7	$5
	7 min, 9 median	$1	$1
roll_SUM06 15	all medians	$23	$16
	7 max, 9 median	$66	$46
	7 min, 9 median	$11	$8
roll_W126 21	all medians	$1	$1
	7 max, 9 median	$2	$2
	7 min, 9 median	$0	$0
roll_W126 13	all medians	$12	$17
	7 max, 9 median	$32	$47
	7 min, 9 median	$6	$8

Source: AGSIM© model simulation results.

Table 6-3: Total Undiscounted Economic Surplus Effect, 2001/02 through 2014/15 (without 10% adjustment)

Scenario	C-R Level	Change in Total Economic Surplus ($ million)			
		Field crops and F&V Avg/year	*Field crops and F&V (less farm payments) Avg/year*	*Field crops only Avg/year*	*Field crops only (less farm payments) Avg/year*
AS-IS	all medians	$2,121	$2,007	$349	$236
	7 max, 9 median	$4,448	$3,095	$2,570	$1,217
	7 min, 9 median	$1,996	$1,899	$317	$220
roll_84	all medians	$93	$87	$18	$11
	7 max, 9 median	$127	$107	$44	$25
	7 min, 9 median	$86	$80	$16	$10
roll_70	all medians	$498	$454	$127	$83
	7 max, 9 median	$948	$686	$545	$282
	7 min, 9 median	$454	$417	$111	$74
roll_SUM06 25	all medians	$219	$206	$35	$22
	7 max, 9 median	$309	$261	$110	$62
	7 min, 9 median	$211	$196	$40	$26
roll_SUM06 15	all medians	$454	$415	$111	$72
	7 max, 9 median	$866	$628	$494	$256
	7 min, 9 median	$421	$385	$104	$68
roll_W126 21	all medians	$174	$164	$26	$16
	7 max, 9 median	$230	$201	$70	$41
	7 min, 9 median	$168	$157	$32	$20
roll_W126 13	all medians	$397	$366	$86	$55
	7 max, 9 median	$699	$529	$363	$192
	7 min, 9 median	$371	$341	$84	$55

Source: AGSIM© model simulation results.

Table 6-4: Total Undiscounted Economic Surplus Effect of Soybean Yield Response, 2001/02 through 2014/15 (without 10% adjustment)

Scenario	C-R Level	Change in Total Economic Surplus ($ million)	
		Avg/year	*(farm payments excl.) Avg/year*
AS-IS	all medians	$114	$163
	7 max, 9 median	$383	$553
	7 min, 9 median	$61	$88
roll_84	all medians	$3	$5
	7 max, 9 median	$5	$7
	7 min, 9 median	$1	$1
roll_70	all medians	$38	$54
	7 max, 9 median	$85	$122
	7 min, 9 median	$16	$22
roll_SUM06 25	all medians	$3	$5
	7 max, 9 median	$6	$9
	7 min, 9 median	$1	$2
roll_SUM06 15	all medians	$30	$43
	7 max, 9 median	$70	$101
	7 min, 9 median	$13	$19
roll_W126 21	all medians	$1	$2
	7 max, 9 median	$2	$3
	7 min, 9 median	$0	$1
roll_W126 13	all medians	$22	$31
	7 max, 9 median	$48	$69
	7 min, 9 median	$9	$13

Source: AGSIM© model simulation results.

Table 6-5: Comparison between Adjusted vs. Non-Adjusted Metric on Undiscounted Economic Surplus Effects, 2001/02 through 2014/15

Scenario	C-R Level	Ratio of Adjusted to Non-Adjusted Metric	
		Field crops and F&V (less farm payments) Avg/year	*Field crops only (less farm payments) Avg/year*
AS-IS	all medians	20%	16%
	7 max, 9 median	31%	52%
	7 min, 9 median	20%	7%
roll_84	all medians	15%	50%
	7 max, 9 median	11%	12%
	7 min, 9 median	13%	32%
roll_70	all medians	19%	79%
	7 max, 9 median	22%	42%
	7 min, 9 median	17%	61%
roll_SUM06 25	all medians	14%	55%
	7 max, 9 median	13%	23%
	7 min, 9 median	14%	43%
roll_SUM06 15	all medians	13%	27%
	7 max, 9 median	18%	31%
	7 min, 9 median	12%	18%
roll_W126 21	all medians	15%	62%
	7 max, 9 median	12%	17%
	7 min, 9 median	15%	47%
roll_W126 13	all medians	18%	89%
	7 max, 9 median	20%	41%
	7 min, 9 median	17%	72%

Source: AGSIM© model simulation results.

Table 6-6: Comparison Between SUM06 vs. W126 Metric on Undiscounted Economic Surplus Effects, 2001/02 through 2014/15

Scenario	C-R Level	Ratio of SUM06 to W126 Metric			
		Field crops and F&V (less farm payments) Avg/year		*Field crops only (less farm payments) Avg/year*	
		10% Adjusted	*Non-Adjusted*	*10% Adjusted*	*Non-Adjusted*
25 ppm-hr SUM06 vs. 21 ppm-hr W126	all medians	26%	26%	34%	40%
	7 max, 9 median	30%	29%	52%	45%
	7 min, 9 median	25%	25%	27%	31%
15 ppm-hr SUM06 vs. 13 ppm-hr W126	all medians	13%	18%	29%	91%
	7 max, 9 median	19%	21%	33%	44%
	7 min, 9 median	13%	18%	25%	82%

Source: AGSIM© model simulation results.

7. Tree Growth Simulation

In the 1996 O_3 Staff Paper, analyses on trees were limited to the seedling growth stage. In order to go beyond the seedling stage for the current review, we used a tree growth simulation model, TREGRO, as a tool to evaluate the effect of just meeting alternate O_3 standards on select O_3-sensitive tree species.

The response of total tree growth of two species, red maple and yellow (or tulip) poplar was simulated in two locations (Shenandoah National Park, VA, and Cranberry, NC) in the southern Appalachian Mountains to the five scenarios of O_3 reduction used previously in this report. These simulations were done using the computer model, TREGRO. The results of this investigation are given below. A report providing the details of the methodology and results from this examination can be found in Appendix J.

7.1 Summary of Results

The simulations produced a prediction of average annual total tree growth over the 3-year period for each scenario. These results were compared to the base scenario, which consisted of a prediction of growth under the hourly meteorology and O_3 conditions for the period 1993-1995.

The predictions indicated substantial increases in 3-year total tree growth increments with reduction of O_3 exposure, particularly under Scenario 3, a rollback to conform to the standard of the 1^{st} highest maximum 8-hour average being no greater than 0.070 ppm. Yellow poplar had nearly a twenty percent increase in growth in response to this scenario, an average annual increase of 6.5%.

Table 7-1 Predicted percent increases in total tree growth over a 3-year period under the 4 ozone (O3) reduction scenarios.

	Red maple, Shenandoah	Red maple, Cranberry	Yellow poplar, Shenandoah	Yellow poplar, Cranberry
Scenario_1	1.22%		0.08%	
Scenario_2	1.02%		0.20%	
Scenario_3	8.14%	6.92%	1.15%	19.61%
Scenario_4	6.72%	4.15%	1.03%	11.73%
Scenario_5	4.49%	2.99%	0.60%	8.26%

Scenario 1: Rollback current EPA standard 4^{th} highest max. 8-hr avg. 0.085 ppm
Scenario 2: Rollback SUM06 25 ppm-hr
Scenario 3: Rollback 1^{st} highest max. 8-hr avg. 0.070 ppm
Scenario 4: Rollback 4^{th} highest max. 8-hr avg. 0.070 ppm
Scenario 5: Rollback SUM06 15ppm-hr

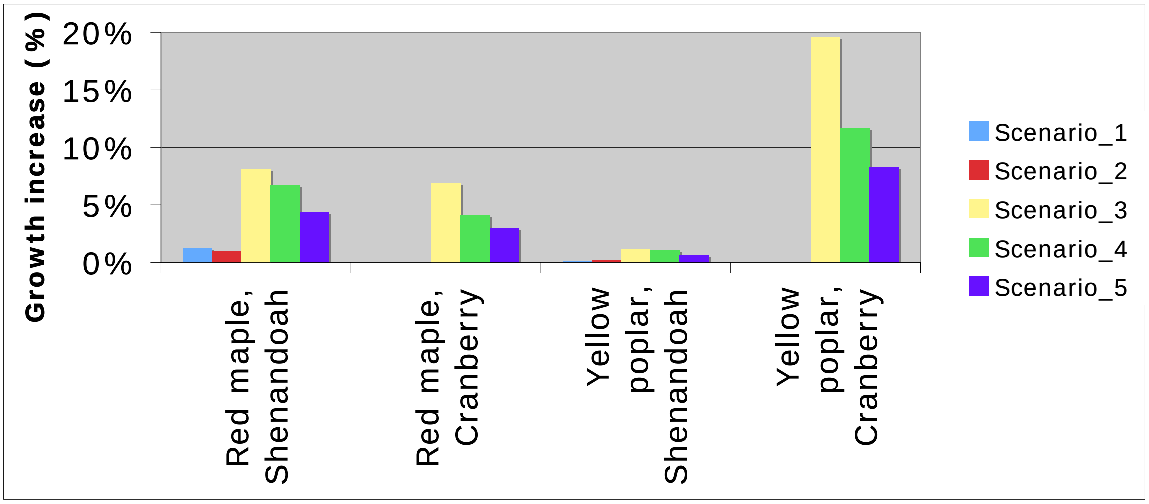


Figure 7-1 Tree growth response of red maple and yellow poplar in forests of Shenandoah National Park, Virginia and Cranberry, North Carolina to ozone (O_3) reduction scenarios.

Red maple was simulated to have a similar response to Scenario 3 in Shenandoah and in Cranberry. However, it had nearly twice the increase to Scenario 4 at Shenandoah as it did at Cranberry. The response to Scenario 5 was slightly less than Scenario 4 for red maple and for yellow poplar in both Shenandoah and Cranberry. The response of yellow poplar at Cranberry to Scenario 5 was still very large, with growth projected to increase more than 8% under this level of O_3 reduction.

Yellow poplar had a very different response to O_3 reduction at Shenandoah compared to Cranberry. The temperatures at Cranberry are more in the middle of the range of temperatures over which yellow poplar is found than are the cool temperatures of Shenandoah, making conditions at Cranberry more ideal for growth. Higher growth rates may cause greater sensitivity to O_3. Red maple has a much larger geographical distribution, so that the temperature differences between Shenandoah and Cranberry are less likely to affect the growth response. This phenomenon was reflected in the simulations.

Finally, Scenarios 1 and 2 produced very little growth response in either species. These scenarios produced no change in the predicted O_3 exposure at Cranberry, so they were not even simulated. At Shenandoah, the change in O_3 exposure to Scenarios 1 and 2 was very slight.

Methodological details, including a discussion of the uncertainty of the investigation, can be found in Appendix J.

Appendices

Appendix A Detailed Results from Dropout Monitor Investigation

Section 3 presents O_3 interpolation performance results for the Eastern U.S. and the Western US. Because the monitor coverage in California is much denser than the rest of the Western US, we examine here the performance results for California alone, as well as for the West excluding California. For a detailed explanation of the data and methods used to generate each metric, please refer section 1-3 of this report.

Choice of Interpolation Approaches

Two interpolation techniques were retained; 1) VNA (distance-weighted averages of neighboring monitor values), and 2) eVNA (VNA with model-adjusted neighboring monitor values).
In the case of eVNA, we also compared two condition-specific adjustment methods; 1) Month-Decile (hourly monitor values are split evenly into ten rank-ordered deciles for every month), and 2) Month-Hour (hourly monitor values are split evenly into 24 groups by time of day for every month). We also included data for predictions based only on the CMAQ-generated values for the Western U.S. at the 36 km x 36 km grid level.
Finally 4 mixed VNA-eVNA interpolations were compiled based on the distance between a monitor and its neighbors. The first mixed approach uses VNA for neighbors under 50 km and HMD for neighbors beyond 50 km (HMD_VNA_50). Similarly the second mixed approach uses VNA for neighbors under 100 km and HMD for neighbors beyond 100 km (HMD_VNA_100). The last 2 mixed approaches use a similar blend of VNA and HMH.

The approaches are named accordingly:

- VNA Distance-weighted averages with no scaling
- HMD eVNA interpolation with Hour-Month-Decile scaling
- HMH eVNA interpolation with Hour-Month-Hour scaling
- CMAQ Model-generated values
- HMD_VNA_50 Mixed VNA and HMD interpolation at 50 km cutoff
- HMD_VNA_100 Mixed VNA and HMD interpolation at 100 km cutoff
- HMH_VNA_50 Mixed VNA and HMH interpolation at 50 km cutoff
- HMH_VNA_100 Mixed VNA and HMH interpolation at 100 km cutoff

Choice of Dropout Monitor Sites

The present iteration includes all “complete” AQS and CASTNET monitor sites in the Western U.S. (299 monitors). Some monitors identified as located in densely populated urban areas were left out. Additional AQS monitors were excluded when it was discovered that they corresponded to CASTNet monitors and contained identical data.

Results

Summary results showing a comparison between seven interpolation methods and the CMAQ model estimations are presented in Tables A-1 through A-6. Tables A1-A3 refer to the set of monitors within California; tables A4-A6 refer to the Western U.S. excluding California. In both sets, one table is given for each of the three metrics considered – (8-hour maximum, SUM06, and W126).

Table A-1: Comparison of Interpolation Methods for California. (8-hour Maximum)

Interpolation	*Measure*	*Count*	*Mean*	*Median*	*Min*	*Max*	*Range*	*STD*
CMAQ	Bias	150	1.01	1.24	-45.13	36.29	81.41	16.12
	Error	150	12.71	11.18	0.05	45.13	45.08	9.97
	Norm. Bias	150	5.4%	1.6%	-37.6%	85.0%	122.6%	21.4%
	Norm. Error	150	16.5%	13.8%	0.0%	85.0%	85.0%	14.6%
HMD	Bias	150	-3.59	-3.76	-41.10	21.76	62.86	9.41
	Error	150	7.75	6.42	0.03	41.10	41.07	6.42
	Norm. Bias	150	-3.4%	-4.3%	-34.2%	53.8%	88.1%	11.7%
	Norm. Error	150	9.4%	7.7%	0.0%	53.8%	53.8%	7.8%
HMD_VNA_100	Bias	150	-4.22	-3.04	-25.34	19.18	44.52	8.84
	Error	150	7.65	6.60	0.07	25.34	25.26	6.13
	Norm. Bias	150	-3.8%	-3.8%	-25.7%	51.5%	77.2%	11.2%
	Norm. Error	150	9.2%	7.9%	0.1%	51.5%	51.4%	7.4%
HMD_VNA_50	Bias	150	-4.13	-3.40	-24.81	20.05	44.86	8.75
	Error	150	7.59	6.60	0.18	24.81	24.63	6.00
	Norm. Bias	150	-3.8%	-4.1%	-25.7%	53.8%	79.6%	11.1%
	Norm. Error	150	9.2%	7.6%	0.2%	53.8%	53.7%	7.4%
HMH	Bias	150	-2.87	-2.71	-40.01	22.19	62.20	9.47
	Error	150	7.64	5.93	0.16	40.01	39.85	6.29
	Norm. Bias	150	-2.6%	-3.1%	-33.3%	53.4%	86.7%	12.0%
	Norm. Error	150	9.4%	7.6%	0.2%	53.4%	53.2%	7.8%
HMH_VNA_100	Bias	150	-4.15	-3.30	-24.64	19.33	43.96	8.89
	Error	150	7.69	6.36	0.07	24.64	24.56	6.09
	Norm. Bias	150	-3.7%	-3.8%	-25.6%	51.9%	77.5%	11.2%
	Norm. Error	150	9.3%	7.9%	0.1%	51.9%	51.8%	7.4%
HMH_VNA_50	Bias	150	-3.86	-3.72	-24.60	19.89	44.48	8.85
	Error	150	7.65	6.15	0.16	24.60	24.44	5.89
	Norm. Bias	150	-3.5%	-4.2%	-25.6%	53.4%	79.0%	11.3%
	Norm. Error	150	9.3%	7.5%	0.2%	53.4%	53.2%	7.3%
VNA	Bias	150	-4.18	-3.26	-26.55	22.65	49.20	9.07
	Error	150	7.80	6.64	0.07	26.55	26.48	6.24
	Norm. Bias	150	-3.7%	-3.7%	-27.6%	60.8%	88.4%	11.8%
	Norm. Error	150	9.5%	7.9%	0.1%	60.8%	60.7%	7.9%

Table A-2: Comparison of Interpolation Methods for California. (SUM06)

Interpolation	*Measure*	*Count*	*Mean*	*Median*	*Min*	*Max*	*Range*	*STD*
CMAQ	Bias	150	-0.04	2.86	-44.93	34.62	79.55	15.38
	Error	150	11.95	9.36	0.00	44.93	44.92	9.69
	Norm. Bias	149	201.8%	14.5%	-73.0%	6816.2%	6889.3%	662.3%
	Norm. Error	149	227.2%	44.6%	0.0%	6816.2%	6816.2%	654.1%
HMD	Bias	150	-1.88	-1.18	-32.15	44.64	76.80	11.22
	Error	150	7.66	4.82	0.13	44.64	44.52	8.42
	Norm. Bias	149	11.6%	-7.6%	-96.7%	342.7%	439.4%	87.4%
	Norm. Error	149	55.8%	37.6%	0.9%	342.7%	341.8%	68.3%
HMD_VNA_100	Bias	150	-3.17	-1.77	-33.75	41.26	75.01	11.16
	Error	150	7.82	5.10	0.13	41.26	41.13	8.56
	Norm. Bias	149	11.9%	-11.7%	-92.6%	430.3%	522.9%	90.8%
	Norm. Error	149	53.9%	32.8%	1.0%	430.3%	429.3%	74.0%
HMD_VNA_50	Bias	150	-2.78	-1.54	-31.81	44.64	76.45	11.11
	Error	150	7.69	4.92	0.08	44.64	44.56	8.49
	Norm. Bias	149	12.4%	-11.4%	-96.7%	430.3%	526.9%	91.8%
	Norm. Error	149	54.0%	28.6%	0.3%	430.3%	430.0%	75.2%
HMH	Bias	150	-1.80	-1.10	-30.79	40.58	71.37	11.19
	Error	150	7.73	4.88	0.04	40.58	40.54	8.28
	Norm. Bias	149	12.8%	-7.3%	-95.1%	422.6%	517.7%	90.5%
	Norm. Error	149	57.3%	36.8%	0.2%	422.6%	422.4%	71.2%
HMH_VNA_100	Bias	150	-3.14	-1.61	-33.81	40.15	73.97	11.00
	Error	150	7.80	5.14	0.01	40.15	40.14	8.37
	Norm. Bias	149	11.7%	-11.7%	-92.6%	430.3%	522.9%	90.1%
	Norm. Error	149	53.5%	32.8%	0.0%	430.3%	430.2%	73.4%
HMH_VNA_50	Bias	150	-2.76	-1.69	-32.27	39.65	71.91	10.89
	Error	150	7.70	4.90	0.01	39.65	39.63	8.18
	Norm. Bias	149	11.0%	-10.4%	-96.7%	430.3%	526.9%	88.9%
	Norm. Error	149	52.7%	28.7%	1.1%	430.3%	429.2%	72.4%
VNA	Bias	150	-3.16	-1.90	-34.39	41.06	75.45	11.08
	Error	150	7.84	5.14	0.04	41.06	41.02	8.45
	Norm. Bias	149	14.5%	-12.0%	-92.6%	499.2%	591.8%	99.1%
	Norm. Error	149	56.3%	32.8%	1.0%	499.2%	498.2%	82.8%

Table A-3: Comparison of Interpolation Methods for California. (W126)

Interpolation	*Measure*	*Count*	*Mean*	*Median*	*Min*	*Max*	*Range*	*STD*
CMAQ	Bias	150	-0.31	2.87	-41.98	26.57	68.54	12.70
	Error	150	9.60	7.32	0.05	41.98	41.93	8.33
	Norm. Bias	150	124.1%	17.1%	-65.0%	5993.6%	6058.6%	510.4%
	Norm. Error	150	148.1%	49.1%	0.2%	5993.6%	5993.3%	503.9%
HMD	Bias	150	-1.36	-0.66	-26.39	27.84	54.23	8.54
	Error	150	5.82	3.54	0.11	27.84	27.73	6.39
	Norm. Bias	150	24.7%	-4.1%	-73.4%	2810.1%	2883.5%	235.5%
	Norm. Error	150	58.9%	28.5%	1.0%	2810.1%	2809.2%	229.4%
HMD_VNA_100	Bias	150	-2.30	-0.92	-29.36	28.41	57.77	8.55
	Error	150	6.00	3.55	0.02	29.36	29.34	6.51
	Norm. Bias	150	21.8%	-5.9%	-72.7%	2401.1%	2473.8%	203.7%
	Norm. Error	150	56.0%	28.4%	0.0%	2401.1%	2401.0%	197.0%
HMD_VNA_50	Bias	150	-2.03	-0.92	-28.32	28.80	57.12	8.49
	Error	150	5.92	3.39	0.02	28.80	28.79	6.42
	Norm. Bias	150	24.6%	-5.9%	-71.1%	2810.1%	2881.3%	235.6%
	Norm. Error	150	58.4%	28.3%	0.0%	2810.1%	2810.1%	229.6%
HMH	Bias	150	-1.14	-0.55	-27.12	28.57	55.69	8.64
	Error	150	5.91	3.29	0.02	28.57	28.55	6.40
	Norm. Bias	150	24.6%	-5.1%	-73.4%	2641.7%	2715.1%	222.4%
	Norm. Error	150	58.4%	30.0%	0.2%	2641.7%	2641.4%	216.0%
HMH_VNA_100	Bias	150	-2.25	-0.85	-29.59	28.07	57.66	8.53
	Error	150	6.02	3.60	0.02	29.59	29.57	6.45
	Norm. Bias	150	22.8%	-5.6%	-74.0%	2548.5%	2622.5%	215.1%
	Norm. Error	150	57.0%	28.4%	0.0%	2548.5%	2548.4%	208.7%
HMH_VNA_50	Bias	150	-1.92	-0.97	-28.59	28.22	56.82	8.44
	Error	150	5.96	3.50	0.02	28.59	28.58	6.27
	Norm. Bias	150	23.5%	-6.5%	-72.6%	2641.7%	2714.3%	222.1%
	Norm. Error	150	57.5%	28.9%	0.0%	2641.7%	2641.6%	215.8%
VNA	Bias	150	-2.29	-1.06	-29.80	28.58	58.37	8.67
	Error	150	6.08	3.70	0.02	29.80	29.78	6.58
	Norm. Bias	150	31.4%	-7.8%	-72.0%	3636.8%	3708.8%	302.2%
	Norm. Error	150	65.9%	27.7%	0.0%	3636.8%	3636.7%	296.6%

Table A-4: Comparison of Interpolation Methods for the Western U.S. Excluding California (8-hour Maximum)

Interpolation	*Measure*	*Count*	*Mean*	*Median*	*Min*	*Max*	*Range*	*STD*
CMAQ	Bias	137	8.59	8.95	-11.09	32.86	43.95	8.12
	Error	137	9.69	9.37	0.10	32.86	32.76	6.76
	Norm. Bias	137	13.4%	13.0%	-19.8%	63.5%	83.4%	14.0%
	Norm. Error	137	15.0%	13.1%	0.1%	63.5%	63.4%	12.3%
HMD	Bias	137	-2.12	-2.41	-18.17	19.65	37.82	5.72
	Error	137	4.87	4.15	0.04	19.65	19.61	3.67
	Norm. Bias	137	-2.5%	-3.2%	-32.5%	43.4%	76.0%	9.1%
	Norm. Error	137	7.2%	6.0%	0.1%	43.4%	43.4%	6.1%
HMD_VNA_100	Bias	137	-2.07	-2.35	-18.17	19.65	37.82	5.80
	Error	137	4.89	4.19	0.01	19.65	19.64	3.75
	Norm. Bias	137	-2.4%	-3.6%	-32.5%	43.4%	76.0%	9.4%
	Norm. Error	137	7.3%	6.1%	0.0%	43.4%	43.4%	6.3%
HMD_VNA_50	Bias	137	-2.09	-2.57	-18.17	19.65	37.82	5.66
	Error	137	4.87	4.26	0.04	19.65	19.61	3.57
	Norm. Bias	137	-2.4%	-3.8%	-32.5%	43.4%	76.0%	9.1%
	Norm. Error	137	7.2%	6.1%	0.1%	43.4%	43.4%	6.0%
HMH	Bias	137	-1.00	-1.89	-16.66	24.83	41.49	6.15
	Error	137	4.92	4.16	0.00	24.83	24.82	3.82
	Norm. Bias	137	-1.0%	-2.6%	-29.8%	35.1%	64.9%	9.4%
	Norm. Error	137	7.3%	5.8%	0.0%	35.1%	35.1%	6.1%
HMH_VNA_100	Bias	137	-1.91	-2.30	-16.66	15.87	32.53	5.63
	Error	137	4.78	3.93	0.02	16.66	16.64	3.52
	Norm. Bias	137	-2.1%	-3.3%	-29.8%	35.1%	64.9%	8.9%
	Norm. Error	137	7.1%	5.6%	0.0%	35.1%	35.0%	5.8%
HMH_VNA_50	Bias	137	-1.74	-2.36	-16.66	15.87	32.53	5.56
	Error	137	4.73	4.16	0.00	16.66	16.66	3.40
	Norm. Bias	137	-2.0%	-3.3%	-29.8%	35.1%	64.9%	8.7%
	Norm. Error	137	7.0%	5.9%	0.0%	35.1%	35.1%	5.6%
VNA	Bias	137	-2.04	-2.33	-13.05	13.56	26.61	5.53
	Error	137	4.80	4.19	0.02	13.56	13.54	3.42
	Norm. Bias	137	-2.3%	-3.3%	-22.3%	26.2%	48.4%	8.7%
	Norm. Error	137	7.1%	5.8%	0.0%	26.2%	26.1%	5.6%

Table A-5: Comparison of Interpolation Methods for the Western U.S. Excluding California (SUM06)

Interpolation	*Measure*	*Count*	*Mean*	*Median*	*Min*	*Max*	*Range*	*STD*
CMAQ	Bias	136	7.98	5.95	-14.52	41.02	55.54	10.31
	Error	136	9.74	7.28	0.00	41.02	41.02	8.66
	Norm. Bias	130	409.5%	39.2%	-100.0%	29019.0%	29119.0%	2615.2%
	Norm. Error	130	420.1%	40.3%	0.6%	29019.0%	29018.4%	2613.5%
HMD	Bias	136	-2.00	-1.10	-26.67	18.13	44.80	7.84
	Error	136	5.78	3.97	0.00	26.67	26.67	5.66
	Norm. Bias	130	20.2%	-13.2%	-100.0%	3246.8%	3346.8%	294.2%
	Norm. Error	130	72.0%	35.0%	0.2%	3246.8%	3246.6%	286.0%
HMD_VNA_100	Bias	136	-2.73	-1.38	-27.49	17.37	44.86	7.56
	Error	136	5.76	4.46	0.00	27.49	27.49	5.61
	Norm. Bias	130	15.9%	-21.1%	-100.0%	2531.7%	2631.7%	243.4%
	Norm. Error	130	69.6%	31.7%	0.1%	2531.7%	2531.7%	233.8%
HMD_VNA_50	Bias	136	-2.59	-1.16	-26.86	17.37	44.23	7.42
	Error	136	5.57	4.31	0.00	26.86	26.86	5.54
	Norm. Bias	130	15.7%	-20.2%	-100.0%	2978.2%	3078.2%	270.7%
	Norm. Error	130	68.5%	31.7%	0.1%	2978.2%	2978.1%	262.4%
HMH	Bias	136	-1.74	-0.66	-25.27	18.27	43.54	7.78
	Error	136	5.68	3.72	0.00	25.27	25.27	5.60
	Norm. Bias	130	24.7%	-10.6%	-100.0%	3211.1%	3311.1%	293.8%
	Norm. Error	130	73.8%	30.1%	0.3%	3211.1%	3210.8%	285.5%
HMH_VNA_100	Bias	136	-2.64	-1.37	-27.75	17.25	45.00	7.50
	Error	136	5.74	4.48	0.00	27.75	27.75	5.50
	Norm. Bias	130	19.2%	-21.0%	-100.0%	2752.4%	2852.4%	263.9%
	Norm. Error	130	72.6%	32.9%	0.1%	2752.4%	2752.4%	254.4%
HMH_VNA_50	Bias	136	-2.46	-1.09	-26.87	17.25	44.11	7.40
	Error	136	5.56	4.22	0.00	26.87	26.87	5.46
	Norm. Bias	130	21.7%	-15.8%	-100.0%	3376.8%	3476.8%	306.4%
	Norm. Error	130	73.0%	31.4%	0.1%	3376.8%	3376.8%	298.4%
VNA	Bias	136	-2.68	-1.28	-28.19	17.31	45.49	7.44
	Error	136	5.70	4.63	0.00	28.19	28.19	5.48
	Norm. Bias	130	22.0%	-17.9%	-100.0%	2619.1%	2719.1%	256.7%
	Norm. Error	130	72.2%	32.9%	0.1%	2619.1%	2619.1%	247.3%

Table A-6: Comparison of Interpolation Methods for the Western U.S. Excluding California (W126)

Interpolation	*Measure*	*Count*	*Mean*	*Median*	*Min*	*Max*	*Range*	*STD*
CMAQ	Bias	136	5.65	4.60	-6.79	26.40	33.19	6.52
	Error	136	6.63	5.42	0.03	26.40	26.38	5.52
	Norm. Bias	136	100.6%	49.3%	-68.4%	1120.0%	1188.5%	176.0%
	Norm. Error	136	106.1%	50.1%	0.9%	1120.0%	1119.1%	172.8%
HMD	Bias	136	-0.77	-0.63	-13.51	11.39	24.90	4.57
	Error	136	3.41	2.32	0.02	13.51	13.49	3.14
	Norm. Bias	136	6.1%	-5.3%	-89.3%	352.8%	442.1%	62.8%
	Norm. Error	136	37.2%	24.0%	0.2%	352.8%	352.6%	51.0%
HMD_VNA_100	Bias	136	-1.17	-0.61	-14.30	11.34	25.63	4.49
	Error	136	3.43	2.43	0.01	14.30	14.28	3.13
	Norm. Bias	136	5.2%	-9.3%	-89.3%	352.8%	442.1%	63.7%
	Norm. Error	136	37.7%	23.8%	0.1%	352.8%	352.7%	51.6%
HMD_VNA_50	Bias	136	-1.11	-0.66	-13.97	11.34	25.30	4.42
	Error	136	3.36	2.30	0.01	13.97	13.95	3.07
	Norm. Bias	136	4.9%	-9.3%	-89.3%	352.8%	442.1%	62.5%
	Norm. Error	136	37.1%	23.9%	0.1%	352.8%	352.7%	50.5%
HMH	Bias	136	-0.51	-0.25	-12.90	12.42	25.32	4.75
	Error	136	3.48	2.52	0.00	12.90	12.90	3.26
	Norm. Bias	136	8.2%	-3.3%	-90.2%	353.5%	443.7%	63.2%
	Norm. Error	136	37.8%	22.7%	0.1%	353.5%	353.4%	51.3%
HMH_VNA_100	Bias	136	-1.14	-0.63	-14.34	11.34	25.68	4.50
	Error	136	3.44	2.38	0.00	14.34	14.34	3.12
	Norm. Bias	136	5.2%	-8.1%	-90.2%	353.5%	443.7%	62.1%
	Norm. Error	136	37.4%	23.5%	0.0%	353.5%	353.5%	49.9%
HMH_VNA_50	Bias	136	-1.03	-0.63	-13.88	11.34	25.22	4.48
	Error	136	3.40	2.30	0.00	13.88	13.88	3.09
	Norm. Bias	136	5.4%	-8.1%	-90.2%	353.5%	443.7%	61.2%
	Norm. Error	136	36.9%	23.2%	0.0%	353.5%	353.5%	49.1%
VNA	Bias	136	-1.21	-0.68	-14.80	11.33	26.13	4.48
	Error	136	3.47	2.56	0.00	14.80	14.80	3.08
	Norm. Bias	136	4.9%	-6.4%	-76.2%	297.9%	374.1%	58.8%
	Norm. Error	136	37.6%	27.7%	0.1%	297.9%	297.9%	45.5%

Appendix B Memorandum Regarding the Quadratic Rollback

The following is an excerpt from a memorandum entitled "A Comparison between Different Rollback methodologies Applied to Ambient Ozone Concentrations". The included section describes in detail the mathematics behind the 8-hour maximum rollback method. The first page of the memorandum was included for reference purposes. The relevant section begins on the second page at *Quadratic Rollback* and continues until *Data*.

UNITED STATES ENVIRONMENTAL PROTECTION AGENCY
Office of Air Quality Planning and Standards (OAQPS)
Research Triangle Park, North Carolina 27711

MEMORANDUM

SUBJECT: A Comparison between Different Rollback Methodologies Applied to Ambient Ozone Concentrations

FROM: Michael Rizzo, EPA-OAQPS, Air Quality Data Analysis Group

TO: Ozone NAAQS Review Docket (OAR-2005-0172)

DATE: November 7, 2005

For the prior ozone NAAQS review, one of the methods, referred to as the "Quadratic Method," developed for adjusting ozone ambient air concentrations to simulate just meeting alternative standards combined both linear and quadratic elements to reduce larger concentrations more than smaller ones.[1] In this regard, the Quadratic method attempts to account for reductions in emissions without greatly affecting lower concentrations near ambient background levels. Other rollback algorithms have either fit the data to a particular distribution such as the Weibull method or used a linear, proportional rollback where all of the ambient measurements are reduced equally regardless of their individual magnitudes.[2]

This memorandum will compare two of the above mentioned rollback methodologies: quadratic and percentile proportional. As the name implies, the quadratic method uses a quadratic equation to reduce higher ozone concentrations more than smaller ones. The amount of rollback depends on the magnitude of the reduction of the existing fourth maximum to meet the standard. Sites which have data with high ozone concentrations are subjected to a more substantial rollback than those which are at or below the National Ambient Air Quality Standards. In contrast, the percentile proportional rollback uses a dual linear approach where ozone concentrations less than a specified percentile are not rolled back while those greater than the percentile value are proportionally rolled back based upon the difference between the measured fourth maximum and the calculated value needed to attain the standard.

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1 Duff, Marcus; Horst, Robert L.; Johnson, Ted R.; "Quadratic Rollback: A Technique to Model Ambient Concentrations Due to Undefined Emission Controls". Paper No. 98-TA32.07 Air and Waste Management Annual Meeting. San Diego, California. June 14-18, 1998.

2 Johnson, Ted; A Guide to Selected Algorithms, Distributions, and Databases Used in Exposure Models Developed by the Office of Air Quality Planning and Standards. EPA Grant No. CR827033. May 2002. http://www.epa.gov/ttn/fera/data/human/report052202.pdf

Methodology

Quadratic Rollback

The Quadratic Rollback method takes the form of the following equation

$$C'_j = r_j C_j$$

where : C'_j is the rolled back concentration
r_j is the quadratic rollback factor unique to each measurement
C_j is the original measured concentration

The quadratic rollback factor is defined as

$$r_j = V - BC_j$$

where: V and B are positive constants determined from an individual site's measurements

In order to calculate the V and B constants, other parameters must be known first. These are listed below:

$$I_i = \sum_{j \in i} C_j / N_i$$

where: I_i is the average concentration for time period i which, in the case of the current ozone standard, refers to an 8 hour time period so I_i is an 8 hour average
C_j is the original measured concentration
N_i is the number of hours for time period i

$$J_i = \max(C_j)_{j \in i}$$

where: J_i is the maximum one hour value for time period i which, in this case, is the maximum 1 hour value in the 8 hour time period

$$Q_i = \sum_{j \in i} C_j^2 / N_i$$

where: Q_i is the average of the squared concentrations for time period i

$$J = \max(J_i)$$

where: J is the maximum of all time periods, i=1, 2, 3, ….. etc. and is also the maximum value over the entire length of time analyzed

For each time period i, a transformation factor, X_i, is computed using the above parameters:

$$X_i = 2JI_i - Q_i$$

The appropriate X_i which corresponds to the metric corresponding the standard that the data being rolled back to is compared to two times the product of the maximum one hour value (J) and a standard concentration level (S). For example, if the current ozone standard is being examined, the fourth highest X_i from all of the time periods is used. The standard concentration value can be the actual value to meet the NAAQS such as 0.084 ppm for the 8 hour ozone standard. In this case, S refers to the target value of the 4th maximum 8 hour average for 2004 whose calculation is described below. A metric is calculated of the following form to determine the final equation used for the rollback calculation:

$$V = 2JS / X$$

The B coefficient is calculated for each concentration for time period i as:

$$B_i = (I_i - S) / Q_i$$

The appropriate B_i is chosen in the same manner as the appropriate X_i described above. For example, if the metric for the standard is the 4th highest 8 hour value, the B_i corresponding to the 4th highest 8 hour value is used in the rollback calculation.

Thus, V is used as the metric to determine which equation is used for the final rollback calculation. If V is greater than or equal to 1 then this is considered to be the pure quadratic case and the V coefficient maintains a value of 1 for all time periods. The rollback equation then becomes:

$$C_j' = C_j - B(C_j^2)$$

where: B has the value of B_i corresponding to the standard's metric being tested

3

If V is between 0 and 1, this is the mixed linear-quadratic case. The rollback equation then becomes:

$$C_j' = VC_j - \{(VI_m - S)/Q_m\}C_j^2$$

where: I_m and Q_m refer to the I and Q quantities for period i which refers to the metric of the standard

Data

Data from eight sites within three major urban areas were used to calculate rolled back ozone concentrations using the quadratic method. For each site, a high and low ozone year was chosen based on historical data. The information detailing the high and low years and the corresponding eight hour averaged 4^{th} maxima are provided in Table I.

Table I: List of Sites and Respective High/Low Ozone Years Utilized

Site ID	High ozone		Low ozone		City
	Year	8 hour 4th max	Year	8 hour 4th max	
060371601	1994	127	2002	74	Los Angeles
060372005	1994	132	2001	90	Los Angeles
060658001	1994	148	2000	106	Los Angeles
060711004	1994	148	2002	105	Los Angeles
171630010	1995	84	2001	78	St. Louis
291831002	1995	112	2001	85	St. Louis
420170012	1995	111	2003	87	Philadelphia
420450002	1995	108	2003	80	Philadelphia

The ozone concentrations measured in the high year were rolled back to the low year concentrations based on the differences in the 4^{th} maxima.

The value to roll the fourth maximum 8 hour ozone values back to for each monitor-year is denoted as S. The value of S for each monitor-year is determined by the amount of rollback required to have the average fourth maximum ozone concentration over three years attain the standard. To accomplish this, the design value for each site is multiplied by a reduction factor calculated as:

$$\text{Reduction Factor} = C_{att}/C_{dv}*100$$

where: C_{att} is the attainment concentration for the ozone standard which is 0.084 ppm

C_{dv} is the average of the fourth maxima at the design value monitor for a particular area over a three year period

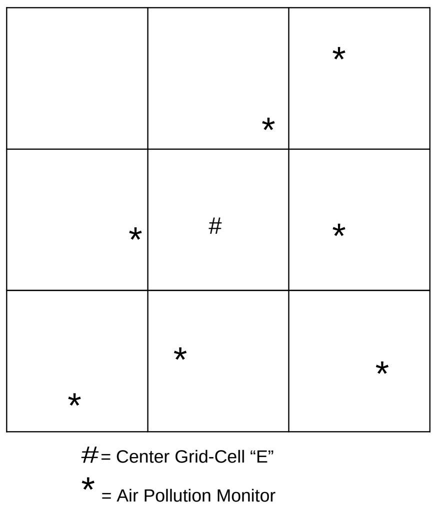
4

Appendix C Numerical Examples of VNA and eVNA

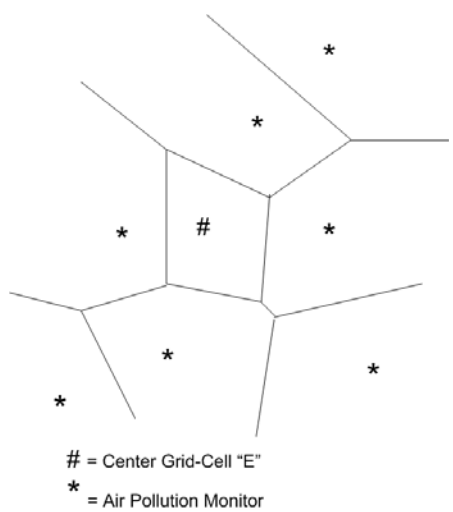
Below are numerical examples of VNA and eVNA. Note that the examples are given for the year 1995; however, the same approach holds for any given year.

Numerical Example VNA

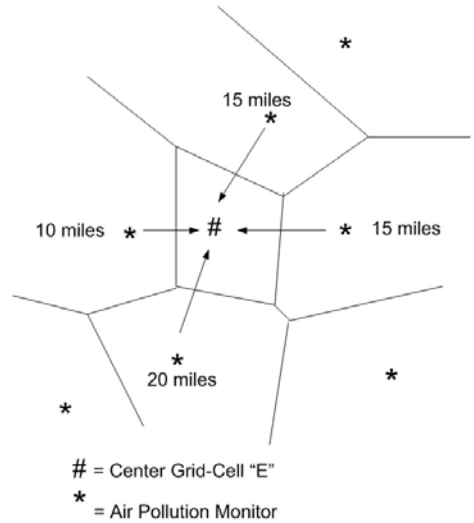
The first step in VNA is to identify the set of nearest monitors for each of the points of interest, such as the centers of the grid-cells in a modeling domain. The figure below presents nine grid-cells and seven monitors, with the focus on identifying the set of nearest neighbors to grid-cell "E."



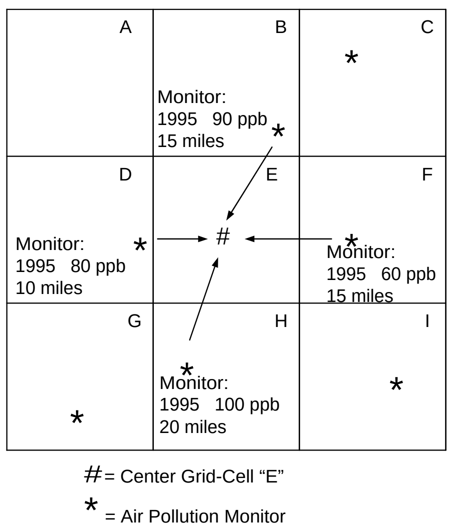
VNA identifies the nearest monitors, or "neighbors," by drawing a polygon, or "Voronoi" cell, around the center of each grid-cell. These polygons have the special property that the boundaries are the same distance from the two closest points.



We then choose those monitors that share a boundary with the center of grid-cell "E." These are the nearest-neighbors, which we use to estimate the air pollution level for this grid-cell.



To estimate the air pollution level in each grid-cell, we calculate the annual and the binned daily metrics for each of the neighboring monitors, and then calculate an inverse-distance weighted average of the metrics. The further the monitor is from the grid-cell, the smaller the weight.



The weight for the monitor 10 miles from the center of grid-cell E is calculated as follows:

$$d_{i,1} = \frac{\frac{1}{10}}{\left(\frac{1}{10} + \frac{1}{15} + \frac{1}{15} + \frac{1}{20}\right)} = 0.35 \ .$$

The weights for the other monitors would be calculated in a similar fashion. We then calculate an inverse-distance weighted average for 1995 air pollution levels in grid-cell E as follows:

$$\text{Forecast}_{1995} = 0.35*80 \text{ ppb} + 0.24*90 \text{ ppb} + 0.24*60 \text{ ppb} + 0.18*100 \text{ ppb} = 81.2 \text{ ppb} \ .$$

Numerical Example eVNA

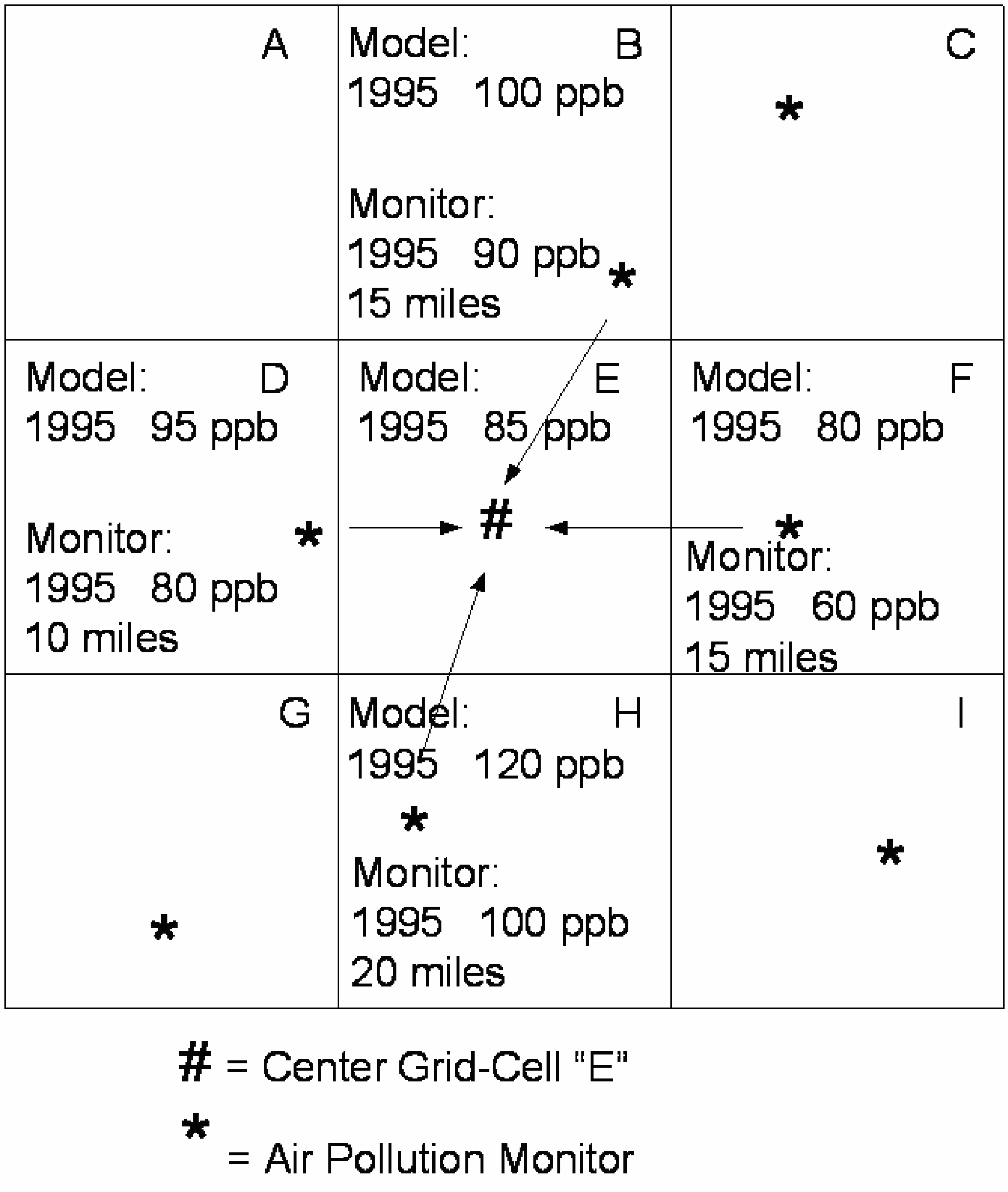
We also use VNA in combination with modeling data; we term this enhanced Voronoi Neighbor Averaging (eVNA). For each of the neighbor monitors, we multiply the monitoring data with the ratio of the base-year modeling data for the destination grid-cell to the base-year modeling data for grid-cell containing the monitor.

Consider the example in the figure below. To forecast air pollution levels for 1995, we would multiply the 1995 monitor value by the ratio of the 1995 model value in grid-cell E to the 1995 model value

$$Forecast_{1995} = \sum_{i=1}^{4} Weight_i * Monitor_i * \frac{Model_{E,1995}}{Model_{i,1995}}$$

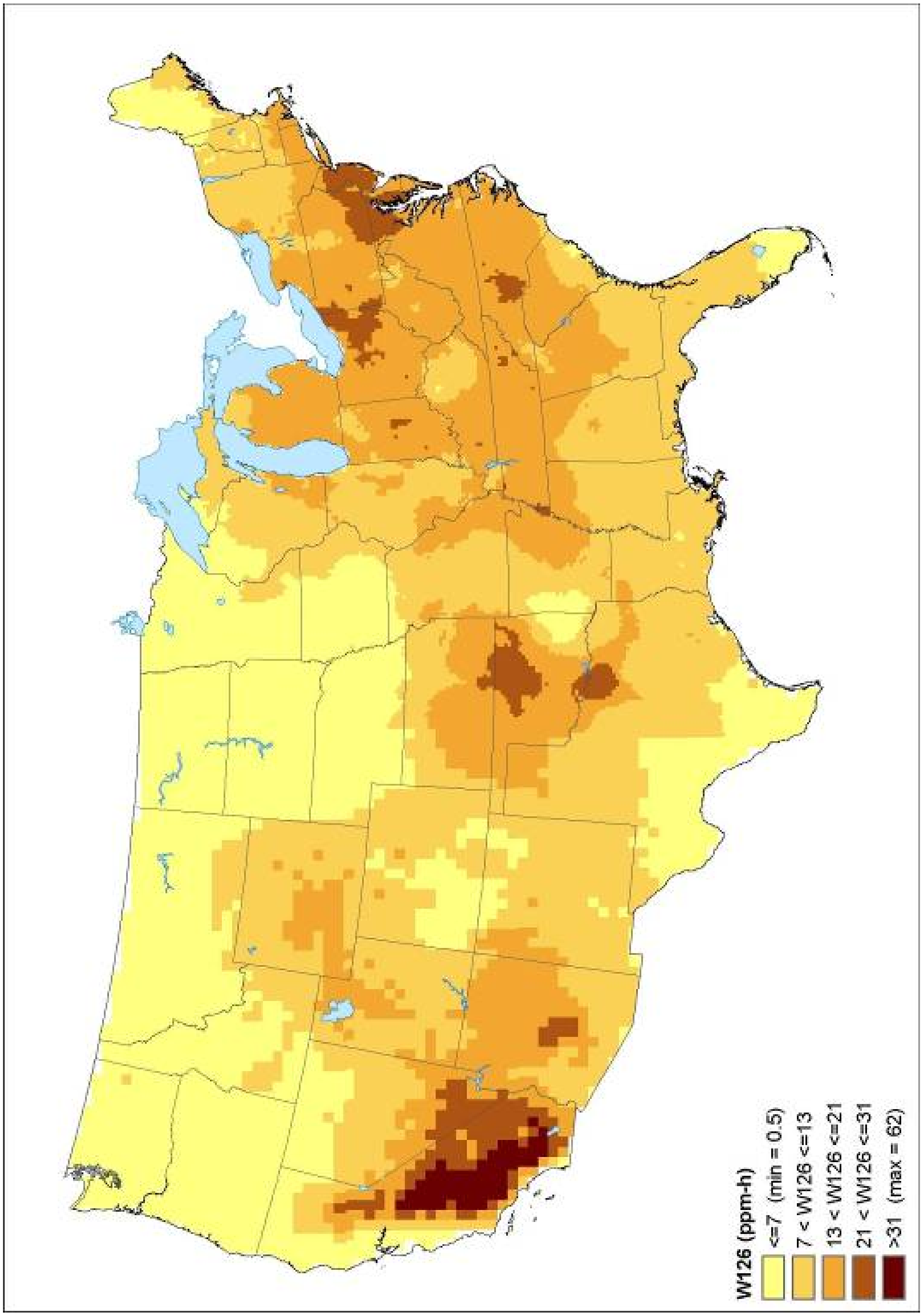
containing each of the neighbor monitors:

$$Forecast_{1995} = \left(0.35 * 80 * \frac{85}{95}\right) + \left(0.24 * 90 * \frac{85}{100}\right) + \left(0.24 * 60 * \frac{85}{80}\right) + \left(0.18 * 100 * \frac{85}{120}\right) = 70.8\,ppb$$

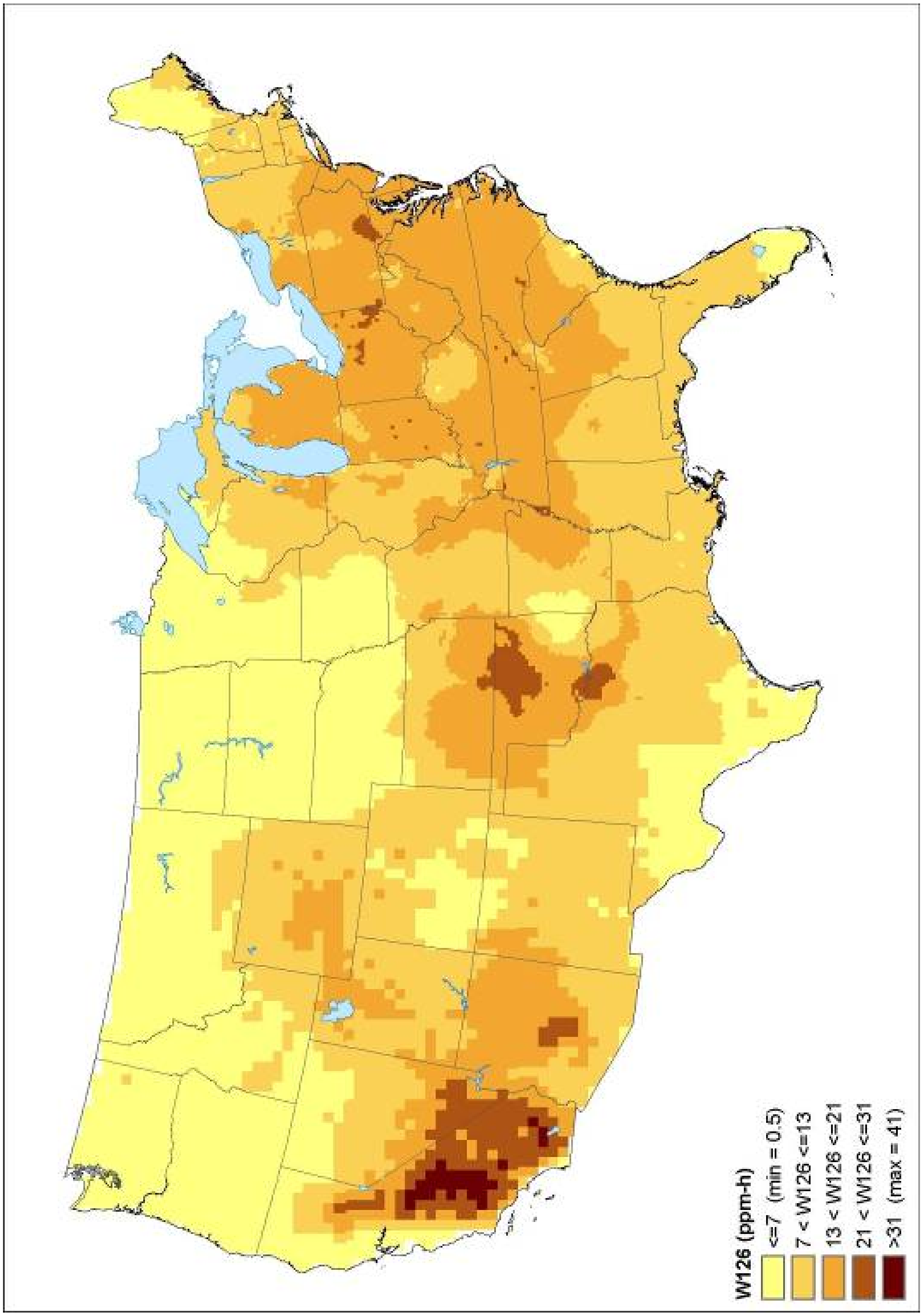

A
Model: B
1995 100 ppb
Monitor:
1995 90 ppb
15 miles
C
Model: D
1995 95 ppb
Monitor:
1995 80 ppb
10 miles
Model: E
1995 85 ppb
#
Model: F
1995 80 ppb
Monitor:
1995 60 ppb
15 miles
G
Model: H
1995 120 ppb
Monitor:
1995 100 ppb
20 miles
I
= Center Grid-Cell "E"
* = Air Pollution Monitor

Appendix D Air Quality Maps

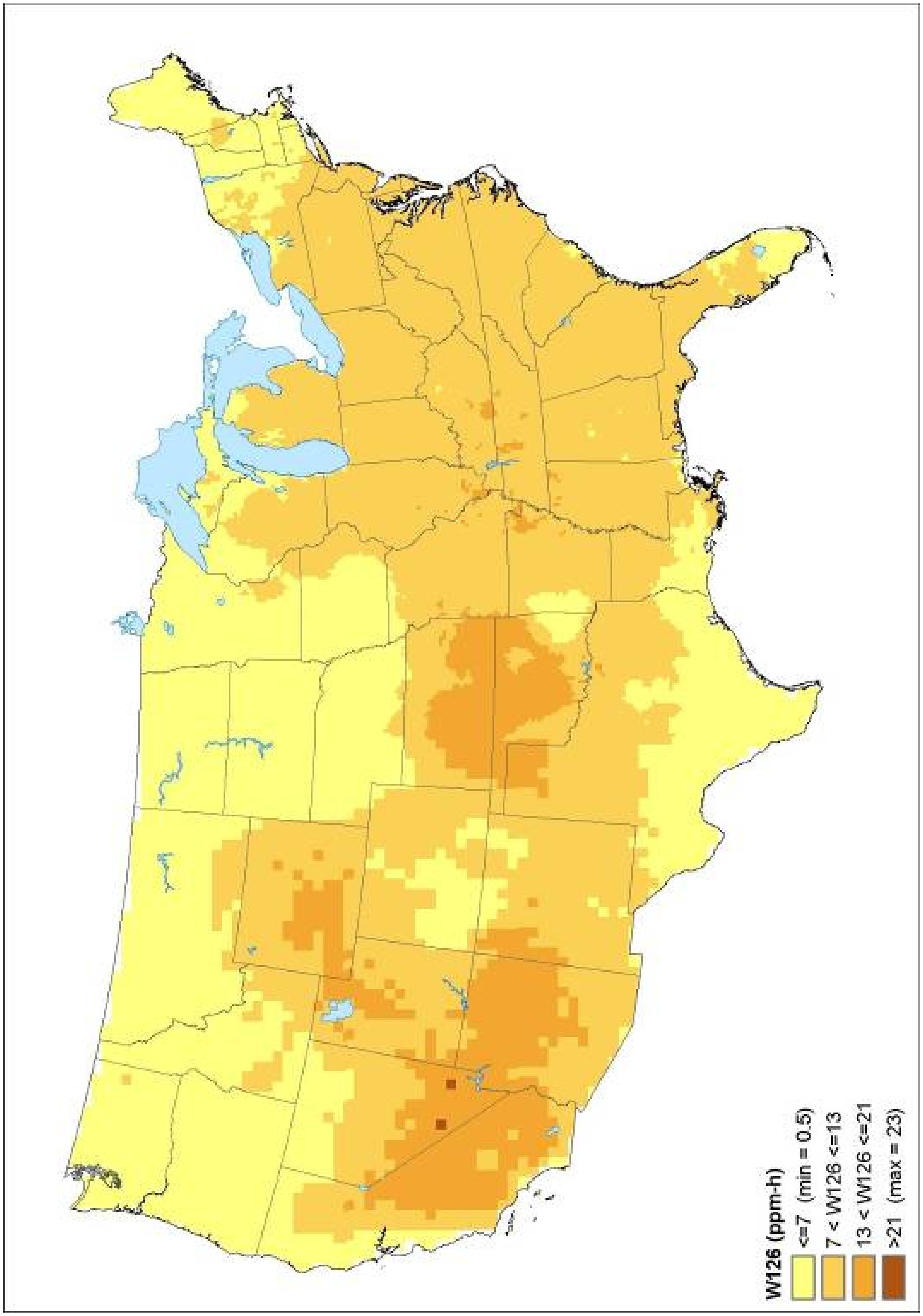
In this Appendix, we present O_3 air quality maps under the four rollback scenarios described above, and under "as is" conditions as described by the POES. O_3 levels are shows in terms of the Maximum 3-month 12-hour W126 metric. The maps show the entire continental U.S. as a whole, even though the data for the East and Western U.S. were generated separately according to slightly different interpolation methods.



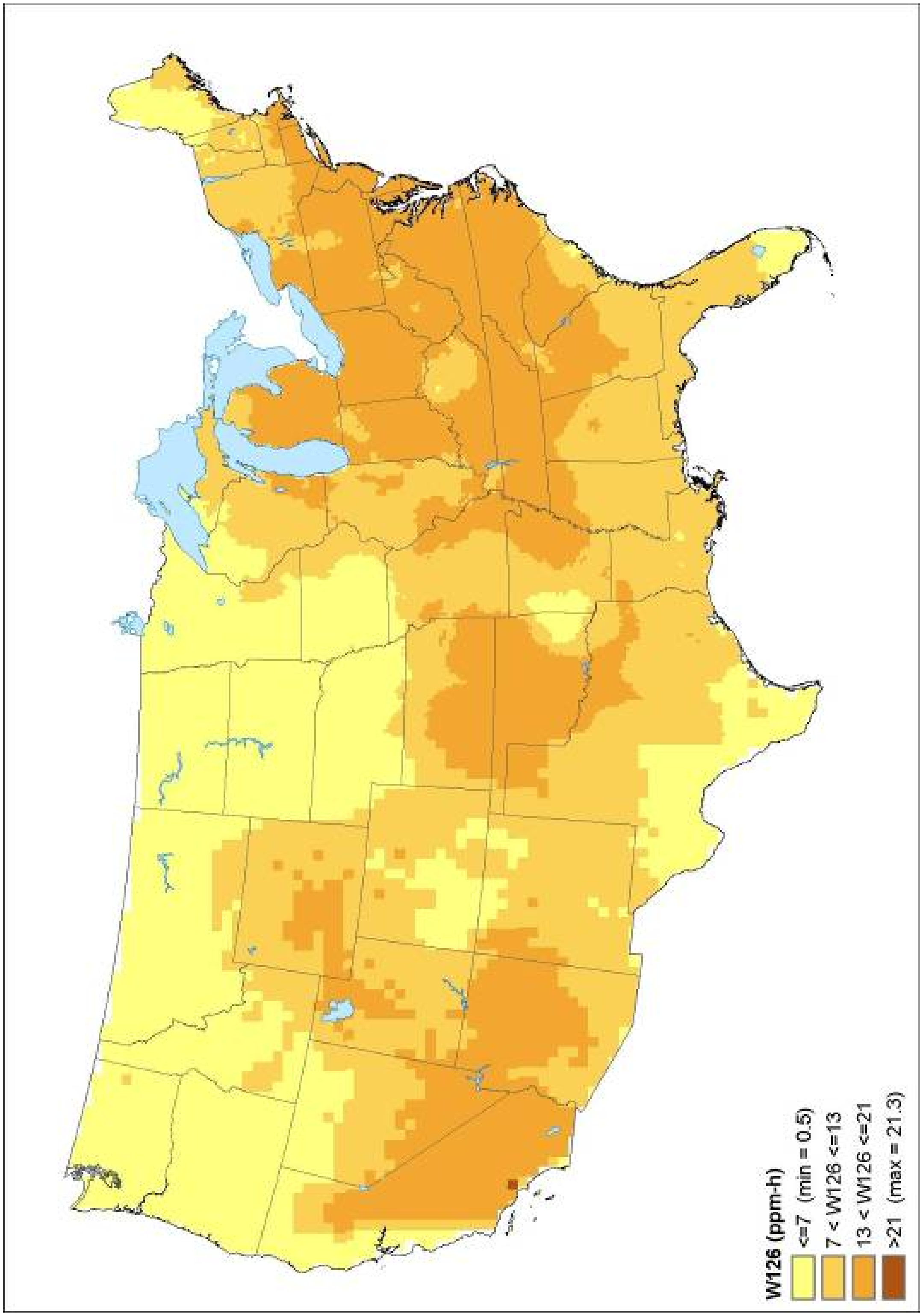
Map D-1: Ozone levels as-is.



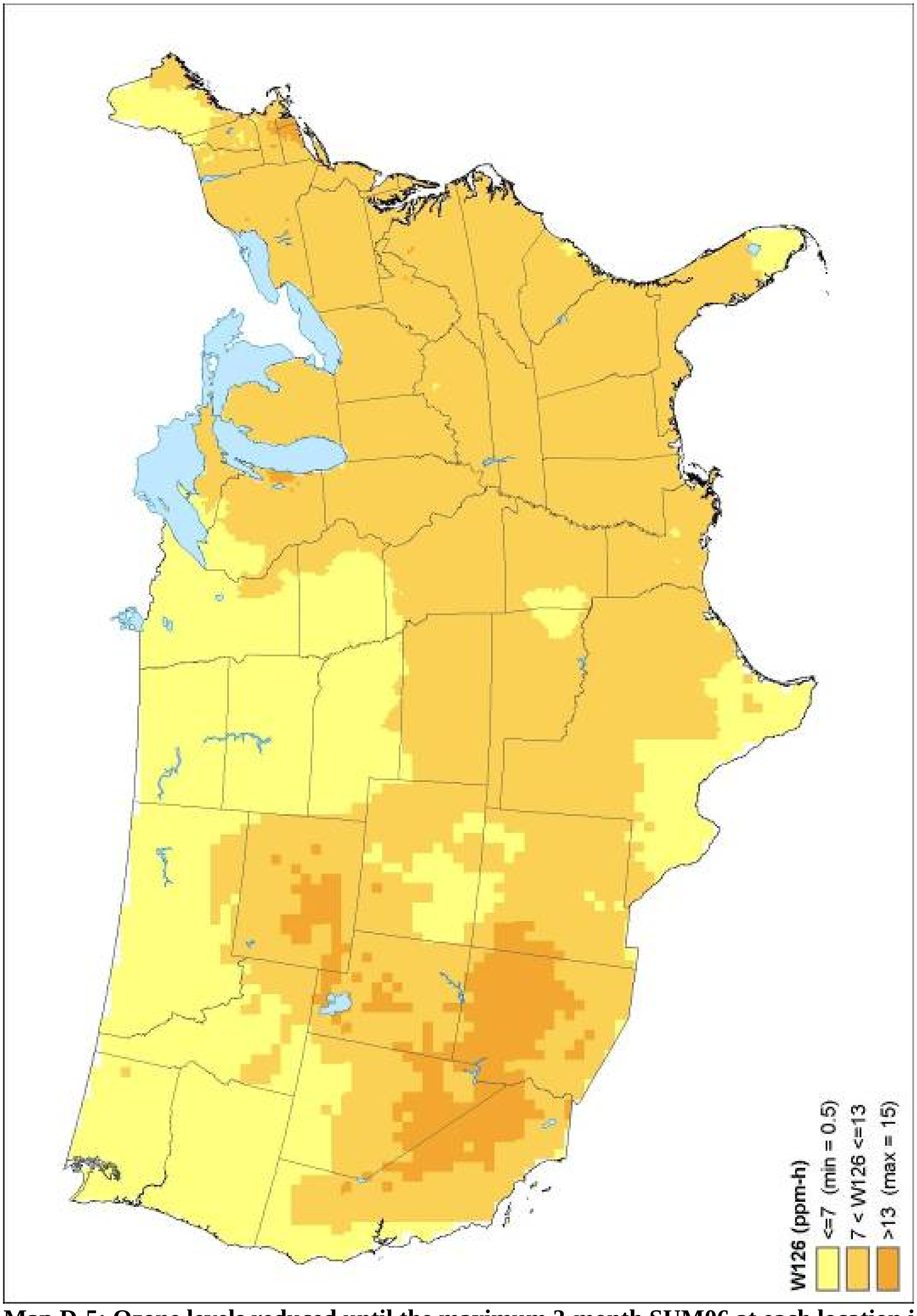
Map D-2: Ozone levels reduced until the maximum 8 hour average at each location is 84 ppb (ppm-h)



Map D-3: Ozone levels reduced until the maximum 8 hour average at each location is 70 ppb (ppm-h)



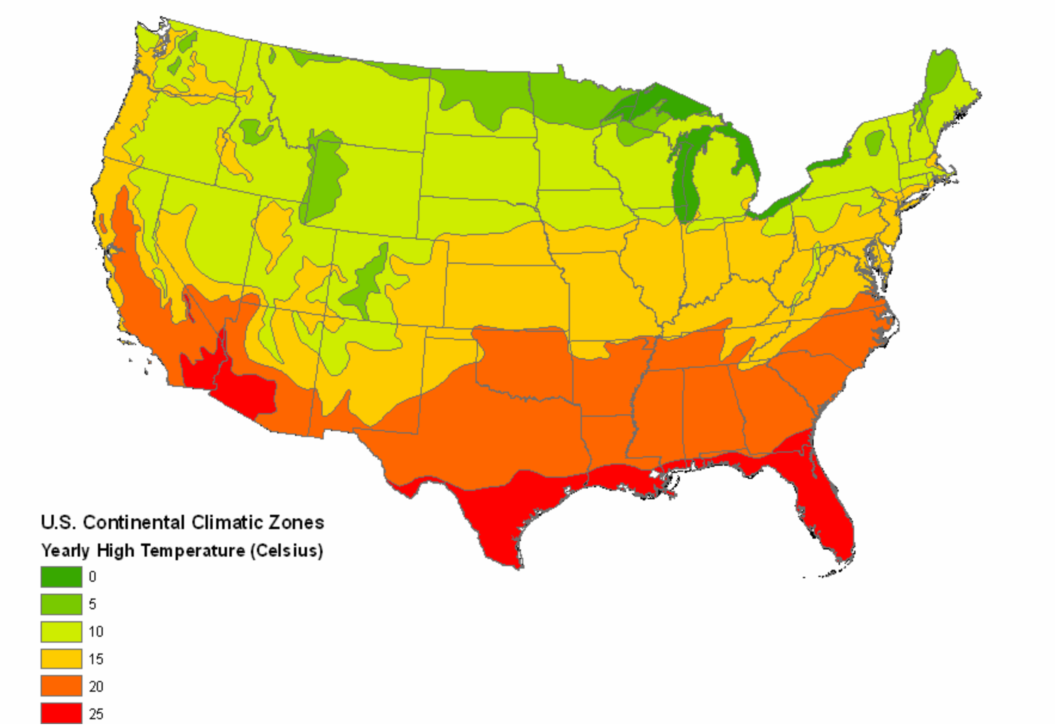
Map D-4: Ozone levels reduced until the maximum 3-month SUM06 at each location is less than 25 ppm-h (parts per million - hour)



Map D-5: Ozone levels reduced until the maximum 3-month SUM06 at each location is less than 15 ppm-h (parts per million - hour)

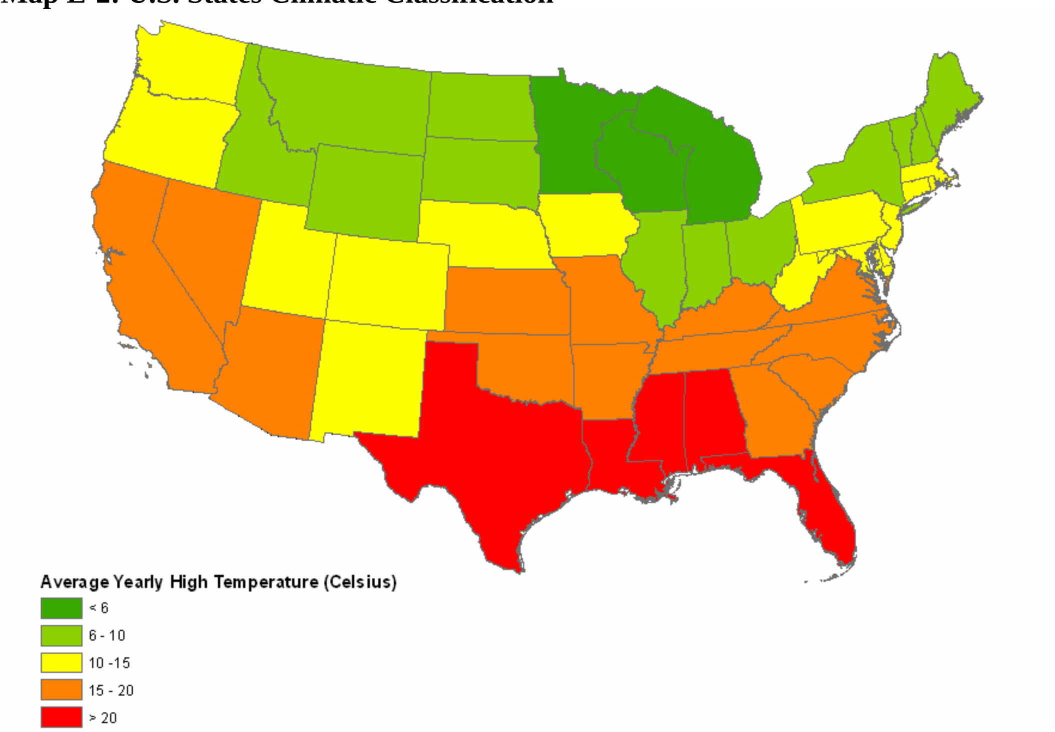
Appendix E Interpolating State Growing Seasons

Map E-1: U.S. Continental Climatic Classification



Source: ESRI Annual World Temperature Zones, 2005.

Map E-2: U.S. States Climatic Classification



Source: Author Estimates. This classification was used to extrapolate typical state growing seasons when primary source data was not available.

Appendix F Growing Seasons for Major Crops by State

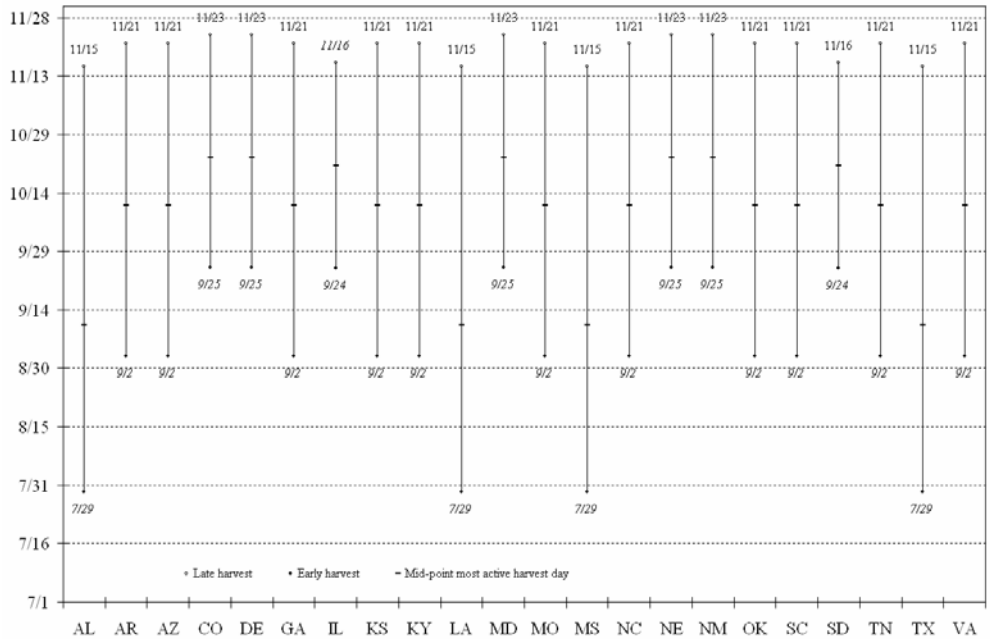


Figure F-1: Typical Harvest Seasons for Sorghum by State

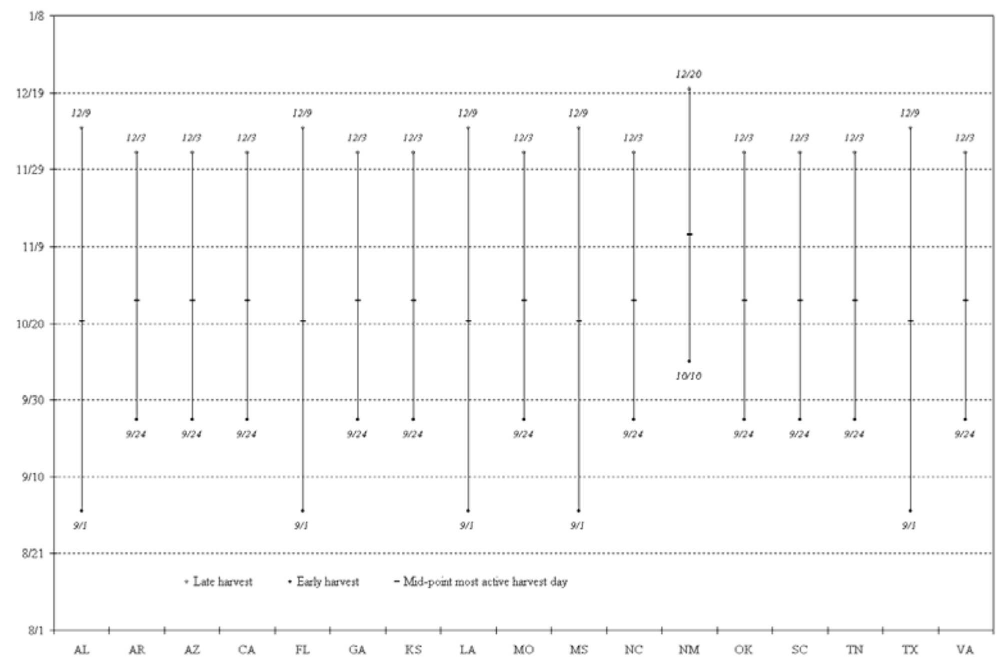


Figure F-2: Typical Harvest Seasons for Cotton by State

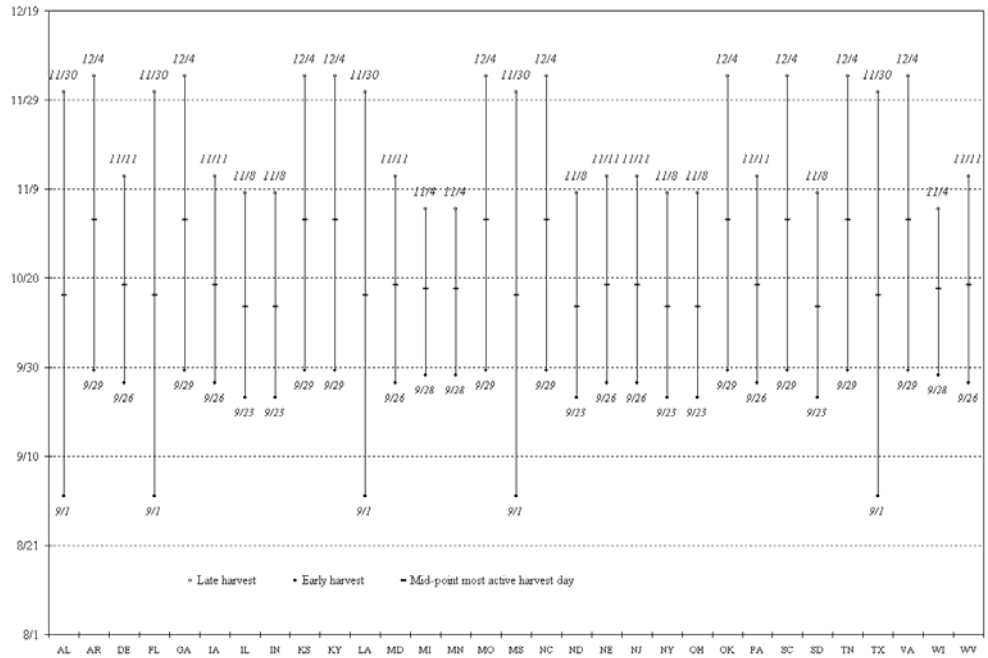


Figure F-3: Typical Harvest Seasons for Soybean by State

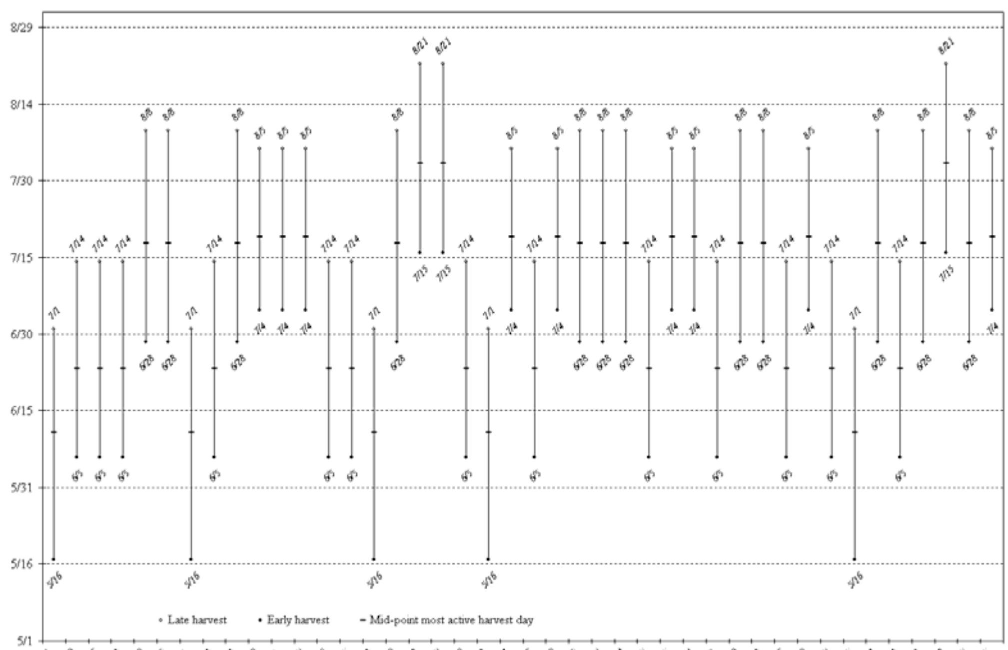


Figure F-4: Typical Harvest Seasons for Winter Wheat by State

Appendix G Summary Statistics for Crop Yield Concentration Responses based on W126 Metric

Appendix G summarizes relative crop yield gains under the six scenarios presented in Section 4:

- Ozone levels which just meet an 84 ppb 4th highest 8-hour maximum standard (in this case, we performed a rollback to 84.999 ppb, since the 4th highest 8-hour maximum standard truncates decimals)
- Ozone levels which just meet a 70 ppb 4th highest 8-hour maximum standard (actually 70.999 for the reasons above)
- Ozone levels which just meet a 25ppm-h 3-month 12-hour SUM06 standard
- Ozone levels which just meet a 15ppm-h 3-month 12-hour SUM06 standard.
- Ozone levels which just meet a 21ppm-h 3-month 12-hour W126 standard.
- Ozone levels which just meet a 13ppm-h 3-month 12-hour W126 standard.

Appendix G.1 presents results based on the reduced or "adjusted" O_3 metric (i.e. hourly O_3 values were adjusted down by 10%). Appendix G.2 presents similar results based on the unreduced metric (unadjusted hourly O_3 values). Refer to Section 5 for a discussion of the data and method used to estimate O_3 concentration responses on vegetation.

G.1 Crop Yield Concentration Responses based on Ten Percent Adjusted W126 Metric

The box plots and tables in this section show yield responses over the continental U.S. at the *county level*. Results were computed at the gridcell level, and subsequently averaged at the county level. The national estimates presented below are simple averages across counties. The crop ranges used to compute national estimates are the ones reported in the 2002 Census of Agriculture. The first box plot shows percent yield loss at the baseline exposure level. The subsequent plots show percent yield gain from the baseline situation. The shaded boxes represent the lowest and highest quartiles; the low and high bars show minimum and maximum values. Exact numbers are presented in tables. Note that the minimums and maximums reported on the maps will differ from the summary results presented in the tables because the maps are based on individual gridcell results whereas the results in the tables and box plots are county level averages.

G.1.1 Median Concentration Responses for Crops

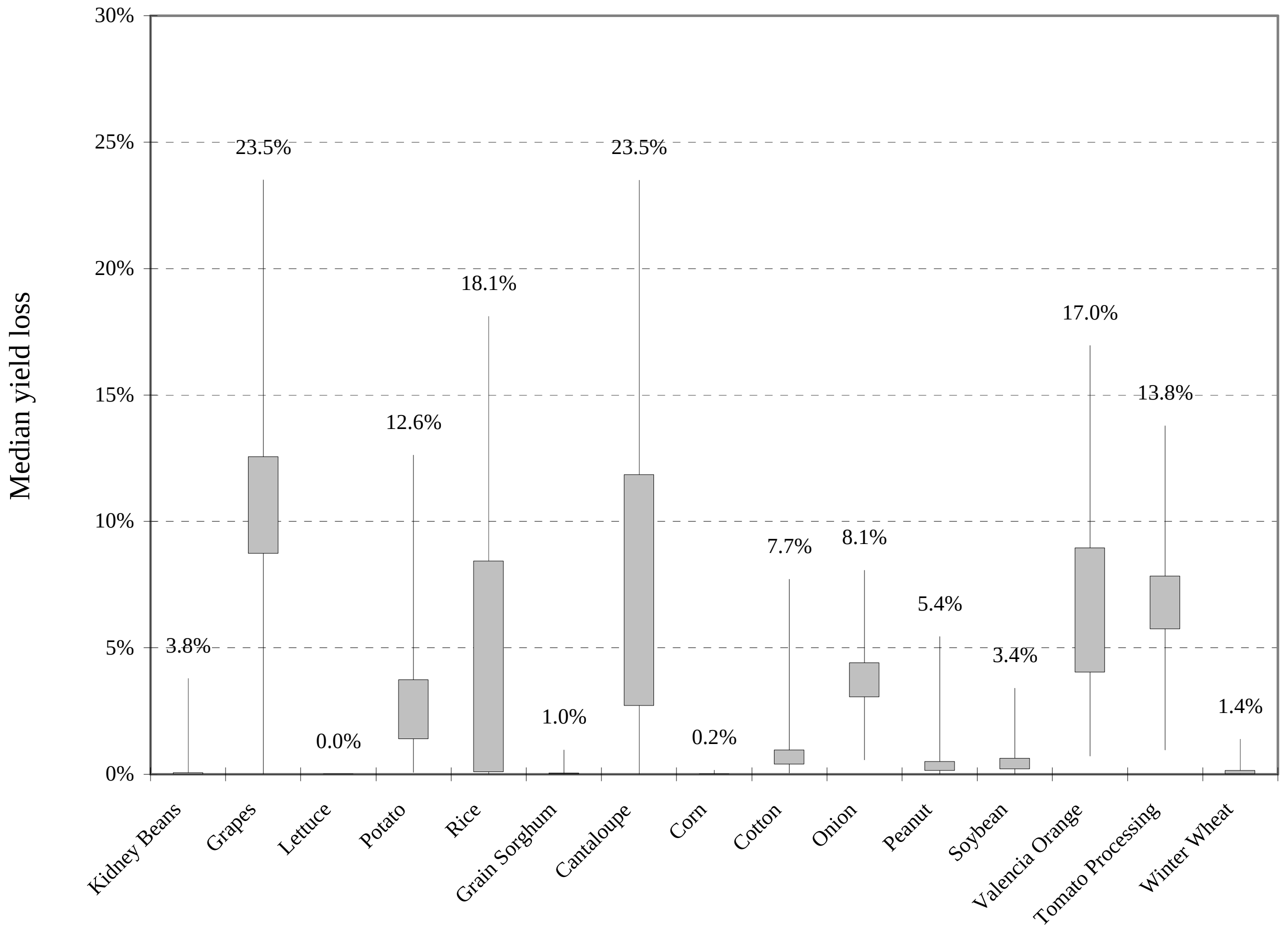


Figure G-1: Yield Losses for Crops - 2001 Baseline (reduced W126, Median C-R)

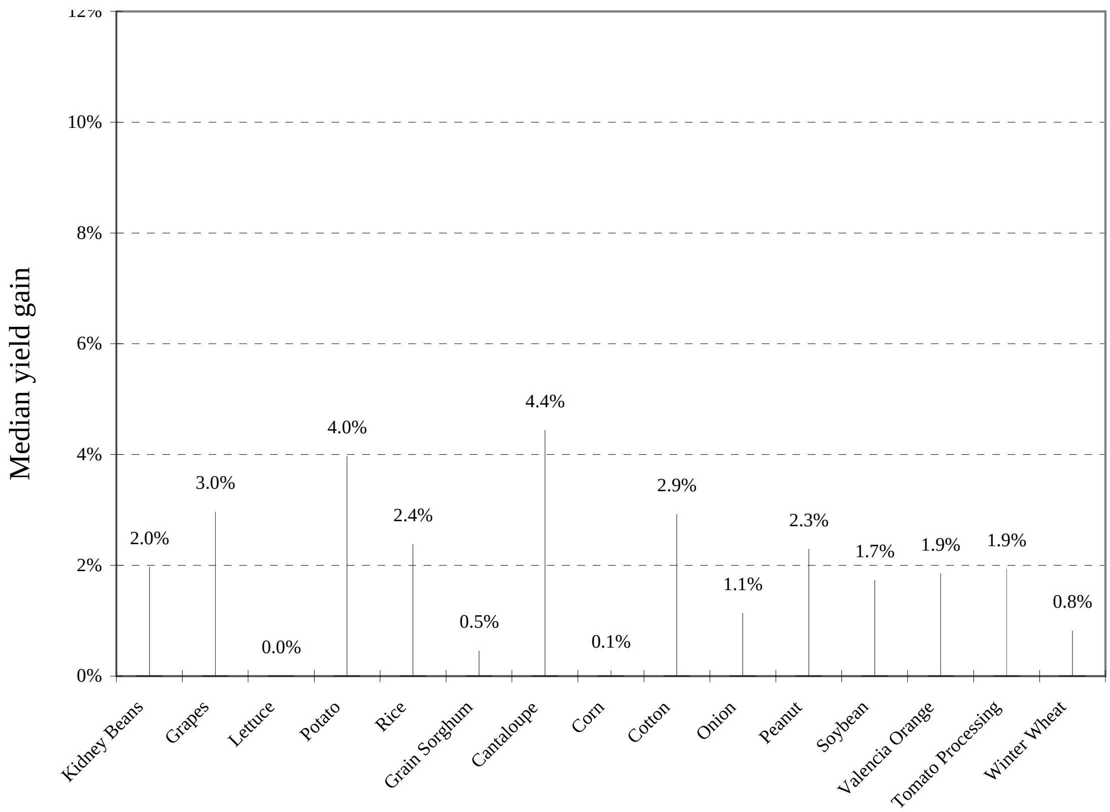


Figure G-2: Yield Gains from Baseline for Crops – 84 ppb Rollback (reduced W126, Median C-R)

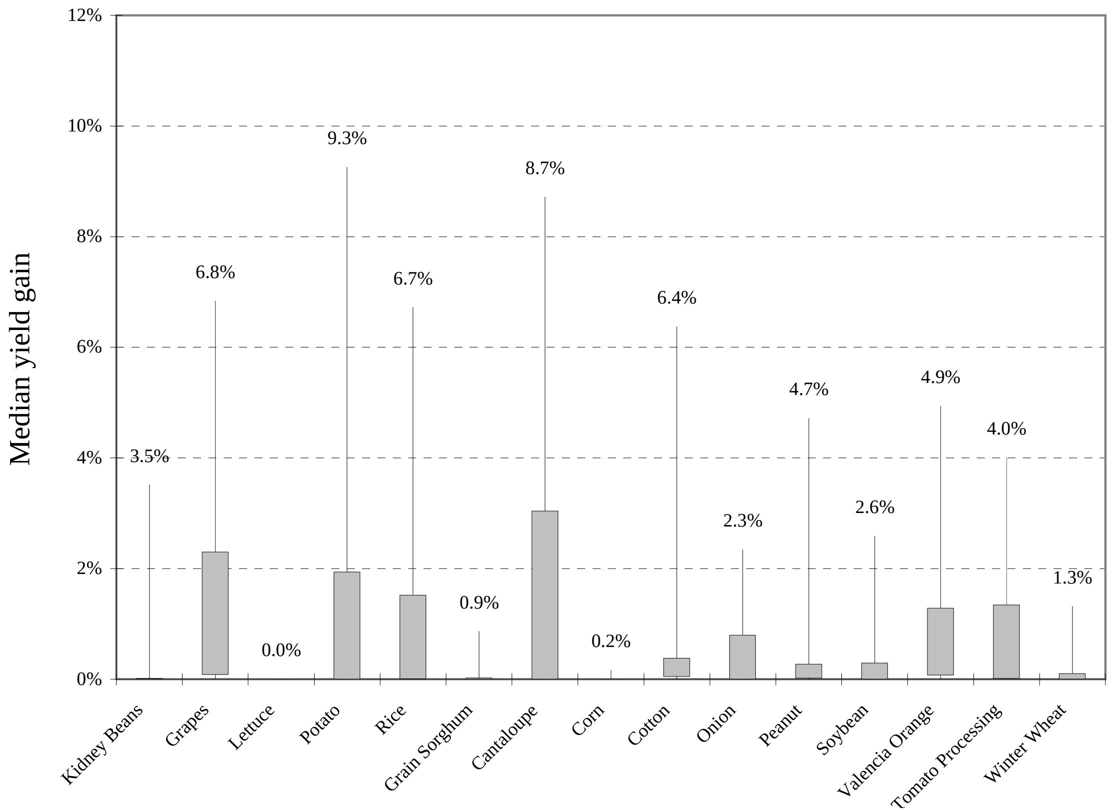


Figure G-3: Yield Gains from Baseline for Crops – 70 ppb Rollback (reduced W126, Median C-R)

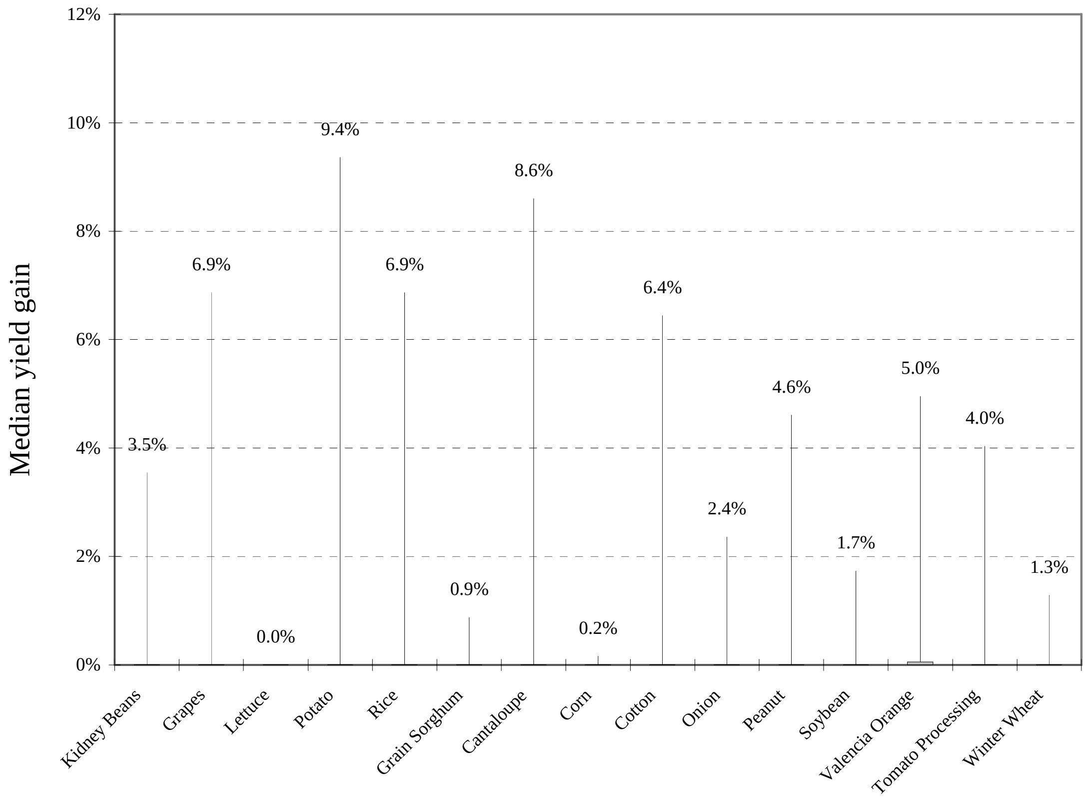


Figure G-4: Yield Gains from Baseline for Crops – 25 ppm-hr Rollback (reduced W126, Median C-R)

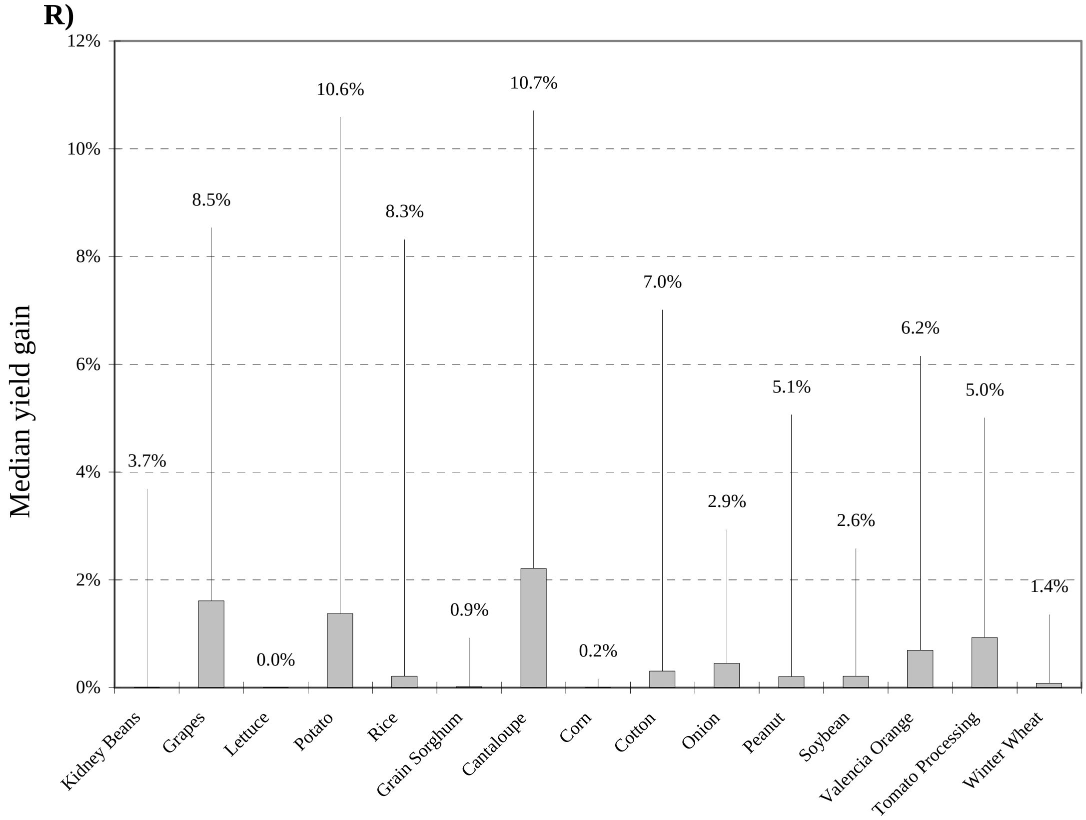


Figure G-5: Yield Gains from Baseline for Crops – 15 ppm-hr Rollback (reduced W126, Median C-R)

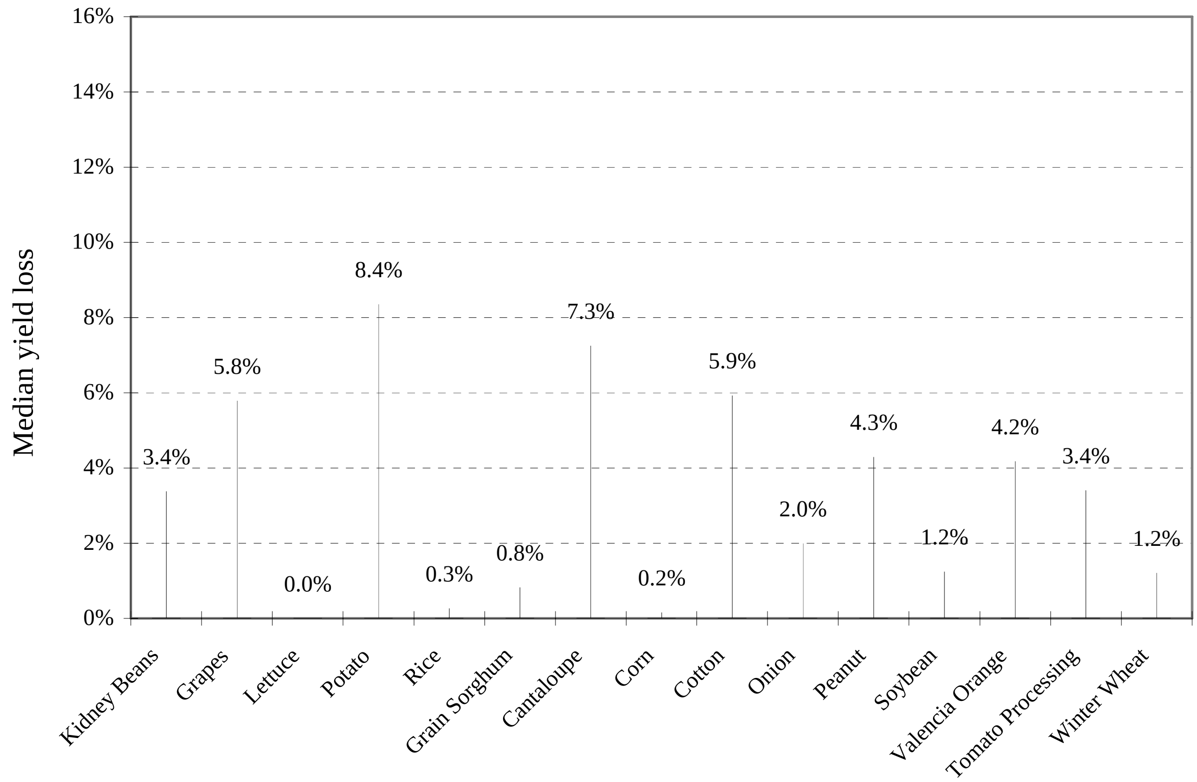


Figure G-6: Yield Gains from Baseline for Crops – 21 ppm-hr W126 Rollback (reduced W126, Median C-R)

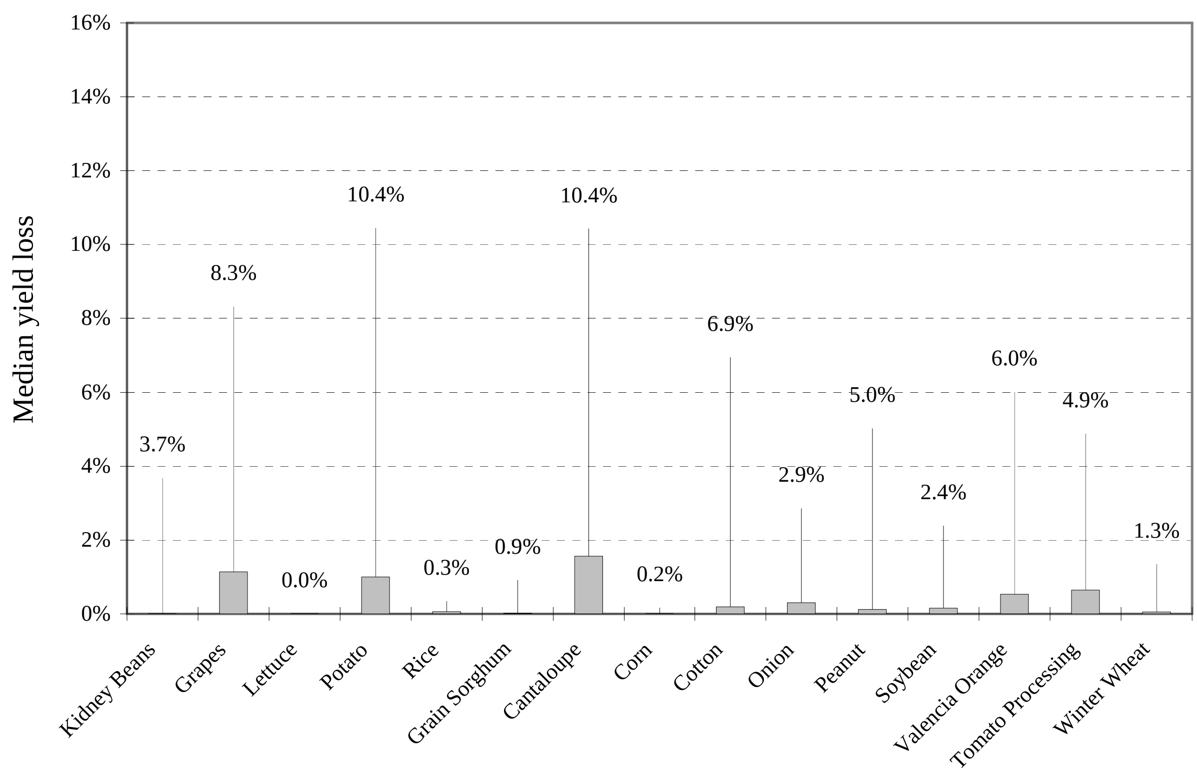


Figure G-7: Yield Gains from Baseline for Crops – 13 ppm-hr W126 Rollback (reduced W126, Median C-R)

G.1.2 Summary Statistics of Concentration Responses for Crops

Similar results as in Chapter 5.4.1 are provided in Tables G-1 through G-5 below. These yield change estimates are based on the *reduced* W126 metric (i.e. hourly O_3 levels have been reduced by 10% to account for the elevation differential between monitor height and crop canopy). In Tables G-1 through G-5 rollback results are presented as differences or yield gains from baseline. Tables G-6 through G-11 present absolute losses instead. Results for Soybean and Cotton are presented in Chapter 5.4.1.

Tables show count, mean, maximum, minimum, median, and standard deviation in yield responses for thirteen commodities and six alternate air quality scenarios. These are based on straight average yield responses at the county-level (no production weights were applied).

Table G-1: Yield Losses for Crops, Fruits and Vegetables - 2001 Baseline (reduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	3.78%	0.00%	0.08%	0.00%	0.27%
	Max		25.75%	0.00%	11.47%	11.90%	3.27%
Grapes	Median	1,883	23.50%	0.00%	10.47%	10.87%	2.99%
	Min		21.26%	0.00%	9.47%	9.83%	2.70%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
	Max		18.47%	0.33%	5.31%	5.28%	2.62%
Potato	Median	1,585	12.62%	0.08%	2.67%	2.55%	1.61%
	Min		9.86%	0.05%	1.93%	1.81%	1.21%
Rice	Median	300	18.11%	0.00%	3.84%	0.53%	5.33%
Sorghum	Median	1,331	0.97%	0.00%	0.04%	0.03%	0.05%
Cantaloupe	Median	1,610	23.49%	0.00%	7.53%	8.82%	5.09%
	Max		0.42%	0.00%	0.01%	0.00%	0.03%
Corn	Median	2,623	0.17%	0.00%	0.00%	0.00%	0.01%
	Min		0.02%	0.00%	0.00%	0.00%	0.00%
Onion	Median	891	8.07%	0.57%	3.72%	3.83%	1.05%
Peanut	Median	409	5.45%	0.01%	0.41%	0.27%	0.47%
Valencia Orange	Median	89	16.95%	0.72%	6.52%	5.39%	3.86%
	Max		19.17%	1.35%	9.30%	9.53%	2.19%
Tomato Processing	Median	2,236	13.78%	0.97%	6.68%	6.85%	1.57%
	Min		12.78%	0.90%	6.20%	6.35%	1.46%
	Max		29.20%	0.44%	8.77%	7.55%	5.65%
Winter Wheat	Median	2,533	1.40%	0.00%	0.10%	0.04%	0.14%
	Min		1.11%	0.00%	0.10%	0.05%	0.13%

Table G-2: Yield Gains from Baseline for Crops, Fruits and Vegetables – 84 ppb 8-Hour Rollback (reduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	1.97%	0.00%	0.02%	0.00%	0.14%
	Max		3.25%	0.00%	0.12%	0.00%	0.41%
Grapes	Median	1,883	2.97%	0.00%	0.11%	0.00%	0.37%
	Min		2.68%	0.00%	0.10%	0.00%	0.34%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
	Max		4.87%	0.00%	0.20%	0.00%	0.64%
Potato	Median	1,585	3.96%	0.00%	0.14%	0.00%	0.46%
	Min		3.23%	0.00%	0.11%	0.00%	0.36%
Rice	Median	300	2.38%	0.00%	0.02%	0.00%	0.16%

Grain Sorghum	Median	1,331	0.46%	0.00%	0.00%	0.00%	0.02%
Cantaloupe	Median	1,610	4.44%	0.00%	0.17%	0.00%	0.57%
	Max		0.23%	0.00%	0.00%	0.00%	0.01%
Corn	Median	2,623	0.10%	0.00%	0.00%	0.00%	0.01%
	Min		0.01%	0.00%	0.00%	0.00%	0.00%
Onion	Median	891	1.13%	0.00%	0.06%	0.00%	0.17%
Peanut	Median	409	2.30%	0.00%	0.02%	0.00%	0.14%
Valencia Orange	Median	89	1.85%	0.00%	0.13%	0.00%	0.35%
	Max		2.69%	0.00%	0.09%	0.00%	0.31%
Tomato Processing	Median	2,236	1.94%	0.00%	0.06%	0.00%	0.23%
	Min		1.80%	0.00%	0.06%	0.00%	0.21%
	Max		9.68%	0.00%	0.23%	0.00%	0.98%
Winter Wheat	Median	2,533	0.82%	0.00%	0.01%	0.00%	0.06%
	Min		0.60%	0.00%	0.01%	0.00%	0.05%

Table G-3: Yield Gains from Baseline for Crops, Fruits and Vegetables – 70 ppb 8-Hour Rollback (reduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	3.52%	0.00%	0.06%	0.00%	0.25%
	Max		7.49%	0.00%	1.52%	1.28%	1.41%
Grapes	Median	1,883	6.84%	0.00%	1.39%	1.16%	1.29%
	Min		6.18%	0.00%	1.25%	1.05%	1.16%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
	Max		11.88%	0.00%	1.87%	1.27%	2.00%
Potato	Median	1,585	9.25%	0.00%	1.16%	0.73%	1.30%
	Min		7.42%	0.00%	0.88%	0.54%	0.99%
Rice	Median	300	6.72%	0.00%	0.76%	0.10%	1.15%
Grain Sorghum	Median	1,331	0.87%	0.00%	0.02%	0.01%	0.05%
Cantaloupe	Median	1,610	8.72%	0.00%	1.75%	1.32%	1.88%
	Max		0.39%	0.00%	0.01%	0.00%	0.02%
Corn	Median	2,623	0.16%	0.00%	0.00%	0.00%	0.01%
	Min		0.02%	0.00%	0.00%	0.00%	0.00%
Onion	Median	891	2.34%	0.00%	0.45%	0.29%	0.50%
Peanut	Median	409	4.72%	0.00%	0.21%	0.09%	0.38%
Valencia Orange	Median	89	4.93%	0.00%	0.92%	0.52%	1.14%
	Max		5.57%	0.00%	1.11%	0.87%	1.08%
Tomato Processing	Median	2,236	4.00%	0.00%	0.80%	0.63%	0.77%
	Min		3.71%	0.00%	0.74%	0.58%	0.72%
	Max		18.62%	0.00%	2.83%	1.34%	3.52%
Winter Wheat	Median	2,533	1.32%	0.00%	0.07%	0.01%	0.13%
	Min		1.02%	0.00%	0.07%	0.01%	0.11%

Table G-4: Yield Gains from Baseline for Crops, Fruits and Vegetables – 25 ppm-hr SUM06 Rollback (reduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	3.54%	0.00%	0.03%	0.00%	0.24%
	Max		7.52%	0.00%	0.13%	0.00%	0.47%
Grapes	Median	1,883	6.87%	0.00%	0.12%	0.00%	0.43%
	Min		6.21%	0.00%	0.10%	0.00%	0.39%

Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
	Max		12.04%	0.00%	0.19%	0.00%	0.76%
Potato	Median	1,585	9.36%	0.00%	0.13%	0.00%	0.56%
	Min		7.50%	0.00%	0.10%	0.00%	0.44%
Rice	Median	300	6.87%	0.00%	0.06%	0.00%	0.46%
Grain Sorghum	Median	1,331	0.88%	0.00%	0.01%	0.00%	0.04%
Cantaloupe	Median	1,610	8.60%	0.00%	0.16%	0.00%	0.59%
	Max		0.40%	0.00%	0.00%	0.00%	0.02%
Corn	Median	2,623	0.16%	0.00%	0.00%	0.00%	0.01%
	Min		0.02%	0.00%	0.00%	0.00%	0.00%
Onion	Median	891	2.36%	0.00%	0.05%	0.00%	0.19%
Peanut	Median	409	4.61%	0.00%	0.05%	0.00%	0.29%
Valencia Orange	Median	89	4.95%	0.00%	0.38%	0.00%	0.95%
	Max		5.61%	0.00%	0.09%	0.00%	0.34%
Tomato Processing	Median	2,236	4.03%	0.00%	0.06%	0.00%	0.24%
	Min		3.74%	0.00%	0.06%	0.00%	0.22%
	Max		18.48%	0.00%	0.23%	0.00%	1.05%
Winter Wheat	Median	2,533	1.29%	0.00%	0.01%	0.00%	0.07%
	Min		0.99%	0.00%	0.01%	0.00%	0.05%

Table G-5: Yield Gains from Baseline for Crops, Fruits and Vegetables – 15 ppm-hr SUM06 Rollback (reduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	3.69%	0.00%	0.05%	0.00%	0.26%
	Max		9.35%	0.00%	1.01%	0.43%	1.23%
Grapes	Median	1,883	8.53%	0.00%	0.92%	0.39%	1.12%
	Min		7.72%	0.00%	0.83%	0.36%	1.02%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
	Max		14.04%	0.00%	1.26%	0.24%	1.76%
Potato	Median	1,585	10.59%	0.00%	0.81%	0.14%	1.18%
	Min		8.42%	0.00%	0.62%	0.11%	0.90%
Rice	Median	300	8.32%	0.00%	0.61%	0.01%	1.29%
Grain Sorghum	Median	1,331	0.92%	0.00%	0.02%	0.00%	0.05%
Cantaloupe	Median	1,610	10.71%	0.00%	1.24%	0.37%	1.58%
	Max		0.41%	0.00%	0.01%	0.00%	0.02%
Corn	Median	2,623	0.16%	0.00%	0.00%	0.00%	0.01%
	Min		0.02%	0.00%	0.00%	0.00%	0.00%
Onion	Median	891	2.93%	0.00%	0.27%	0.00%	0.43%
Peanut	Median	409	5.07%	0.00%	0.18%	0.01%	0.41%
	Max		5.03%	0.00%	0.61%	0.19%	0.82%
Soybean	Median	2,090	2.58%	0.00%	0.18%	0.04%	0.32%
	Min		0.97%	0.00%	0.11%	0.03%	0.15%
Valencia Orange	Median	89	6.16%	0.00%	0.72%	0.00%	1.39%
	Max		6.97%	0.00%	0.73%	0.24%	0.93%
Tomato Processing	Median	2,236	5.01%	0.00%	0.52%	0.17%	0.67%
	Min		4.65%	0.00%	0.48%	0.16%	0.62%
	Max		21.73%	0.00%	2.02%	0.27%	3.00%
Winter Wheat	Median	2,533	1.36%	0.00%	0.06%	0.00%	0.12%
	Min		1.06%	0.00%	0.05%	0.00%	0.10%

Table G-6: Yield Gains from Baseline for Crops, Fruits and Vegetables – 21 ppm-hr W126 Rollback (reduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	3.38%	0.00%	0.02%	0.00%	0.22%
Grapes	Max	1,883	6.34%	0.00%	0.06%	0.00%	0.33%
	Median		5.79%	0.00%	0.05%	0.00%	0.30%
	Min		5.24%	0.00%	0.05%	0.00%	0.28%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
Potato	Max	1,585	10.50%	0.00%	0.09%	0.00%	0.56%
	Median		8.35%	0.00%	0.07%	0.00%	0.43%
	Min		6.73%	0.00%	0.06%	0.00%	0.35%
Rice	Median	300	0.26%	0.00%	0.00%	0.00%	0.02%
Sorghum	Median	1,331	0.82%	0.00%	0.00%	0.00%	0.03%
Cantaloupe	Median	1,610	7.25%	0.00%	0.07%	0.00%	0.43%
Corn	Max	2,623	0.38%	0.00%	0.00%	0.00%	0.01%
	Median		0.16%	0.00%	0.00%	0.00%	0.01%
	Min		0.02%	0.00%	0.00%	0.00%	0.00%
Onion	Median	891	1.99%	0.00%	0.03%	0.00%	0.14%
Peanut	Median	409	4.29%	0.00%	0.03%	0.00%	0.25%
Soybean	Max	2,090	1.98%	0.00%	0.03%	0.00%	0.16%
	Median		1.25%	0.00%	0.01%	0.00%	0.09%
	Min		0.38%	0.00%	0.01%	0.00%	0.03%
Valencia Orange	Median	89	4.18%	0.00%	0.29%	0.00%	0.78%
Tomato Processing	Max	2,236	4.74%	0.00%	0.04%	0.00%	0.24%
	Median		3.40%	0.00%	0.03%	0.00%	0.17%
	Min		3.16%	0.00%	0.03%	0.00%	0.16%
Winter Wheat	Max	2,533	16.08%	0.00%	0.11%	0.00%	0.76%
	Median		1.21%	0.00%	0.01%	0.00%	0.06%
	Min		0.92%	0.00%	0.01%	0.00%	0.04%

Table G-7: Yield Gains from Baseline for Crops, Fruits and Vegetables – 13 ppm-hr W126 Rollback (reduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	3.67%	0.00%	0.04%	0.00%	0.25%
Grapes	Max	1,883	9.11%	0.00%	0.73%	0.09%	1.04%
	Median		8.32%	0.00%	0.67%	0.08%	0.95%
	Min		7.53%	0.00%	0.61%	0.08%	0.86%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
Potato	Max	1,585	13.80%	0.00%	0.96%	0.02%	1.53%
	Median		10.45%	0.00%	0.63%	0.01%	1.04%
	Min		8.32%	0.00%	0.49%	0.01%	0.81%
Rice	Median	300	0.35%	0.00%	0.04%	0.00%	0.06%
Grain Sorghum	Median	1,331	0.92%	0.00%	0.02%	0.00%	0.05%
Cantaloupe	Median	1,610	10.43%	0.00%	0.93%	0.05%	1.33%
Corn	Max	2,623	0.41%	0.00%	0.01%	0.00%	0.02%
	Median		0.16%	0.00%	0.00%	0.00%	0.01%
	Min		0.02%	0.00%	0.00%	0.00%	0.00%

Onion	Median	891	2.86%	0.00%	0.20%	0.00%	0.37%
Peanut	Median	409	5.02%	0.00%	0.14%	0.00%	0.38%
Valencia Orange	Median	89	6.00%	0.00%	0.66%	0.00%	1.32%
	Max		6.79%	0.00%	0.52%	0.02%	0.78%
Tomato Processing	Median	2,236	4.88%	0.00%	0.38%	0.02%	0.56%
	Min		4.53%	0.00%	0.35%	0.02%	0.52%
	Max		21.30%	0.00%	1.47%	0.00%	2.50%
Winter Wheat	Median	2,533	1.35%	0.00%	0.05%	0.00%	0.11%
	Min		1.05%	0.00%	0.04%	0.00%	0.10%

Table G-8: Absolute Crop Yield Losses - 84 ppb 8-Hour Rollback (reduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	1.87%	0.00%	0.06%	0.00%	0.15%
	Max		23.44%	0.00%	11.35%	11.73%	3.21%
Grapes	Median	1,883	21.40%	0.00%	10.36%	10.71%	2.93%
	Min		19.35%	0.00%	9.37%	9.69%	2.65%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
	Max		14.42%	0.33%	5.11%	5.17%	2.33%
Potato	Median	1,585	9.11%	0.08%	2.53%	2.49%	1.38%
	Min		6.96%	0.05%	1.82%	1.77%	1.03%
Rice	Median	300	17.79%	0.00%	3.83%	0.51%	5.32%
Sorghum	Median	1,331	0.51%	0.00%	0.03%	0.03%	0.04%
Cantaloupe	Median	1,610	20.82%	0.00%	7.35%	8.57%	4.94%
	Max		0.18%	0.00%	0.01%	0.00%	0.01%
Corn	Median	2,623	0.06%	0.00%	0.00%	0.00%	0.00%
	Min		0.00%	0.00%	0.00%	0.00%	0.00%
	Max		21.84%	0.86%	5.53%	5.14%	2.57%
Cotton	Median	666	4.83%	0.04%	0.74%	0.65%	0.53%
	Min		8.44%	0.11%	1.33%	1.14%	0.87%
Onion	Median	891	7.34%	0.57%	3.66%	3.78%	1.00%
Peanut	Median	409	3.15%	0.01%	0.39%	0.27%	0.37%
	Max		6.94%	0.26%	2.34%	2.23%	1.28%
Soybean	Median	2,090	2.61%	0.01%	0.49%	0.40%	0.39%
	Min		1.20%	0.03%	0.35%	0.33%	0.22%
Valencia Orange	Median	89	15.43%	0.72%	6.39%	5.39%	3.62%
	Max		17.44%	1.35%	9.21%	9.45%	2.12%
Tomato Processing	Median	2,236	12.53%	0.97%	6.62%	6.79%	1.53%
	Min		11.62%	0.90%	6.14%	6.30%	1.41%
	Max		23.00%	0.44%	8.55%	7.53%	5.26%
Winter Wheat	Median	2,533	0.66%	0.00%	0.09%	0.04%	0.10%
	Min		0.58%	0.00%	0.09%	0.05%	0.10%

Table G-9: Absolute Crop Yield Losses - 70 ppb 8-Hour Rollback (reduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	0.27%	0.00%	0.02%	0.00%	0.04%
	Max		19.21%	0.00%	9.96%	10.05%	2.84%
Grapes	Median	1,883	17.53%	0.00%	9.09%	9.17%	2.59%
	Min		15.86%	0.00%	8.22%	8.30%	2.34%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%

Potato	Max		6.59%	0.33%	3.44%	3.64%	1.10%
	Median	1,585	3.37%	0.08%	1.51%	1.59%	0.58%
	Min		2.44%	0.05%	1.05%	1.11%	0.42%
Rice	Median	300	14.46%	0.00%	3.09%	0.37%	4.45%
Sorghum	Median	1,331	0.10%	0.00%	0.02%	0.01%	0.01%
Cantaloupe	Median	1,610	16.26%	0.00%	5.78%	6.63%	4.16%
Corn	Max		0.05%	0.00%	0.00%	0.00%	0.00%
	Median	2,623	0.01%	0.00%	0.00%	0.00%	0.00%
	Min		0.00%	0.00%	0.00%	0.00%	0.00%
Cotton	Max		9.69%	0.86%	3.98%	3.96%	1.37%
	Median	666	1.45%	0.04%	0.46%	0.40%	0.25%
	Min		2.71%	0.11%	0.83%	0.81%	0.38%
Onion	Median	891	5.97%	0.57%	3.27%	3.24%	0.86%
Peanut	Median	409	0.73%	0.01%	0.20%	0.17%	0.14%
Soybean	Max		4.10%	0.26%	1.63%	1.58%	0.77%
	Median	2,090	1.09%	0.01%	0.29%	0.26%	0.17%
	Min		0.65%	0.03%	0.23%	0.22%	0.12%
Valencia Orange	Median	89	12.10%	0.72%	5.59%	5.19%	2.94%
Tomato Processing	Max		14.19%	1.35%	8.19%	8.35%	1.79%
	Median	2,236	10.20%	0.97%	5.89%	6.00%	1.29%
	Min		9.46%	0.90%	5.46%	5.57%	1.20%
Winter Wheat	Max		12.83%	0.44%	5.94%	5.71%	2.89%
	Median	2,533	0.14%	0.00%	0.03%	0.02%	0.03%
	Min		0.15%	0.00%	0.04%	0.03%	0.03%

Table G-10: Absolute Crop Yield Losses - 25 ppm-hr SUM06 Rollback (reduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	0.65%	0.00%	0.05%	0.00%	0.09%
Grapes	Max		19.74%	0.00%	11.35%	11.82%	3.12%
	Median	1,883	18.02%	0.00%	10.36%	10.79%	2.85%
	Min		16.30%	0.00%	9.37%	9.76%	2.58%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
Potato	Max		11.01%	0.33%	5.12%	5.27%	2.31%
	Median	1,585	6.45%	0.08%	2.54%	2.54%	1.36%
	Min		4.82%	0.05%	1.83%	1.81%	1.02%
Rice	Median	300	17.04%	0.00%	3.78%	0.48%	5.30%
Sorghum	Median	1,331	0.14%	0.00%	0.03%	0.03%	0.03%
Cantaloupe	Median	1,610	16.02%	0.00%	7.37%	8.82%	4.89%
Corn	Max		0.10%	0.00%	0.01%	0.00%	0.01%
	Median	2,623	0.03%	0.00%	0.00%	0.00%	0.00%
	Min		0.00%	0.00%	0.00%	0.00%	0.00%
Cotton	Max		11.44%	0.86%	5.36%	5.14%	2.16%
	Median	666	2.81%	0.04%	0.70%	0.64%	0.41%
	Min		3.39%	0.11%	1.26%	1.14%	0.67%
Onion	Median	891	5.98%	0.57%	3.67%	3.83%	0.97%
Peanut	Median	409	1.25%	0.01%	0.36%	0.27%	0.27%
Soybean	Max		5.99%	0.26%	2.33%	2.24%	1.24%
	Median	2,090	2.09%	0.01%	0.49%	0.40%	0.40%
	Min		1.01%	0.03%	0.35%	0.33%	0.21%

Valencia Orange	Median	89	12.30%	0.72%	6.14%	5.39%	3.18%
	Max		14.21%	1.35%	9.21%	9.53%	2.07%
Tomato Processing	Median	2,236	10.21%	0.97%	6.62%	6.85%	1.49%
	Min		9.47%	0.90%	6.14%	6.35%	1.38%
	Max		24.66%	0.44%	8.54%	7.49%	5.28%
Winter Wheat	Median	2,533	0.79%	0.00%	0.09%	0.04%	0.11%
	Min		0.68%	0.00%	0.09%	0.05%	0.10%

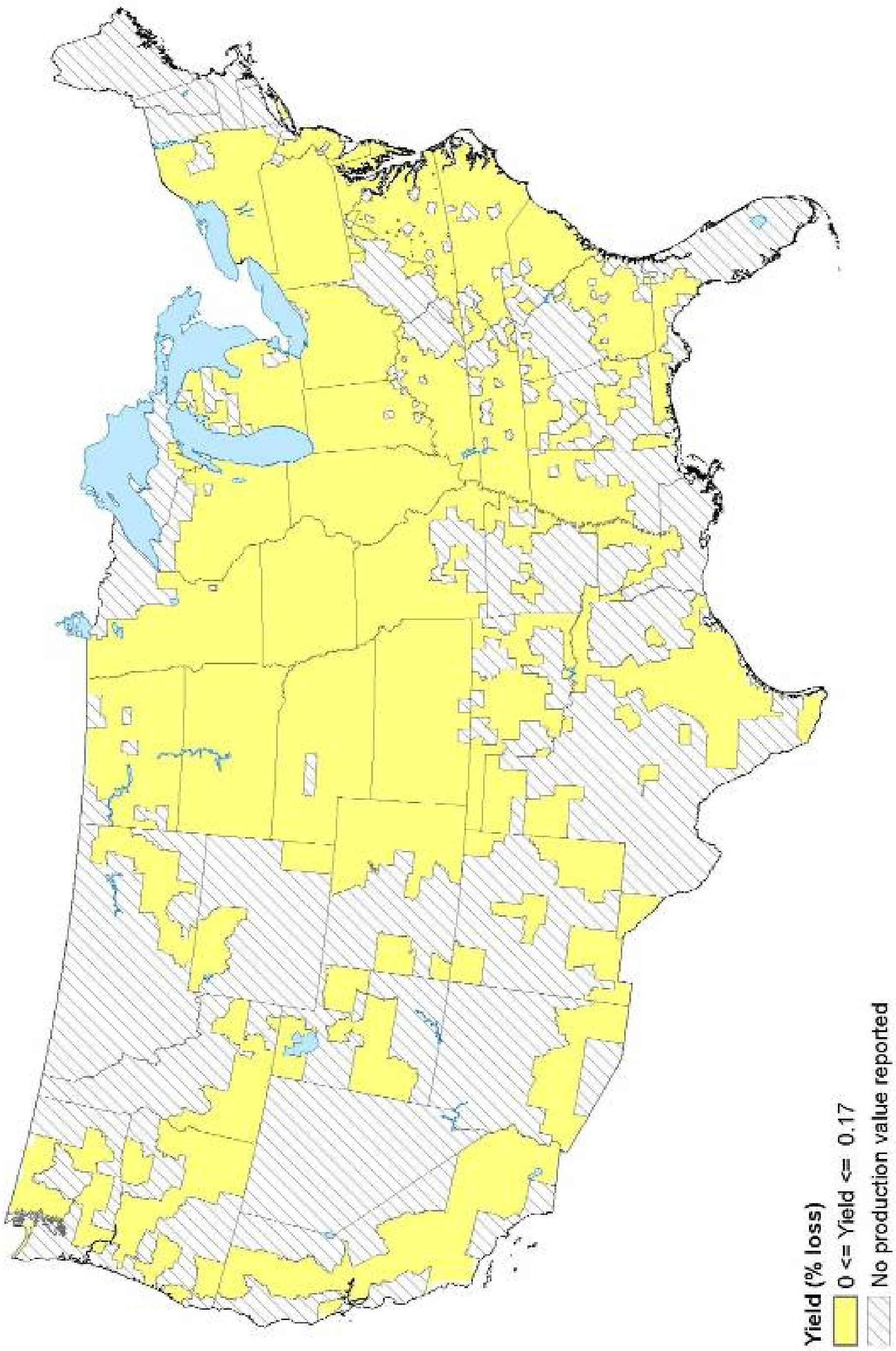
Table G-11: Absolute Crop Yield Losses - 15 ppm-hr SUM06 Rollback (reduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	0.37%	0.00%	0.03%	0.00%	0.05%
	Max		18.05%	0.00%	10.46%	10.79%	2.68%
Grapes	Median	1,883	16.48%	0.00%	9.55%	9.85%	2.44%
	Min		14.91%	0.00%	8.64%	8.91%	2.21%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
	Max		7.51%	0.33%	4.05%	4.41%	1.36%
Potato	Median	1,585	3.96%	0.08%	1.86%	2.03%	0.73%
	Min		2.89%	0.05%	1.31%	1.43%	0.53%
Rice	Median	300	13.48%	0.00%	3.24%	0.41%	4.41%
Sorghum	Median	1,331	0.07%	0.00%	0.02%	0.02%	0.01%
Cantaloupe	Median	1,610	14.24%	0.00%	6.28%	7.83%	4.19%
	Max		0.04%	0.00%	0.00%	0.00%	0.00%
Corn	Median	2,623	0.01%	0.00%	0.00%	0.00%	0.00%
	Min		0.00%	0.00%	0.00%	0.00%	0.00%
	Max		6.89%	0.86%	4.29%	4.48%	1.16%
Cotton	Median	666	1.42%	0.04%	0.52%	0.46%	0.29%
	Min		1.70%	0.11%	0.91%	0.95%	0.32%
Onion	Median	891	5.47%	0.57%	3.45%	3.58%	0.82%
Peanut	Median	409	0.60%	0.01%	0.23%	0.22%	0.12%
	Max		3.95%	0.26%	1.80%	1.83%	0.77%
Soybean	Median	2,090	1.55%	0.01%	0.34%	0.29%	0.23%
	Min		0.63%	0.03%	0.26%	0.26%	0.12%
Valencia Orange	Median	89	11.14%	0.72%	5.80%	5.39%	2.74%
	Max		13.03%	1.35%	8.57%	8.90%	1.67%
Tomato Processing	Median	2,236	9.36%	0.97%	6.16%	6.39%	1.20%
	Min		8.68%	0.90%	5.71%	5.93%	1.11%
	Max		14.60%	0.44%	6.75%	6.89%	3.49%
Winter Wheat	Median	2,533	0.20%	0.00%	0.04%	0.03%	0.04%
	Min		0.20%	0.00%	0.05%	0.04%	0.04%

G.1.3 Yield Response Maps for Selected Field Crops based on Ten Percent Adjusted W126 Metric

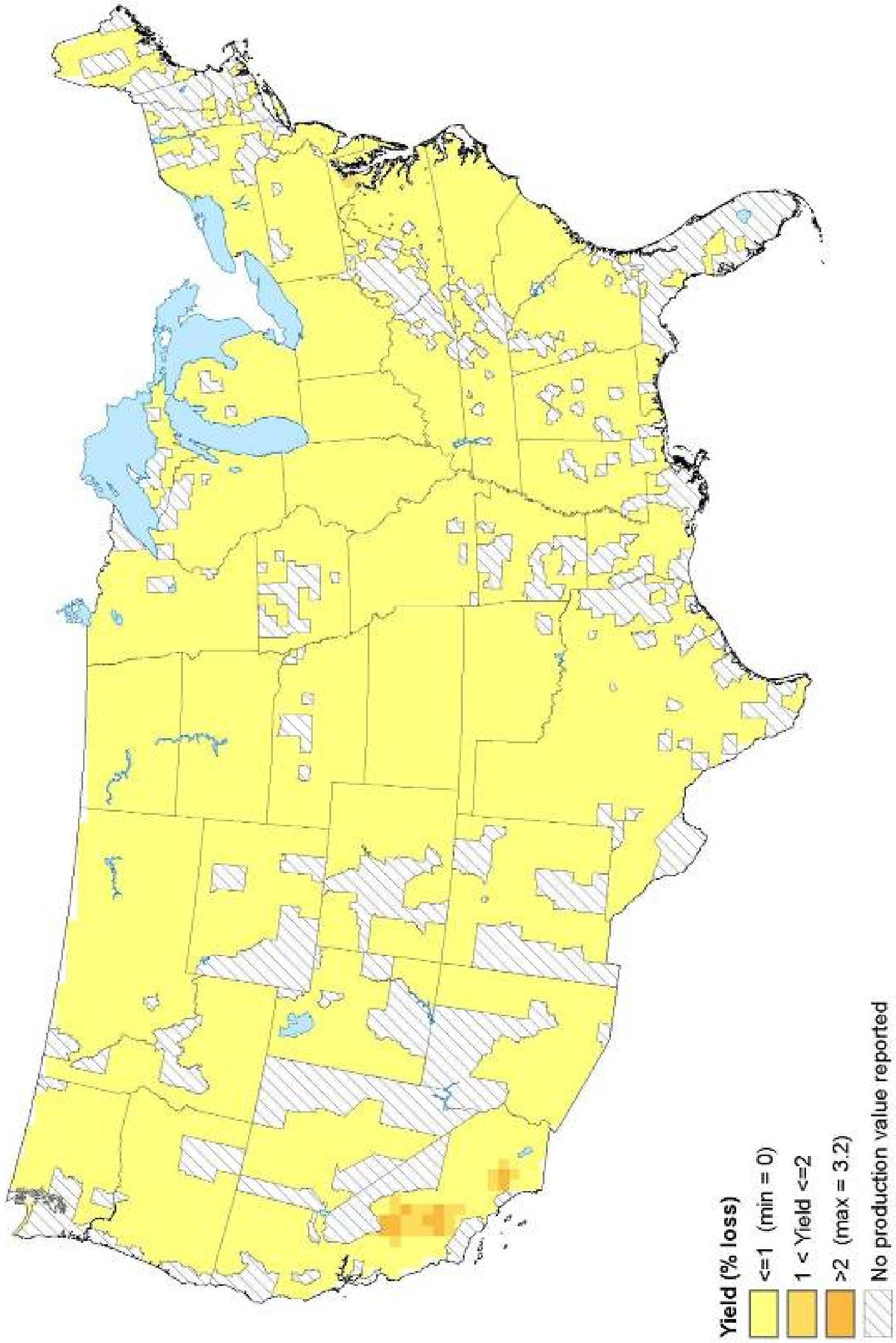
Maps for cotton and soybean based on the reduced O_3 metric are presented in the body of the document under Section 5.

Corn Response Maps

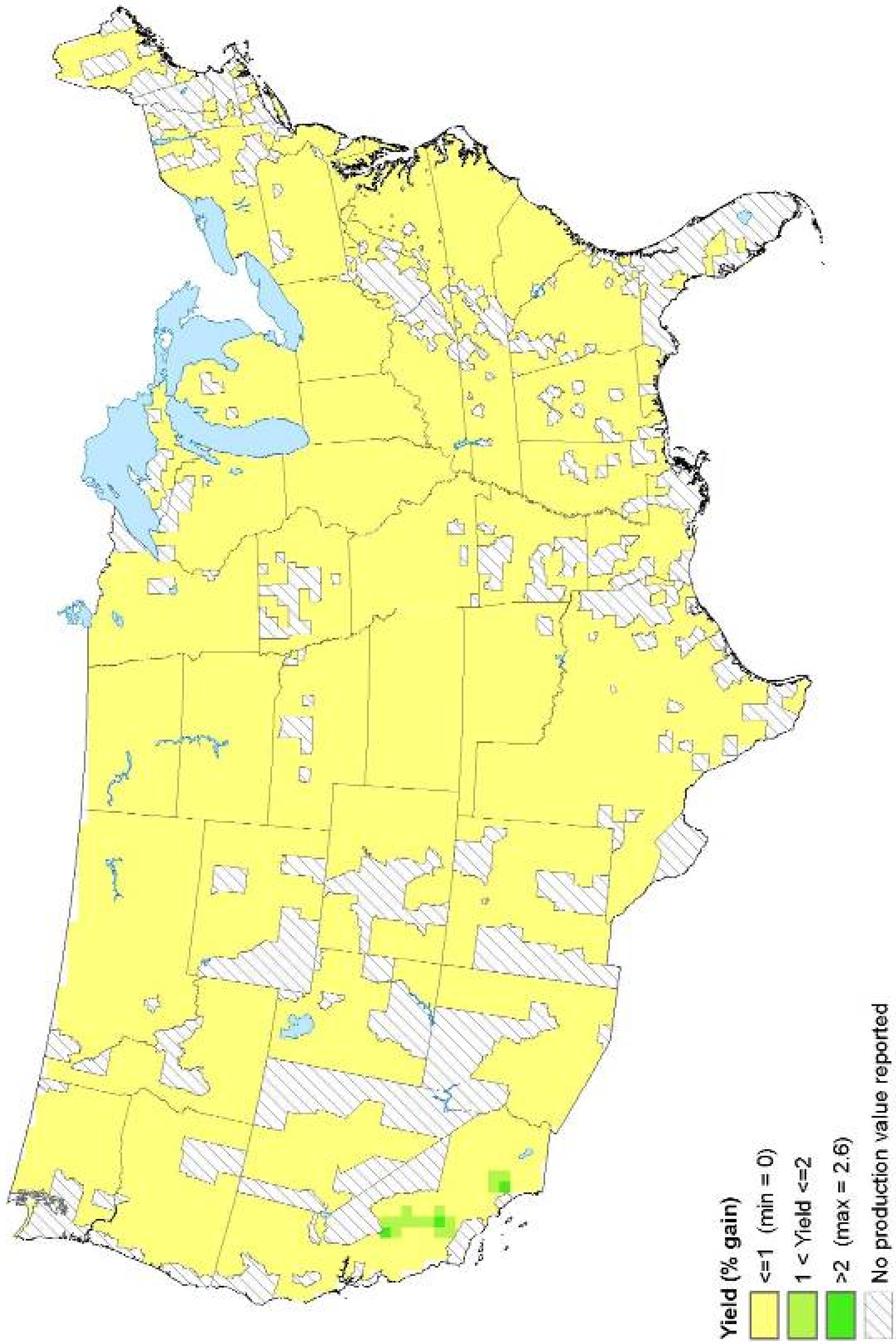


Map G-1: As-is Yield Loss for Corn (Zea mays) (Reduced W126)
Corn was unresponsive at the levels of air quality evaluated and therefore we are not including maps of the six rollback scenarios.

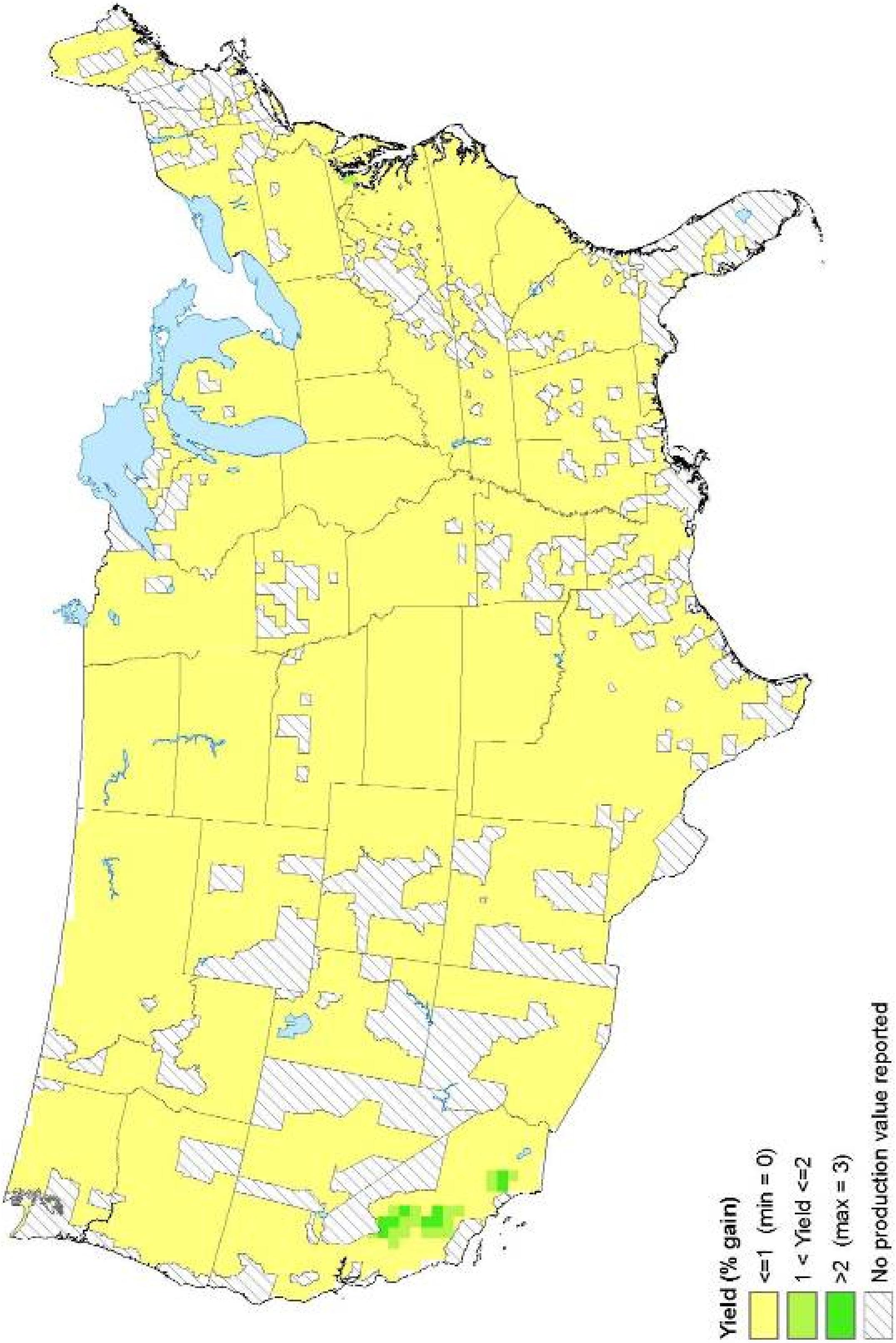
Wheat Response Maps



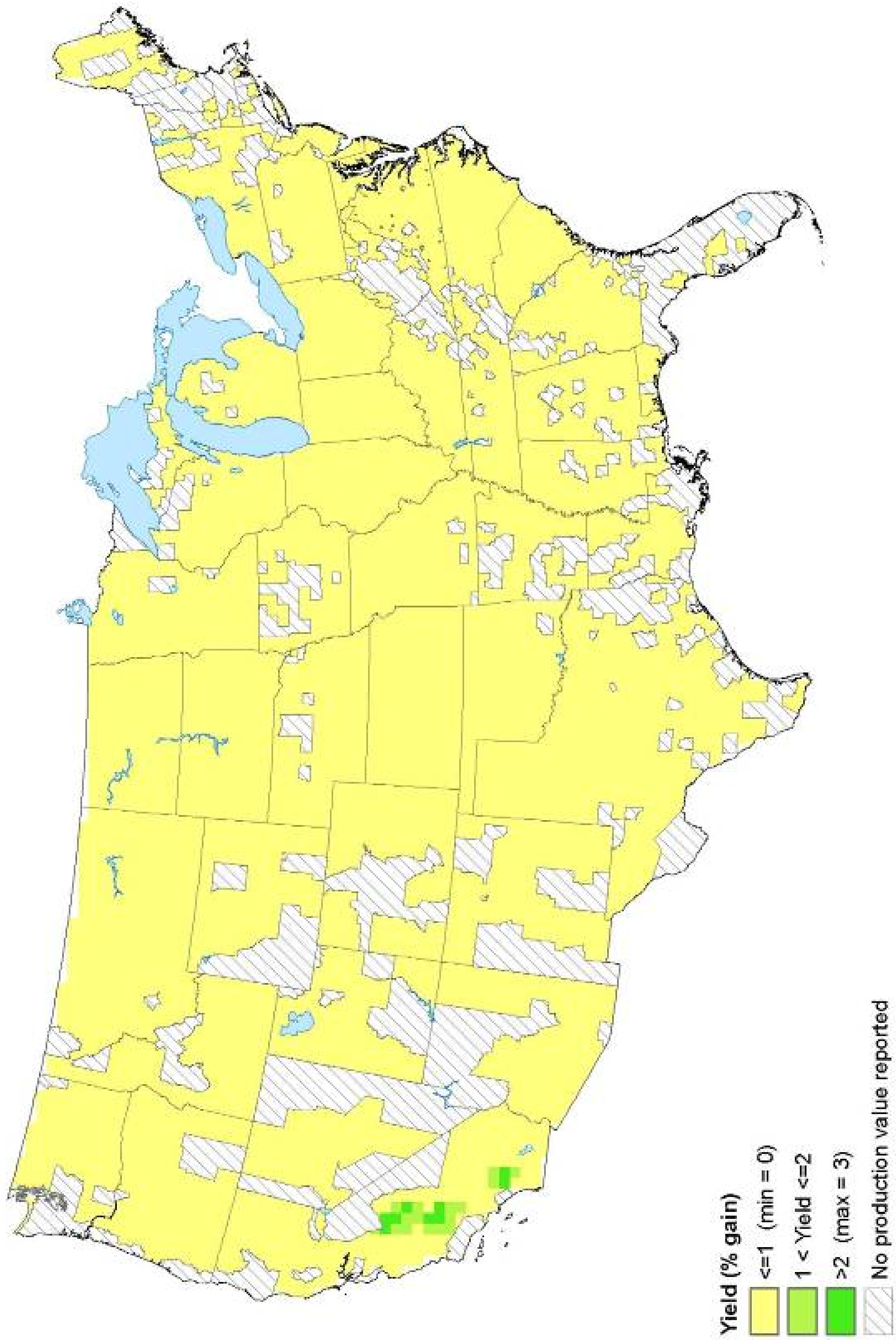
Map G-2: As-is Yield loss for Wheat (Triticum aestivum) (Reduced W126).



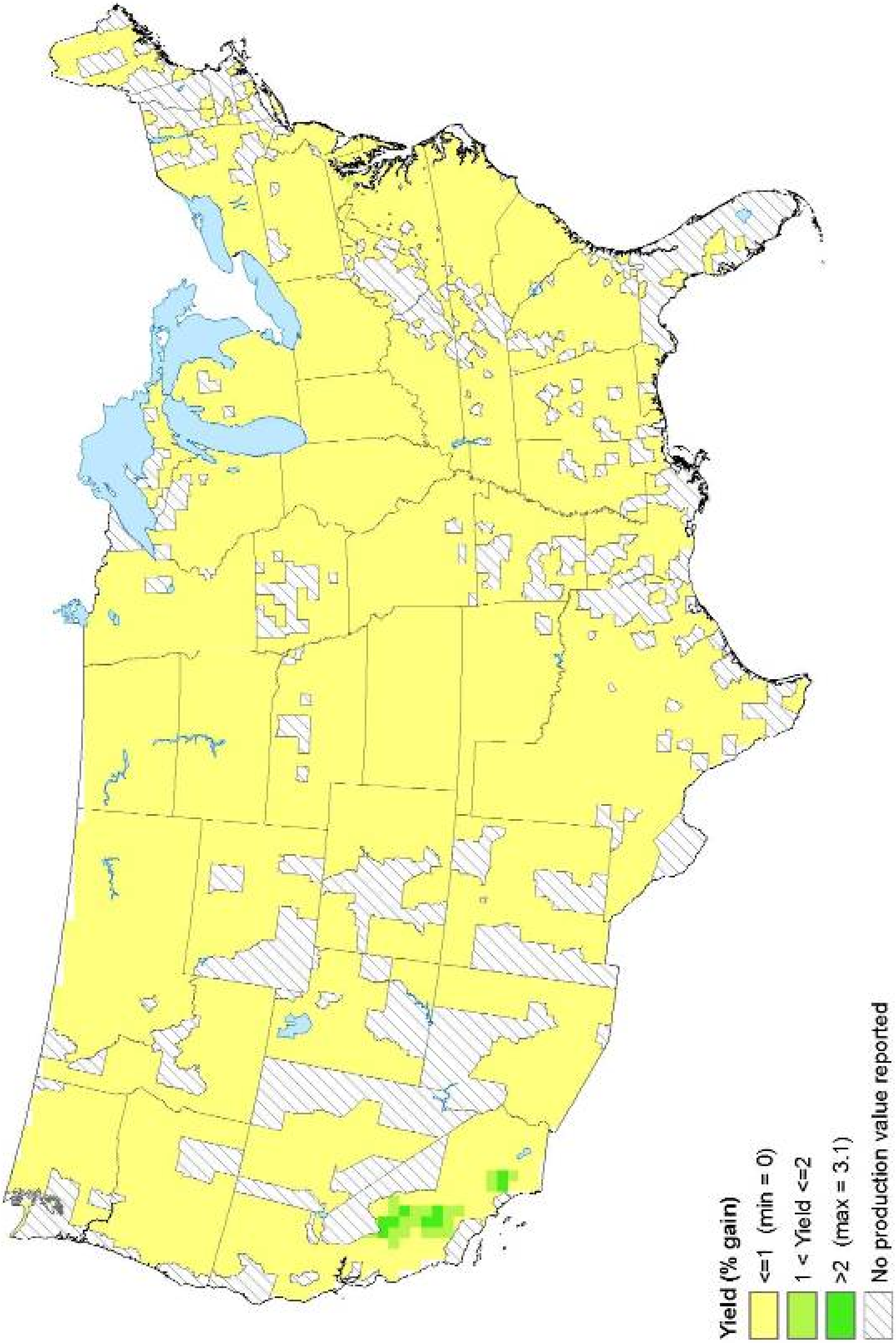
Map G-3: Yield Gain from Baseline for Wheat (Triticum aestivum). Quadratic Rollback 4th Highest 8-hour Maximum to 84 ppb (Reduced W126).



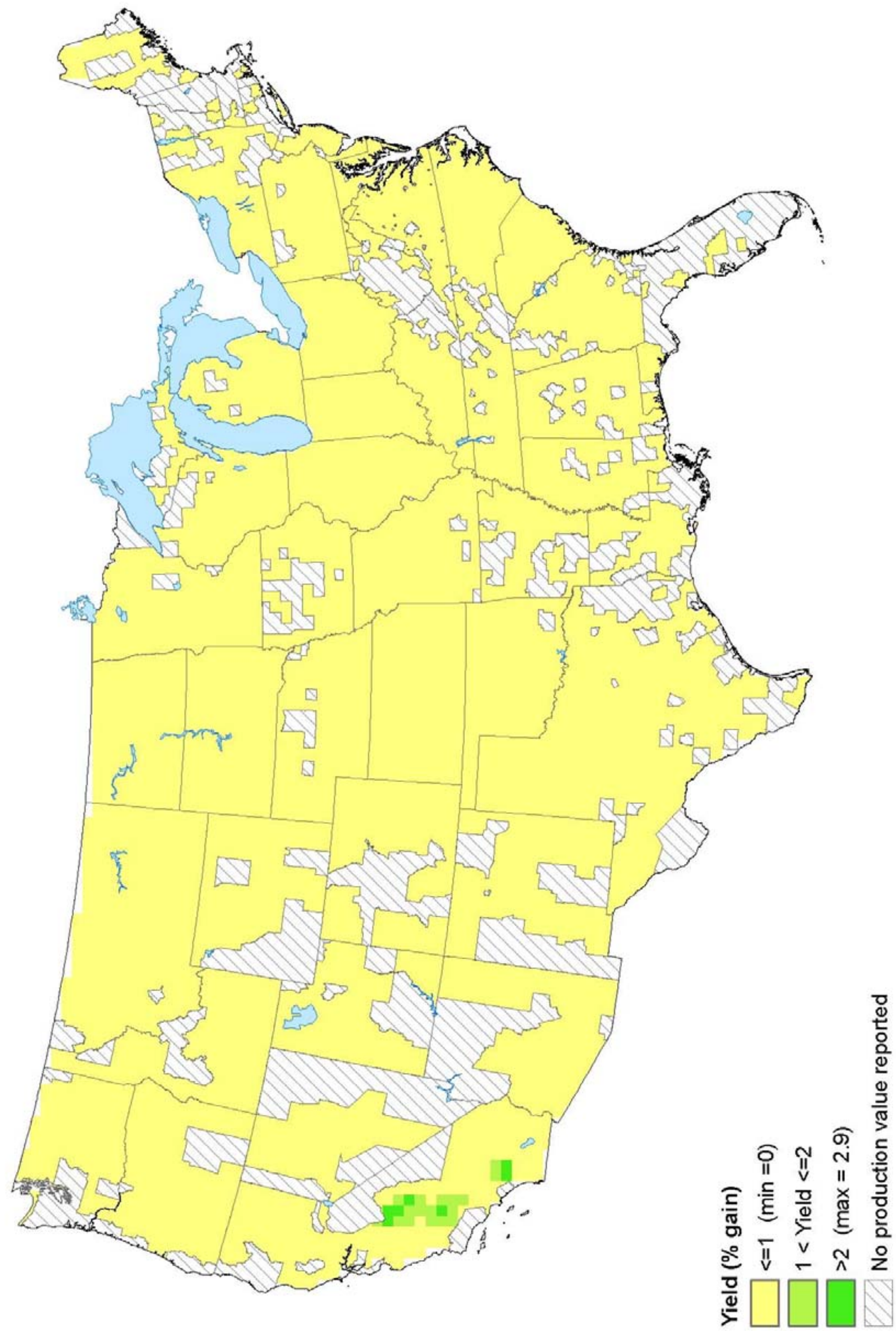
Map G-4: Yield Gain from Baseline for Wheat (Triticum aestivum). Quadratic Rollback 4th Highest 8-hour Maximum to 70 ppb (Reduced W126).



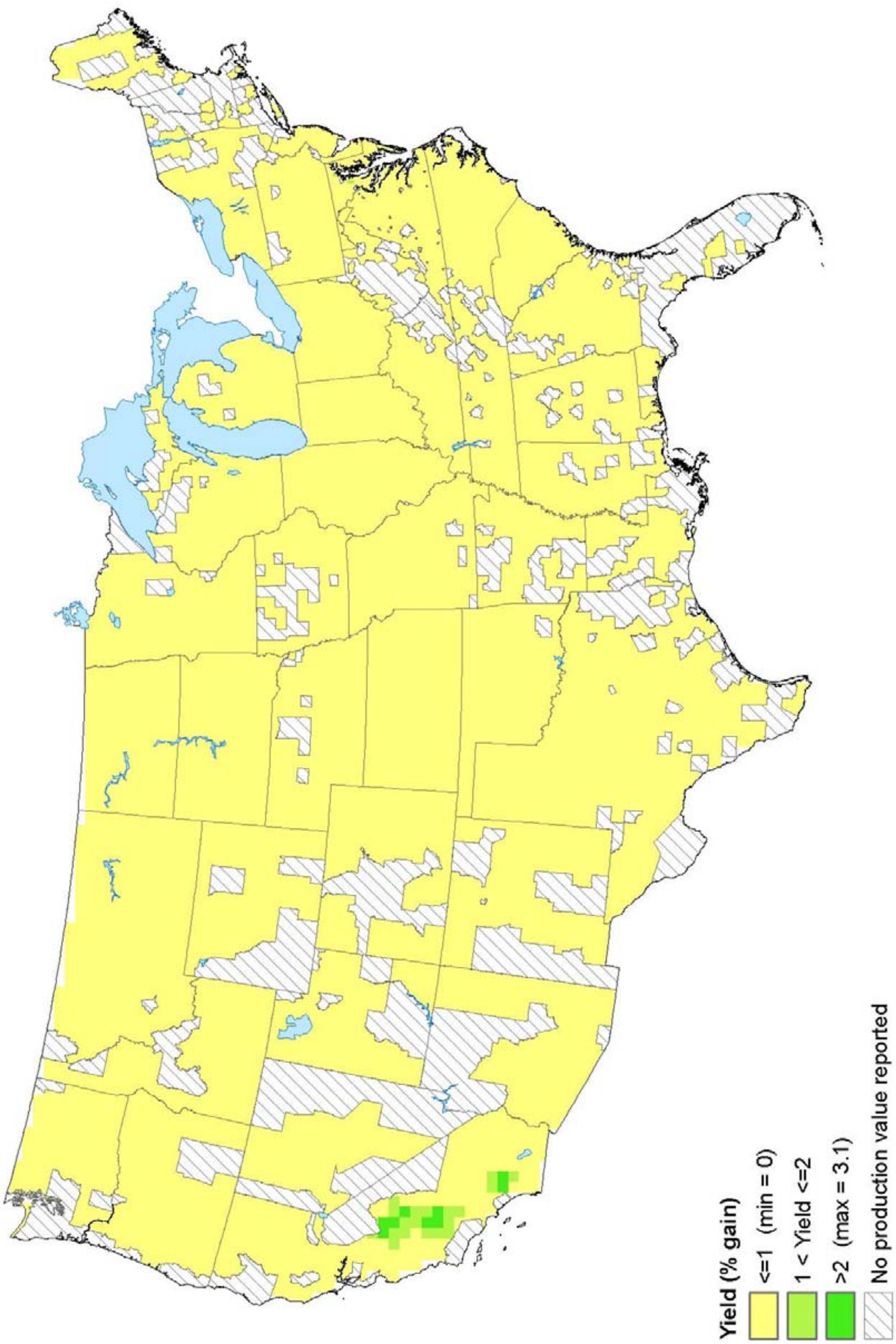
Map G-5: Yield Gain from Baseline for Wheat (Triticum aestivum). Quadratic Rollback 3-month SUM06 to 25 ppm-hour (Reduced W126).



Map G-6: Yield Gain from Baseline for Wheat (Triticum aestivum). Quadratic Rollback 3-month SUM06 to 15 ppm-hour (Reduced W126).



Map G-7: Yield Gain from Baseline for Wheat (Triticum aestivum). Quadratic Rollback W126 to 21 ppm-hour (Reduced W126).



Map G-8: Yield Gain from Baseline for Wheat (Triticum aestivum). Quadratic Rollback W126 to 13 ppm-hour (Reduced W126).

G.2 Crop Yield Concentration Responses based on Non-Adjusted W126 Metric

Crop yield responses for all crops based on unreduced O_3 metrics are presented below.

G.2.1 Median Concentration Responses for Crops

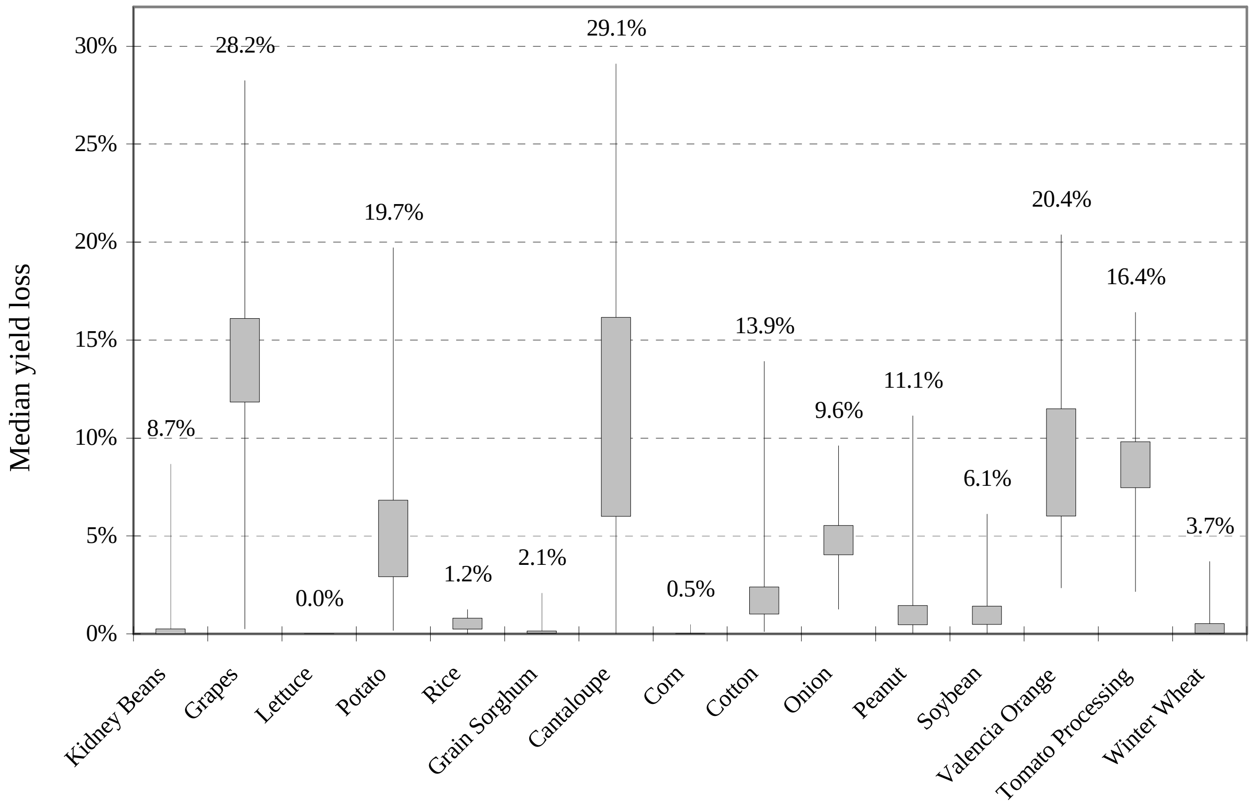


Figure G-8: Yield Losses for Crops - 2001 Baseline (unreduced W126, Median C-R)

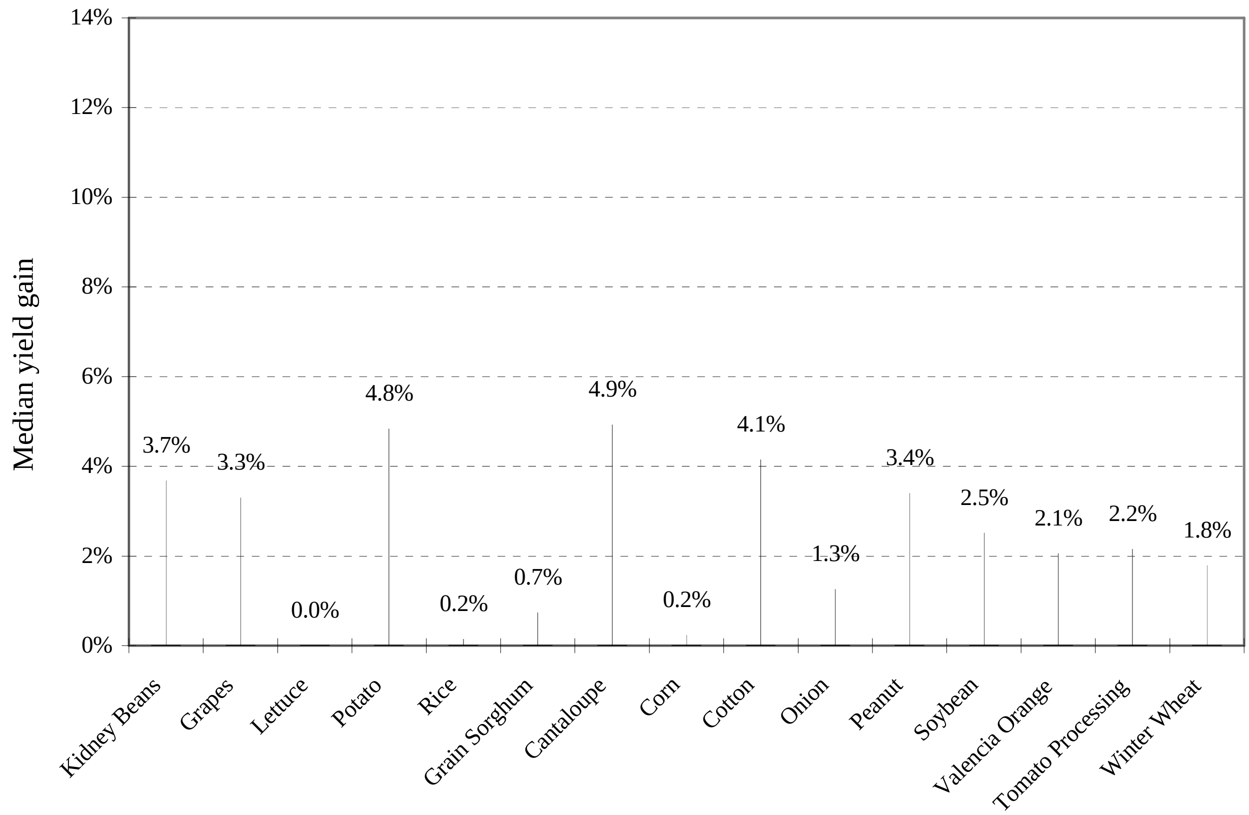


Figure G-9: Yield Gains from Baseline – 84 ppb Rollback (unreduced W126, Median C-R)

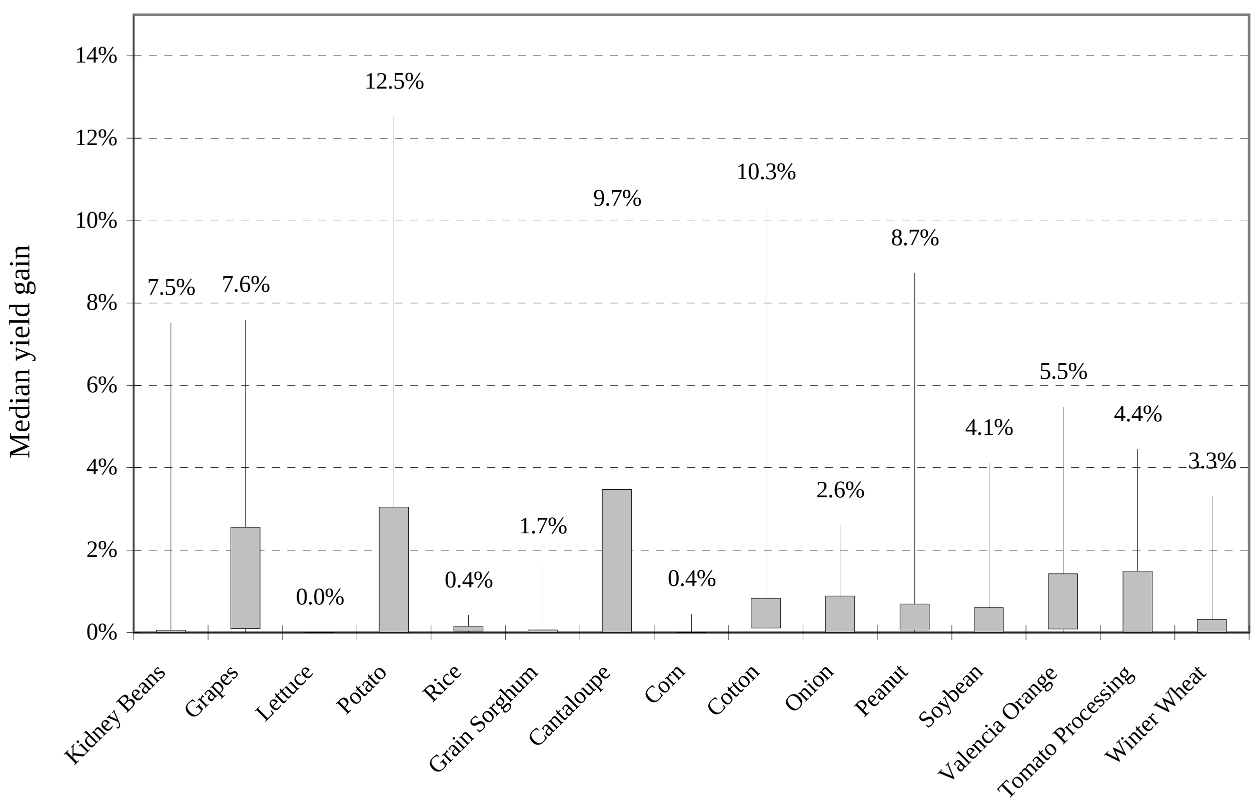


Figure G-10: Yield Gains from Baseline – 70 ppb Rollback (unreduced W126, Median C-R)

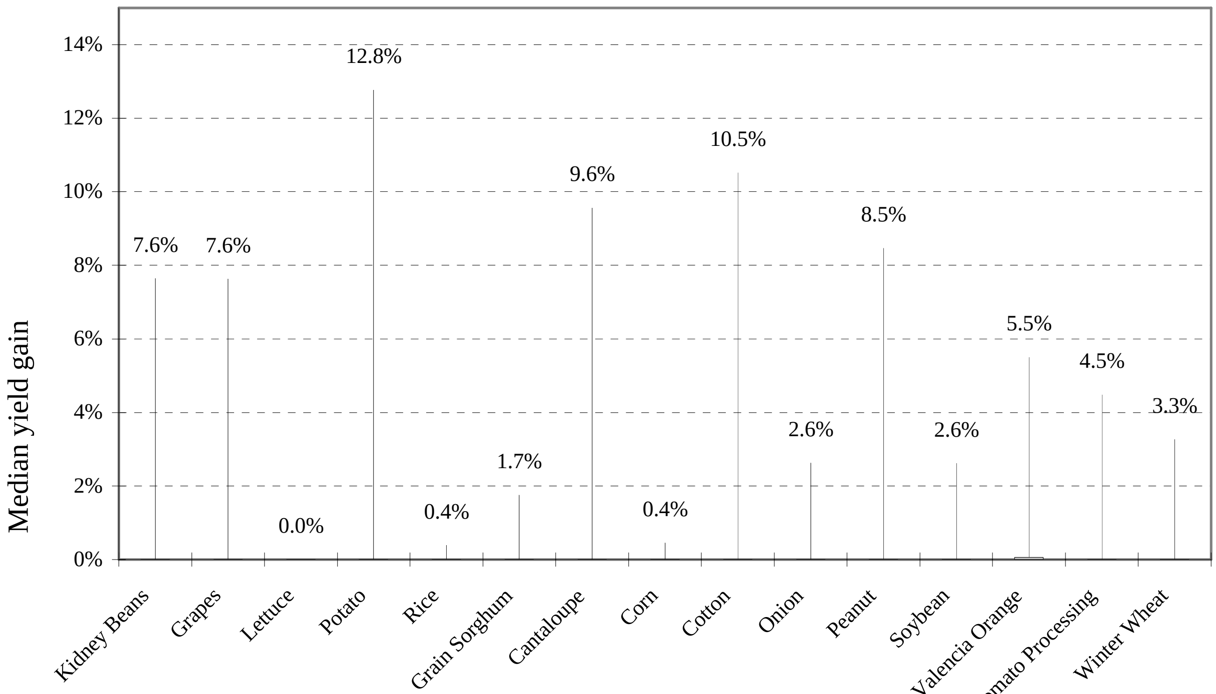


Figure G-11: Yield Gains from Baseline – 25 ppm-hr Rollback (unreduced W126, Median C-R)

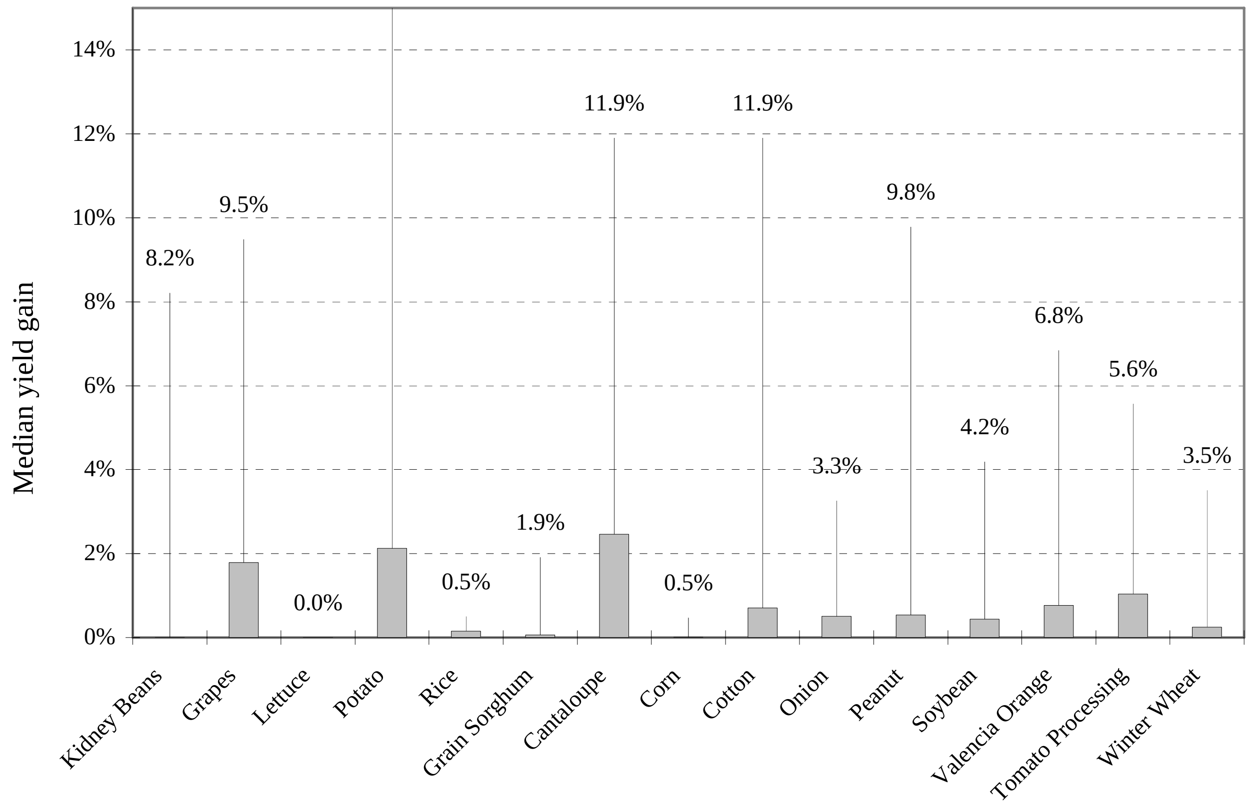


Figure G-12: Yield Gains from Baseline – 15 ppm-hr Rollback (unreduced W126, Median C-R)

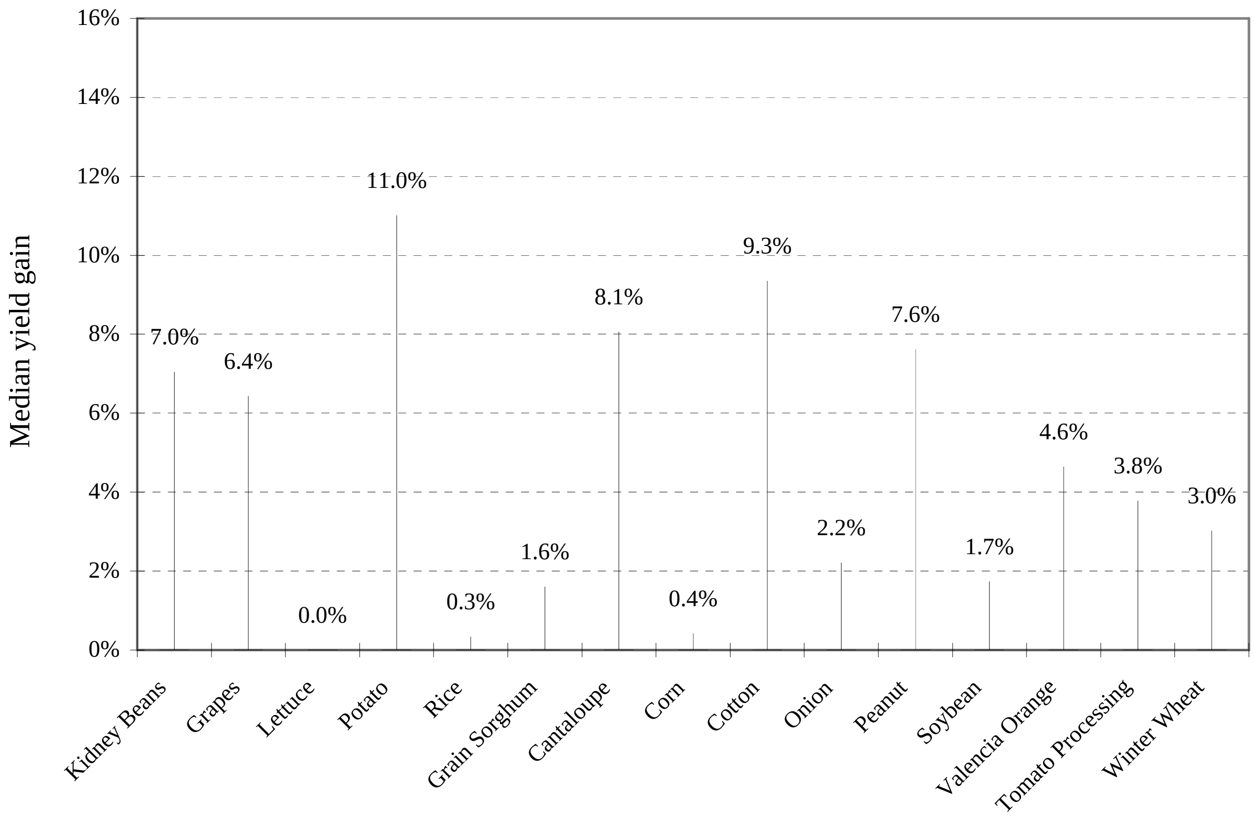


Figure G-13: Yield Gains from Baseline – 21 ppm-hr Rollback (unreduced W126, Median C-R)

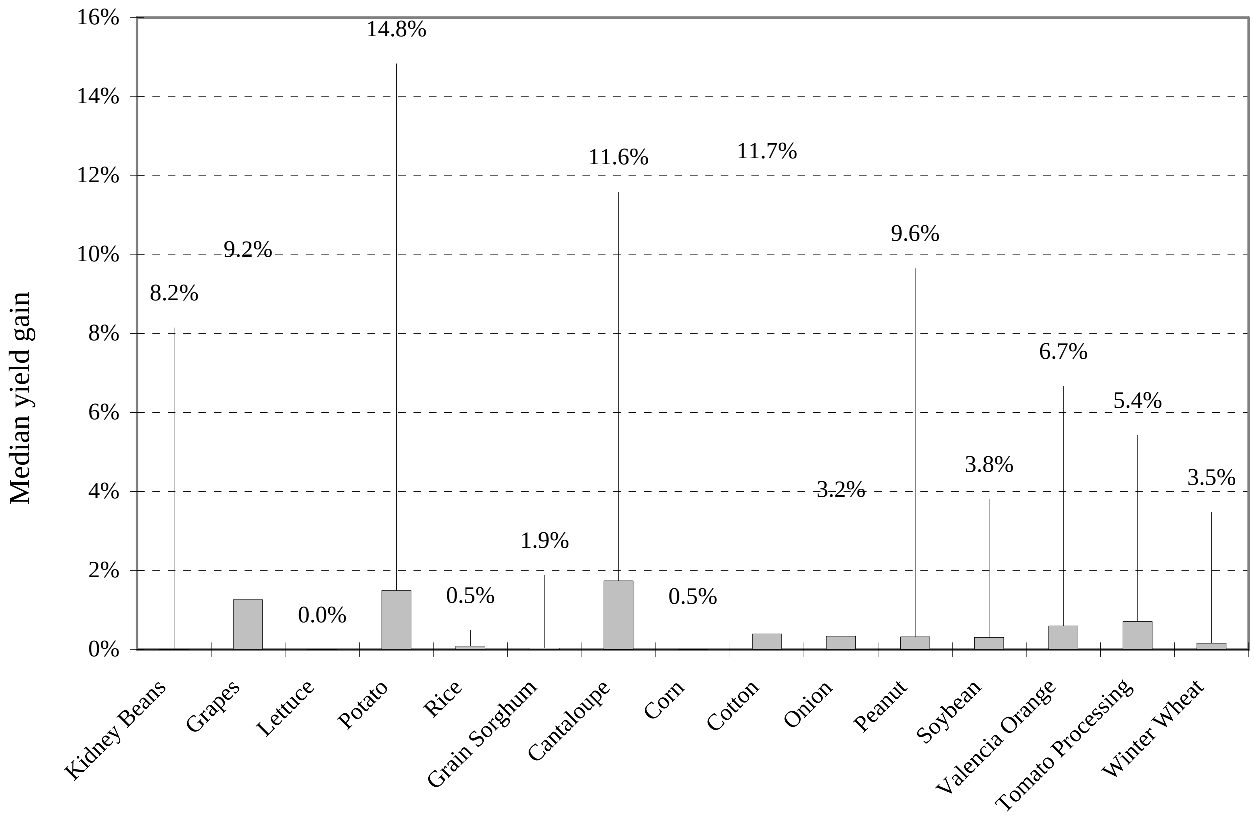


Figure G-14: Yield Gains from Baseline – 13 ppm-hr Rollback (unreduced W126, Median C-R)

G.2.2 Summary Statistics of Concentration Responses for Crops

Similar results as in Chapter 5.4.1 are provided in Tables G-12 through G-18 below. These yield change estimates are based on *unreduced* W126 metric (i.e. hourly O_3 values have *not* been reduced by 10%). Rollback results are presented as differences or yield gains from baseline. Non-adjusted results for Soybean and Cotton are presented in Chapter 5.4.1.

Table G-12: Yield Losses for Crops, Fruits and Vegetables - 2001 Baseline (unreduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	8.67%	0.00%	0.24%	0.02%	0.66%
	Max		30.94%	0.28%	15.07%	15.56%	3.68%
Grapes	Median	1,883	28.25%	0.26%	13.76%	14.20%	3.36%
	Min		25.55%	0.23%	12.45%	12.85%	3.04%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
	Max		26.15%	0.59%	8.71%	8.96%	3.75%
Potato	Median	1,585	19.71%	0.17%	4.95%	4.96%	2.59%
	Min		15.84%	0.10%	3.69%	3.66%	2.02%
Rice	Median	300	1.24%	0.00%	0.56%	0.63%	0.35%
Sorghum	Median	1,331	2.07%	0.00%	0.11%	0.08%	0.13%
Cantaloupe	Median	1,610	29.09%	0.00%	10.87%	12.79%	6.42%
	Max		1.06%	0.00%	0.04%	0.01%	0.08%
Corn	Median	2,623	0.48%	0.00%	0.01%	0.00%	0.03%
	Min		0.07%	0.00%	0.00%	0.00%	0.00%
Cotton	Max	666	40.17%	1.68%	10.12%	9.54%	4.50%

	Median		13.90%	0.12%	1.87%	1.64%	1.36%
	Min		20.99%	0.26%	3.03%	2.64%	2.01%
Onion	Median	891	9.60%	1.27%	4.77%	4.90%	1.17%
Peanut	Median	409	11.13%	0.04%	1.17%	0.85%	1.11%
Soybean	Max	2,090	12.27%	0.50%	4.21%	4.03%	2.23%
	Median		6.11%	0.03%	1.12%	0.92%	0.89%
	Min		2.34%	0.06%	0.69%	0.64%	0.41%
Valencia Orange	Median	89	20.38%	2.34%	8.77%	7.53%	4.29%
Tomato Processing	Max	2,236	22.82%	3.01%	11.85%	12.11%	2.43%
	Median		16.40%	2.17%	8.52%	8.70%	1.75%
	Min		15.21%	2.01%	7.90%	8.07%	1.62%
Winter Wheat	Max	2,533	41.57%	0.78%	14.35%	13.47%	8.07%
	Median		3.69%	0.00%	0.32%	0.16%	0.39%
	Min		2.65%	0.00%	0.29%	0.17%	0.31%

Table G-13: Yield Gains from Baseline for Crops, Fruits and Vegetables – 84 ppb Rollback (unreduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	3.68%	0.00%	0.03%	0.00%	0.25%
Grapes	Max	1,883	3.61%	0.00%	0.14%	0.00%	0.46%
	Median		3.30%	0.00%	0.12%	0.00%	0.42%
	Min		2.98%	0.00%	0.11%	0.00%	0.38%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
Potato	Max	1,585	6.01%	0.00%	0.24%	0.00%	0.75%
	Median		4.83%	0.00%	0.18%	0.00%	0.59%
	Min		4.10%	0.00%	0.15%	0.00%	0.48%
Rice	Median	300	0.15%	0.00%	0.00%	0.00%	0.01%
Grain Sorghum	Median	1,331	0.74%	0.00%	0.01%	0.00%	0.04%
Cantaloupe	Median	1,610	4.93%	0.00%	0.19%	0.00%	0.63%
Corn	Max	2,623	0.48%	0.00%	0.01%	0.00%	0.04%
	Median		0.23%	0.00%	0.00%	0.00%	0.02%
	Min		0.05%	0.00%	0.00%	0.00%	0.00%
Cotton	Max	666	7.83%	0.00%	0.11%	0.00%	0.69%
	Median		4.15%	0.00%	0.05%	0.00%	0.33%
	Min		5.69%	0.00%	0.07%	0.00%	0.44%
Onion	Median	891	1.26%	0.00%	0.06%	0.00%	0.19%
Peanut	Median	409	3.40%	0.00%	0.03%	0.00%	0.23%
Soybean	Max	2,090	3.56%	0.00%	0.09%	0.00%	0.36%
	Median		2.52%	0.00%	0.05%	0.00%	0.23%
	Min		0.73%	0.00%	0.02%	0.00%	0.07%
Valencia Orange	Median	89	2.06%	0.00%	0.14%	0.00%	0.39%
Tomato Processing	Max	2,236	2.99%	0.00%	0.10%	0.00%	0.35%
	Median		2.15%	0.00%	0.07%	0.00%	0.25%
	Min		2.00%	0.00%	0.07%	0.00%	0.23%
Winter Wheat	Max	2,533	10.17%	0.00%	0.25%	0.00%	1.04%
	Median		1.79%	0.00%	0.03%	0.00%	0.13%
	Min		1.16%	0.00%	0.02%	0.00%	0.09%

Table G-14: Yield Gains from Baseline for Crops, Fruits and Vegetables – 70 ppb Rollback (unreduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	7.52%	0.00%	0.15%	0.00%	0.56%
	Max		8.32%	0.00%	1.69%	1.42%	1.57%
Grapes	Median	1,883	7.60%	0.00%	1.54%	1.29%	1.43%
	Min		6.87%	0.00%	1.39%	1.17%	1.29%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
	Max		14.26%	0.00%	2.51%	1.83%	2.57%
Potato	Median	1,585	12.53%	0.00%	1.78%	1.24%	1.90%
	Min		10.43%	0.00%	1.39%	0.94%	1.50%
Rice	Median	300	0.42%	0.00%	0.10%	0.09%	0.08%
Grain Sorghum	Median	1,331	1.72%	0.00%	0.05%	0.02%	0.10%
Cantaloupe	Median	1,610	9.69%	0.00%	1.99%	1.49%	2.07%
	Max		0.95%	0.00%	0.03%	0.00%	0.07%
Corn	Median	2,623	0.44%	0.00%	0.01%	0.00%	0.03%
	Min		0.07%	0.00%	0.00%	0.00%	0.00%
	Max		21.99%	0.00%	2.49%	1.95%	2.67%
Cotton	Median	666	10.32%	0.00%	0.66%	0.47%	0.96%
	Min		14.48%	0.00%	1.02%	0.68%	1.37%
Onion	Median	891	2.60%	0.00%	0.50%	0.32%	0.55%
Peanut	Median	409	8.73%	0.00%	0.53%	0.28%	0.80%
	Max		7.54%	0.00%	1.18%	0.79%	1.30%
Soybean	Median	2,090	4.12%	0.00%	0.45%	0.25%	0.63%
	Min		1.57%	0.00%	0.22%	0.14%	0.25%
Valencia Orange	Median	89	5.48%	0.00%	1.02%	0.57%	1.26%
	Max		6.19%	0.00%	1.23%	0.97%	1.20%
Tomato Processing	Median	2,236	4.45%	0.00%	0.89%	0.70%	0.86%
	Min		4.12%	0.00%	0.82%	0.65%	0.80%
	Max		22.31%	0.00%	3.71%	2.06%	4.31%
Winter Wheat	Median	2,533	3.30%	0.00%	0.20%	0.05%	0.32%
	Min		2.27%	0.00%	0.16%	0.05%	0.24%

Table G-15: Yield Gains from Baseline for Crops, Fruits and Vegetables – 25 ppm-hr Rollback (unreduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	7.64%	0.00%	0.06%	0.00%	0.51%
	Max		8.36%	0.00%	0.14%	0.00%	0.53%
Grapes	Median	1,883	7.63%	0.00%	0.13%	0.00%	0.48%
	Min		6.90%	0.00%	0.12%	0.00%	0.43%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
	Max		14.48%	0.00%	0.23%	0.00%	0.91%
Potato	Median	1,585	12.77%	0.00%	0.18%	0.00%	0.76%
	Min		10.63%	0.00%	0.15%	0.00%	0.62%
Rice	Median	300	0.39%	0.00%	0.01%	0.00%	0.04%
Grain Sorghum	Median	1,331	1.75%	0.00%	0.01%	0.00%	0.08%
Cantaloupe	Median	1,610	9.56%	0.00%	0.18%	0.00%	0.66%
	Max		0.96%	0.00%	0.01%	0.00%	0.04%
Corn	Median	2,623	0.45%	0.00%	0.00%	0.00%	0.02%
	Min		0.07%	0.00%	0.00%	0.00%	0.00%
	Max		22.52%	0.00%	0.34%	0.00%	1.69%
Cotton	Median	666	10.52%	0.00%	0.13%	0.00%	0.73%
	Min		14.79%	0.00%	0.19%	0.00%	1.03%
Onion	Median	891	2.62%	0.00%	0.06%	0.00%	0.21%
Peanut	Median	409	8.46%	0.00%	0.11%	0.00%	0.56%
	Max		3.47%	0.00%	0.10%	0.00%	0.37%
Soybean	Median	2,090	2.61%	0.00%	0.05%	0.00%	0.21%
	Min		0.73%	0.00%	0.02%	0.00%	0.08%
Valencia Orange	Median	89	5.50%	0.00%	0.42%	0.00%	1.05%
	Max		6.24%	0.00%	0.10%	0.00%	0.37%
Tomato Processing	Median	2,236	4.48%	0.00%	0.07%	0.00%	0.27%
	Min		4.16%	0.00%	0.06%	0.00%	0.25%
	Max		22.26%	0.00%	0.28%	0.00%	1.19%
Winter Wheat	Median	2,533	3.26%	0.00%	0.03%	0.00%	0.16%
	Min		2.25%	0.00%	0.02%	0.00%	0.11%

Table G-16: Yield Gains from Baseline for Crops, Fruits and Vegetables – 15 ppm-hr W126 Rollback (unreduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	8.20%	0.00%	0.12%	0.00%	0.59%
Grapes	Max	1,883	10.39%	0.00%	1.12%	0.48%	1.37%
	Median		9.48%	0.00%	1.03%	0.44%	1.25%
	Min		8.58%	0.00%	0.93%	0.40%	1.13%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
Potato	Max	1,585	17.70%	0.00%	1.66%	0.33%	2.26%
	Median		15.10%	0.00%	1.23%	0.24%	1.72%
	Min		12.46%	0.00%	0.97%	0.19%	1.37%
Rice	Median	300	0.50%	0.00%	0.08%	0.01%	0.10%
Grain Sorghum	Median	1,331	1.91%	0.00%	0.05%	0.01%	0.11%
Cantaloupe	Median	1,610	11.90%	0.00%	1.39%	0.46%	1.75%
Corn	Max	2,623	1.02%	0.00%	0.02%	0.00%	0.07%
	Median		0.47%	0.00%	0.01%	0.00%	0.03%
	Min		0.07%	0.00%	0.00%	0.00%	0.00%
Cotton	Max	666	27.52%	0.00%	2.01%	0.51%	3.05%
	Median		11.90%	0.00%	0.52%	0.11%	1.05%
	Min		17.09%	0.00%	0.87%	0.19%	1.55%
Onion	Median	891	3.26%	0.00%	0.30%	0.00%	0.48%
Peanut	Median	409	9.79%	0.00%	0.45%	0.02%	0.89%
Soybean	Max	2,090	6.55%	0.00%	0.92%	0.30%	1.18%
	Median		4.18%	0.00%	0.33%	0.09%	0.54%
	Min		1.38%	0.00%	0.18%	0.05%	0.23%
Valencia Orange	Median	89	6.84%	0.00%	0.80%	0.00%	1.54%
Tomato Processing	Max	2,236	7.74%	0.00%	0.81%	0.27%	1.03%
	Median		5.57%	0.00%	0.58%	0.19%	0.74%
	Min		5.16%	0.00%	0.54%	0.18%	0.69%
Winter Wheat	Max	2,533	27.43%	0.00%	2.60%	0.41%	3.63%
	Median		3.50%	0.00%	0.16%	0.01%	0.30%
	Min		2.46%	0.00%	0.13%	0.01%	0.22%

Table G-17: Yield Gains from Baseline for Crops, Fruits and Vegetables – 21 ppm-hr W126 Rollback (unreduced W126)

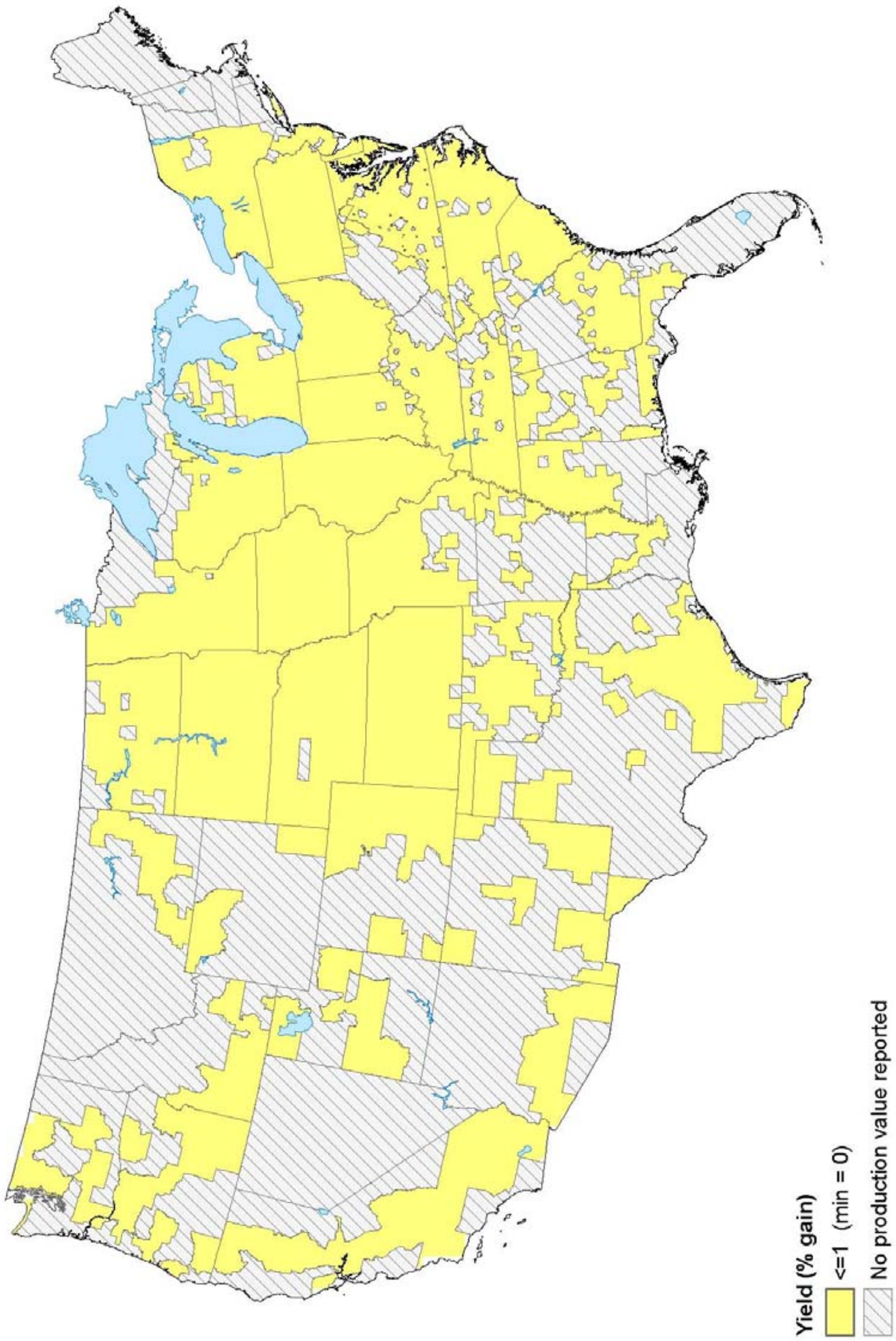
Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	7.06%	0.00%	0.05%	0.00%	0.46%
	Max		7.05%	0.00%	0.06%	0.00%	0.37%
Grapes	Median	1,883	6.43%	0.00%	0.06%	0.00%	0.34%
	Min		5.82%	0.00%	0.05%	0.00%	0.31%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
	Max		12.22%	0.00%	0.11%	0.00%	0.65%
Potato	Median	1,585	11.01%	0.00%	0.09%	0.00%	0.57%
	Min		9.22%	0.00%	0.08%	0.00%	0.47%
Rice	Median	300	0.34%	0.00%	0.00%	0.00%	0.03%
Sorghum	Median	1,331	1.60%	0.00%	0.01%	0.00%	0.07%
Cantaloupe	Median	1,610	8.06%	0.00%	0.08%	0.00%	0.47%
	Max		0.90%	0.00%	0.00%	0.00%	0.04%
Corn	Median	2,623	0.42%	0.00%	0.00%	0.00%	0.02%
	Min		0.07%	0.00%	0.00%	0.00%	0.00%
	Max		18.96%	0.00%	0.18%	0.00%	1.31%
Cotton	Median	666	9.35%	0.00%	0.08%	0.00%	0.61%
	Min		12.94%	0.00%	0.11%	0.00%	0.85%
Onion	Median	891	2.21%	0.00%	0.03%	0.00%	0.16%
Peanut	Median	409	7.61%	0.00%	0.05%	0.00%	0.45%
	Max		2.34%	0.00%	0.03%	0.00%	0.20%
Soybean	Median	2,090	1.74%	0.00%	0.02%	0.00%	0.13%
	Min		0.49%	0.00%	0.01%	0.00%	0.04%
Valencia Orange	Median	89	4.64%	0.00%	0.32%	0.00%	0.87%
	Max		5.26%	0.00%	0.04%	0.00%	0.26%
Tomato Processing	Median	2,236	3.78%	0.00%	0.03%	0.00%	0.19%
	Min		3.51%	0.00%	0.03%	0.00%	0.17%
	Max		18.71%	0.00%	0.12%	0.00%	0.84%
Winter Wheat	Median	2,533	3.02%	0.00%	0.02%	0.00%	0.13%
	Min		2.06%	0.00%	0.01%	0.00%	0.09%

Table G-18: Yield Gains from Baseline for Crops, Fruits and Vegetables – 13 ppm-hr W126 Rollback (unreduced W126)

Crop	*Response*	*N*	*Max*	*Min*	*Mean*	*Median*	*STD*
Kidney Beans	Median	587	8.15%	0.00%	0.11%	0.00%	0.58%
	Max		10.13%	0.00%	0.81%	0.10%	1.16%
Grapes	Median	1,883	9.24%	0.00%	0.74%	0.09%	1.06%
	Min		8.36%	0.00%	0.67%	0.09%	0.96%
Lettuce	Median	678	0.00%	0.00%	0.00%	0.00%	0.00%
	Max		17.30%	0.00%	1.24%	0.03%	1.93%
Potato	Median	1,585	14.83%	0.00%	0.93%	0.02%	1.49%
	Min		12.25%	0.00%	0.74%	0.01%	1.19%
Rice	Median	300	0.49%	0.00%	0.05%	0.00%	0.08%
Grain Sorghum	Median	1,331	1.89%	0.00%	0.04%	0.00%	0.10%
Cantaloupe	Median	1,610	11.59%	0.00%	1.03%	0.09%	1.47%
	Max		1.01%	0.00%	0.02%	0.00%	0.06%
Corn	Median	2,623	0.46%	0.00%	0.01%	0.00%	0.03%
	Min		0.07%	0.00%	0.00%	0.00%	0.00%
	Max		26.90%	0.00%	1.38%	0.00%	2.69%
Cotton	Median	666	11.75%	0.00%	0.38%	0.00%	0.98%
	Min		16.82%	0.00%	0.63%	0.00%	1.43%
Onion	Median	891	3.18%	0.00%	0.23%	0.00%	0.41%
Peanut	Median	409	9.65%	0.00%	0.33%	0.00%	0.81%
	Max		5.85%	0.00%	0.67%	0.05%	0.99%
Soybean	Median	2,090	3.80%	0.00%	0.25%	0.01%	0.47%
	Min		1.25%	0.00%	0.13%	0.01%	0.20%
Valencia Orange	Median	89	6.67%	0.00%	0.73%	0.00%	1.47%
	Max		7.55%	0.00%	0.58%	0.03%	0.87%
Tomato Processing	Median	2,236	5.43%	0.00%	0.42%	0.02%	0.62%
	Min		5.03%	0.00%	0.39%	0.02%	0.58%
	Max		26.74%	0.00%	1.84%	0.00%	2.96%
Winter Wheat	Median	2,533	3.48%	0.00%	0.13%	0.00%	0.27%
	Min		2.43%	0.00%	0.10%	0.00%	0.20%

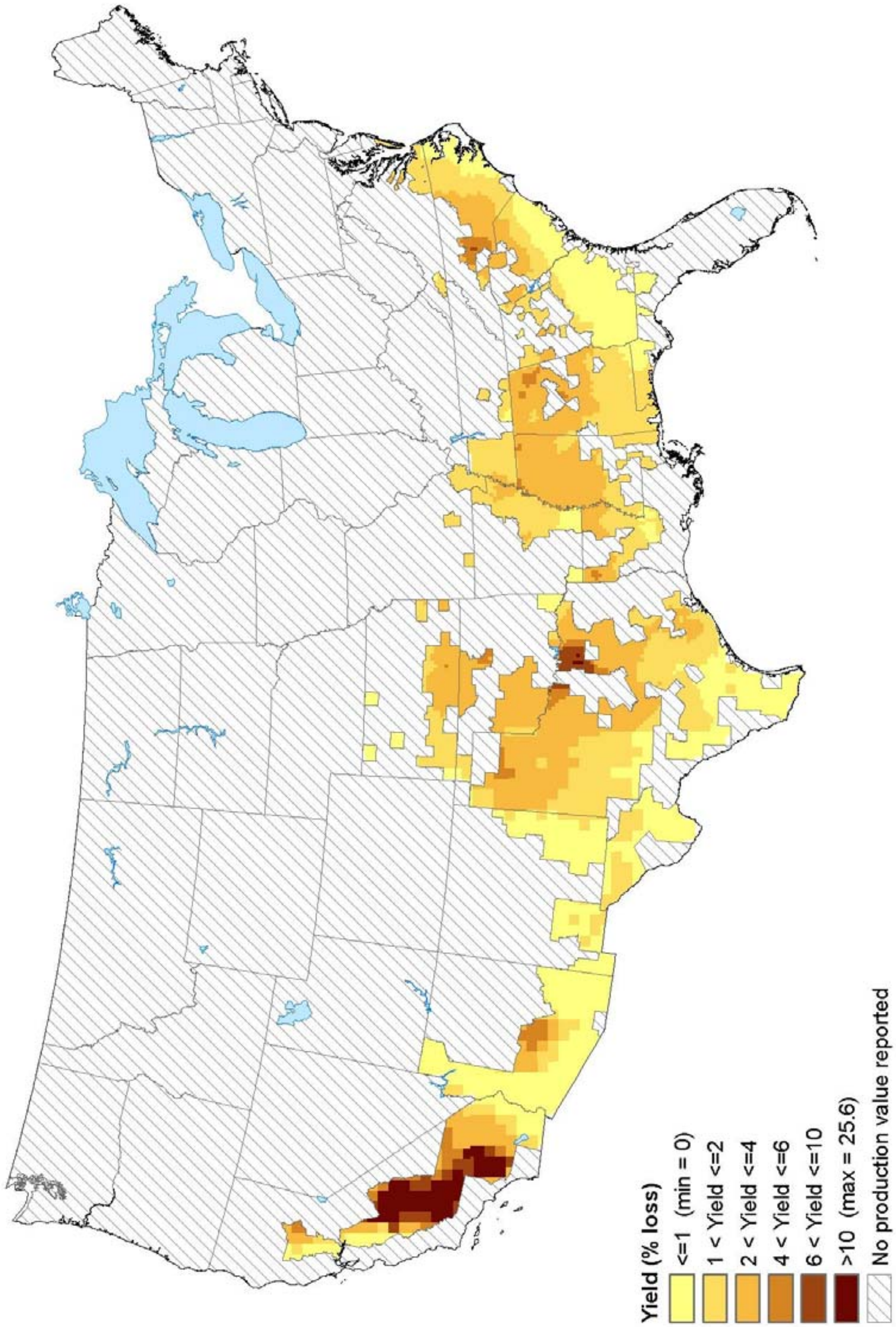
G.2.3 Yield Response Maps for Selected Field Crops based on Non-Adjusted W126 Metric.

Corn Response Maps

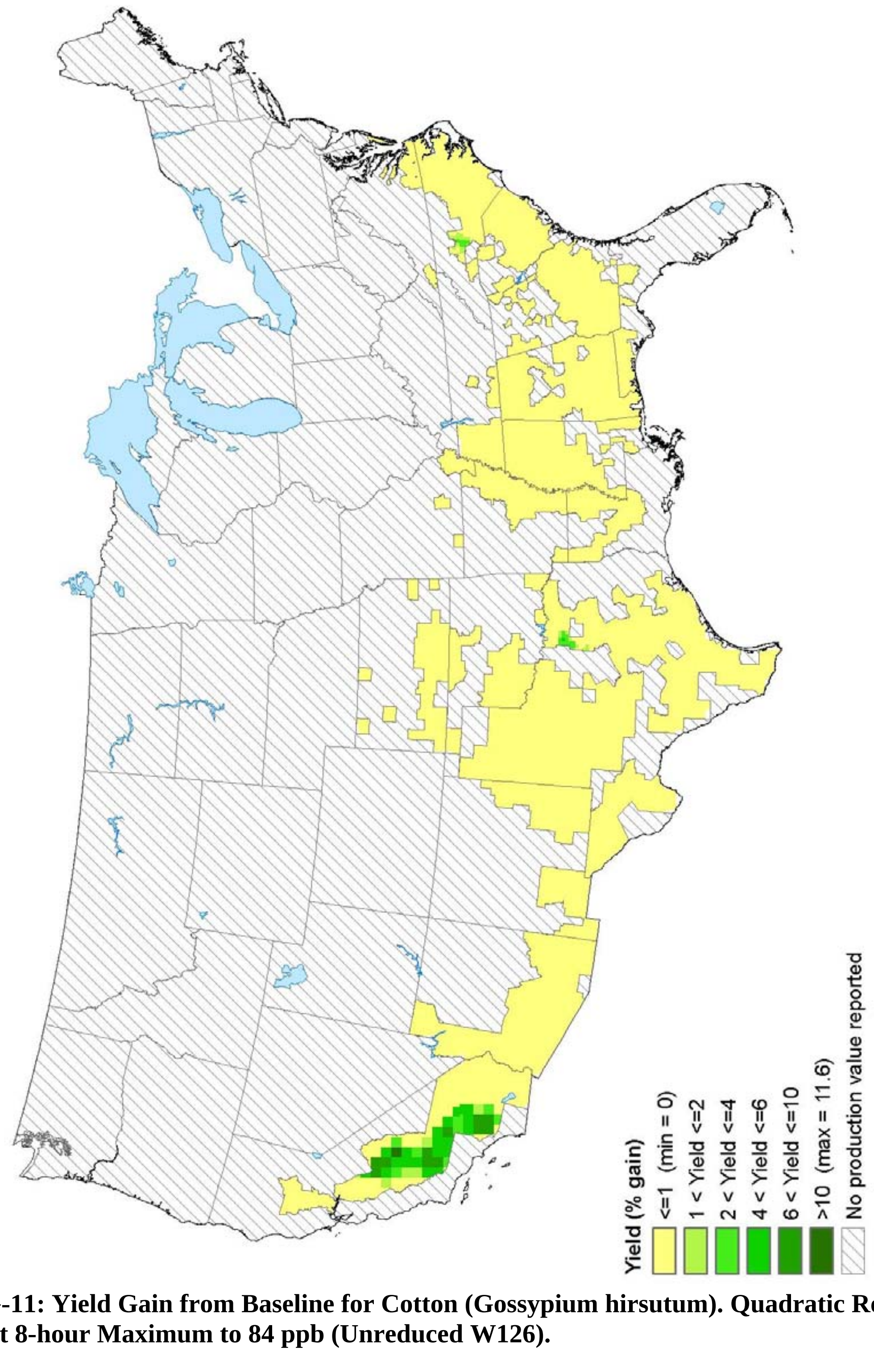


Map G-9: As-is Yield Loss for Corn (Zea mays) (Unreduced W126)
Corn was unresponsive at the levels of air quality evaluated and therefore we are not including maps of the four rollback scenarios.

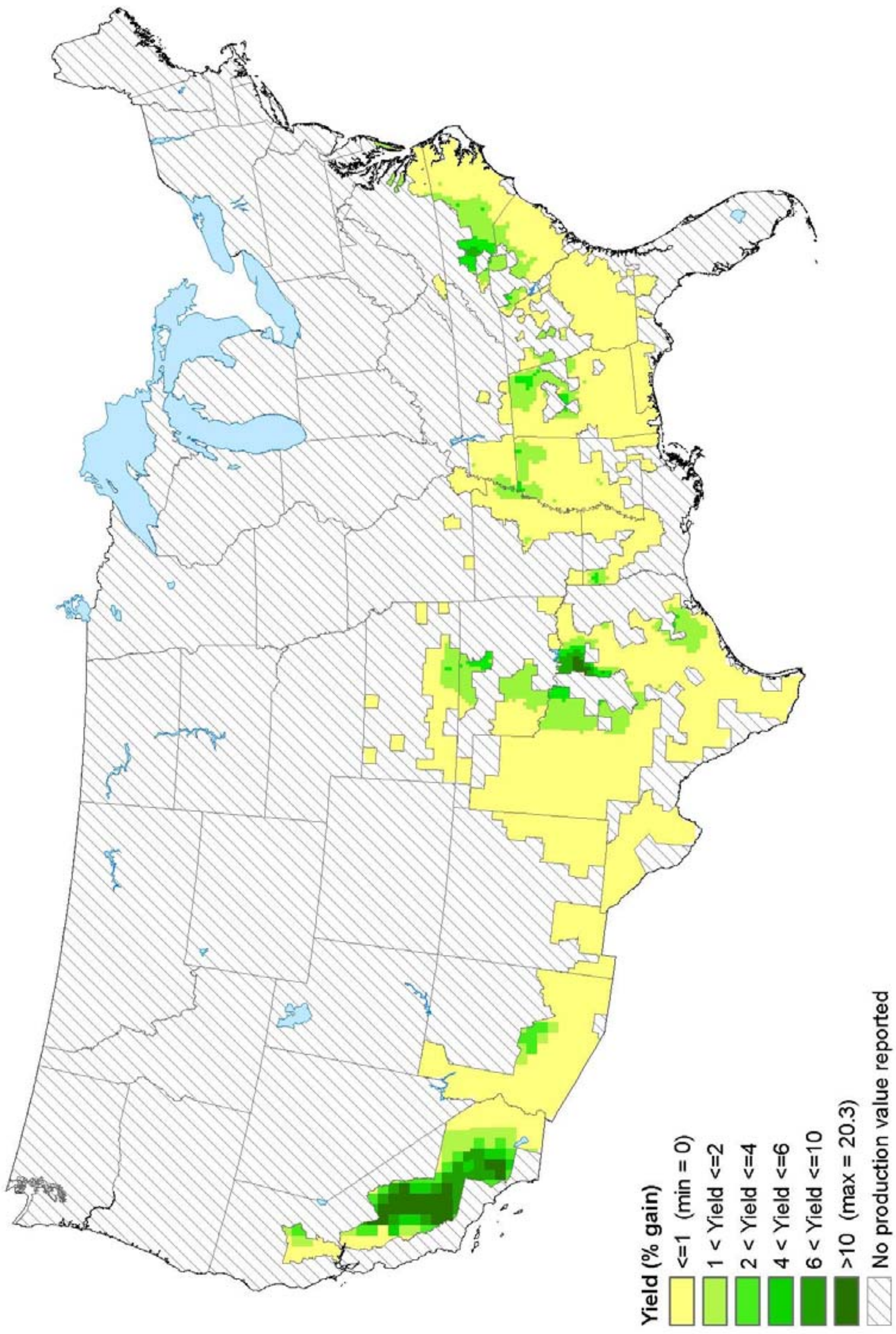
Cotton Response Maps



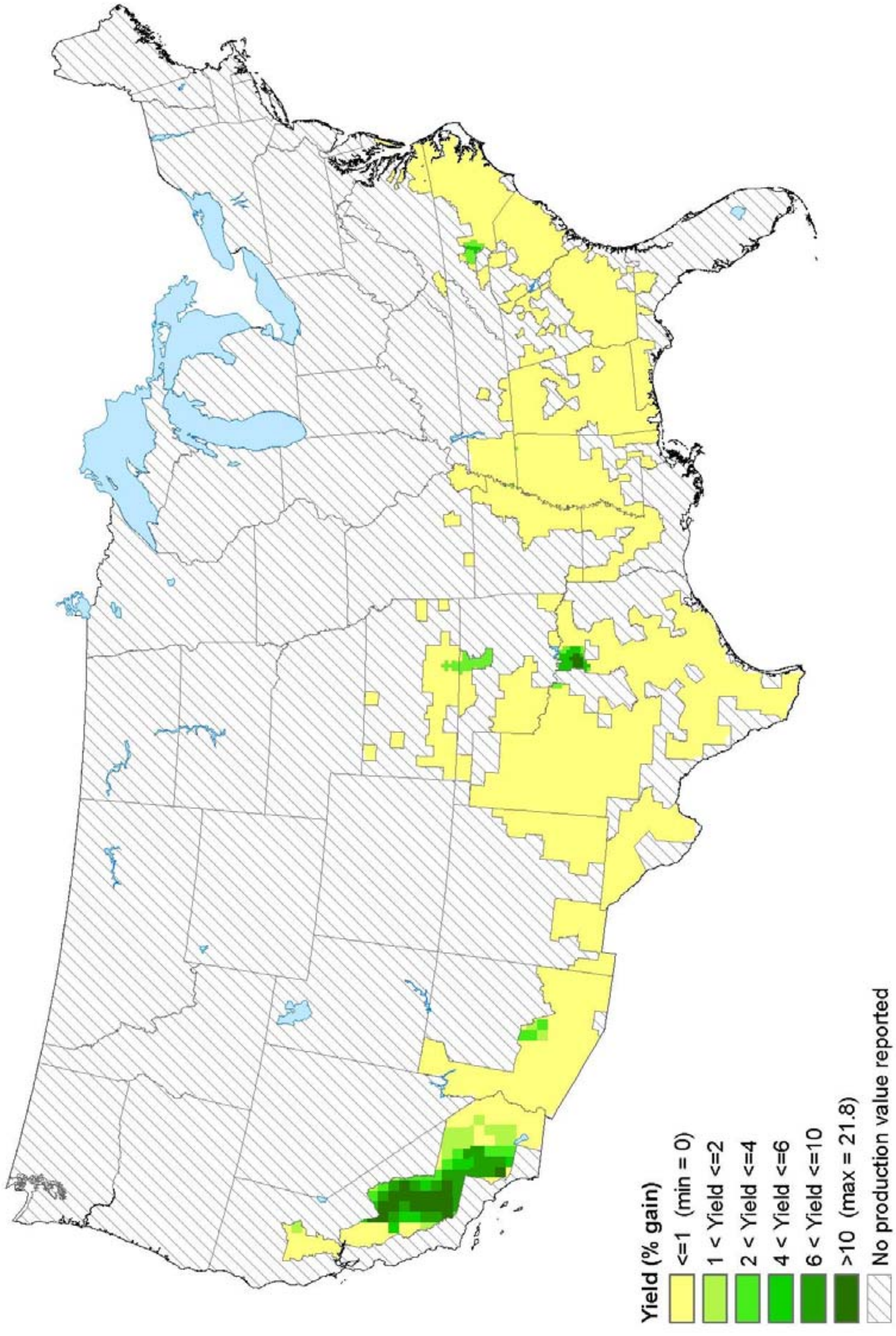
Map G-10: As-is Yield loss for Cotton (Gossypium hirsutum) (Unreduced W126).



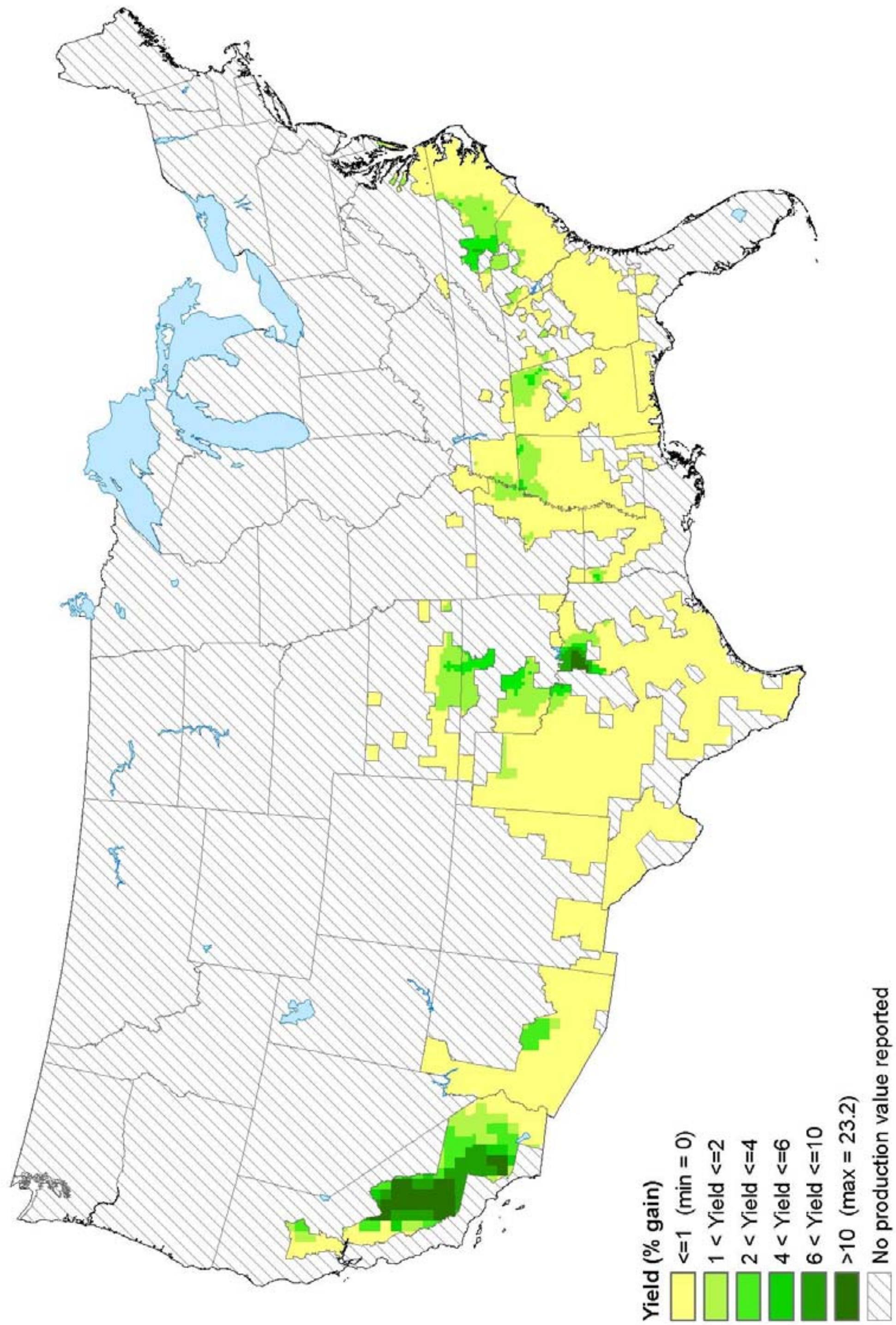
Map G-11: Yield Gain from Baseline for Cotton (Gossypium hirsutum). Quadratic Rollback 4th Highest 8-hour Maximum to 84 ppb (Unreduced W126).



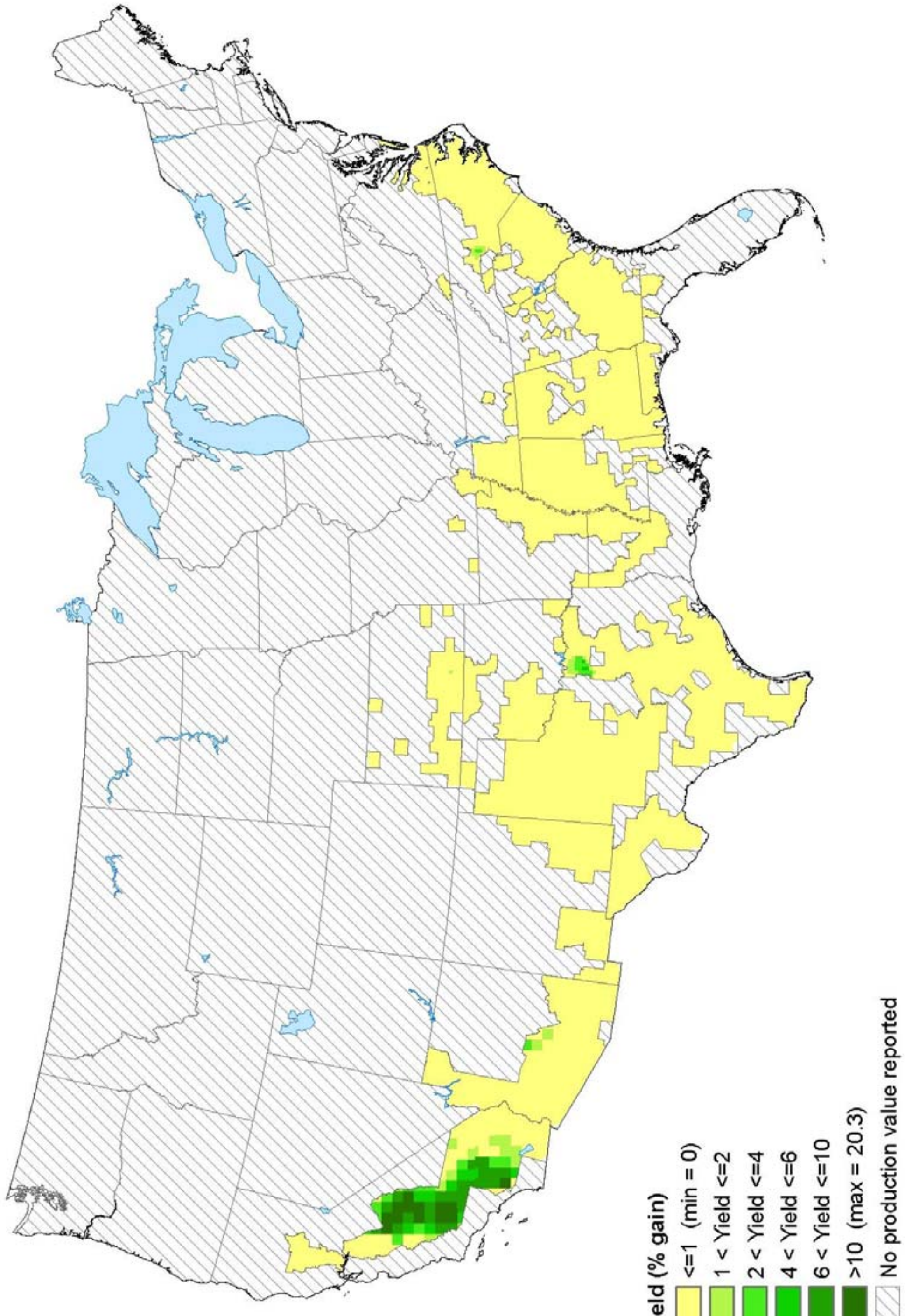
Map G-12: Yield Gain from Baseline for Cotton (Gossypium hirsutum). Quadratic Rollback 4th Highest 8-hour Maximum to 70 ppb (Unreduced W126).



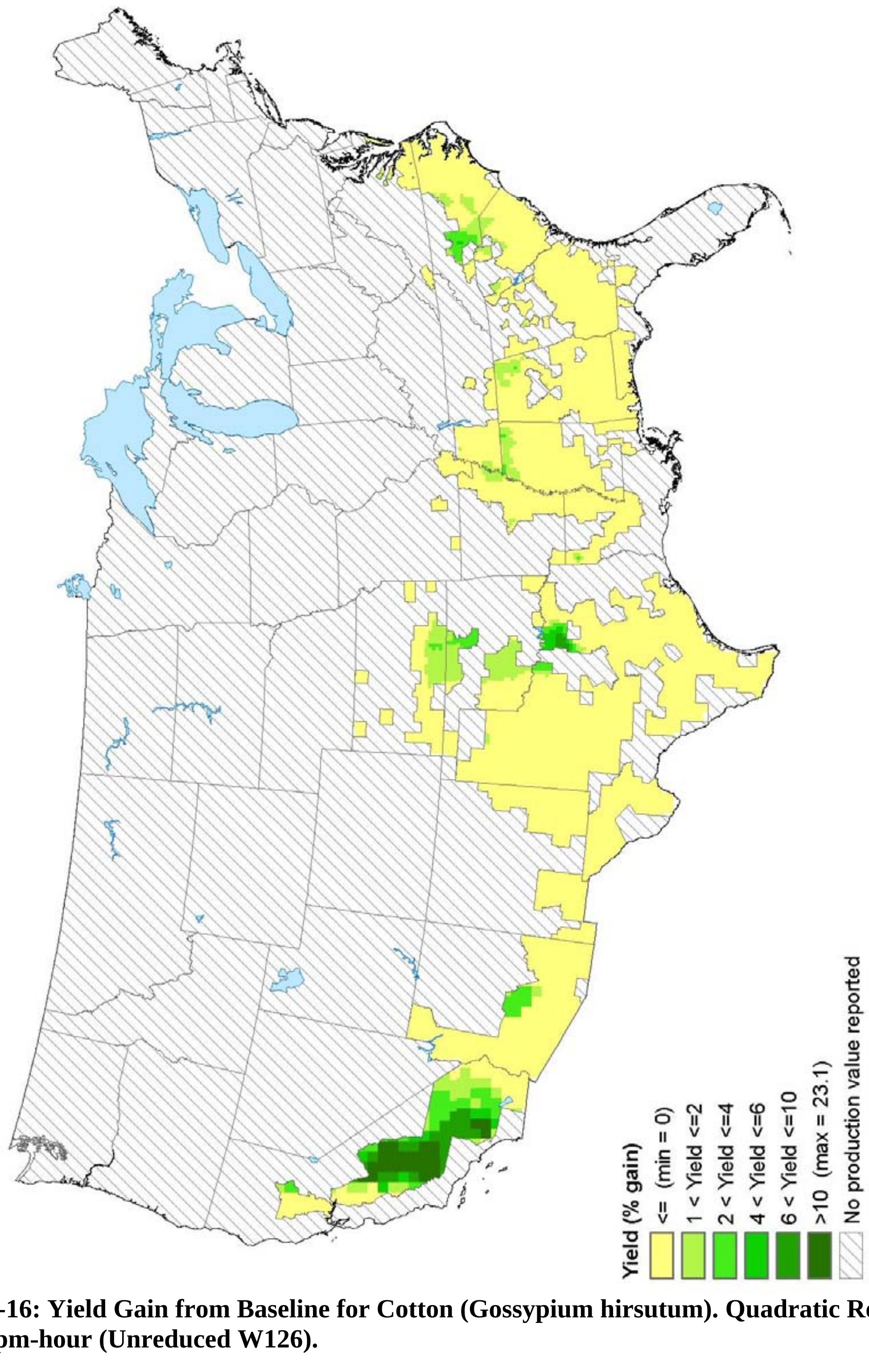
Map G-13: Yield Gain from Baseline for Cotton (Gossypium hirsutum). Quadratic Rollback 3-month SUM06 to 25 ppm-hour (Unreduced W126).



Map G-14: Yield Gain from Baseline for Cotton (Gossypium hirsutum). Quadratic Rollback 3-month SUM06 to 15 ppm-hour (Unreduced W126).

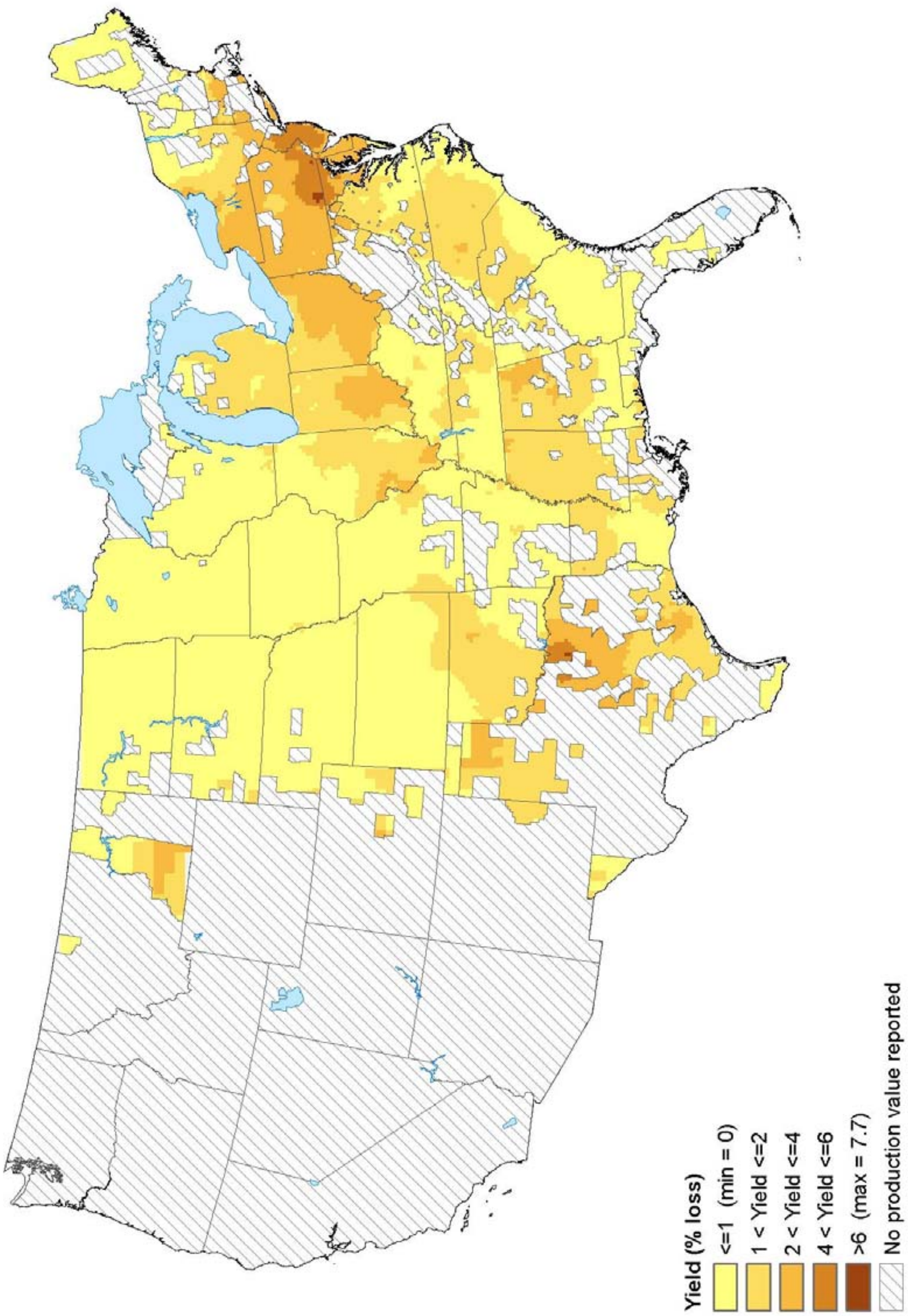


Map G-15: Yield Gain from Baseline for Cotton (Gossypium hirsutum). Quadratic Rollback W126 to 21 ppm-hr (Unreduced W126).

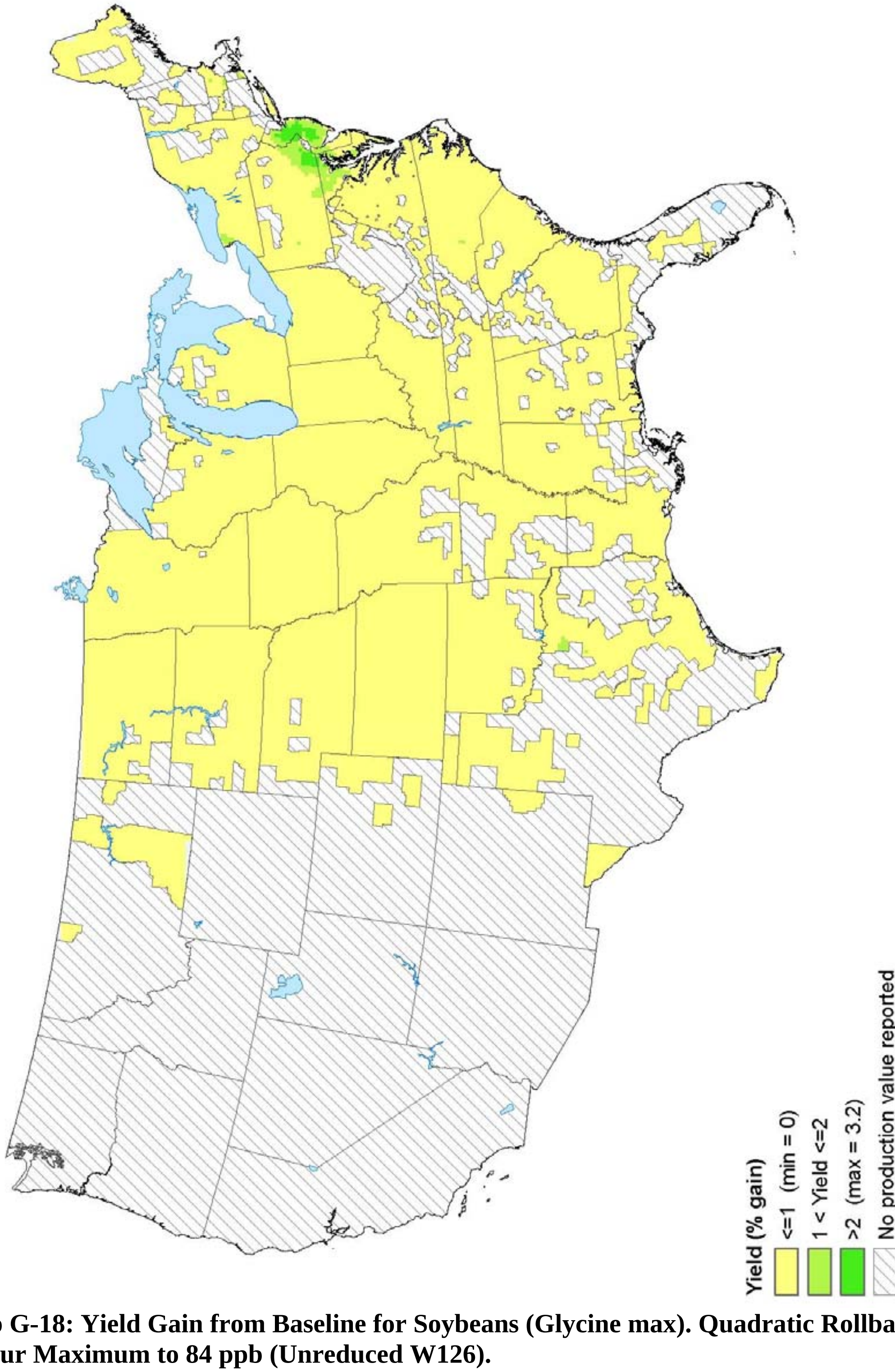


Map G-16: Yield Gain from Baseline for Cotton (Gossypium hirsutum). Quadratic Rollback W126 to 13 ppm-hour (Unreduced W126).

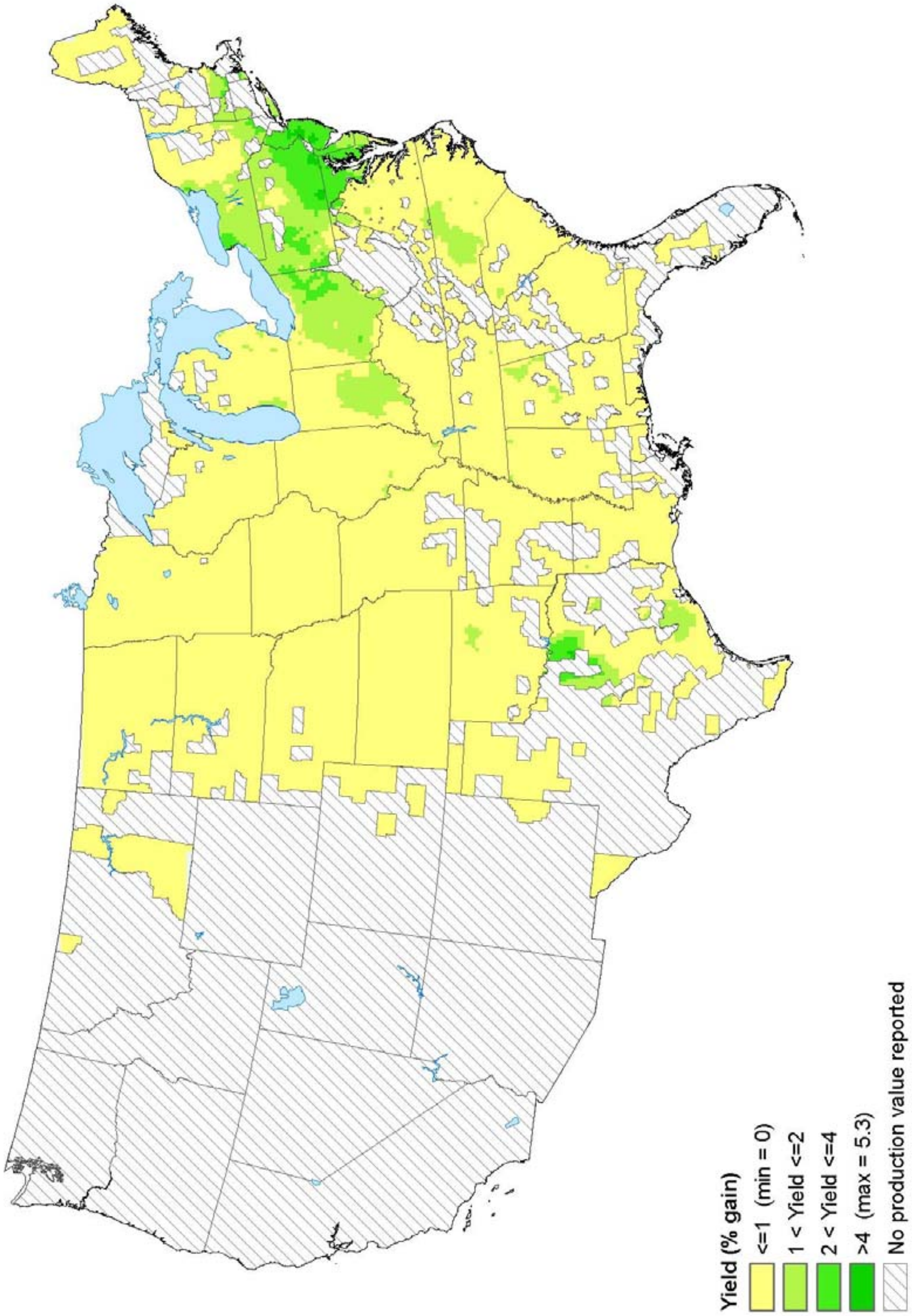
Soybean Response Maps



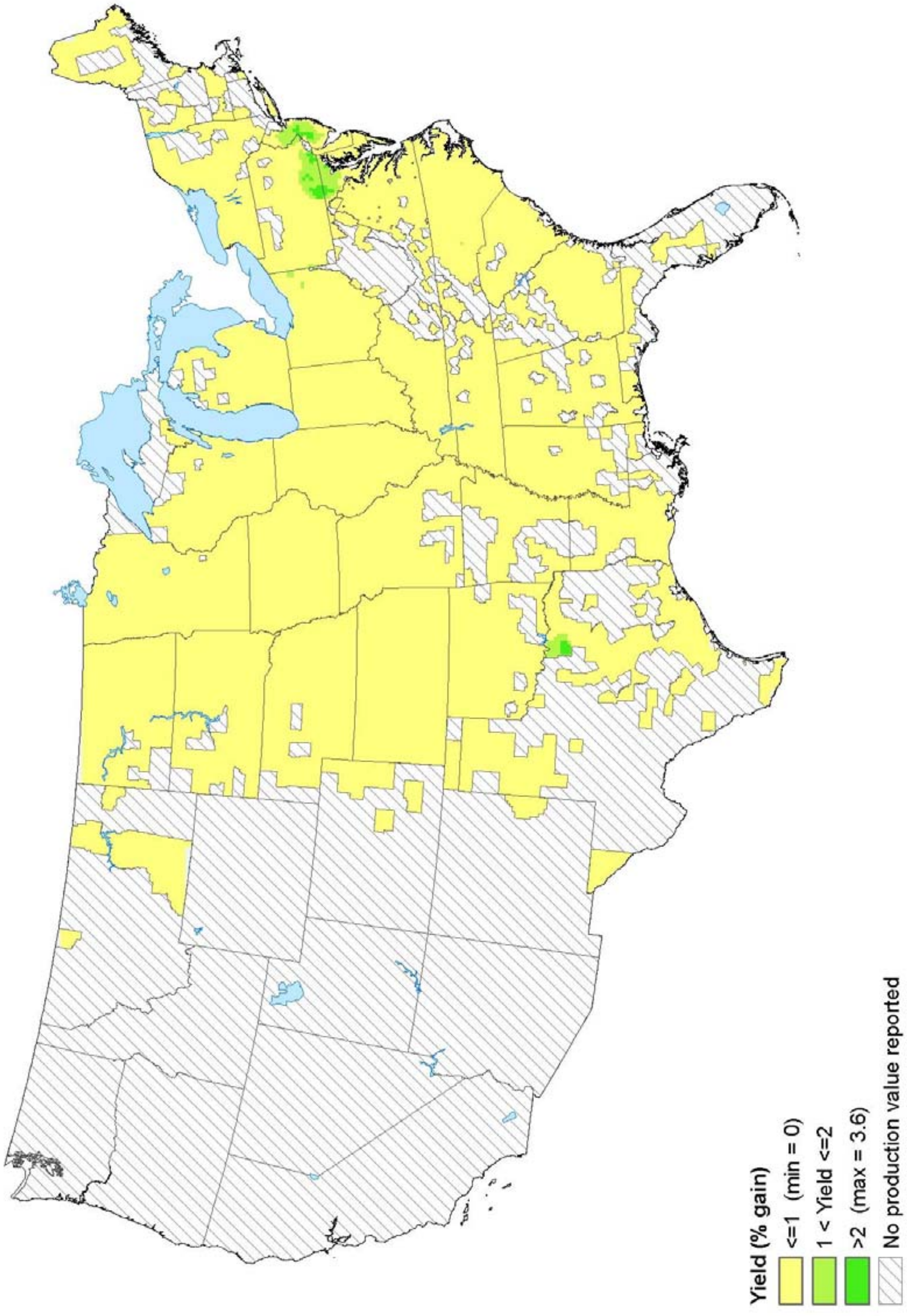
Map G-17: As-is Yield loss for Soybeans (Glycine max) (Unreduced W126).



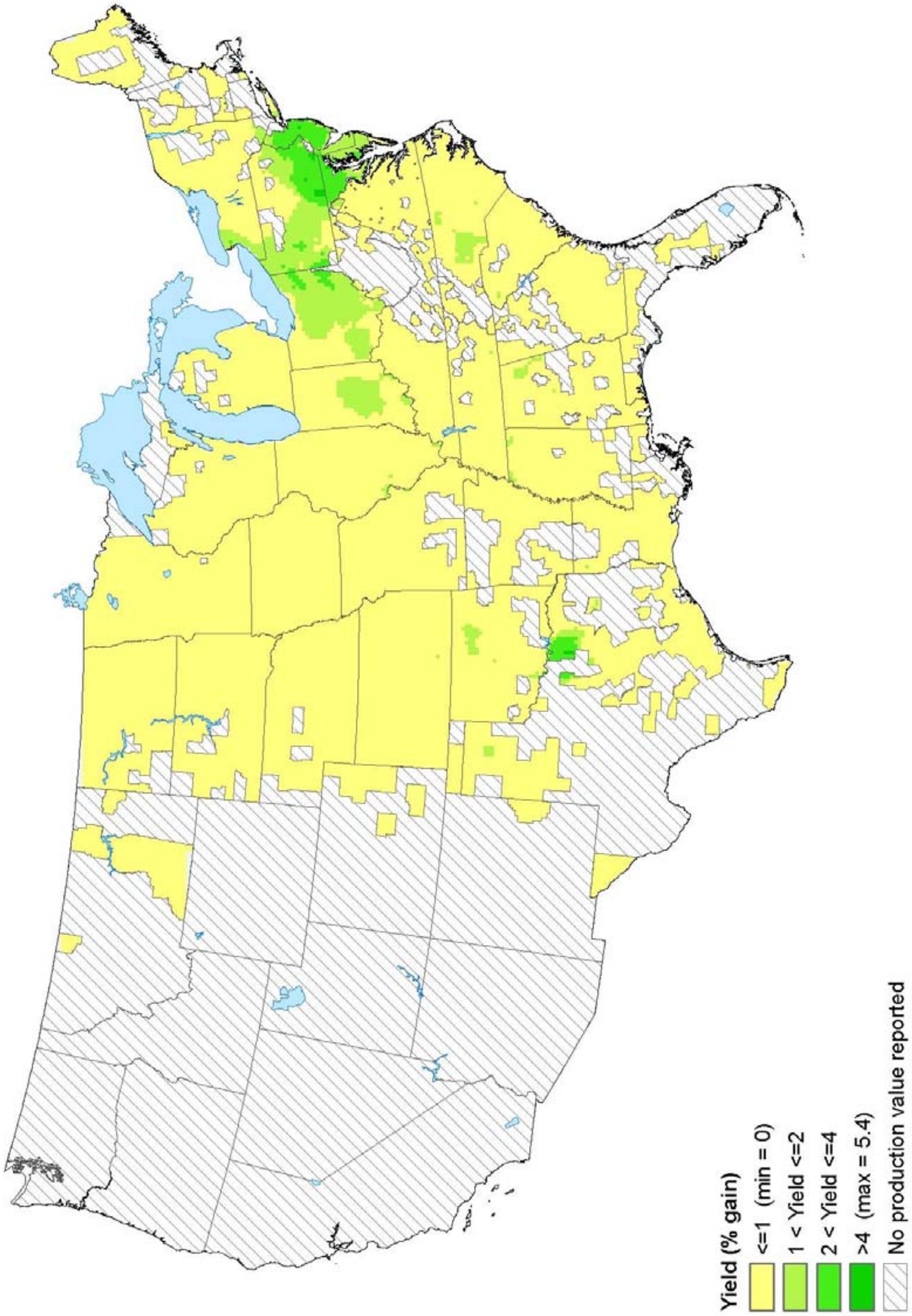
Map G-18: Yield Gain from Baseline for Soybeans (Glycine max). Quadratic Rollback 4th Highest 8-hour Maximum to 84 ppb (Unreduced W126).



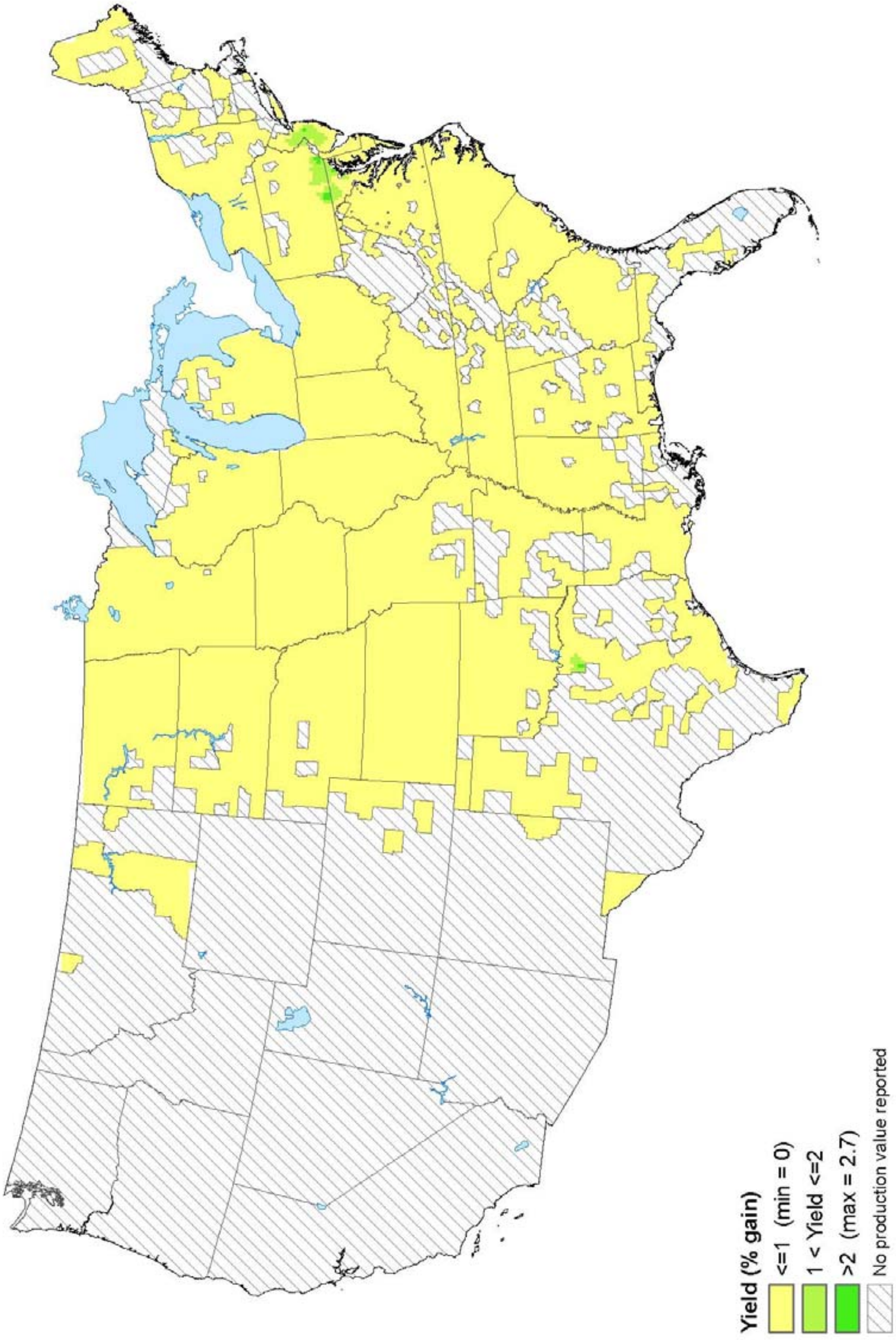
Map G-19: Yield Gain from Baseline for Soybeans (Glycine max). Quadratic Rollback 4th Highest 8-hour Maximum to 70 ppb (Unreduced W126).



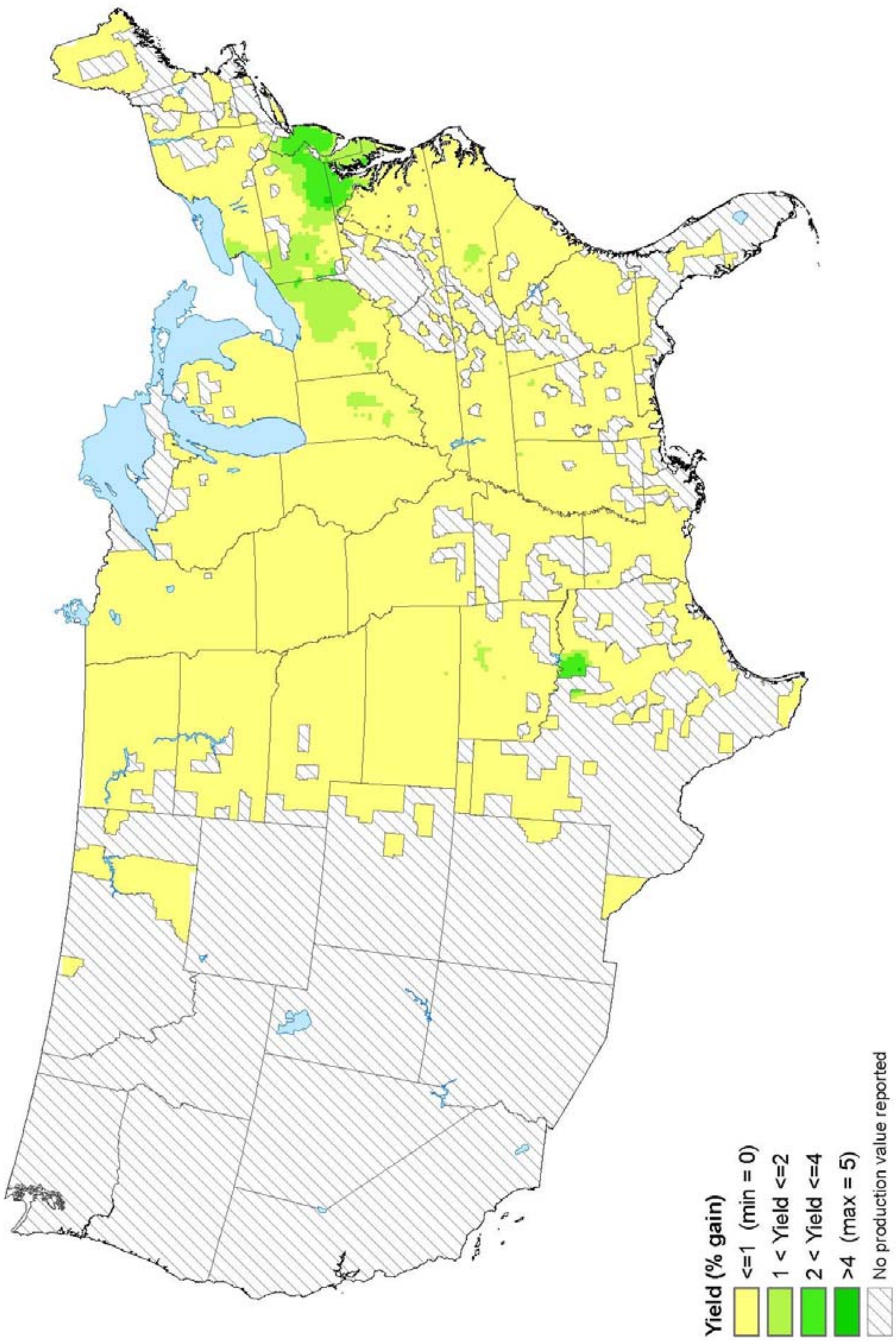
Map G-20: Yield Gain from Baseline for Soybeans (Glycine max). Quadratic Rollback 3-month SUM06 to 25 ppm-hour (Unreduced W126).



Map G-21: Yield Gain from Baseline for Soybeans (Glycine max). Quadratic Rollback 3-month SUM06 to 15 ppm-hour (Unreduced W126).

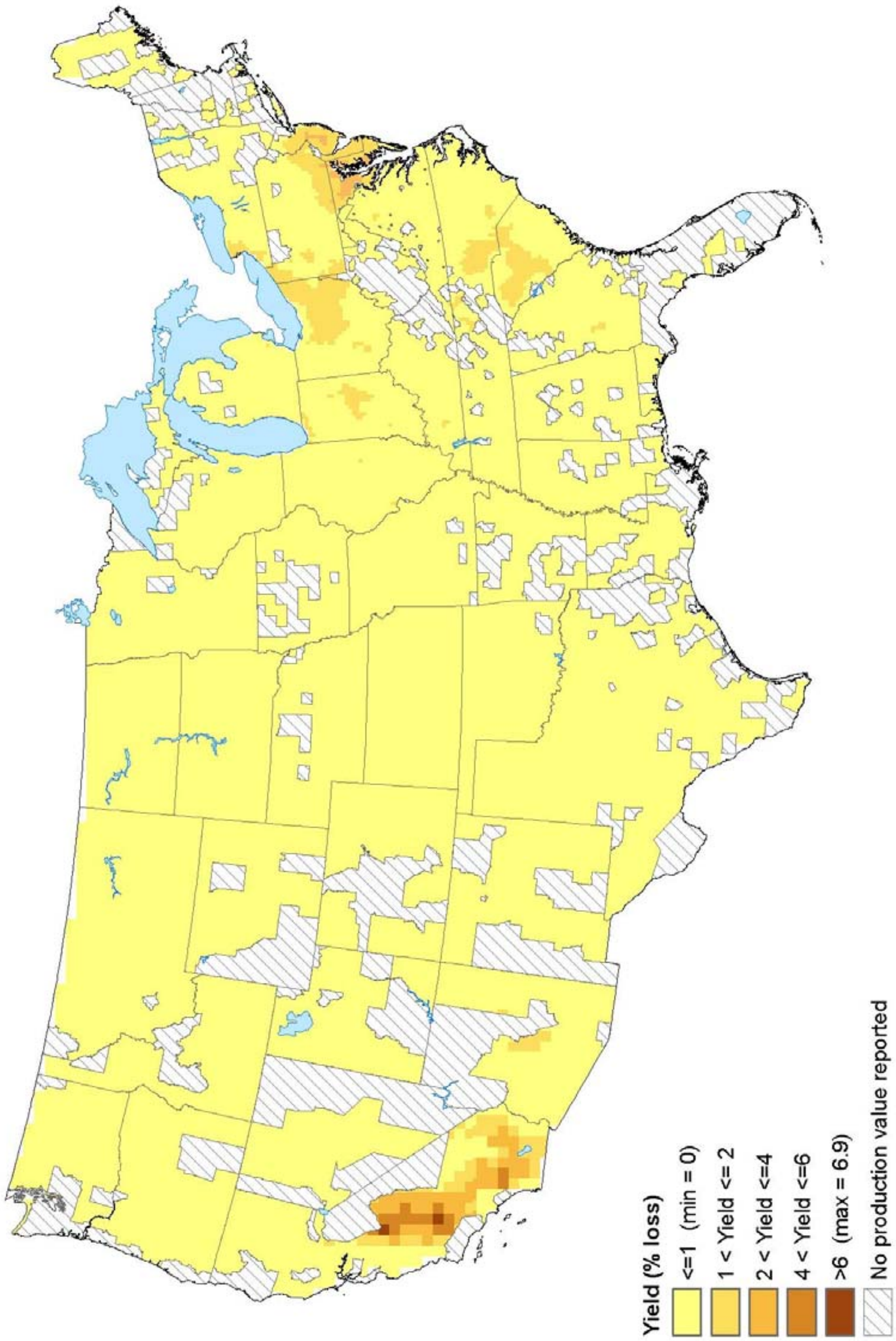


Map G-22: Yield Gain from Baseline for Soybeans (Glycine max). Quadratic Rollback W126 to 21 ppm-hour (Unreduced W126).

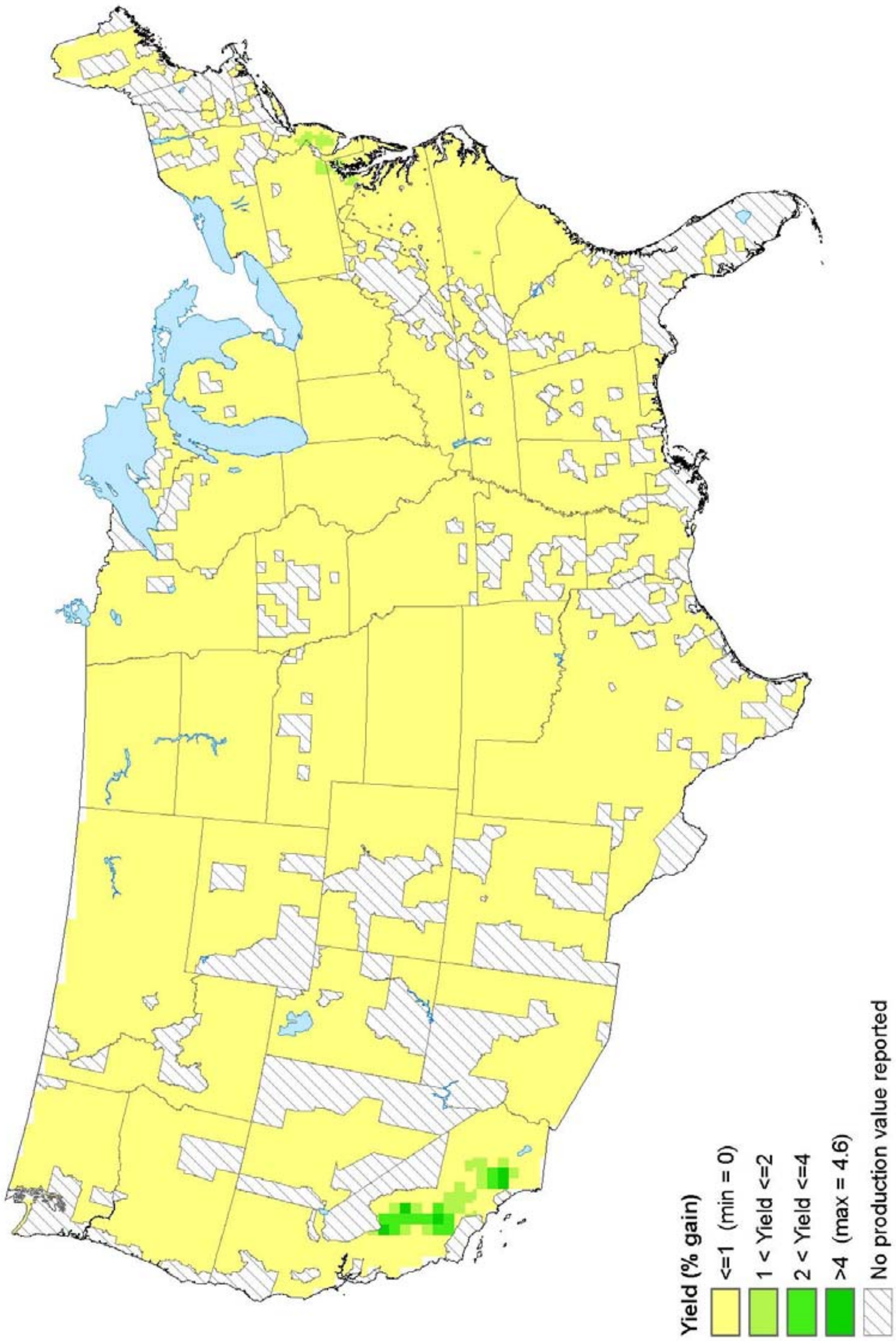


Map G-23: Yield Gain from Baseline for Soybeans (Glycine max). Quadratic Rollback W126 to 13 ppm-hour (Unreduced W126).

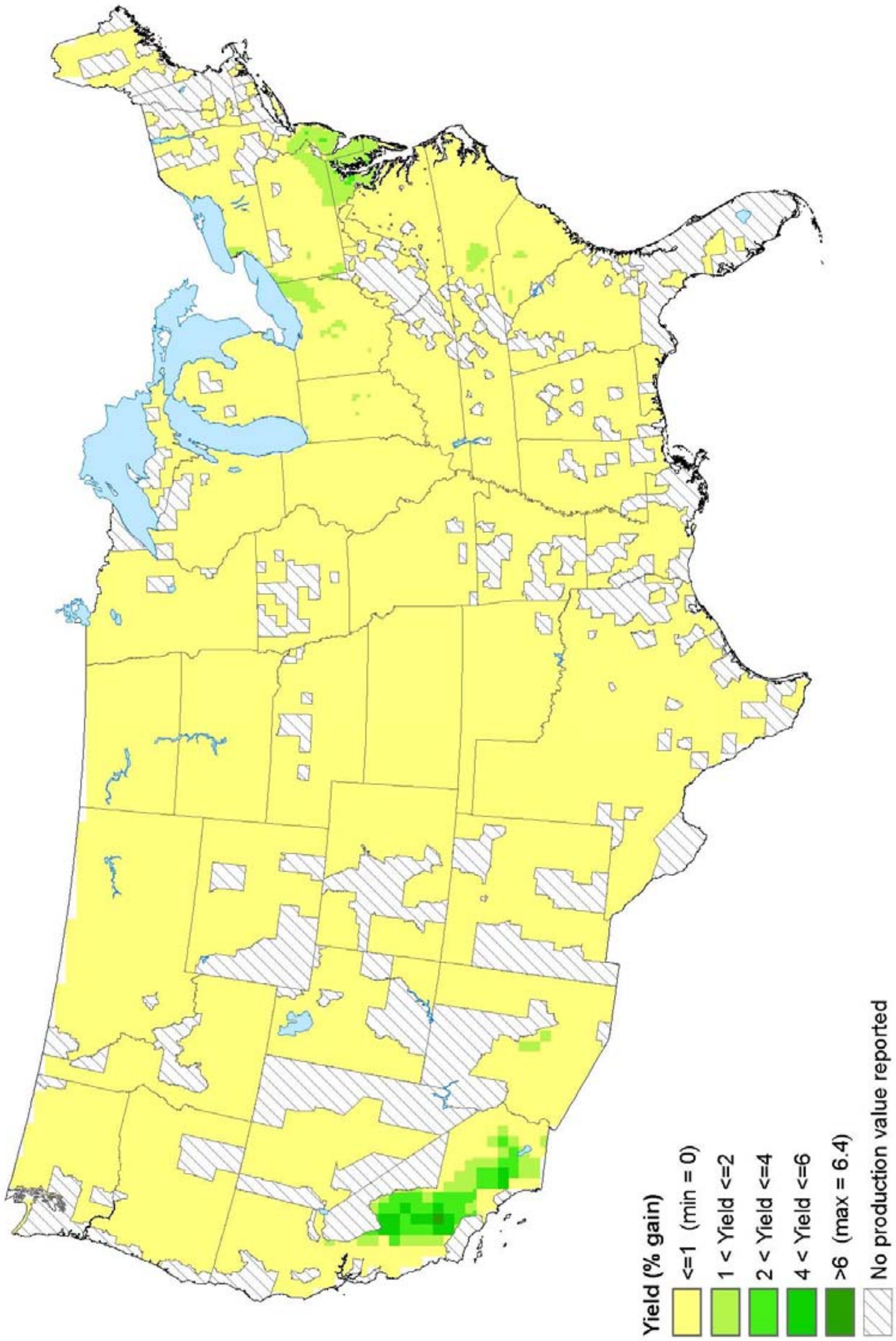
Wheat Response Maps



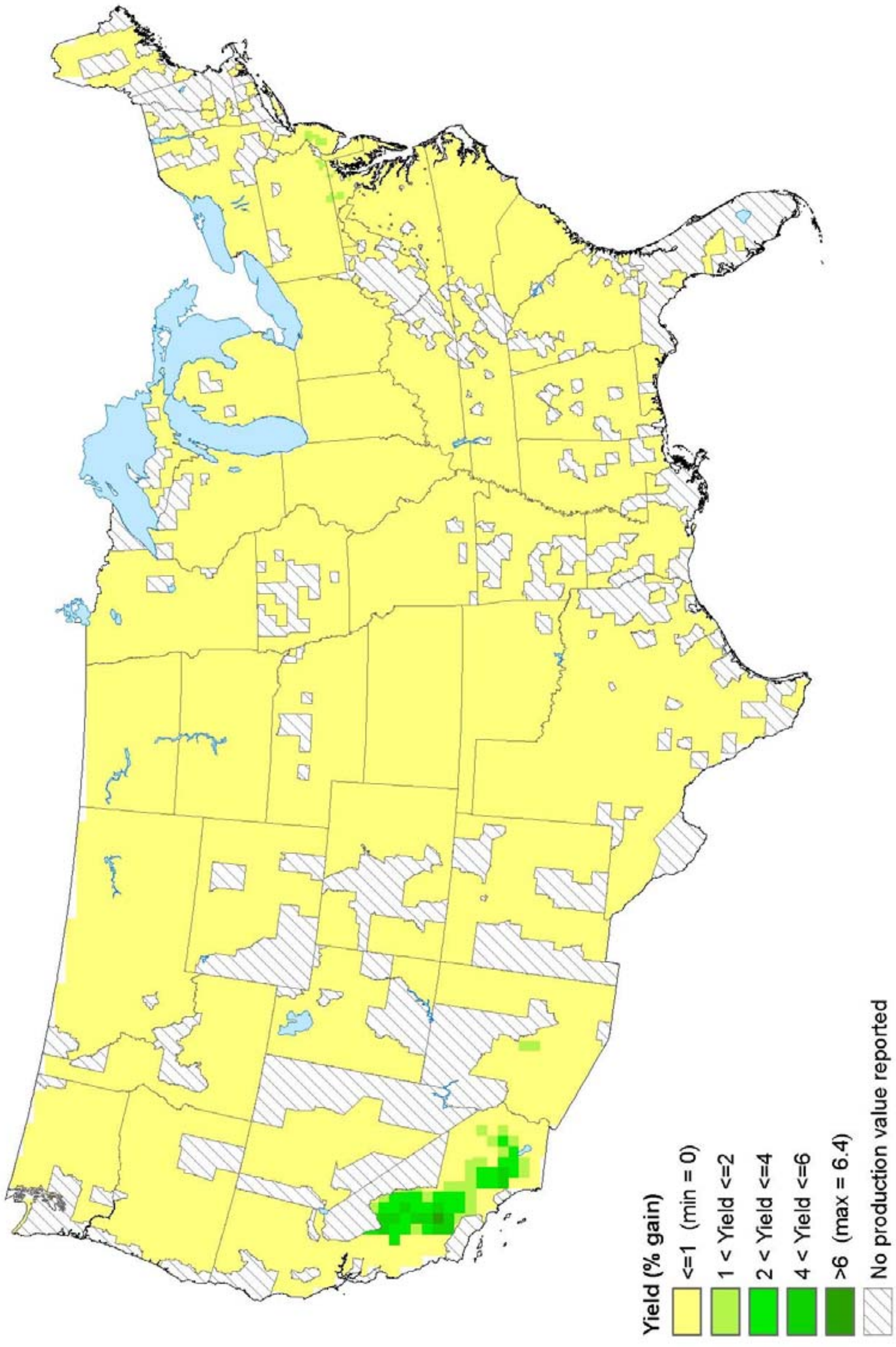
Map G-24: As-is Yield loss for Wheat (Triticum aestivum) (Unreduced W126).



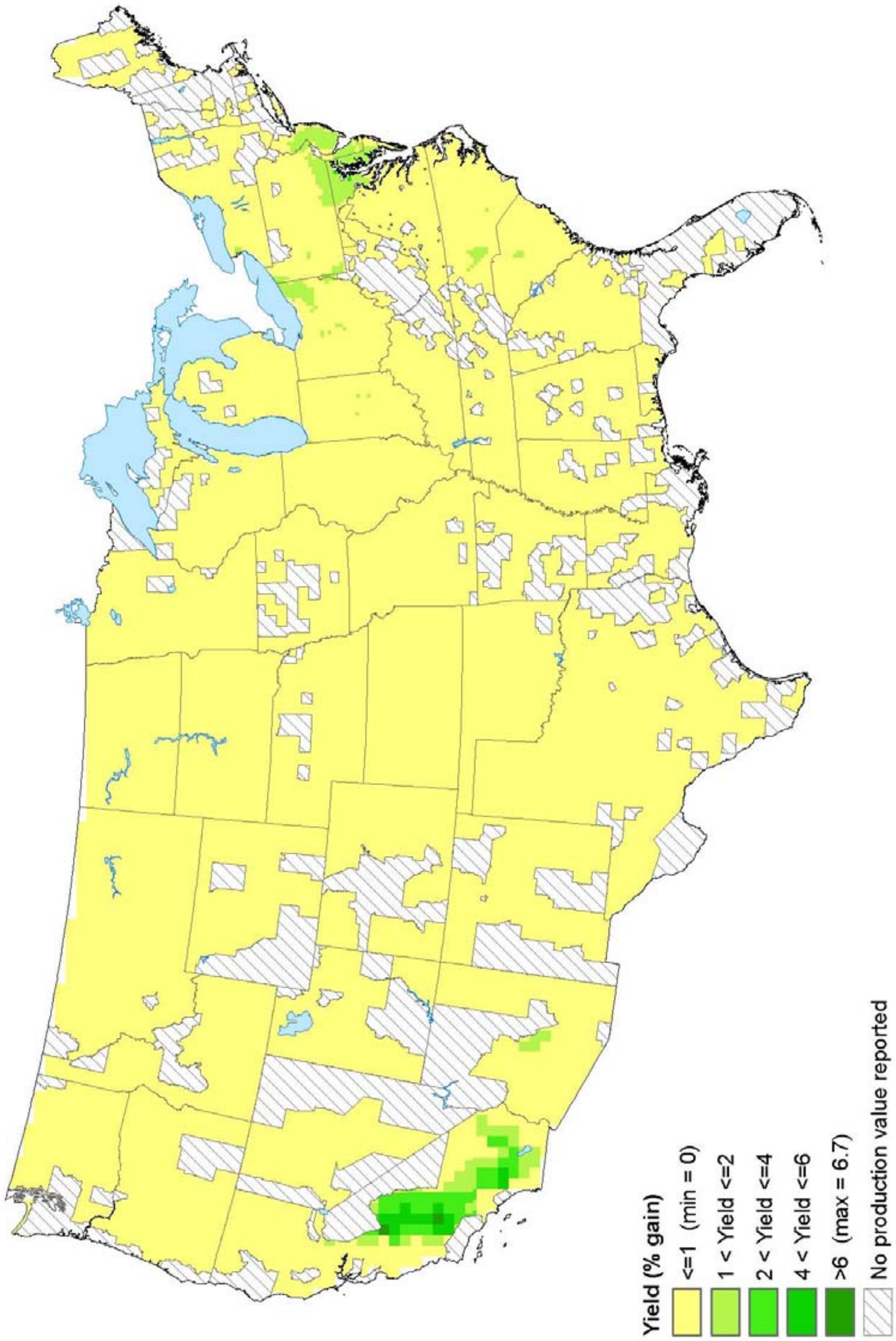
Map G-25: Yield Gain from Baseline for Wheat (Triticum aestivum). Quadratic Rollback 4th Highest 8-hour Maximum to 84 ppb (Unreduced W126).



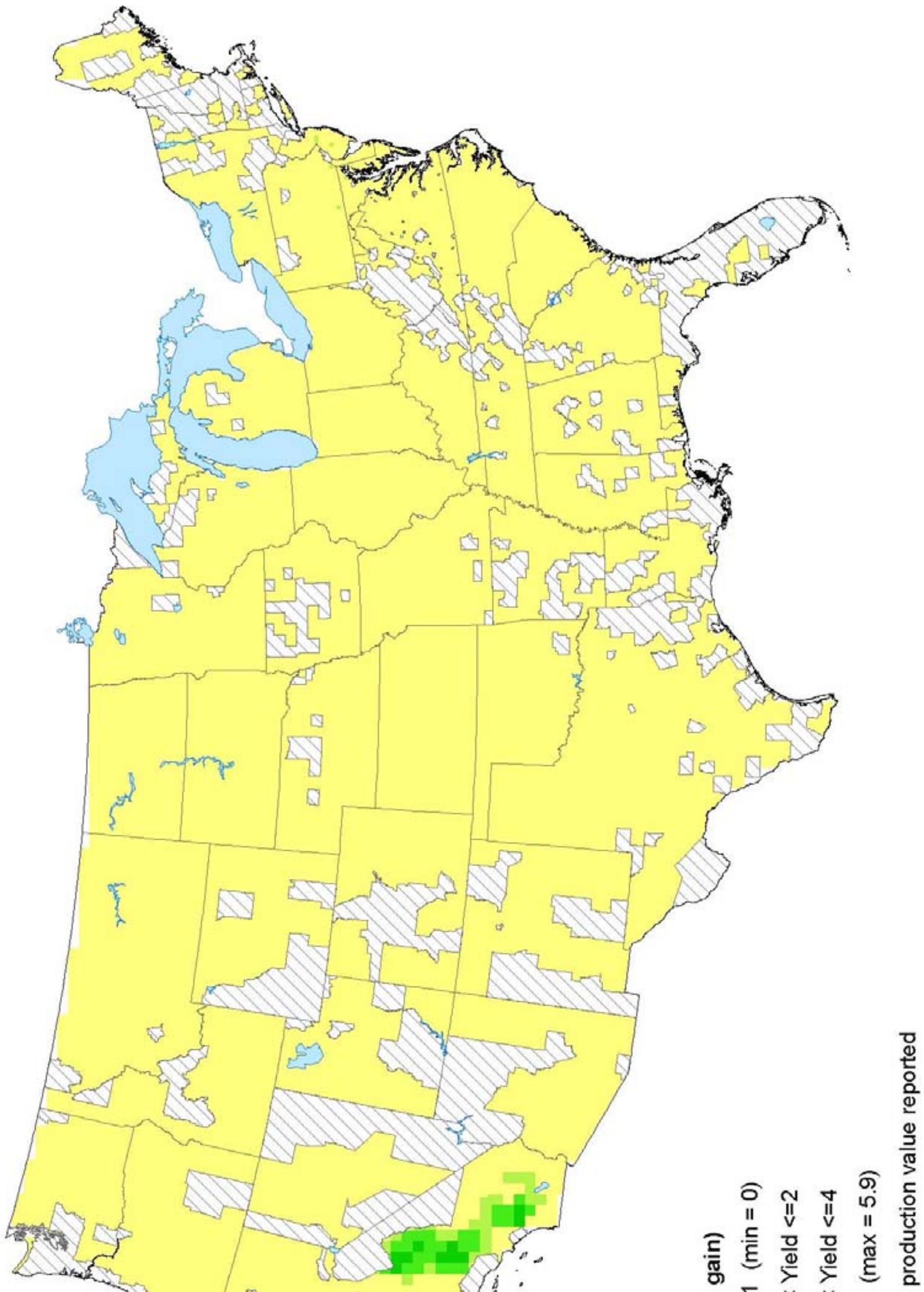
Map G-26: Yield Gain from Baseline for Wheat (Triticum aestivum). Quadratic Rollback 4th Highest 8-hour Maximum to 70 ppb (Unreduced W126).



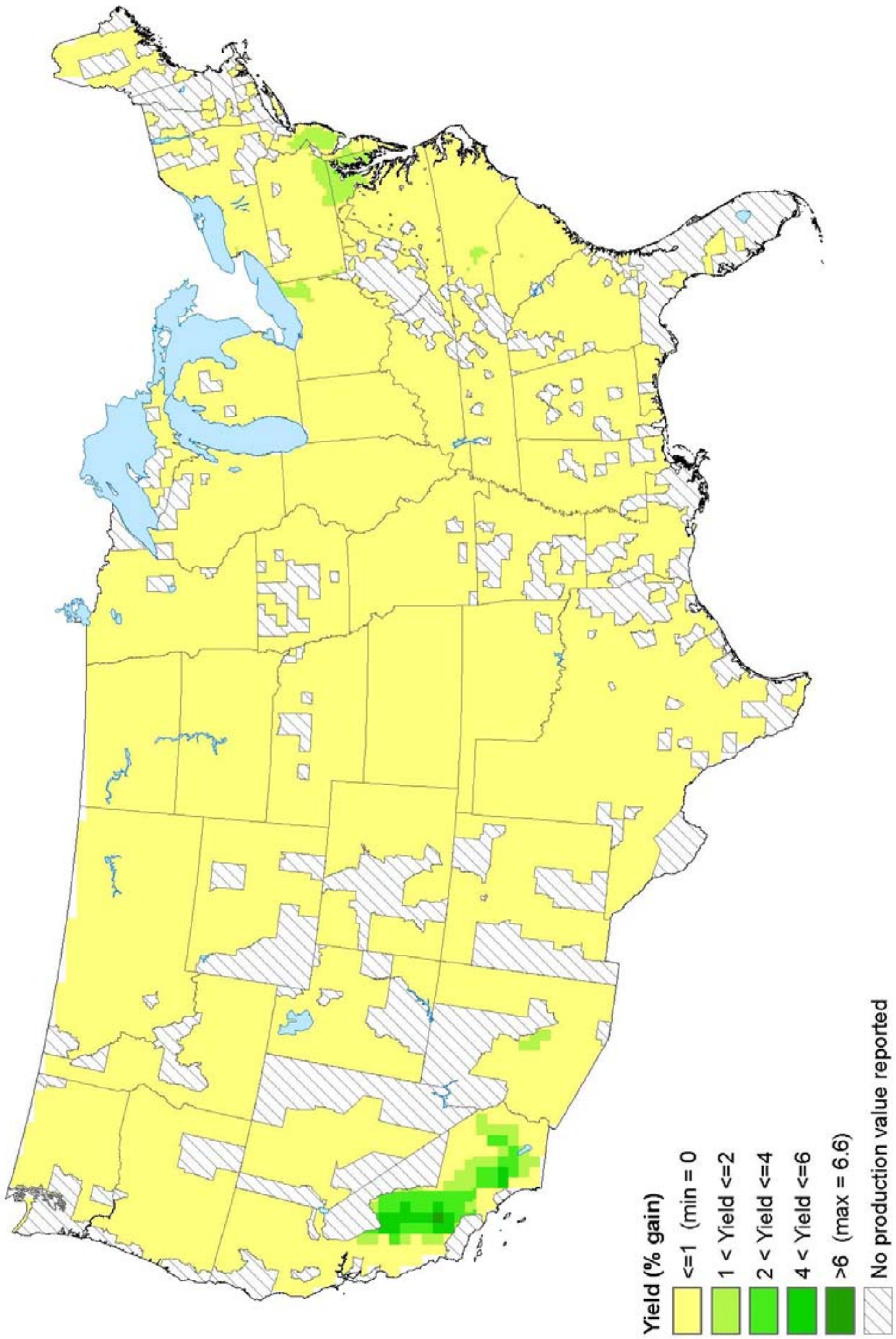
Map G-27: Yield Gain from Baseline for Wheat (Triticum aestivum). Quadratic Rollback 3-month SUM06 to 25 ppm-hour (Unreduced W126).



Map G-28: Yield Gain from Baseline for Wheat (Triticum aestivum). Quadratic Rollback 3-month SUM06 to 15 ppm-hour (Unreduced W126).



Map G-29: Yield Gain from Baseline for Wheat (Triticum aestivum). Quadratic Rollback W126 to 21 ppm-hour (Unreduced W126).



Map G-30: Yield Gain from Baseline for Wheat (Triticum aestivum). Quadratic Rollback W126 to 13 ppm-hour (Unreduced W126).

Appendix H Summary Statistics for Tree Seedling Biomass Responses based on Ten Percent Adjusted W126 Metric

Appendix H summarizes relative tree seedling biomass gains under the six scenarios presented in Section 4:

- Ozone levels which just meet an 84 ppb 4th highest 8-hour maximum standard (in this case, we performed a rollback to 84.999 ppb, since the 4th highest 8-hour maximum standard truncates decimals)
- Ozone levels which just meet a 70 ppb 4th highest 8-hour maximum standard (actually 70.999 for the reasons above)
- Ozone levels which just meet a 25ppm-h 3-month 12-hour SUM06 standard
- Ozone levels which just meet a 15ppm-h 3-month 12-hour SUM06 standard.
- Ozone levels which just meet a 21ppm-h 3-month 12-hour W126 standard.
- Ozone levels which just meet a 13ppm-h 3-month 12-hour W126 standard.

Appendix H.1 present results based on the reduced or "adjusted" O_3 metric (i.e. hourly O_3 values were adjusted down by 10%). Appendix H.2 present similar results based on the unreduced metric (unadjusted hourly O_3 values). Refer to Section 5 for a discussion of the data and method used to estimate O_3 concentration responses on vegetation.

H.1 Tree Seedling Biomass Responses based on Ten Percent Adjusted W126 Metric

This section includes summary box plots and tables showing concentration responses for all ten tree species based on *reduced* hourly O_3 values for the six O_3 standards under consideration. Maps for aspen, black cherry, and ponderosa pine are included in the body of the document.

H.1.1 Median Concentration Responses for Tree Seedlings

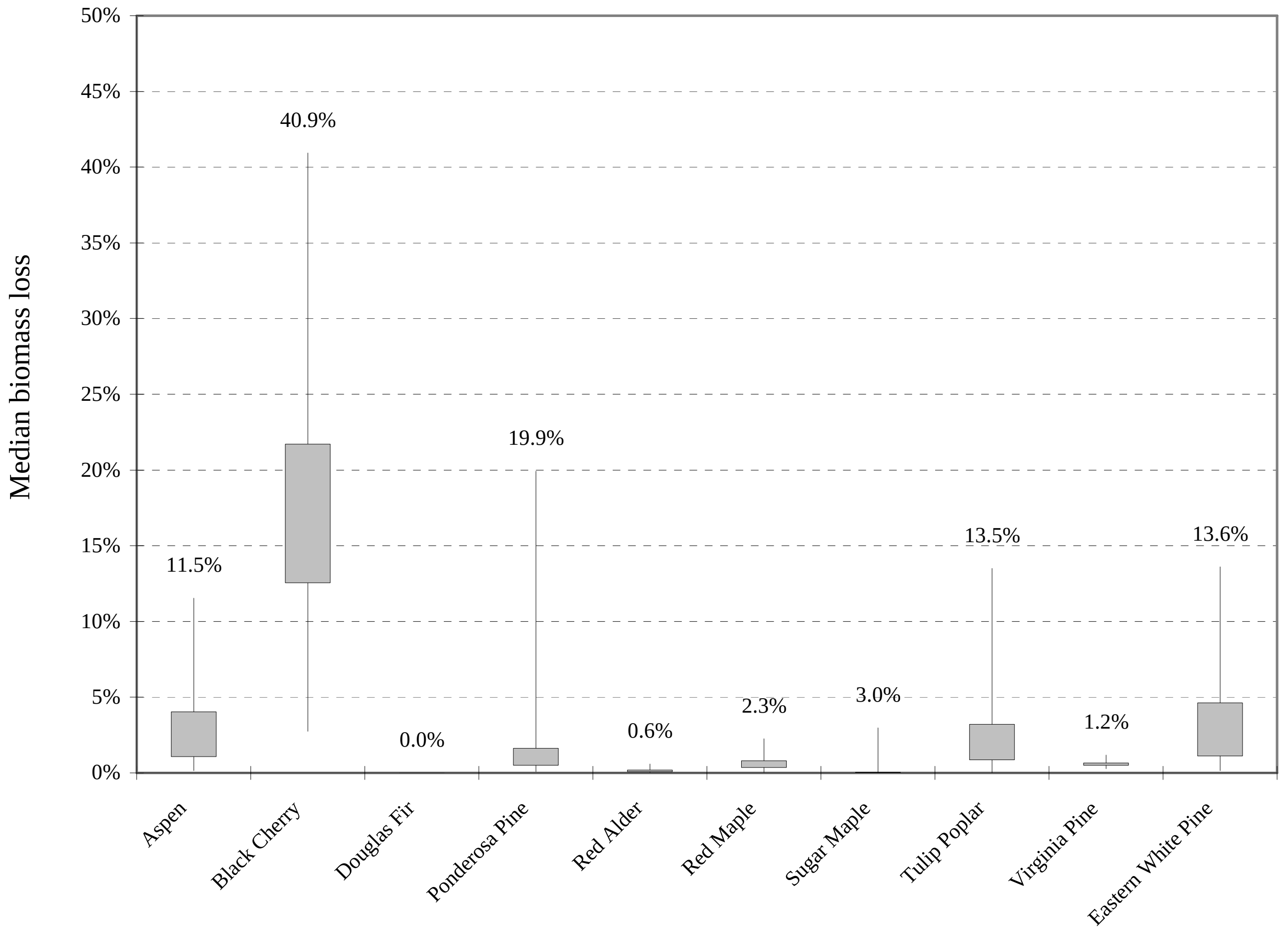


Figure H-1: Median Tree Seedling Biomass Loss - 2001 Baseline (reduced W126)

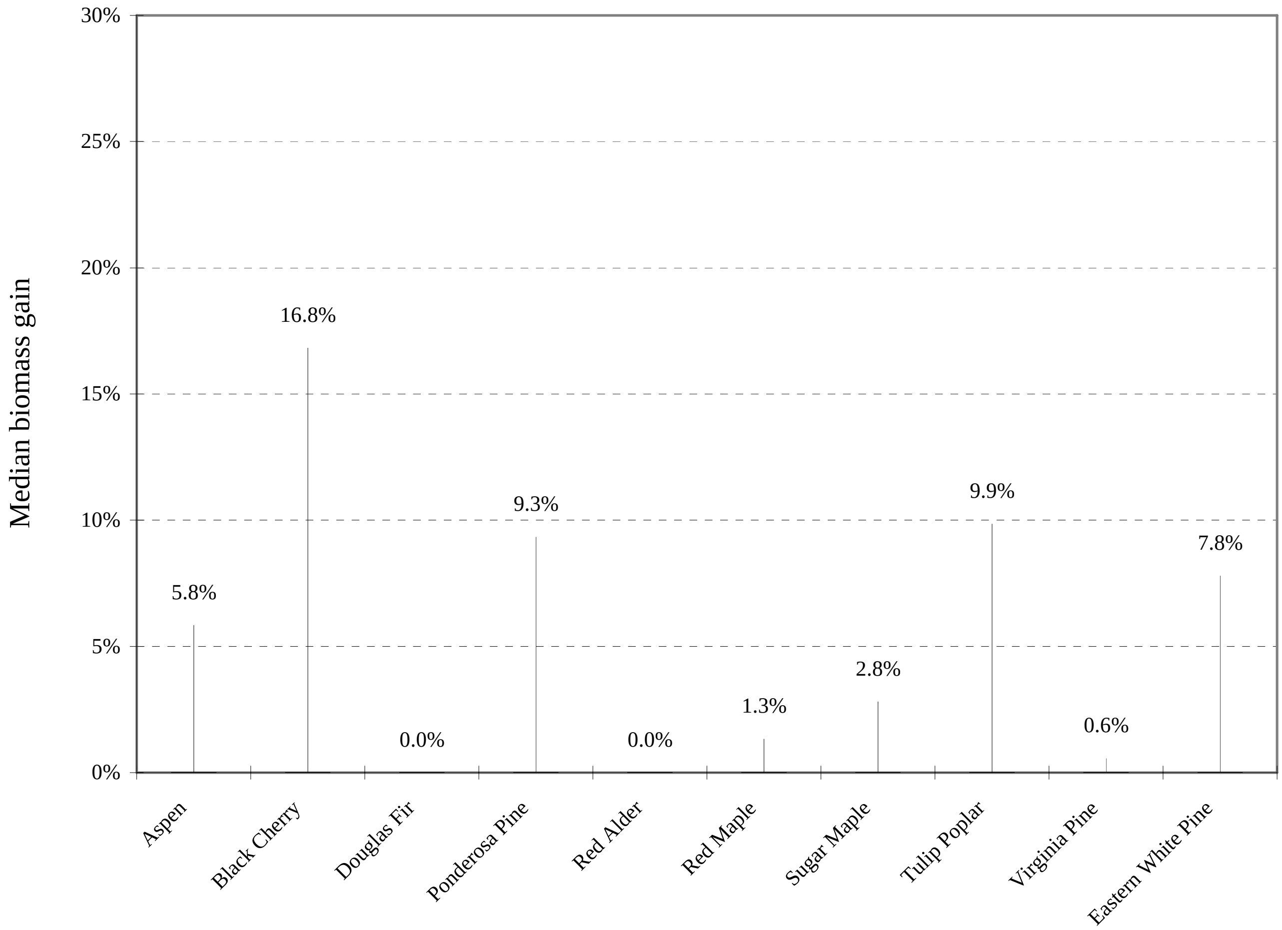


Figure H-2: Median Tree Seedling Biomass Gain from Baseline - 84 ppb Rollback (reduced W126)

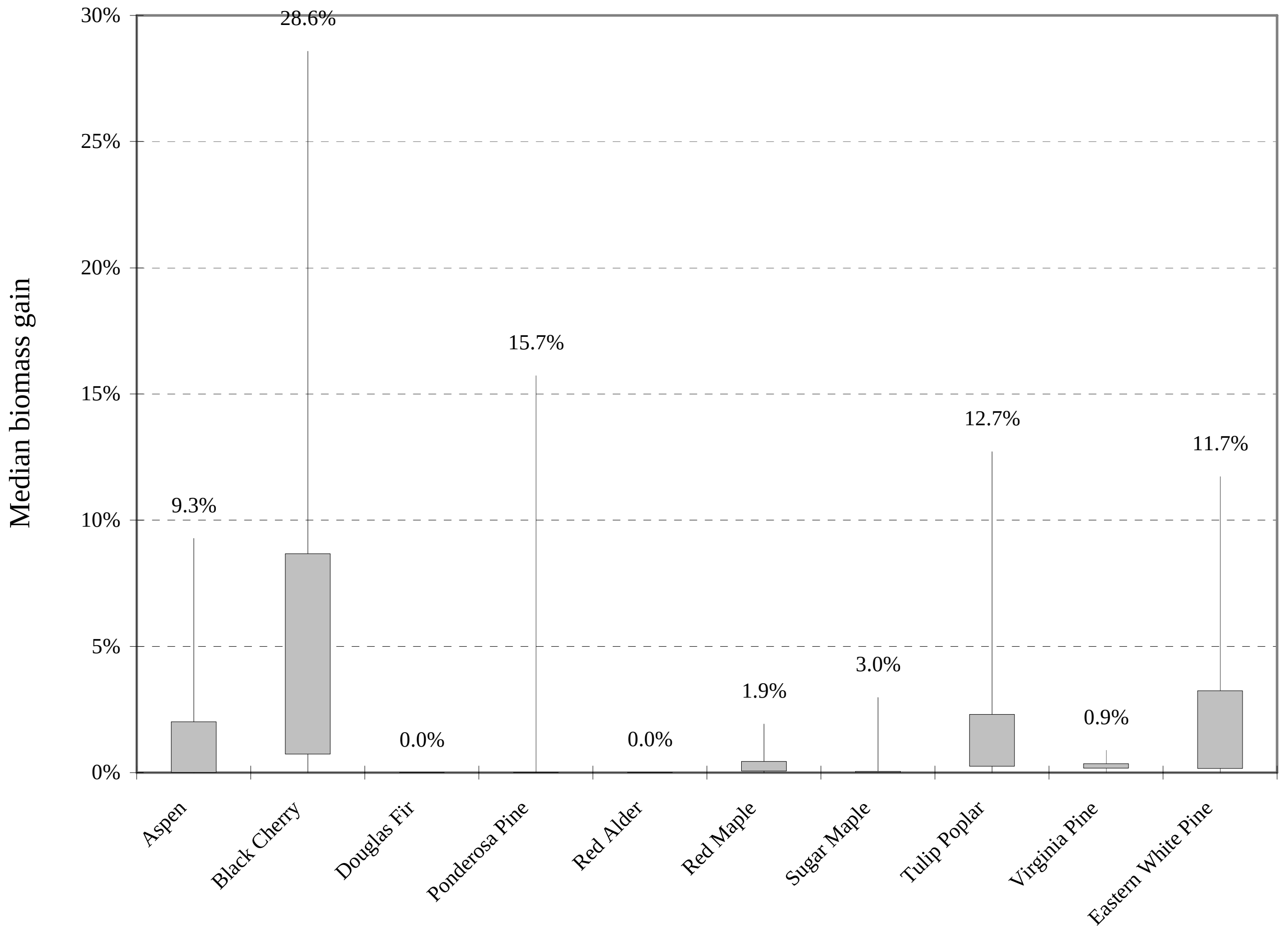


Figure H-3: Median Tree Seedling Biomass Gain from Baseline - 70 ppb Rollback (reduced W126)

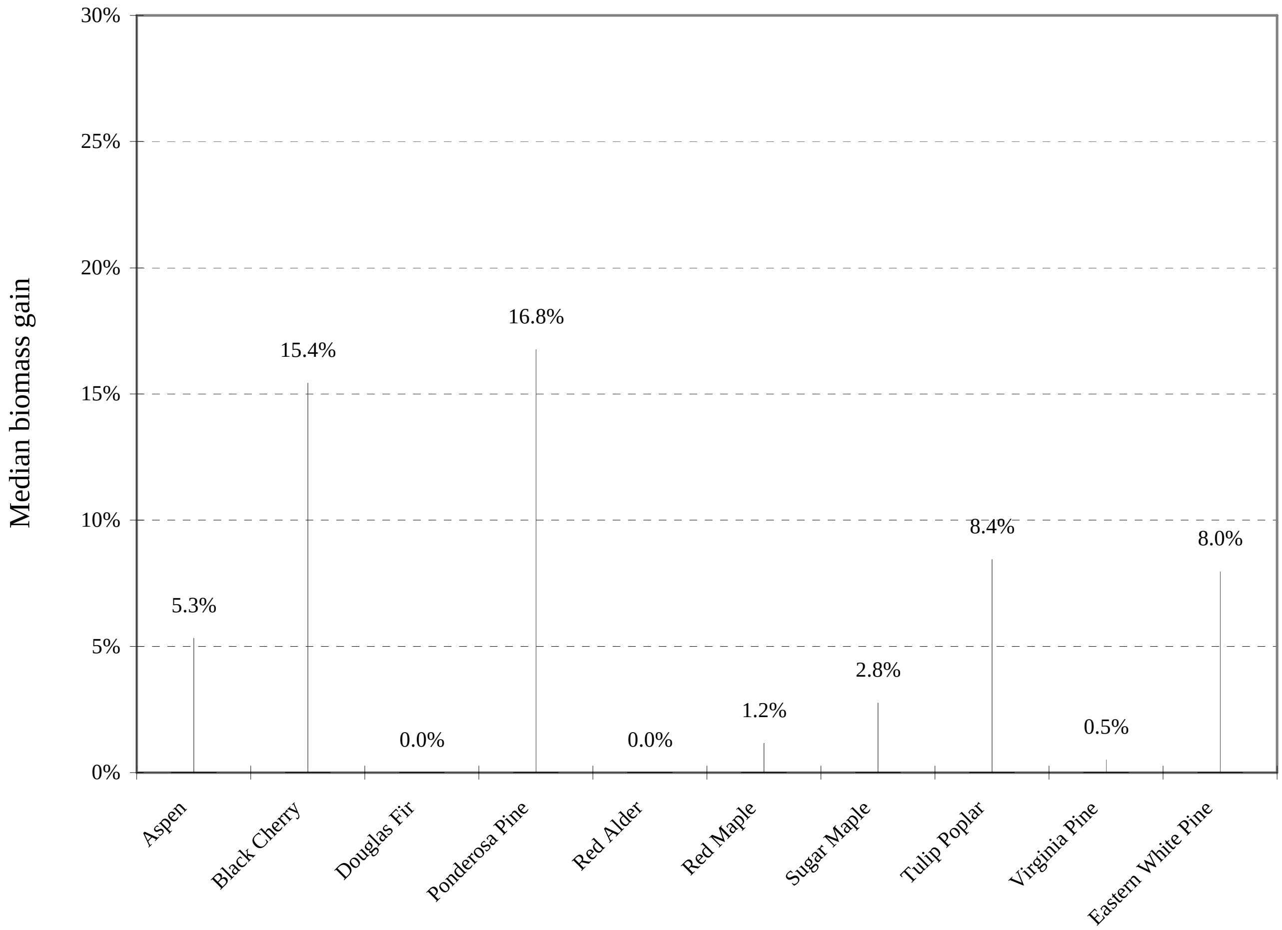


Figure H-4: Median Tree Seedling Biomass Gain from Baseline - 25 ppm-hr Rollback (reduced W126)

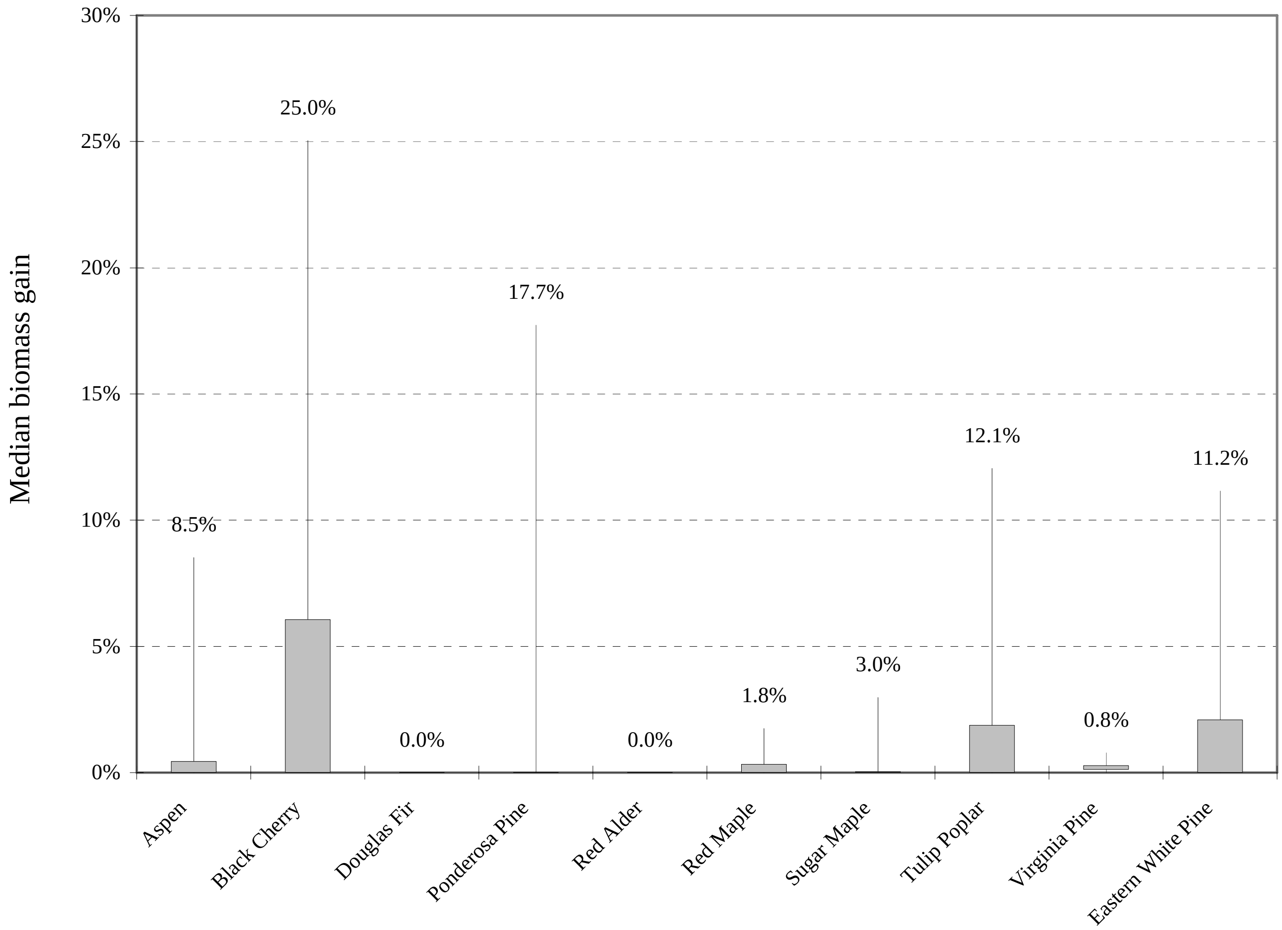


Figure H-5: Median Tree Seedling Biomass Gain from Baseline – 15 ppm-hr Rollback (reduced W126)

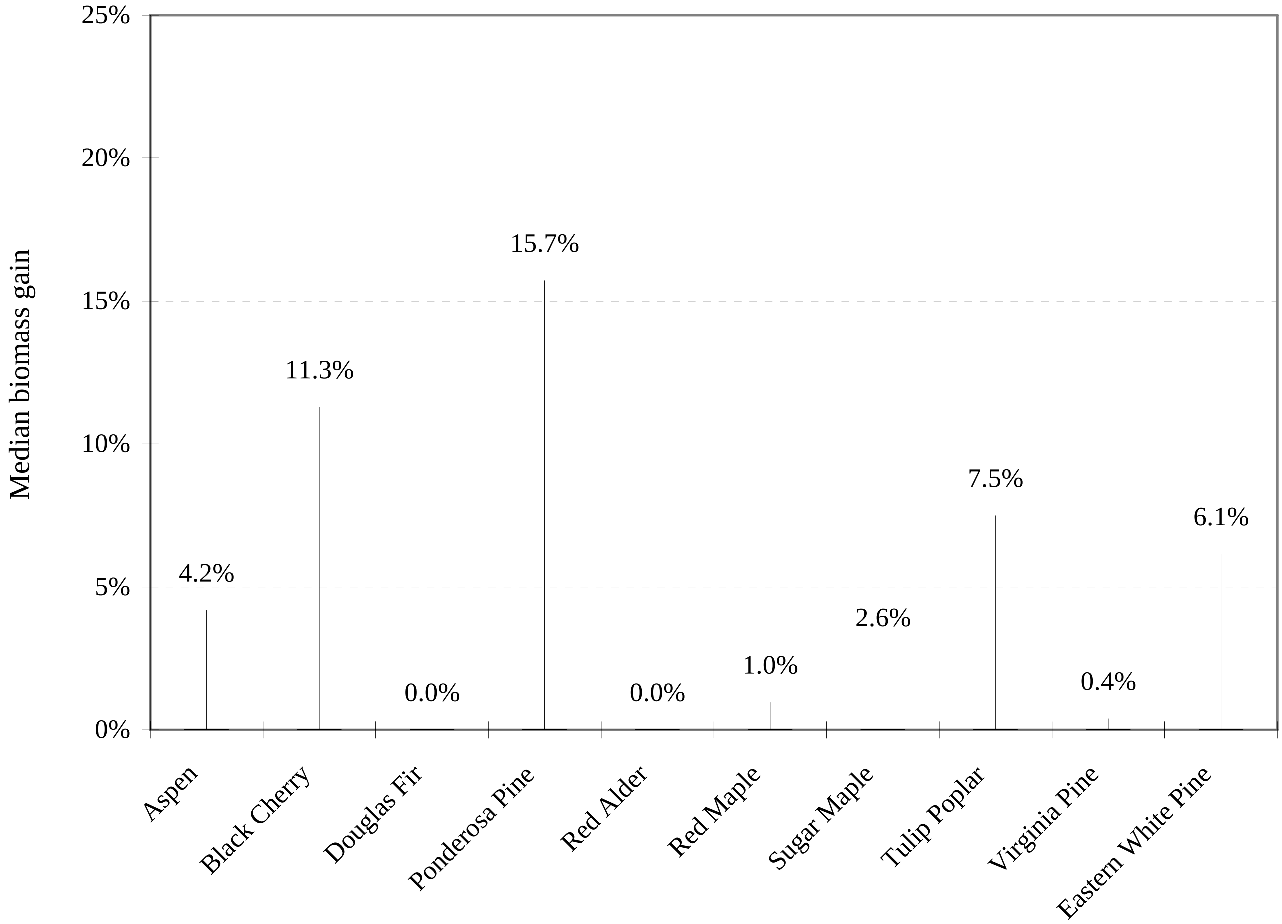


Figure H-6: Median Tree Seedling Biomass Gain from Baseline – 21 ppm-hr Rollback (reduced W126)

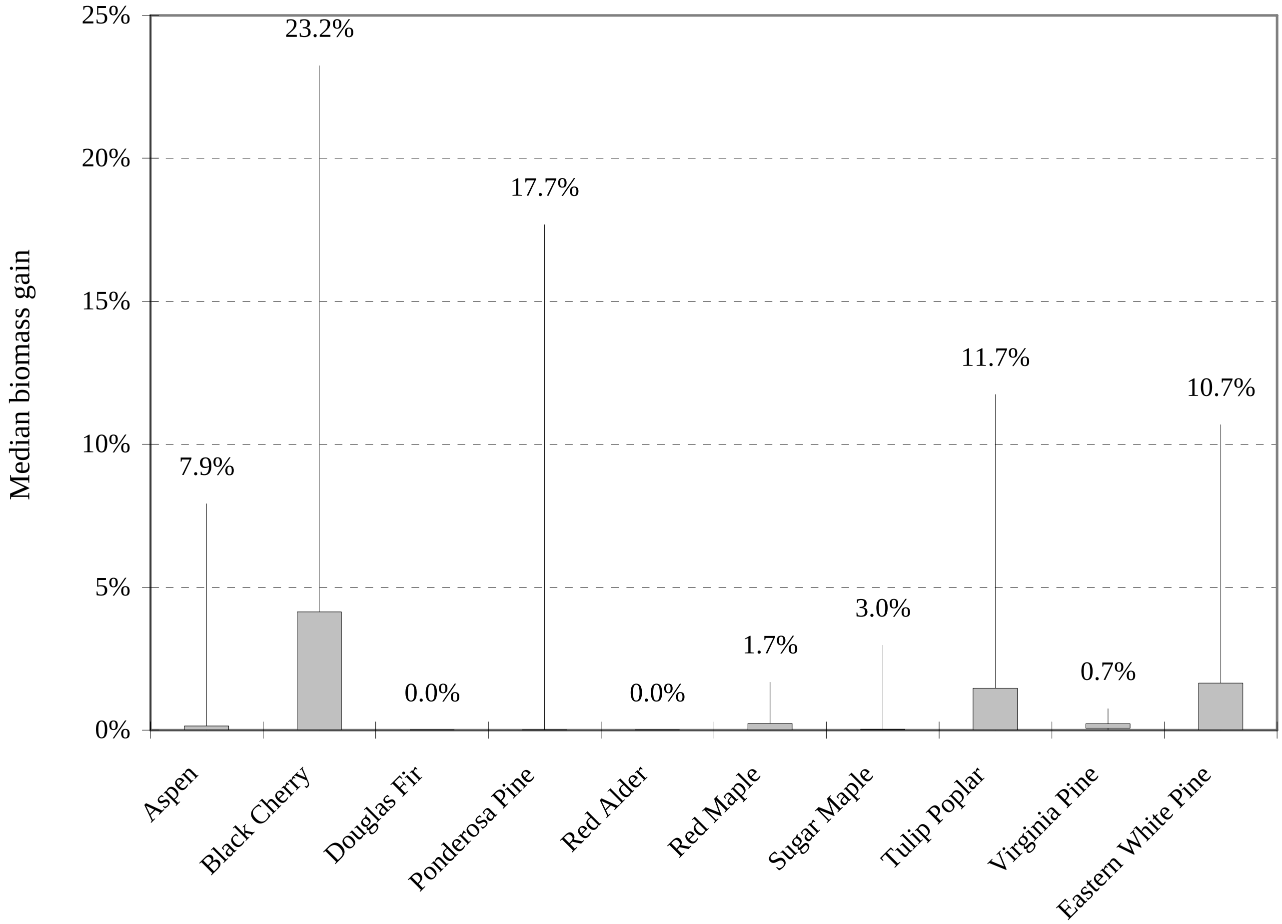


Figure H-7: Median Tree Seedling Biomass Gain from Baseline – 13 ppm-hr Rollback (reduced W126)

H.1.2 Summary Statistics of Concentration Responses for Tree Seedlings

Table H-1: Absolute Tree Seedling Biomass Loss - 2001 Baseline (reduced W126)

Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	11.5%	0.1%	2.7%	2.0%	2.5%
Black Cherry	19,860	40.9%	2.8%	17.2%	16.8%	6.5%
Douglas Fir	538	0.0%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	19.9%	0.1%	1.3%	0.8%	5.5%
Red Alder	103	0.6%	0.0%	0.1%	0.1%	0.3%
Red Maple	17,889	2.3%	0.1%	0.6%	0.6%	0.3%
Sugar Maple	11,396	3.0%	0.0%	0.1%	0.0%	0.2%
Tulip Poplar	13,551	13.5%	0.0%	2.3%	2.0%	1.9%
Virginia Pine	3,632	1.2%	0.3%	0.6%	0.6%	0.2%
Eastern White Pine	6,874	13.6%	0.2%	3.2%	2.9%	2.4%

Table H-2: Median Tree Seedling Biomass Gain – 84 ppb Rollback (reduced W126)

Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	5.8%	0.0%	0.1%	0.0%	0.6%
Black Cherry	19,860	16.8%	0.0%	0.4%	0.0%	1.6%
Douglas Fir	538	0.0%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	9.3%	0.0%	0.1%	0.0%	2.1%
Red Alder	103	0.0%	0.0%	0.0%	0.0%	0.0%
Red Maple	17,889	1.3%	0.0%	0.0%	0.0%	0.1%
Sugar Maple	11,396	2.8%	0.0%	0.0%	0.0%	0.1%
Tulip Poplar	13,551	9.9%	0.0%	0.2%	0.0%	0.9%
Virginia Pine	3,632	0.6%	0.0%	0.0%	0.0%	0.1%
Eastern White Pine	6,874	7.8%	0.0%	0.3%	0.0%	0.9%

Table H-3: Median Tree Seedling Biomass Gain – 70 ppb Rollback (reduced W126)

Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	9.3%	0.0%	1.1%	0.0%	1.9%
Black Cherry	19,860	28.6%	0.0%	5.4%	4.0%	5.3%
Douglas Fir	538	0.0%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	15.7%	0.0%	0.3%	0.0%	4.1%
Red Alder	103	0.0%	0.0%	0.0%	0.0%	0.0%
Red Maple	17,889	1.9%	0.0%	0.3%	0.2%	0.3%
Sugar Maple	11,396	3.0%	0.0%	0.1%	0.0%	0.2%
Tulip Poplar	13,551	12.7%	0.0%	1.6%	1.1%	1.8%
Virginia Pine	3,632	0.9%	0.0%	0.3%	0.3%	0.2%
Eastern White Pine	6,874	11.7%	0.0%	2.1%	1.7%	2.1%

Table H-4: Median Tree Seedling Biomass Gain – 25 ppm-hr Rollback (reduced W126)

Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	5.3%	0.0%	0.1%	0.0%	0.5%
Black Cherry	19,860	15.4%	0.0%	0.3%	0.0%	1.4%
Douglas Fir	538	0.0%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	16.8%	0.0%	0.2%	0.0%	3.8%
Red Alder	103	0.0%	0.0%	0.0%	0.0%	0.0%
Red Maple	17,889	1.2%	0.0%	0.0%	0.0%	0.1%
Sugar Maple	11,396	2.8%	0.0%	0.0%	0.0%	0.1%
Tulip Poplar	13,551	8.4%	0.0%	0.2%	0.0%	0.8%
Virginia Pine	3,632	0.5%	0.0%	0.0%	0.0%	0.1%
Eastern White Pine	6,874	8.0%	0.0%	0.2%	0.0%	0.8%

Table H-5: Median Tree Seedling Biomass Gain – 15 ppm-hr Rollback (reduced W126)

Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	8.5%	0.0%	0.6%	0.0%	1.5%
Black Cherry	19,860	25.0%	0.0%	3.4%	0.9%	4.6%
Douglas Fir	538	0.0%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	17.7%	0.0%	0.3%	0.0%	4.5%
Red Alder	103	0.0%	0.0%	0.0%	0.0%	0.0%
Red Maple	17,889	1.8%	0.0%	0.2%	0.1%	0.3%
Sugar Maple	11,396	3.0%	0.0%	0.1%	0.0%	0.2%
Tulip Poplar	13,551	12.1%	0.0%	1.2%	0.7%	1.7%
Virginia Pine	3,632	0.8%	0.0%	0.2%	0.2%	0.2%
Eastern White Pine	6,874	11.2%	0.0%	1.3%	0.0%	1.9%

Table H-6: Median Tree Seedling Biomass Gain – 21 ppm-hr Rollback (reduced W126)

Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	4.2%	0.0%	0.0%	0.0%	0.3%
Black Cherry	19,860	11.3%	0.0%	0.1%	0.0%	0.8%
Douglas Fir	538	0.0%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	15.7%	0.0%	0.2%	0.0%	3.4%
Red Alder	103	0.0%	0.0%	0.0%	0.0%	0.0%
Red Maple	17,889	1.0%	0.0%	0.0%	0.0%	0.1%
Sugar Maple	11,396	2.6%	0.0%	0.0%	0.0%	0.1%
Tulip Poplar	13,551	7.5%	0.0%	0.1%	0.0%	0.5%
Virginia Pine	3,632	0.4%	0.0%	0.0%	0.0%	0.1%
Eastern White Pine	6,874	6.1%	0.0%	0.1%	0.0%	0.5%

Table H-7: Median Tree Seedling Biomass Gain – 13 ppm-hr Rollback (reduced W126)

Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	7.9%	0.0%	0.5%	0.0%	1.3%
Black Cherry	19,860	23.2%	0.0%	2.4%	0.0%	3.8%
Douglas Fir	538	0.0%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	17.7%	0.0%	0.3%	0.0%	4.4%
Red Alder	103	0.0%	0.0%	0.0%	0.0%	0.0%
Red Maple	17,889	1.7%	0.0%	0.1%	0.0%	0.2%
Sugar Maple	11,396	3.0%	0.0%	0.1%	0.0%	0.2%
Tulip Poplar	13,551	11.7%	0.0%	1.0%	0.3%	1.5%
Virginia Pine	3,632	0.7%	0.0%	0.2%	0.1%	0.1%
Eastern White Pine	6,874	10.7%	0.0%	1.1%	0.0%	1.7%

H.2.3 Seedling Biomass Response Maps for Selected Tree Species:

Response maps for aspen, ponderosa pine and black cherry based on the reduced O_3 metric are presented in the body of the document under Section 5.

H.2 Tree Seedling Biomass Responses based on Non-Adjusted W126 Metric

This section include summary tables and maps showing concentration responses for tree seedlings based on *unreduced* hourly O_3 values.

H.2.1 Median Concentration Responses for Tree Seedlings

The following box plots and tables show count, mean, maximum, minimum, median, and standard deviation statistics for the ten tree species and the six O_3 standards under consideration. The concentration responses were derived from *unreduced* hourly O_3 values.

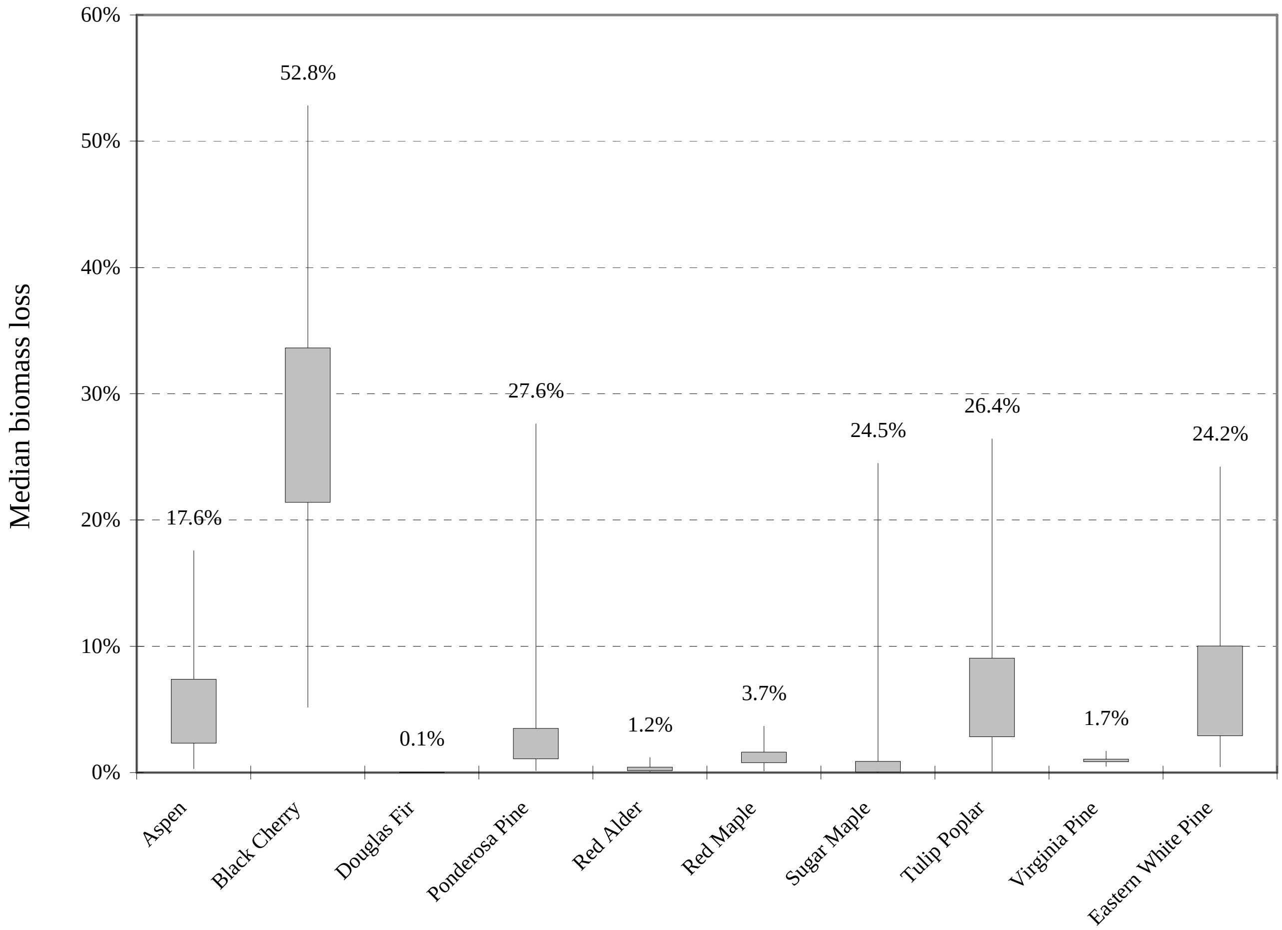


Figure H-8: Median Tree Seedling Biomass Loss - 2001 Baseline (unreduced W126)

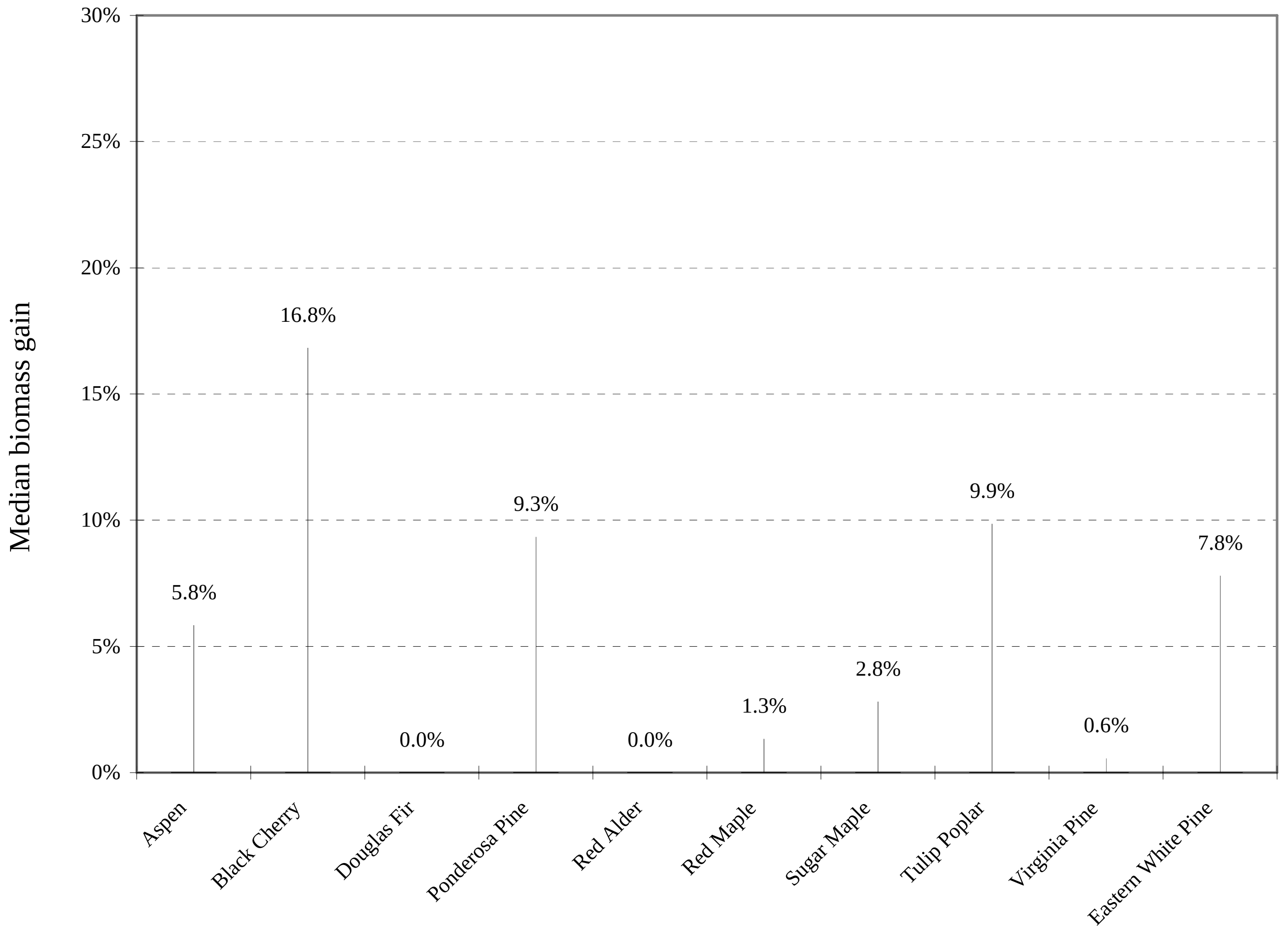


Figure H-9: Median Tree Seedling Biomass Gain from Baseline - 84 ppb Rollback (unreduced W126)

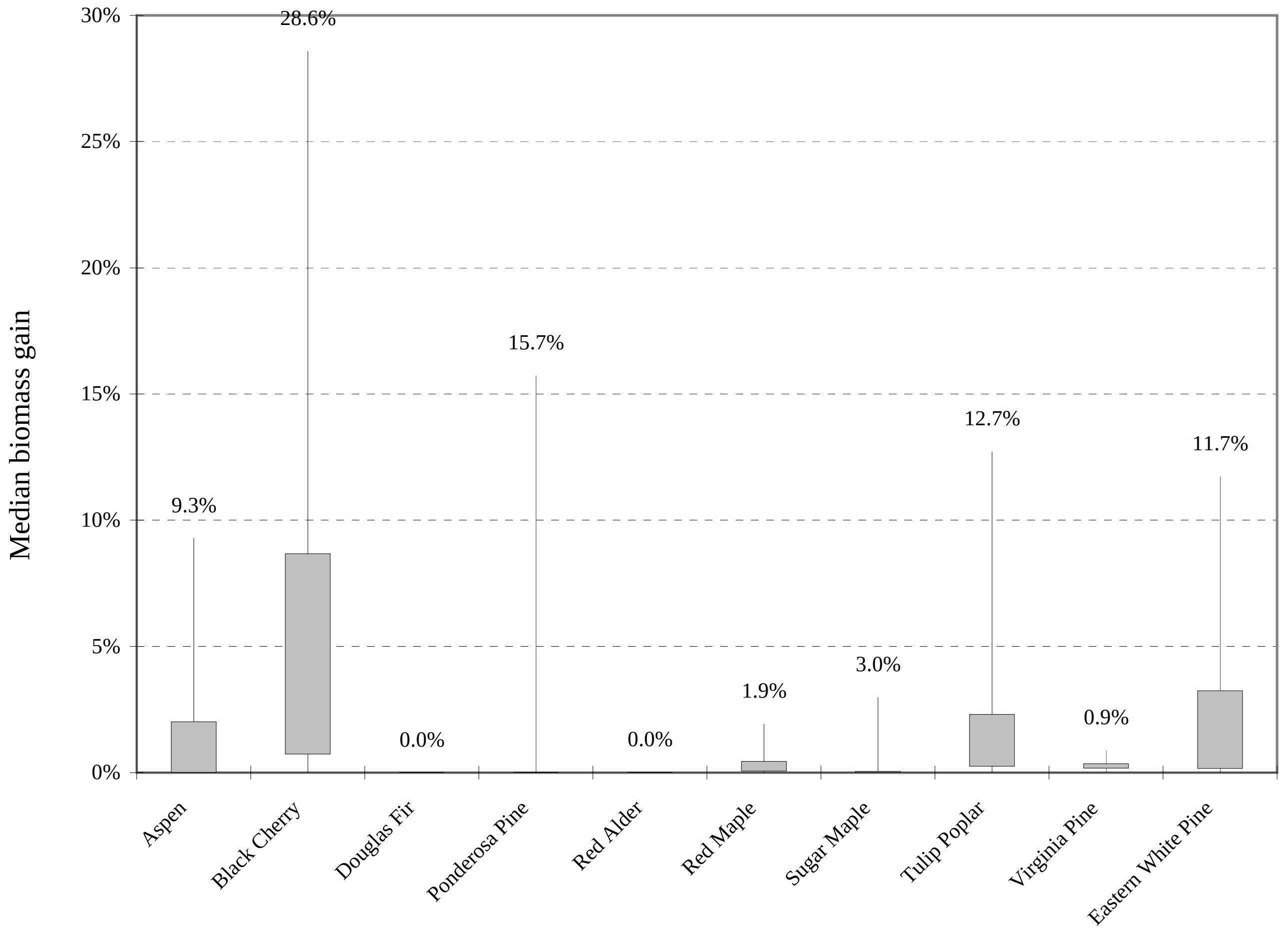


Figure H-10: Median Tree Seedling Biomass Gain from Baseline - 70 ppb Rollback (unreduced W126)

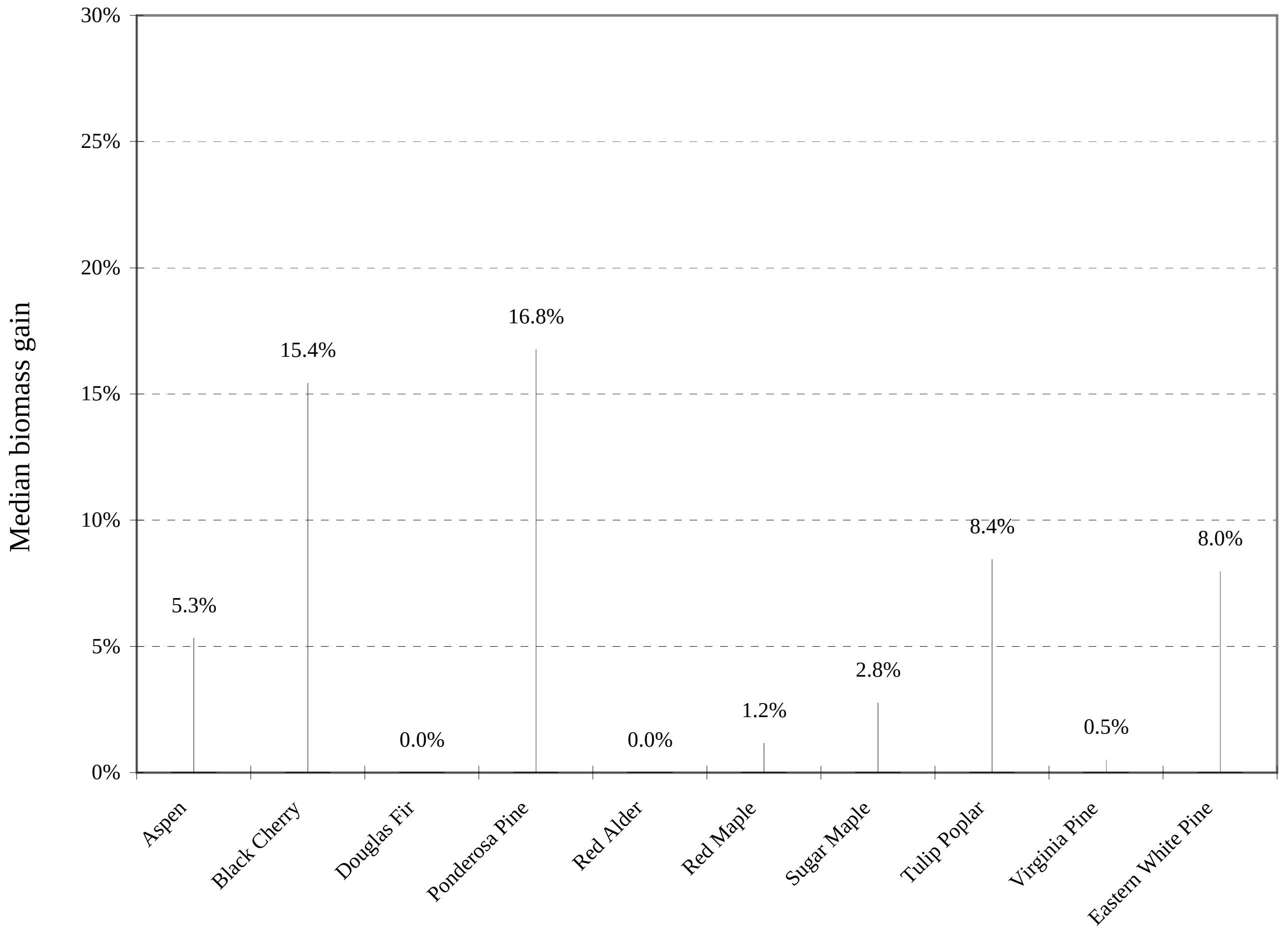


Figure H-11: Median Tree Seedling Biomass Gain from Baseline - 25 ppm-hr Rollback (unreduced W126)

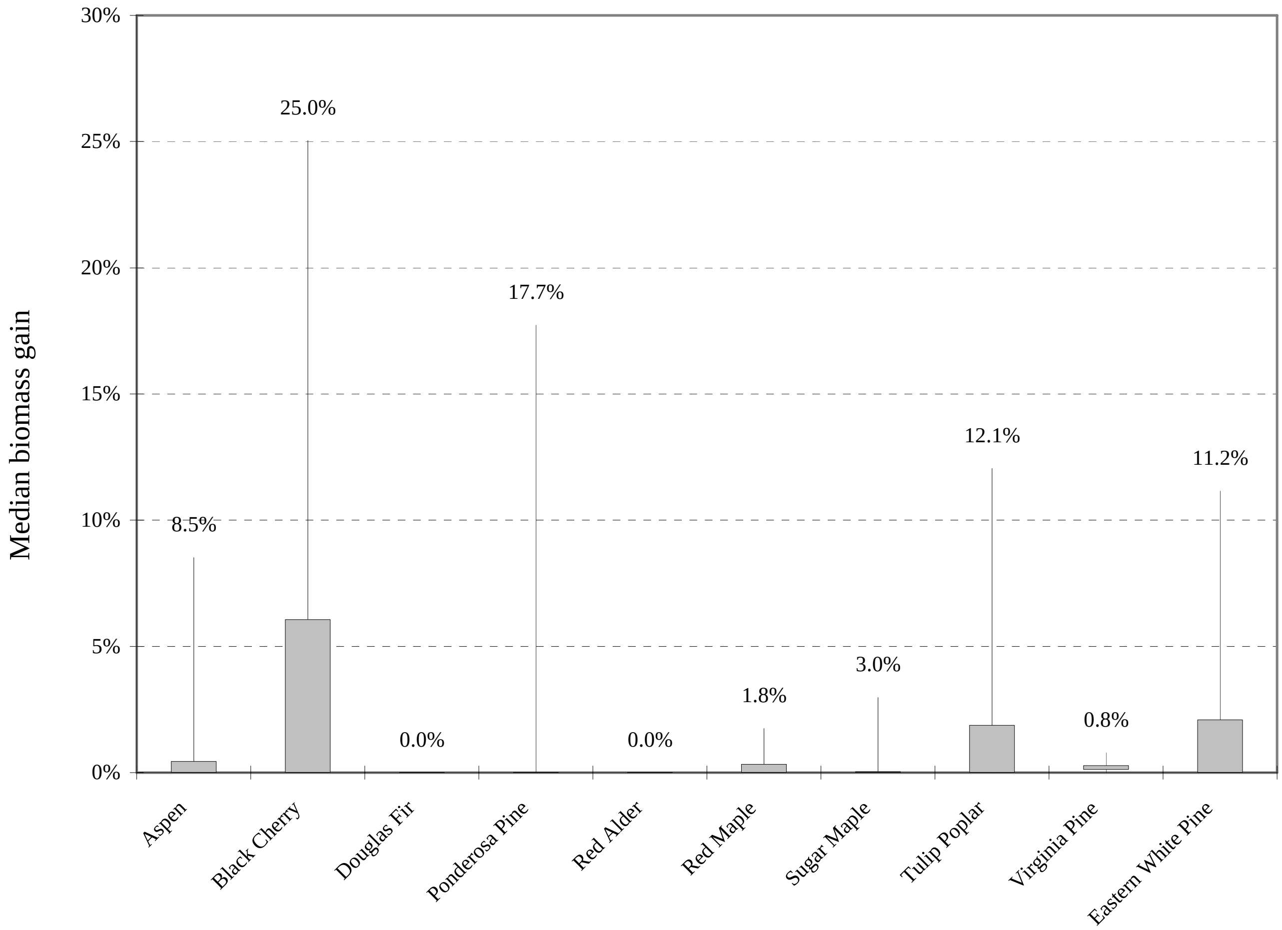


Figure H-12: Median Tree Seedling Biomass Gain from Baseline – 15 ppm-hr Rollback (unreduced W126)

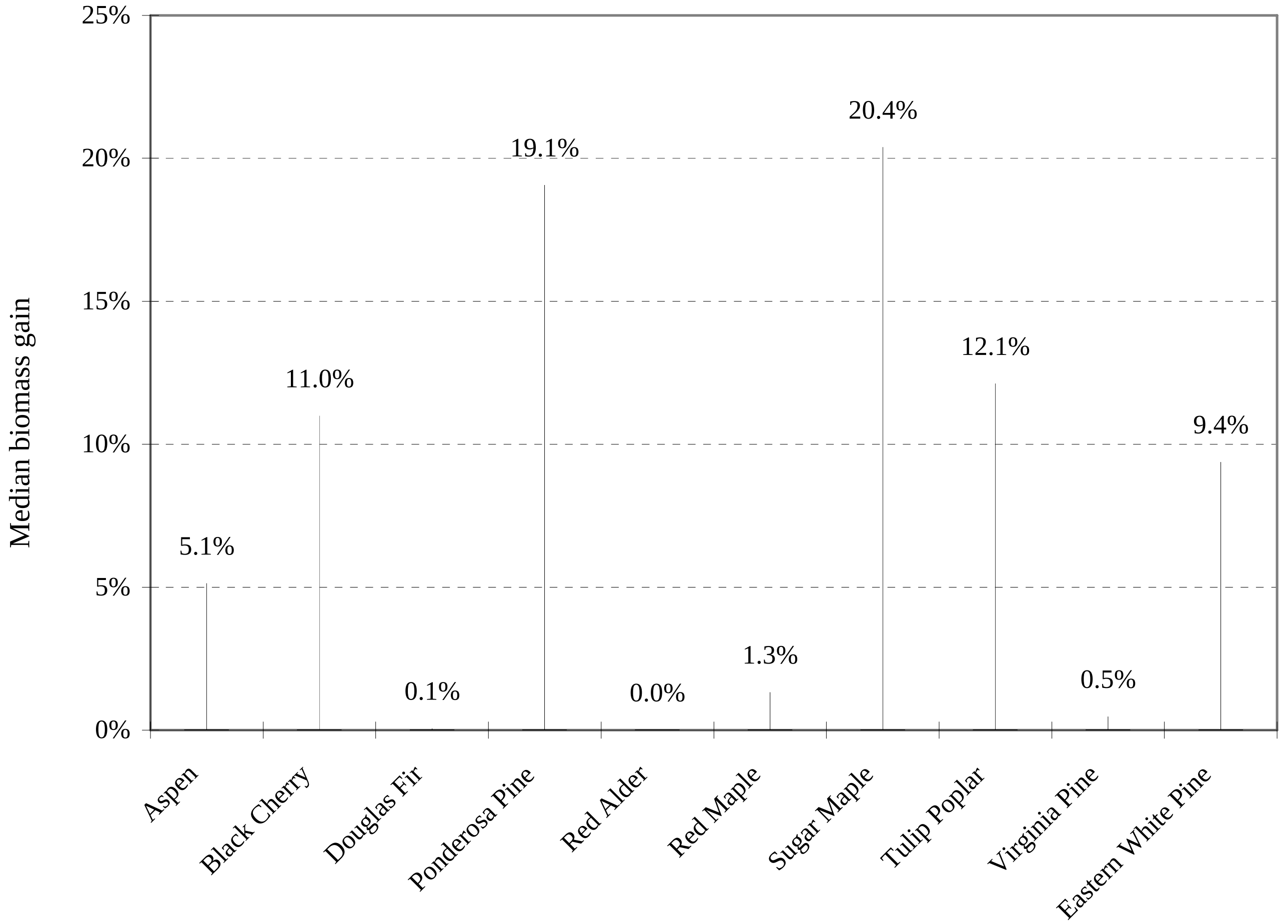


Figure H-13: Median Tree Seedling Biomass Gain from Baseline – 21 ppm-hr Rollback (unreduced W126)

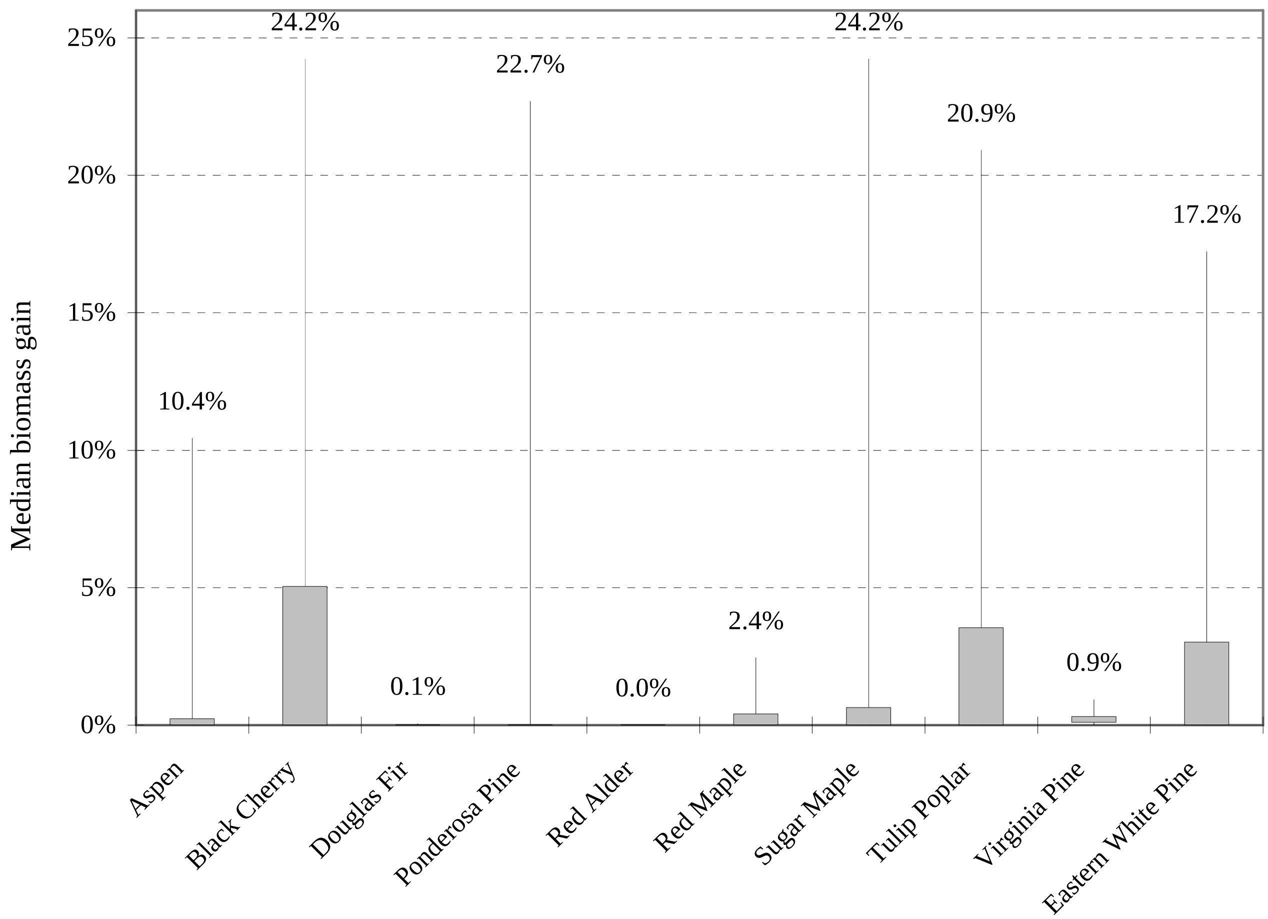


Figure H-14: Median Tree Seedling Biomass Gain from Baseline – 13 ppm-hr Rollback (unreduced W126)

H.2.2 Summary Statistics of Concentration Responses for Tree Seedlings

Table H-8: Tree Seedling Biomass Loss - 2001 Baseline (unreduced W126)

Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	17.6%	0.3%	5.1%	4.1%	4.0%
Black Cherry	19,860	52.8%	5.2%	27.3%	27.4%	8.6%
Douglas Fir	538	0.1%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	27.6%	0.2%	2.7%	1.7%	8.7%
Red Alder	103	1.2%	0.1%	0.3%	0.2%	0.7%
Red Maple	17,889	3.7%	0.1%	1.2%	1.2%	0.6%
Sugar Maple	11,396	24.5%	0.0%	0.8%	0.2%	1.8%
Tulip Poplar	13,551	26.4%	0.1%	6.4%	6.2%	4.4%
Virginia Pine	3,632	1.7%	0.5%	1.0%	1.0%	0.2%
Eastern White Pine	6,874	24.2%	0.4%	6.9%	6.6%	4.6%

Table H-9: Median Tree Seedling Biomass Gain from Baseline – 84 ppb Rollback (unreduced W126)

Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	5.8%	0.0%	0.1%	0.0%	0.6%
Black Cherry	19,860	16.8%	0.0%	0.4%	0.0%	1.7%
Douglas Fir	538	0.0%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	10.0%	0.0%	0.1%	0.0%	2.3%
Red Alder	103	0.0%	0.0%	0.0%	0.0%	0.0%
Red Maple	17,889	1.9%	0.0%	0.0%	0.0%	0.2%
Sugar Maple	11,396	20.5%	0.0%	0.2%	0.0%	1.2%
Tulip Poplar	13,551	16.7%	0.0%	0.4%	0.0%	1.6%
Virginia Pine	3,632	0.7%	0.0%	0.0%	0.0%	0.1%
Eastern White Pine	6,874	11.5%	0.0%	0.5%	0.0%	1.4%

Table H-10: Median Tree Seedling Biomass Gain from Baseline – 70 ppb Rollback (unreduced W126)

Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	9.3%	0.0%	1.1%	0.0%	1.9%
Black Cherry	19,860	31.2%	0.0%	6.8%	5.4%	6.3%
Douglas Fir	538	0.1%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	19.1%	0.0%	0.4%	0.0%	5.3%
Red Alder	103	0.0%	0.0%	0.0%	0.0%	0.0%
Red Maple	17,889	2.9%	0.0%	0.5%	0.4%	0.5%
Sugar Maple	11,396	24.3%	0.0%	0.8%	0.2%	1.8%
Tulip Poplar	13,551	23.6%	0.0%	3.8%	3.1%	3.8%
Virginia Pine	3,632	1.1%	0.0%	0.4%	0.4%	0.2%
Eastern White Pine	6,874	18.4%	0.0%	3.9%	3.4%	3.7%

Table H-11: Median Tree Seedling Biomass Gain from Baseline – 25 ppm-hr Rollback (unreduced W126)

Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	5.3%	0.0%	0.1%	0.0%	0.5%
Black Cherry	19,860	15.8%	0.0%	0.3%	0.0%	1.4%
Douglas Fir	538	0.1%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	20.9%	0.0%	0.2%	0.0%	4.8%
Red Alder	103	0.0%	0.0%	0.0%	0.0%	0.0%
Red Maple	17,889	1.8%	0.0%	0.0%	0.0%	0.1%
Sugar Maple	11,396	22.9%	0.0%	0.3%	0.0%	1.3%
Tulip Poplar	13,551	16.0%	0.0%	0.4%	0.0%	1.4%
Virginia Pine	3,632	0.7%	0.0%	0.0%	0.0%	0.1%
Eastern White Pine	6,874	12.7%	0.0%	0.3%	0.0%	1.2%

Table H-12: Median Tree Seedling Biomass Gain from Baseline – 15 ppm-hr Rollback (unreduced W126)

Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	8.5%	0.0%	0.6%	0.0%	1.5%
Black Cherry	19,860	26.8%	0.0%	4.2%	1.2%	5.4%
Douglas Fir	538	0.1%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	22.8%	0.0%	0.4%	0.0%	6.1%
Red Alder	103	0.0%	0.0%	0.0%	0.0%	0.0%
Red Maple	17,889	2.6%	0.0%	0.3%	0.1%	0.4%
Sugar Maple	11,396	24.4%	0.0%	0.7%	0.1%	1.8%
Tulip Poplar	13,551	22.0%	0.0%	2.9%	1.7%	3.6%
Virginia Pine	3,632	1.0%	0.0%	0.3%	0.3%	0.2%
Eastern White Pine	6,874	18.4%	0.0%	2.3%	0.0%	3.4%

Table H-13: Median Tree Seedling Biomass Loss – 21 ppm-hr W126 Rollback (unreduced W126)

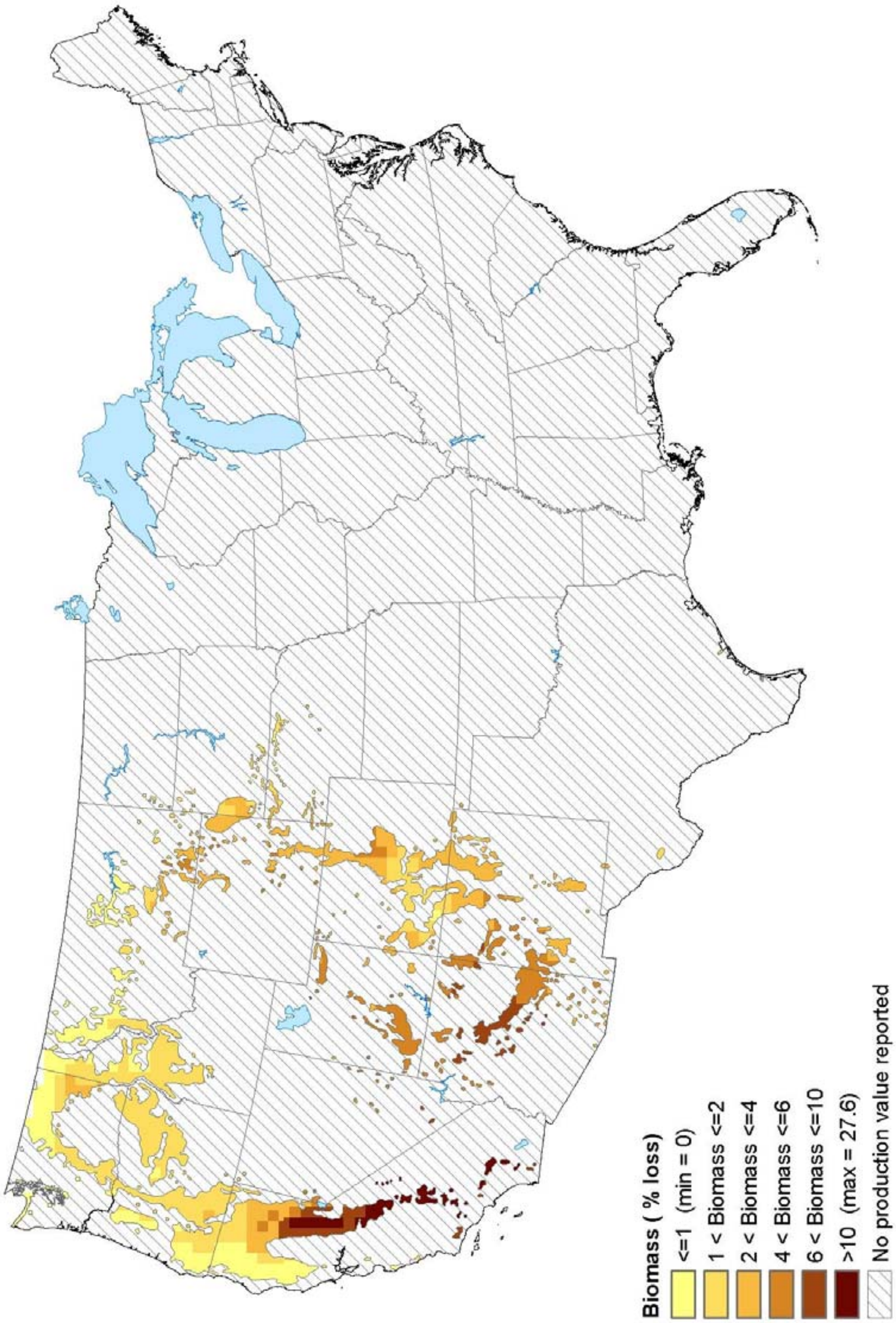
Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	5.1%	0.0%	0.0%	0.0%	0.3%
Black Cherry	19,860	11.3%	0.0%	0.1%	0.0%	0.8%
Douglas Fir	538	0.0%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	15.7%	0.0%	0.2%	0.0%	3.4%
Red Alder	103	0.0%	0.0%	0.0%	0.0%	0.0%
Red Maple	17,889	1.0%	0.0%	0.0%	0.0%	0.1%
Sugar Maple	11,396	2.6%	0.0%	0.0%	0.0%	0.1%
Tulip Poplar	13,551	7.5%	0.0%	0.1%	0.0%	0.5%
Virginia Pine	3,632	0.4%	0.0%	0.0%	0.0%	0.1%
Eastern White Pine	6,874	6.1%	0.0%	0.1%	0.0%	0.5%

Table H-14: Median Tree Seedling Biomass Gain from Baseline – 13 ppm-hr W126 Rollback (unreduced W126)

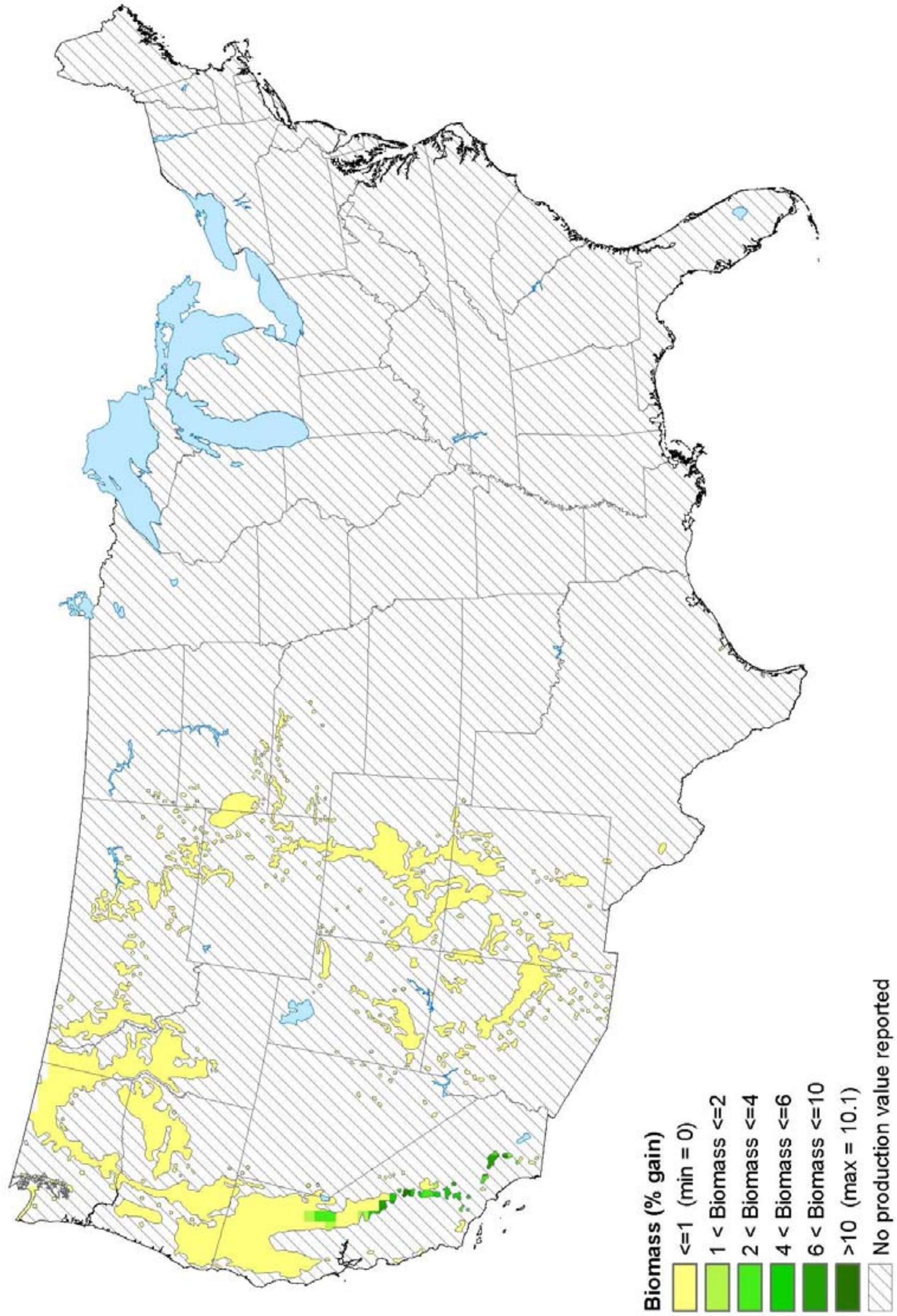
Tree Species	N	Max	Min	Mean	Median	STD
Aspen	8,241	10.4%	0.0%	0.7%	0.0%	1.8%
Black Cherry	19,860	24.2%	0.0%	2.9%	0.0%	4.4%
Douglas Fir	538	0.1%	0.0%	0.0%	0.0%	0.0%
Ponderosa Pine	432	22.7%	0.0%	0.4%	0.0%	5.9%
Red Alder	103	0.0%	0.0%	0.0%	0.0%	0.0%
Red Maple	17,889	2.4%	0.0%	0.2%	0.0%	0.4%
Sugar Maple	11,396	24.2%	0.0%	0.7%	0.0%	1.7%
Tulip Poplar	13,551	20.9%	0.0%	2.2%	0.7%	3.2%
Virginia Pine	3,632	0.9%	0.0%	0.2%	0.2%	0.2%
Eastern White Pine	6,874	17.2%	0.0%	1.8%	0.0%	2.9%

H.2.3 Seedling Biomass Response Maps for Selected Tree Species:

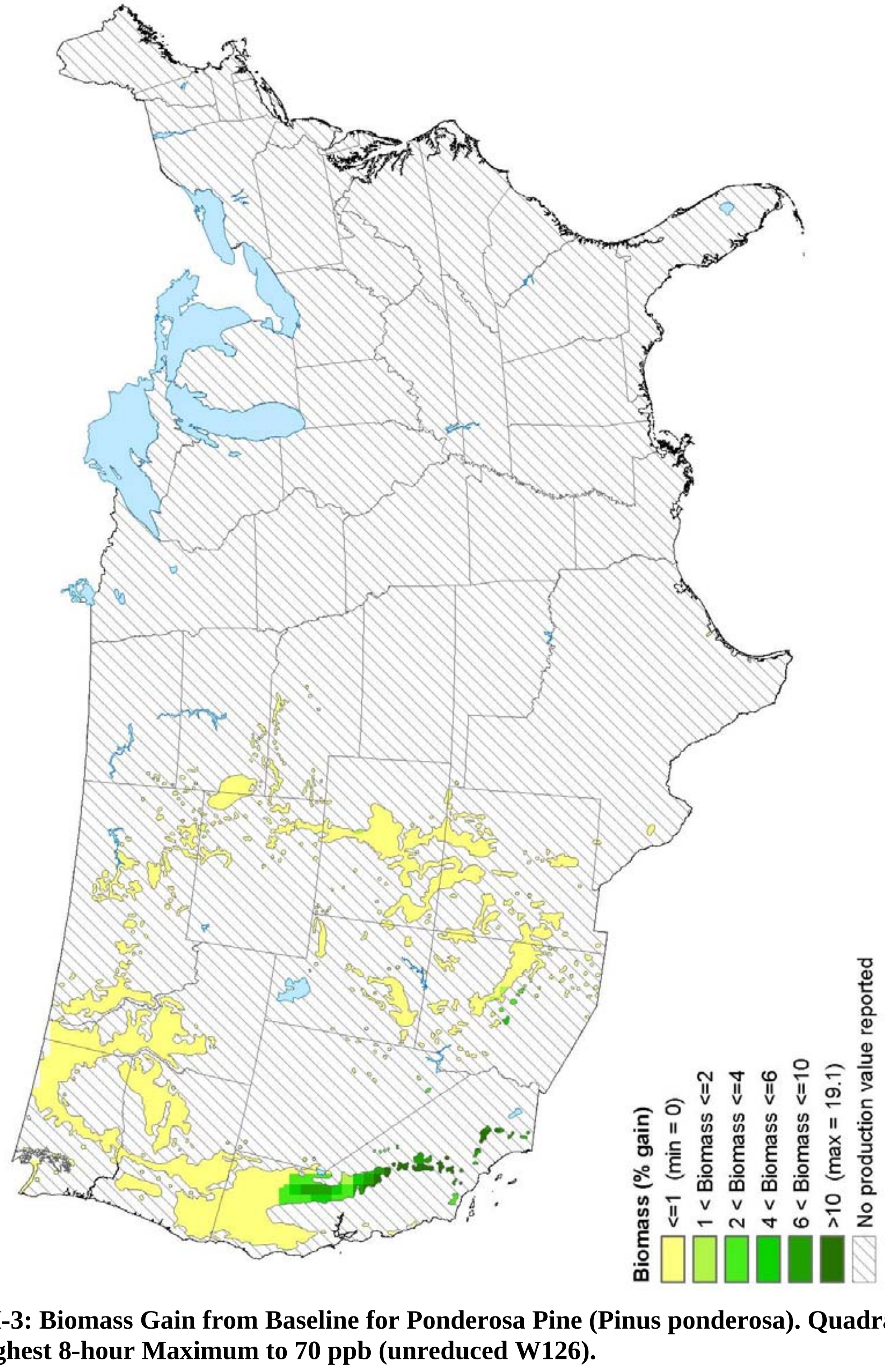
Ponderosa Pine Response Maps



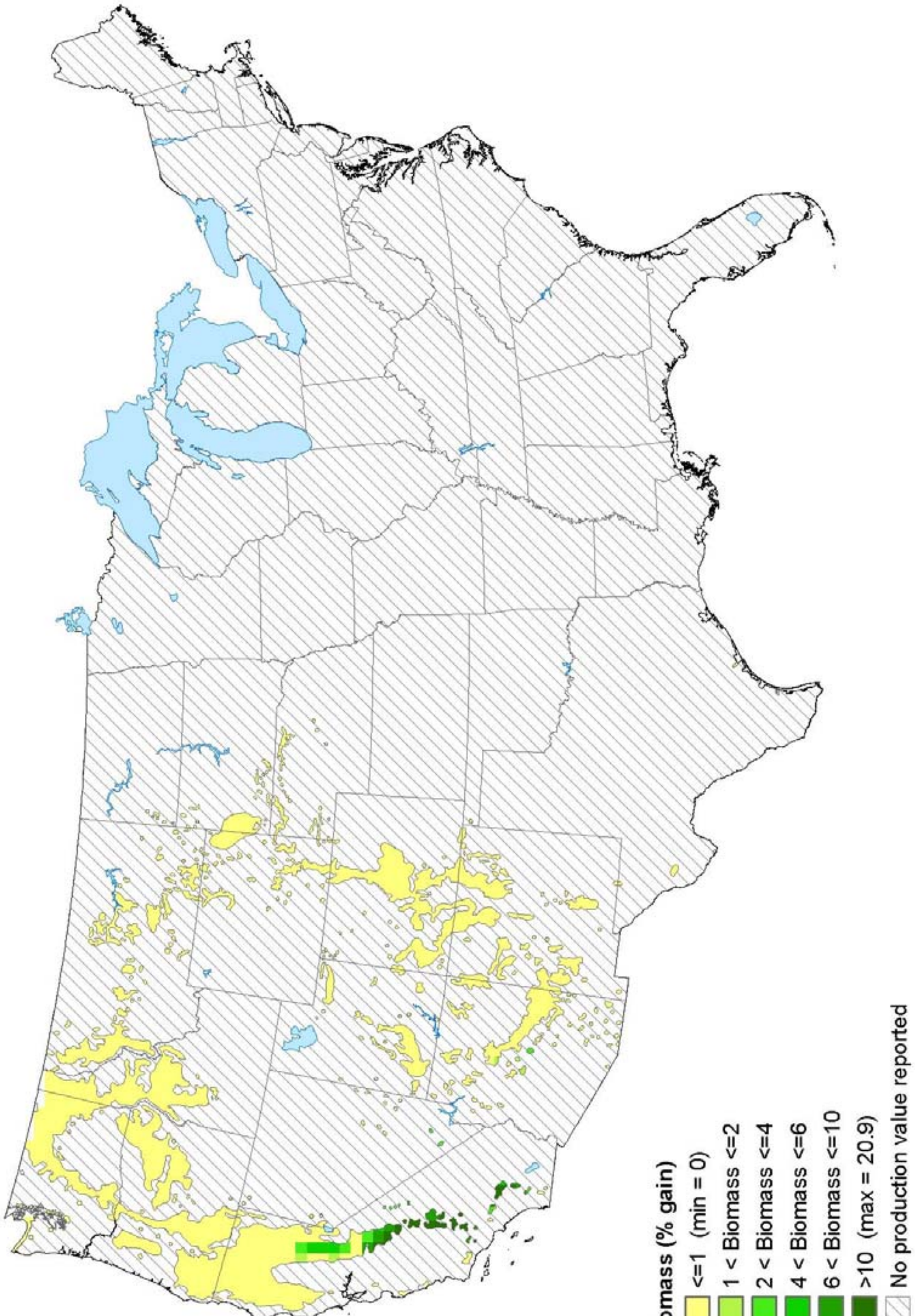
Map H-1: As is Biomass Loss for Ponderosa Pine (Pinus ponderosa) seedlings. April – October (unreduced W126).



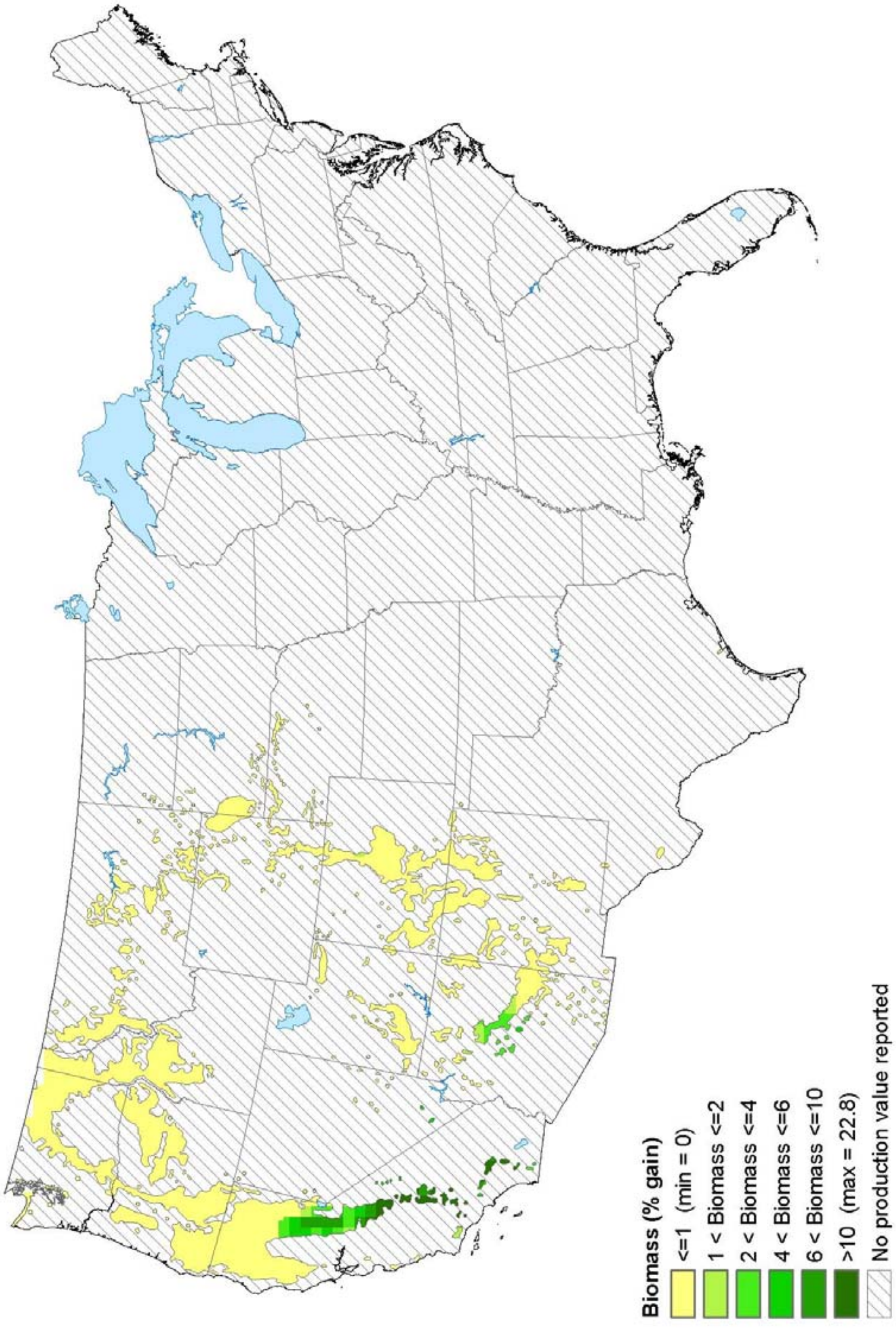
Map H-2: Biomass Gain from Baseline for Ponderosa Pine (Pinus ponderosa). Quadratic Rollback 4th Highest 8-hour Maximum to 84 ppb (unreduced W126).



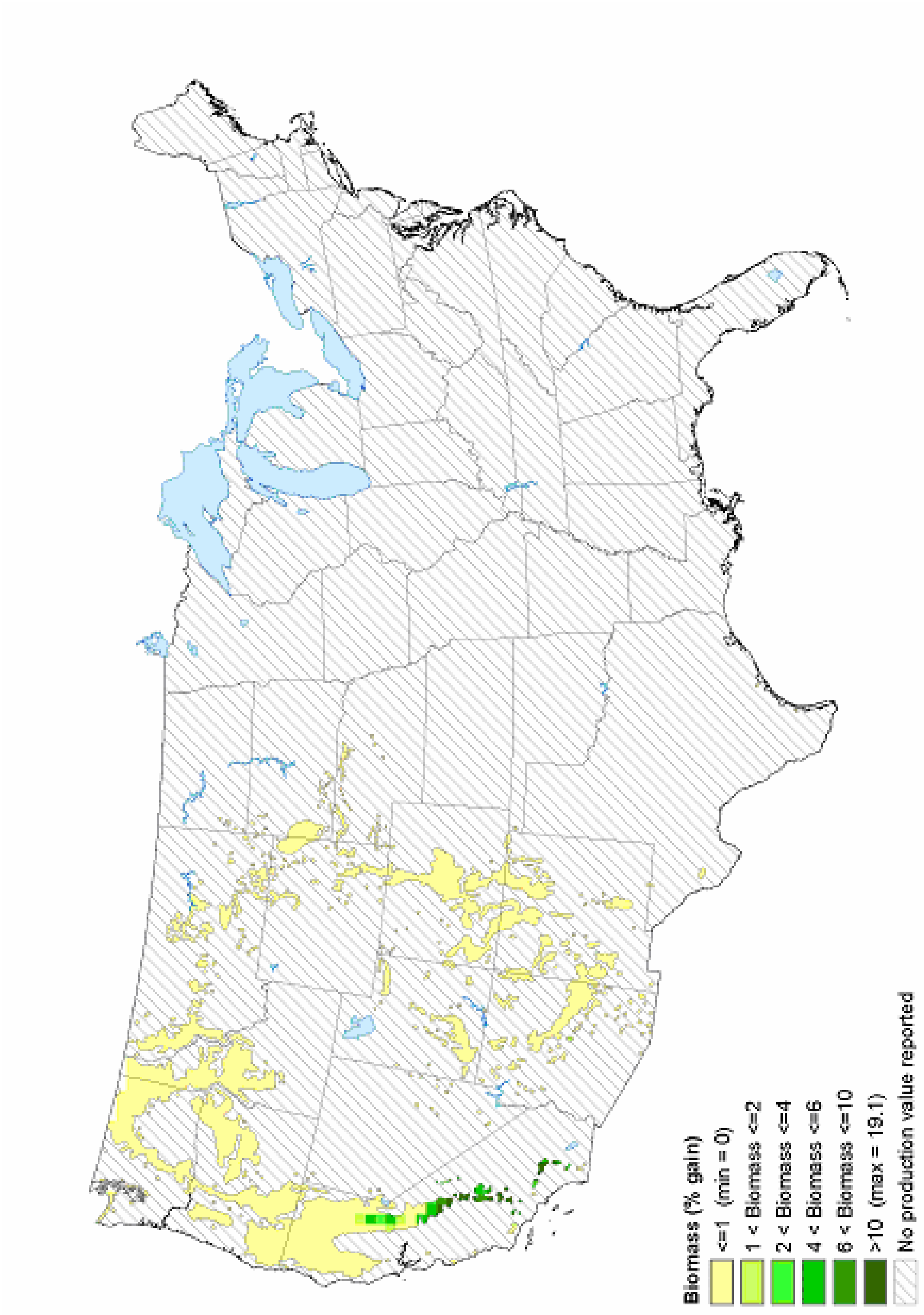
Map H-3: Biomass Gain from Baseline for Ponderosa Pine (Pinus ponderosa). Quadratic Rollback 4th Highest 8-hour Maximum to 70 ppb (unreduced W126).



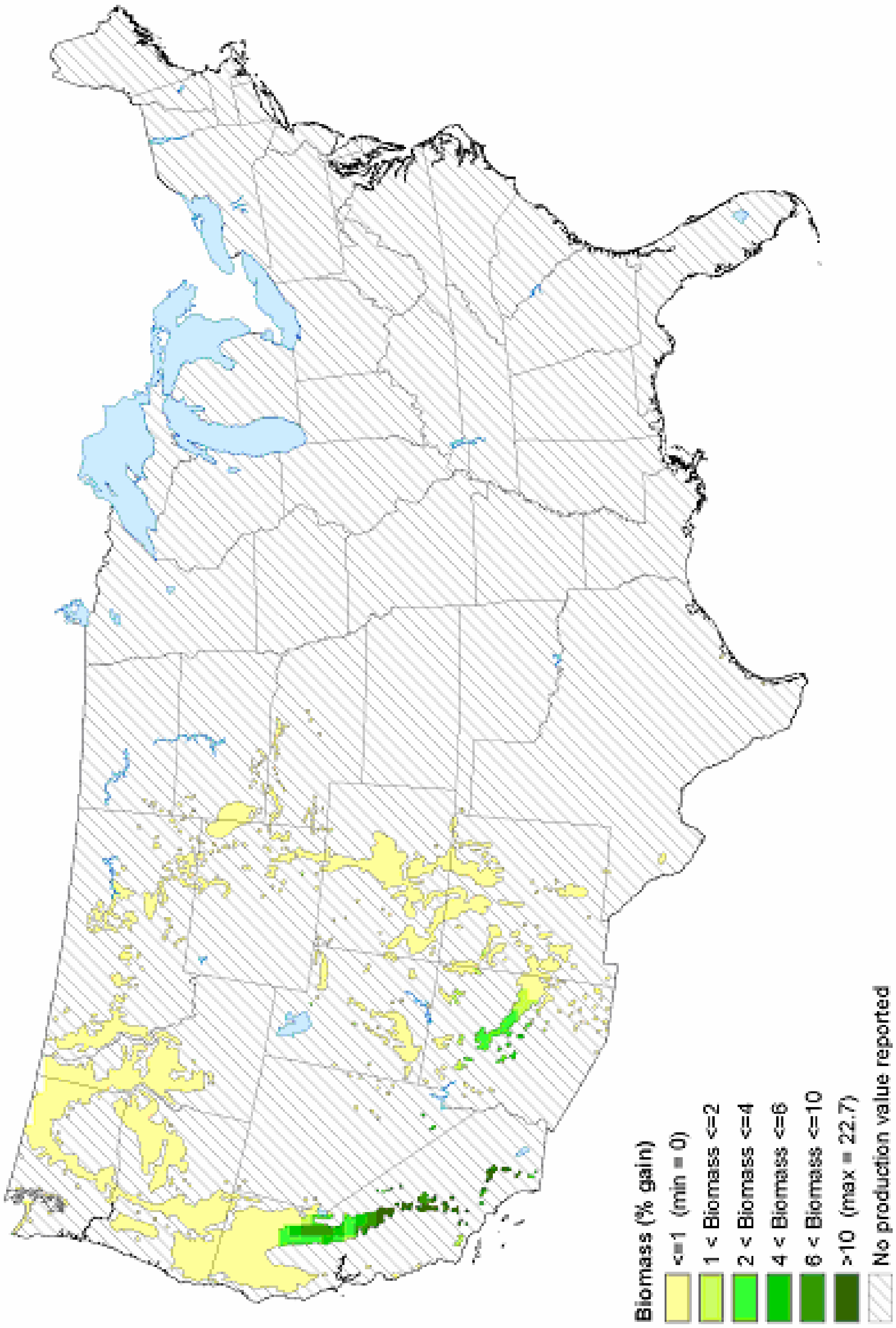
Map H-4: Biomass Gain from Baseline for Ponderosa Pine (Pinus ponderosa). Quadratic Rollback 3-month SUM06 to 25 ppm-hour (unreduced W126).



Map H-5: Biomass Gain from Baseline for Ponderosa Pine (Pinus ponderosa). Quadratic Rollback 3-month SUM06 to 15 ppm-hour (unreduced W126).

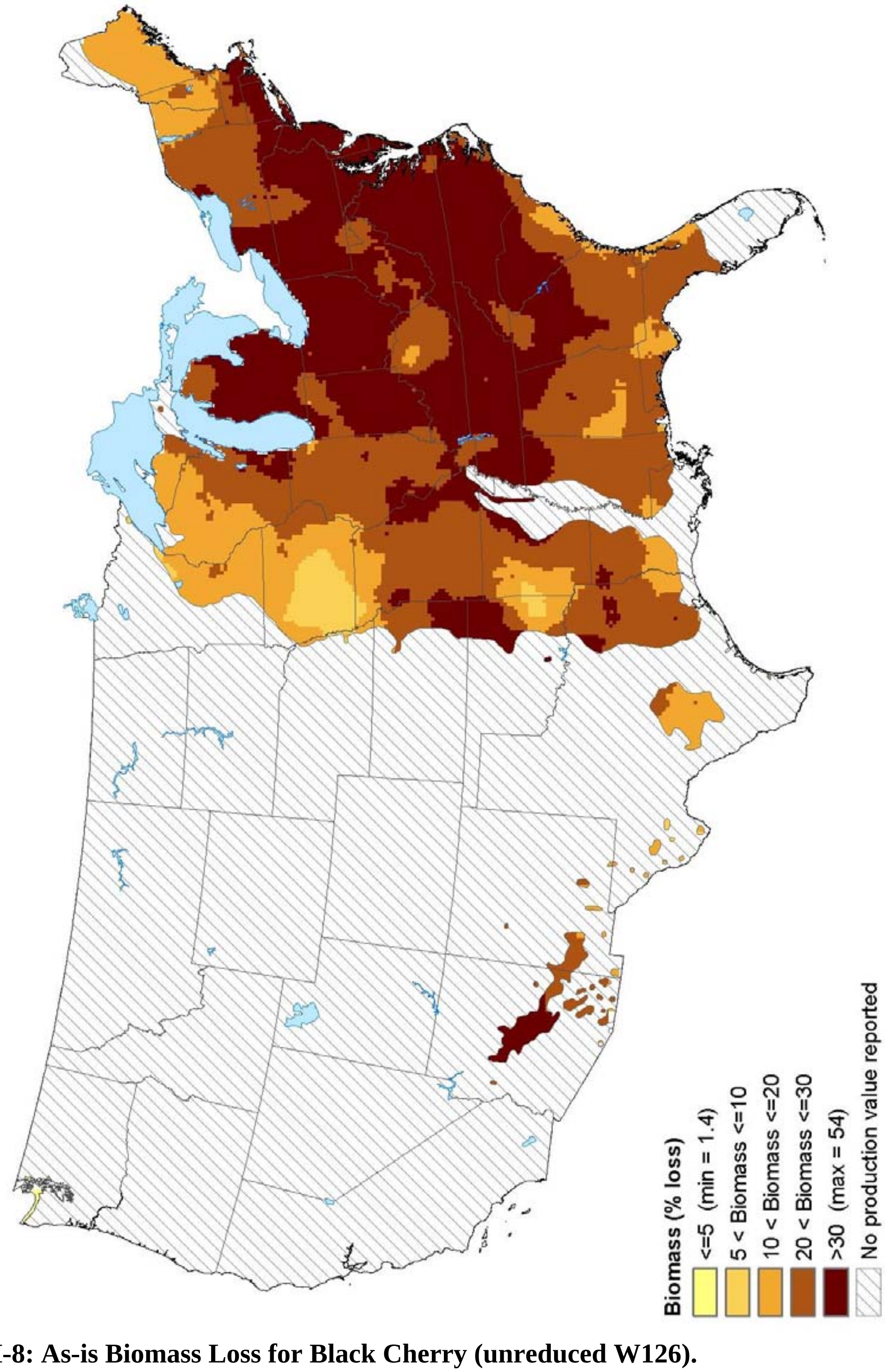


Map H-6: Biomass Gain from Baseline for Ponderosa Pine (Pinus ponderosa). Quadratic Rollback W126 to 21 ppm-hour (unreduced W126).

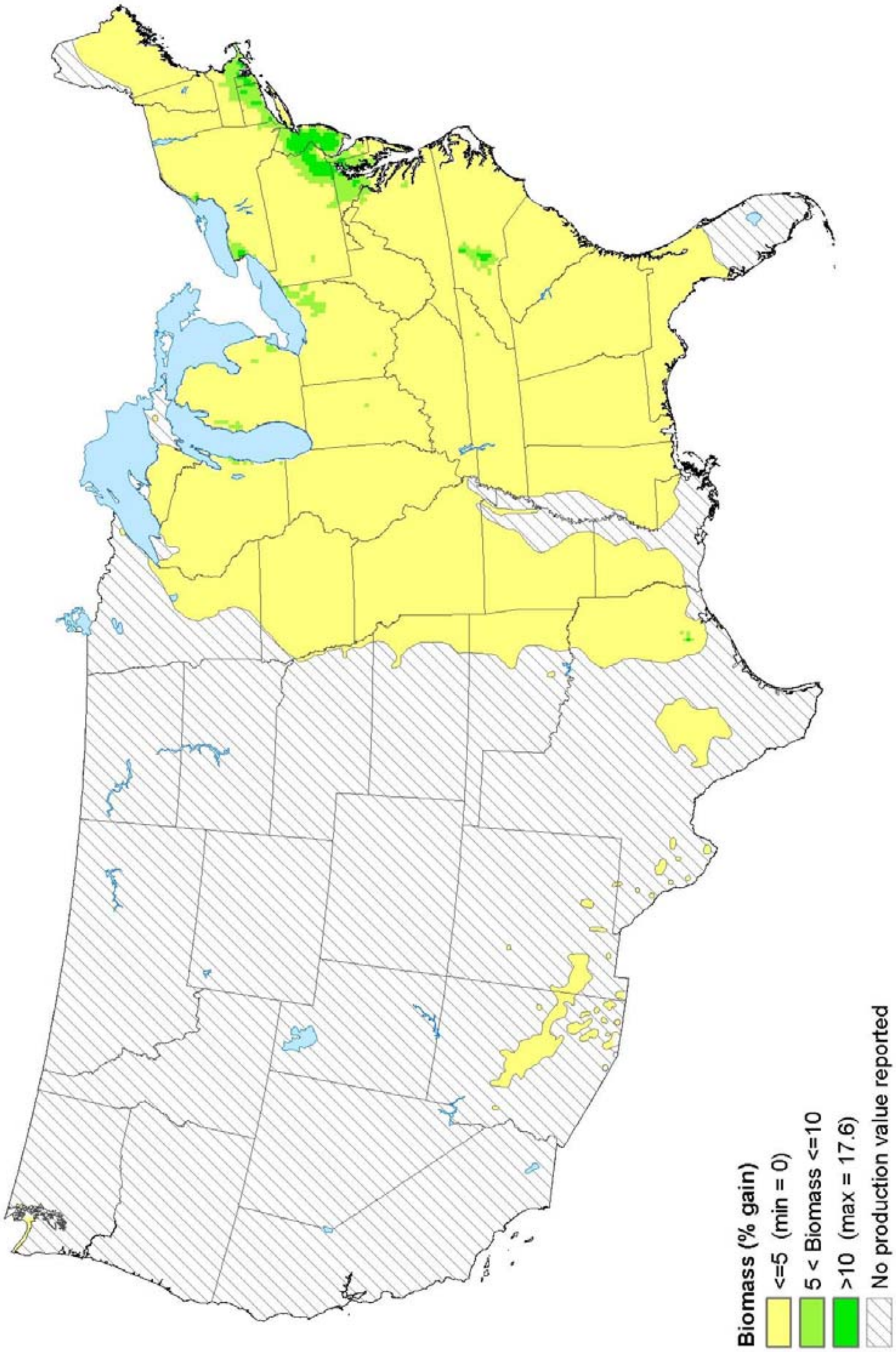


Map H-7: Biomass Gain from Baseline for Ponderosa Pine (Pinus ponderosa). Quadratic Rollback W126 to 13 ppm-hour (unreduced W126).

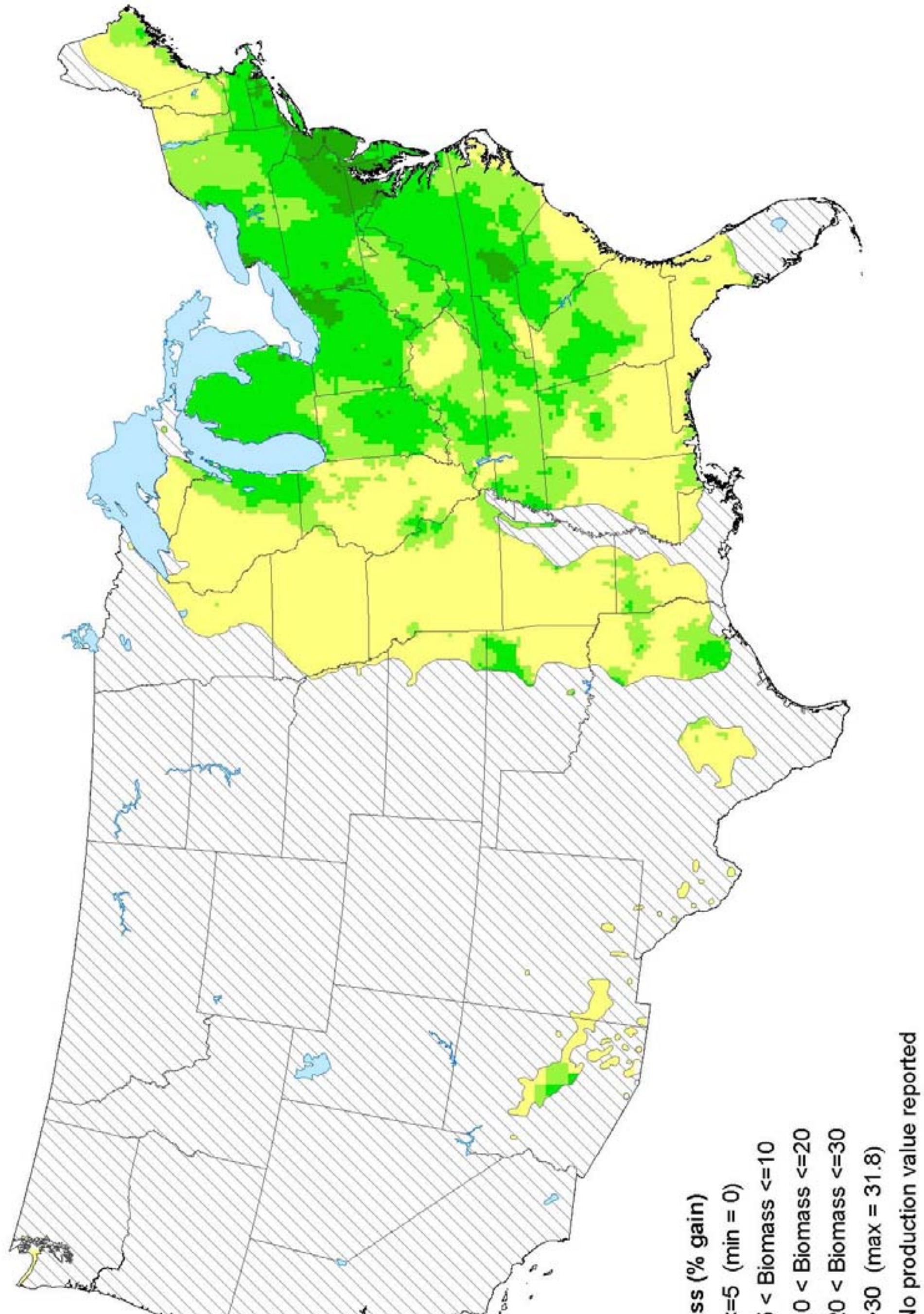
Black Cherry Response Maps



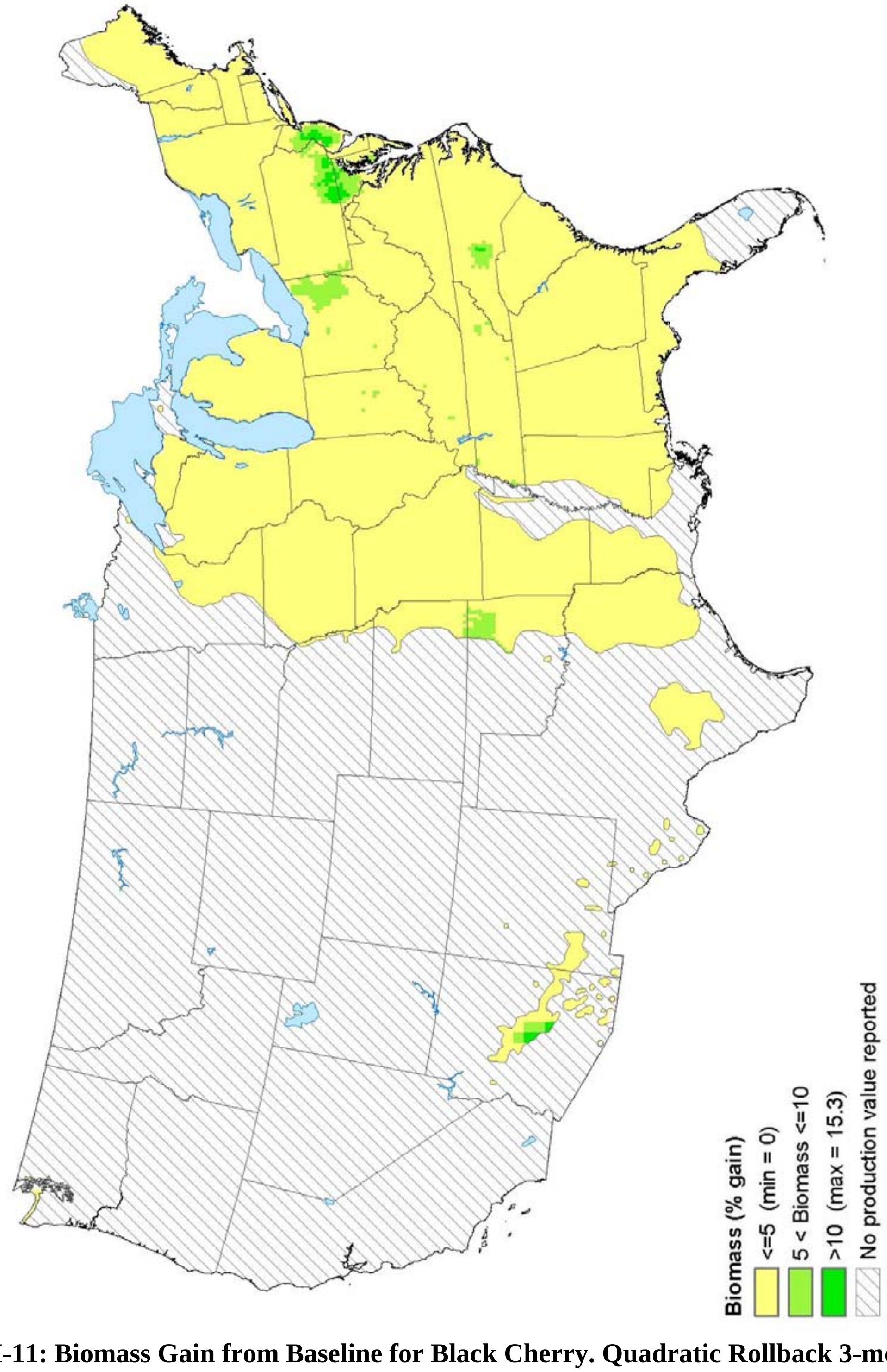
Map H-8: As-is Biomass Loss for Black Cherry (unreduced W126).



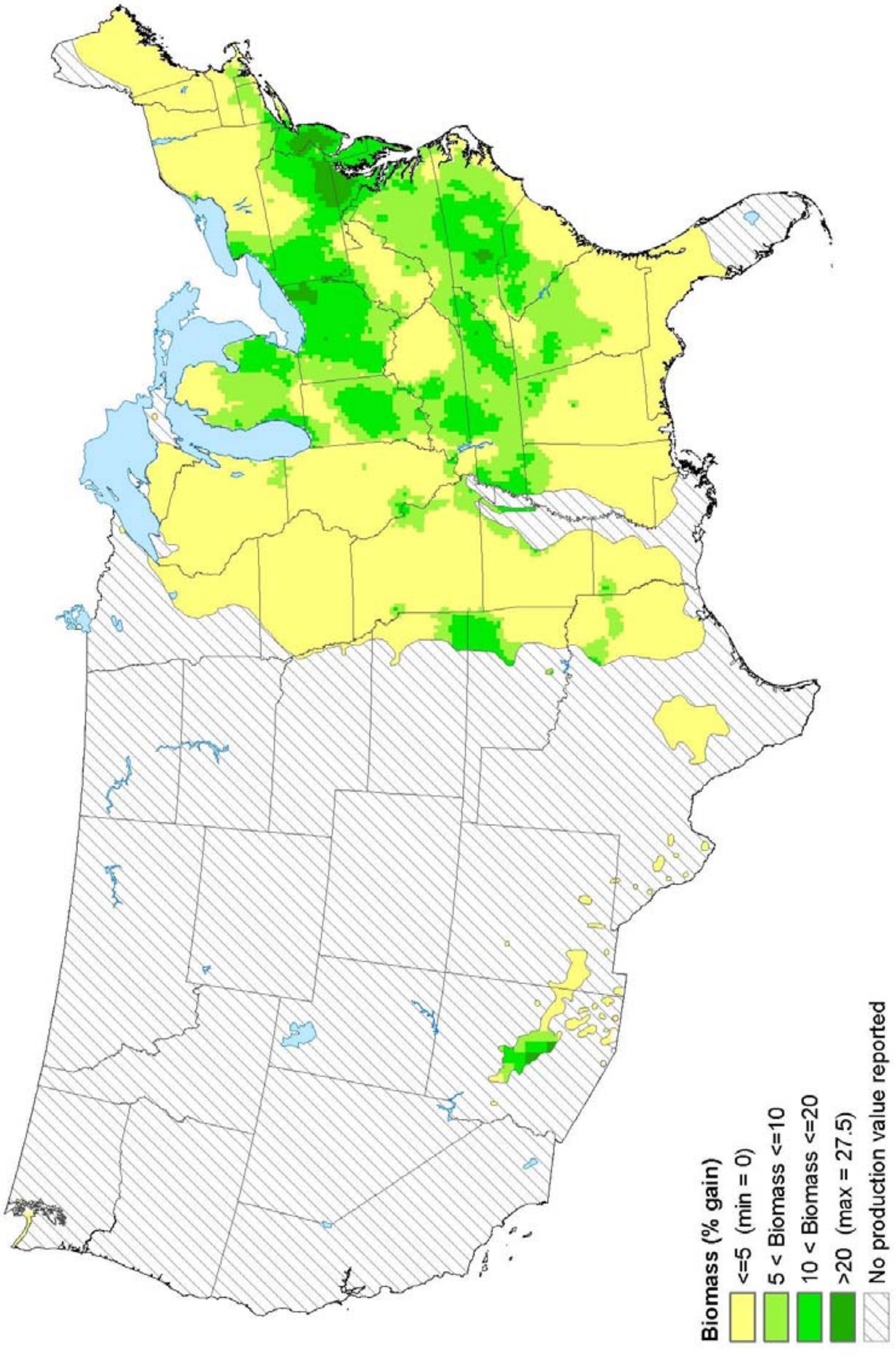
Map H-9: Biomass Gain from Baseline for Black Cherry. Quadratic Rollback 4th Highest 8-hour Maximum to 84 ppb (unreduced W126).



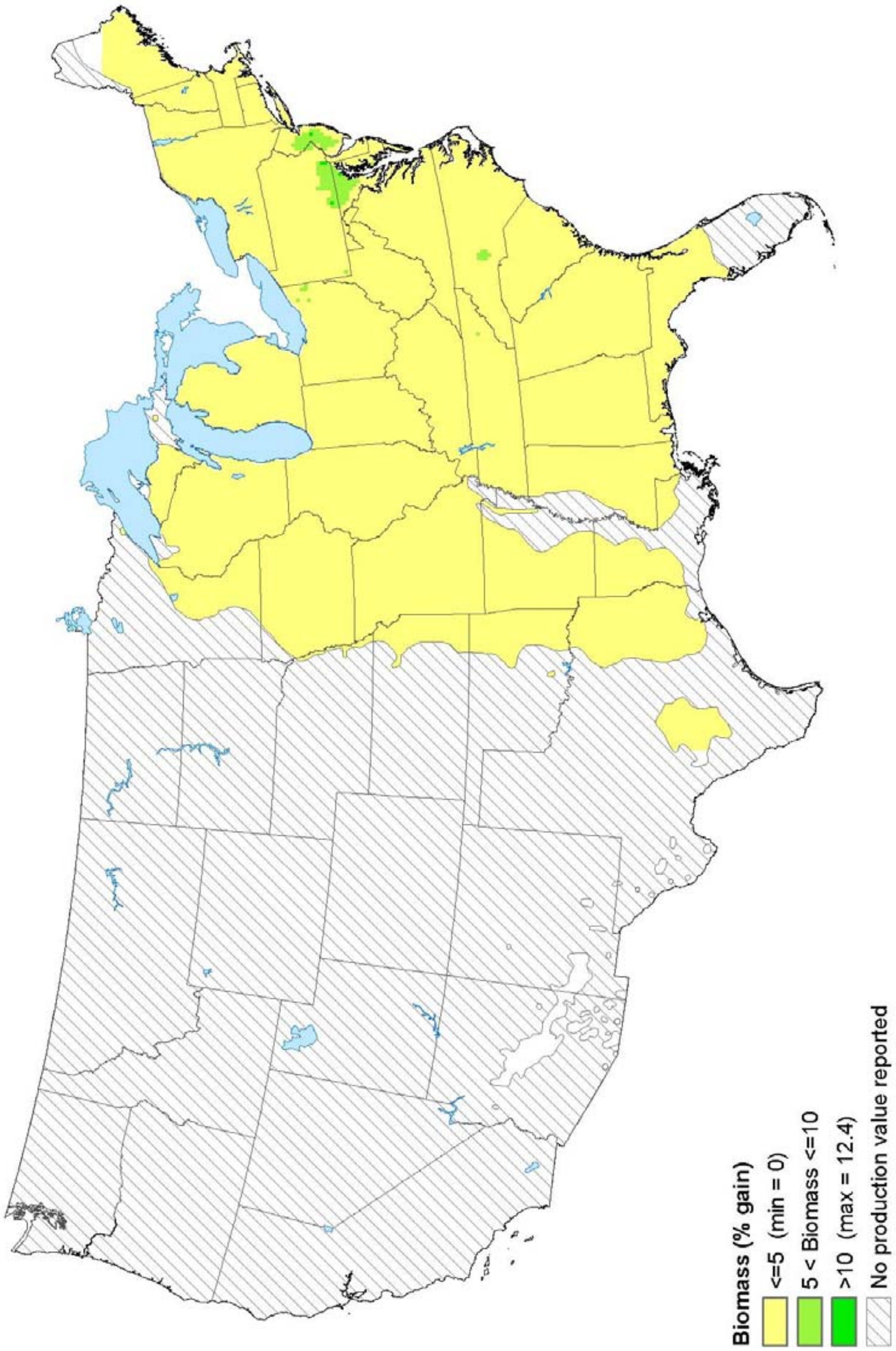
Map H-10: Biomass Gain from Baseline for Black Cherry. Quadratic Rollback 4th Highest 8-hour Maximum to 70 ppb (unreduced W126).



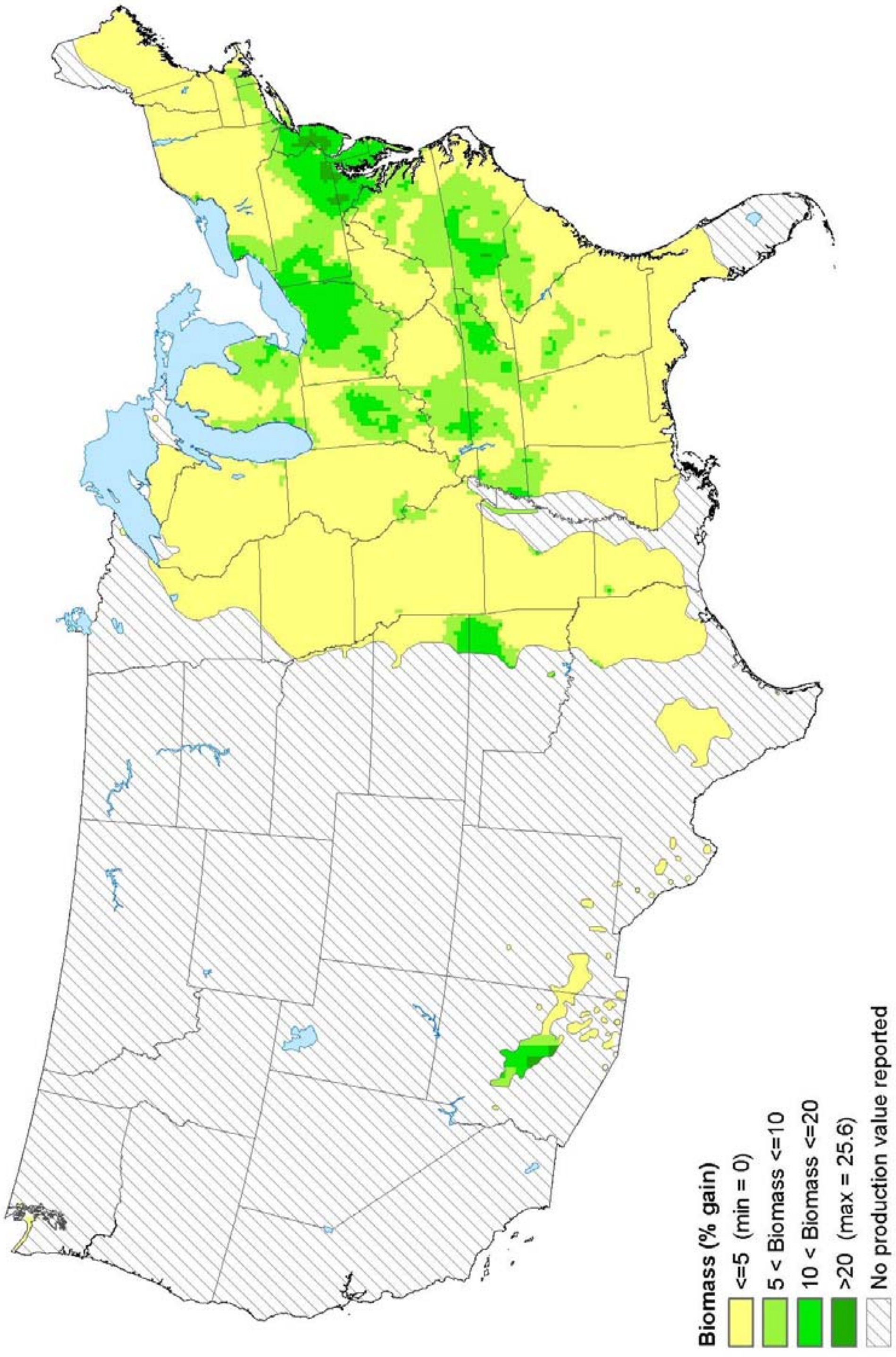
Map H-11: Biomass Gain from Baseline for Black Cherry. Quadratic Rollback 3-month SUM06 to 25 ppm-hour (unreduced W126).



Map H-12: Biomass Gain from Baseline for Black Cherry. Quadratic Rollback 3-month SUM06 to 15 ppm-hour (unreduced W126).

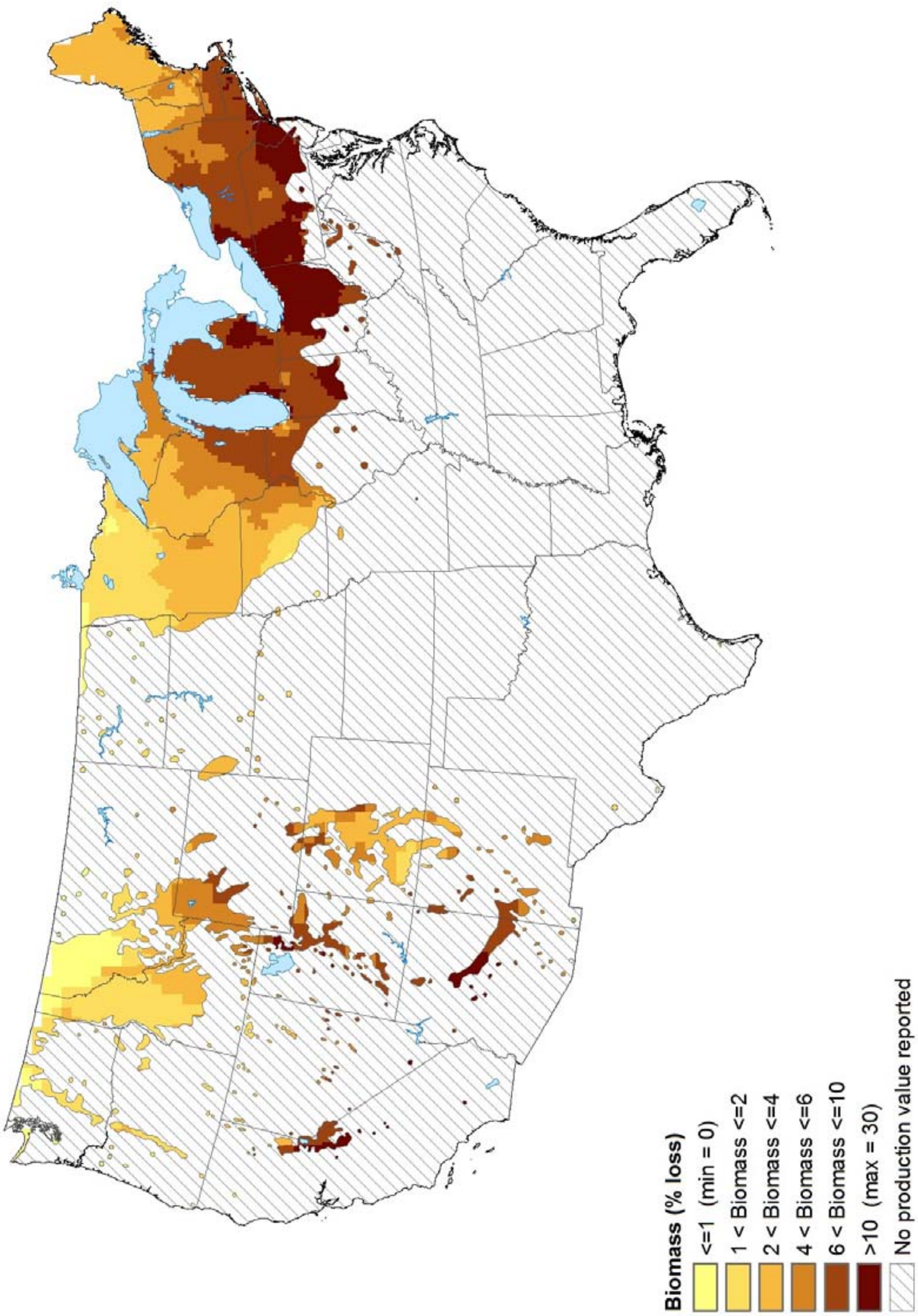


Map H-13: Biomass Gain from Baseline for Black Cherry. Quadratic Rollback W126 to 21 ppm-hour (unreduced W126).

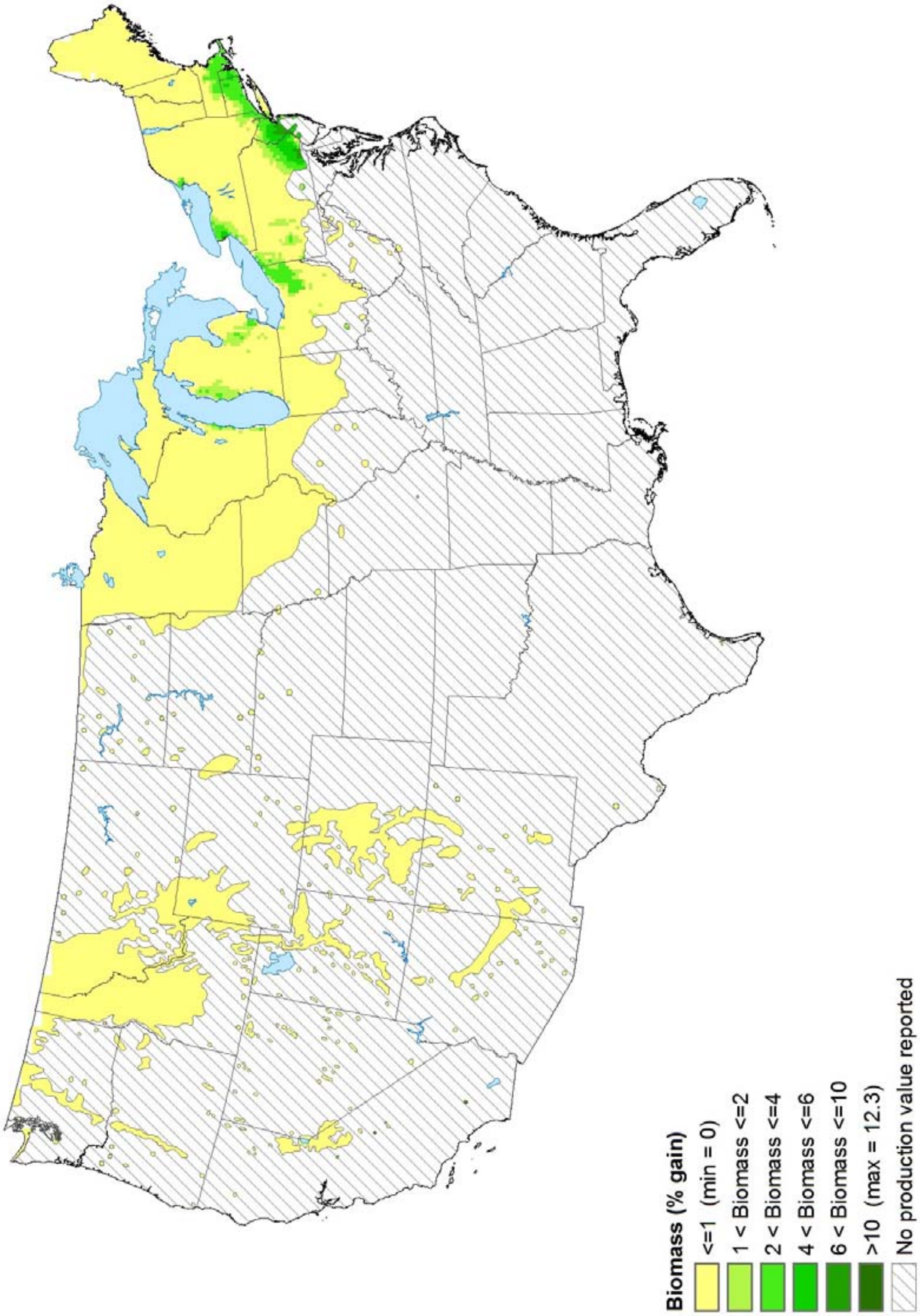


Map H-14: Biomass Gain from Baseline for Black Cherry. Quadratic Rollback W126 to 13 ppm-hour (unreduced W126).

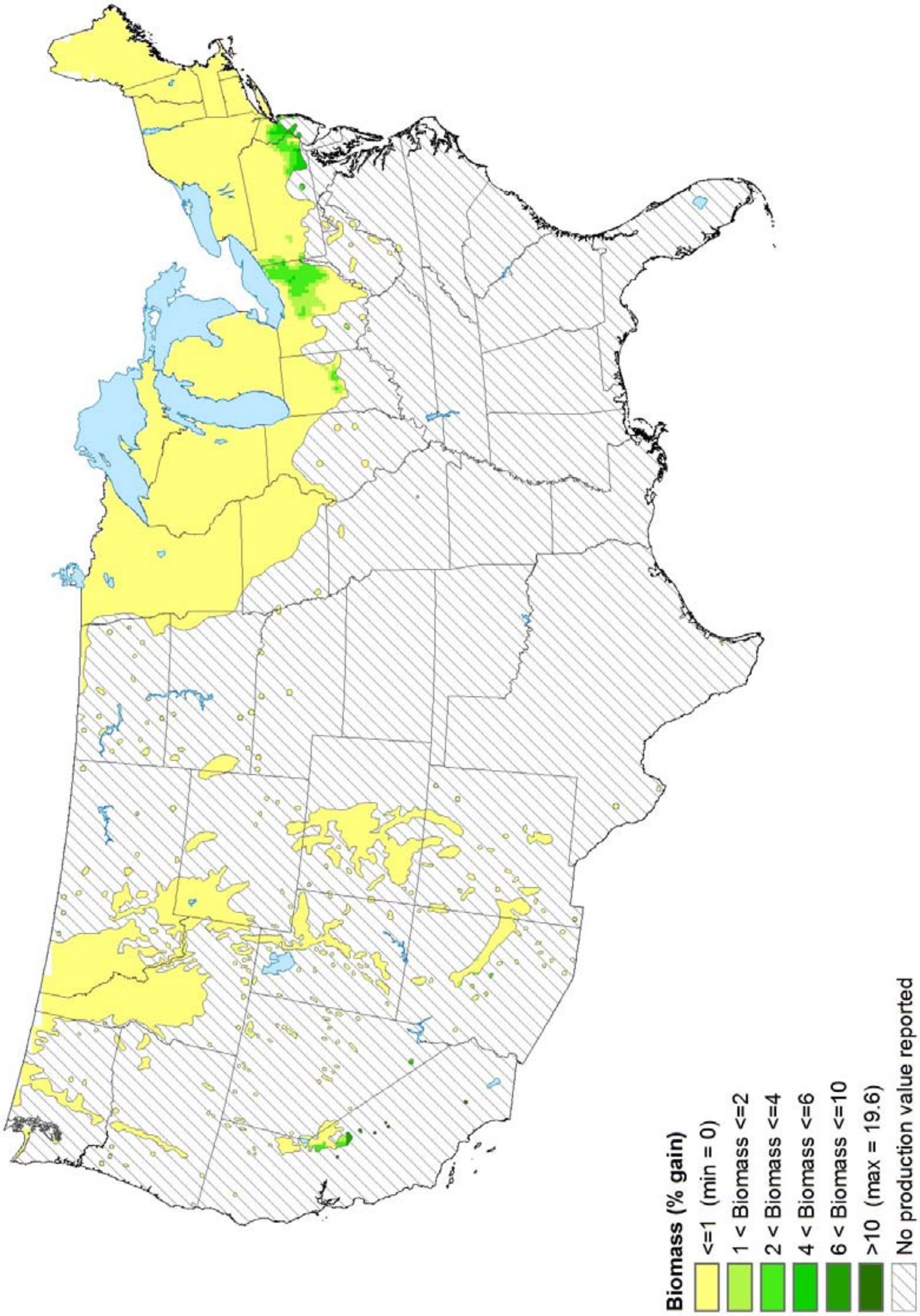
Aspen Response Maps



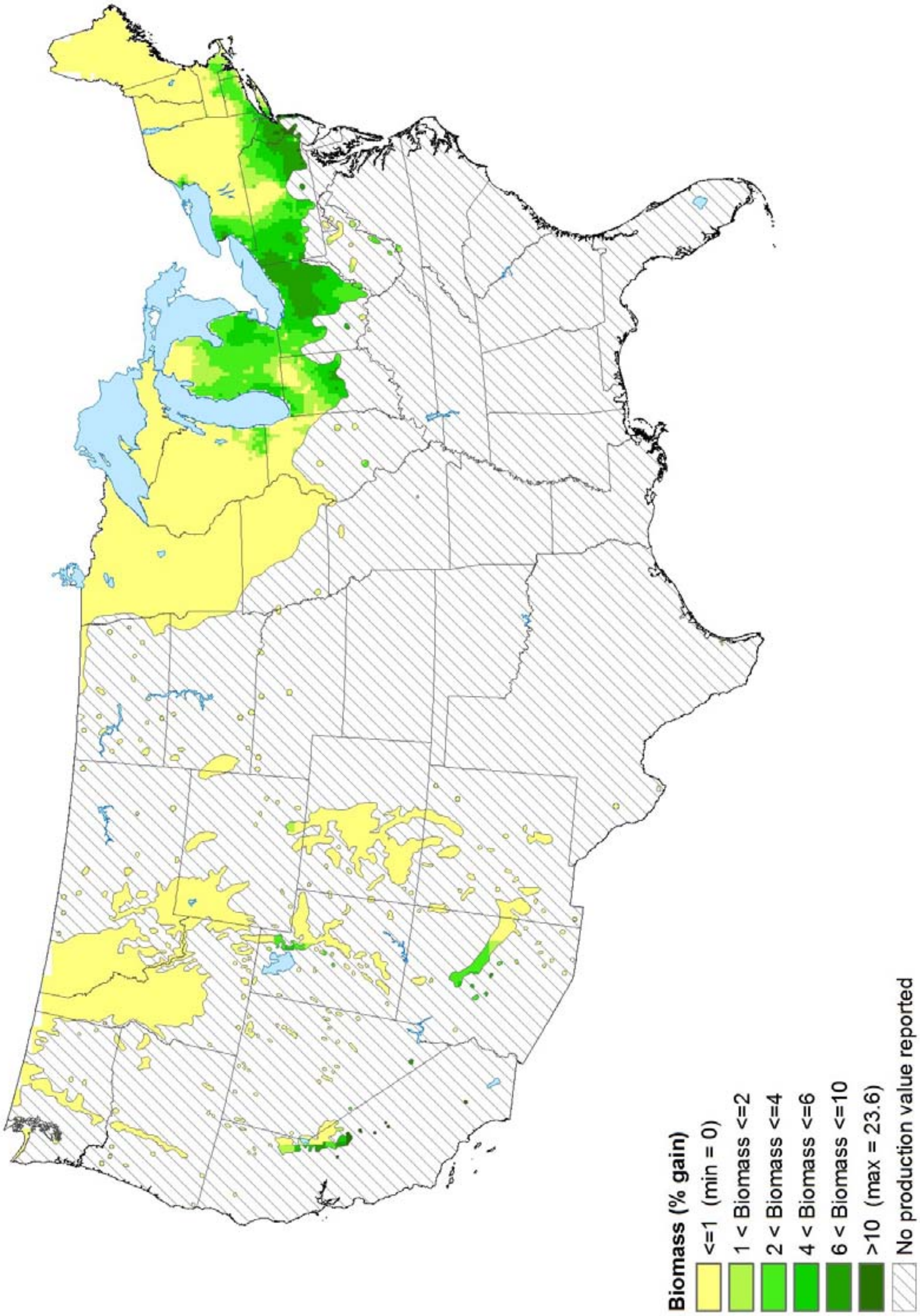
Map H-15: As-is Biomass Loss for Aspen (unreduced W126).



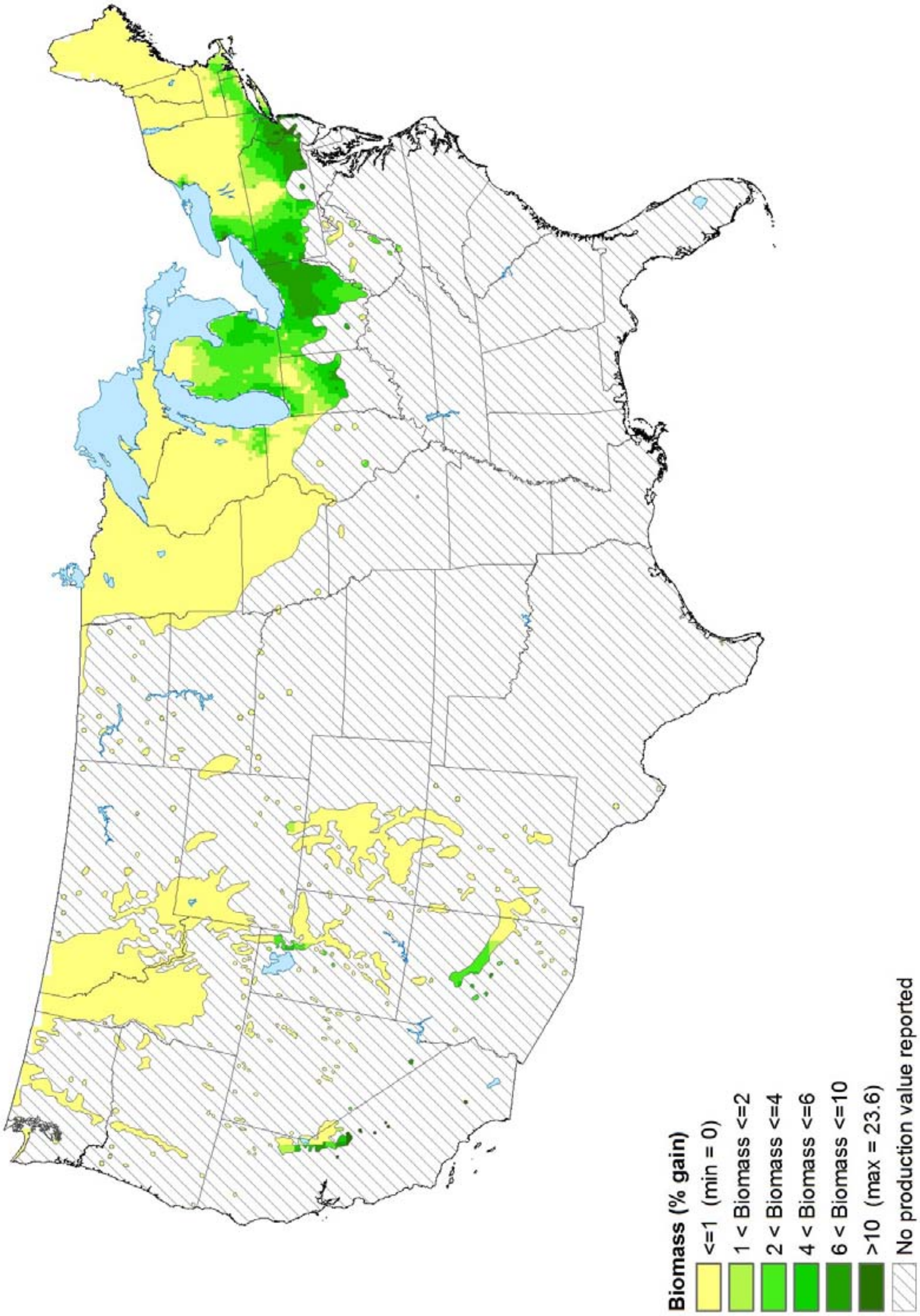
Map H-16: Biomass Gain from Baseline for Aspen. Quadratic Rollback 4th Highest 8-hour Maximum to 84 ppb (unreduced W126).



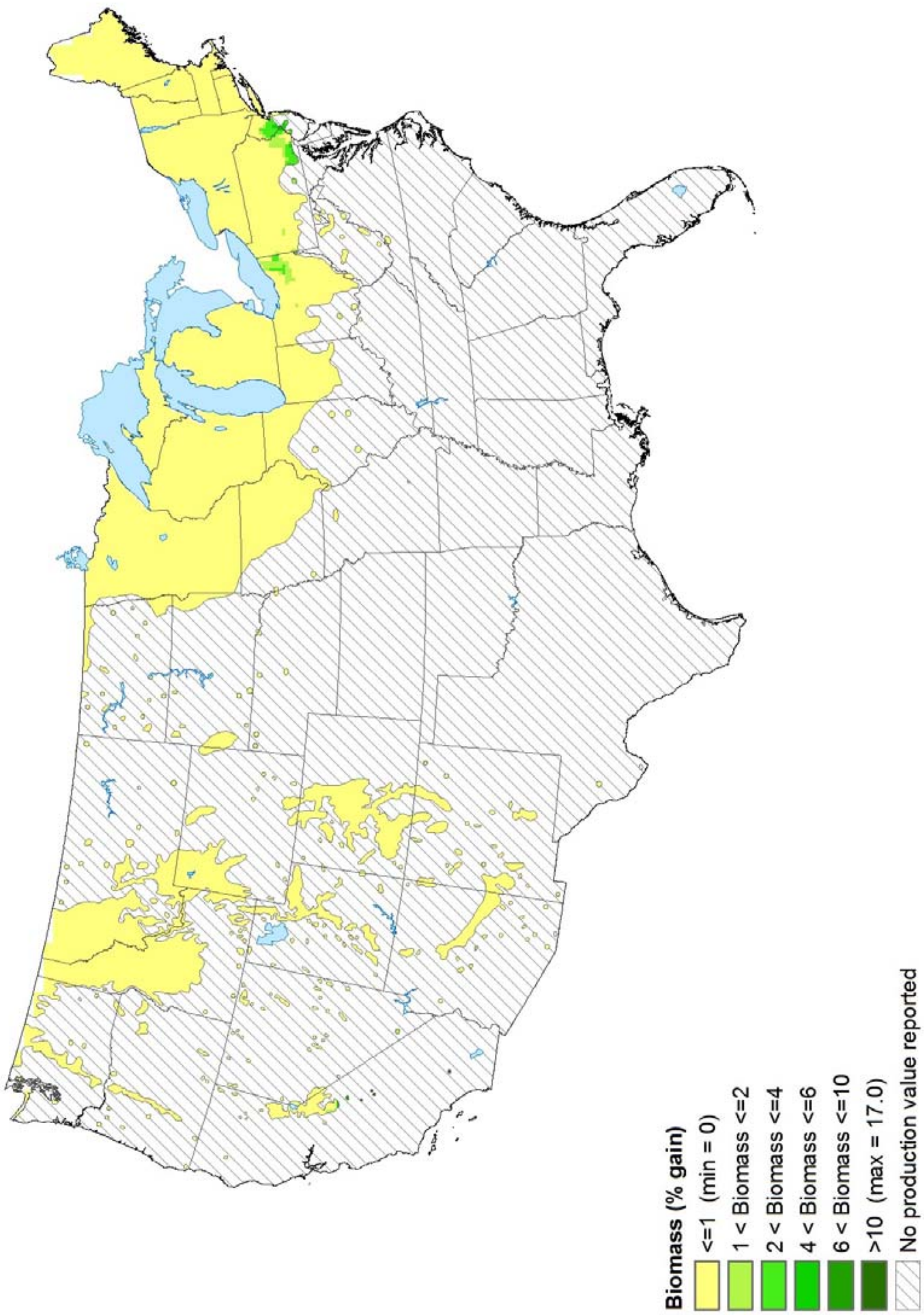
Map H-17: Biomass Gain from Baseline for Aspen. Quadratic Rollback 4th Highest 8-hour Maximum to 70 ppb (unreduced W126).



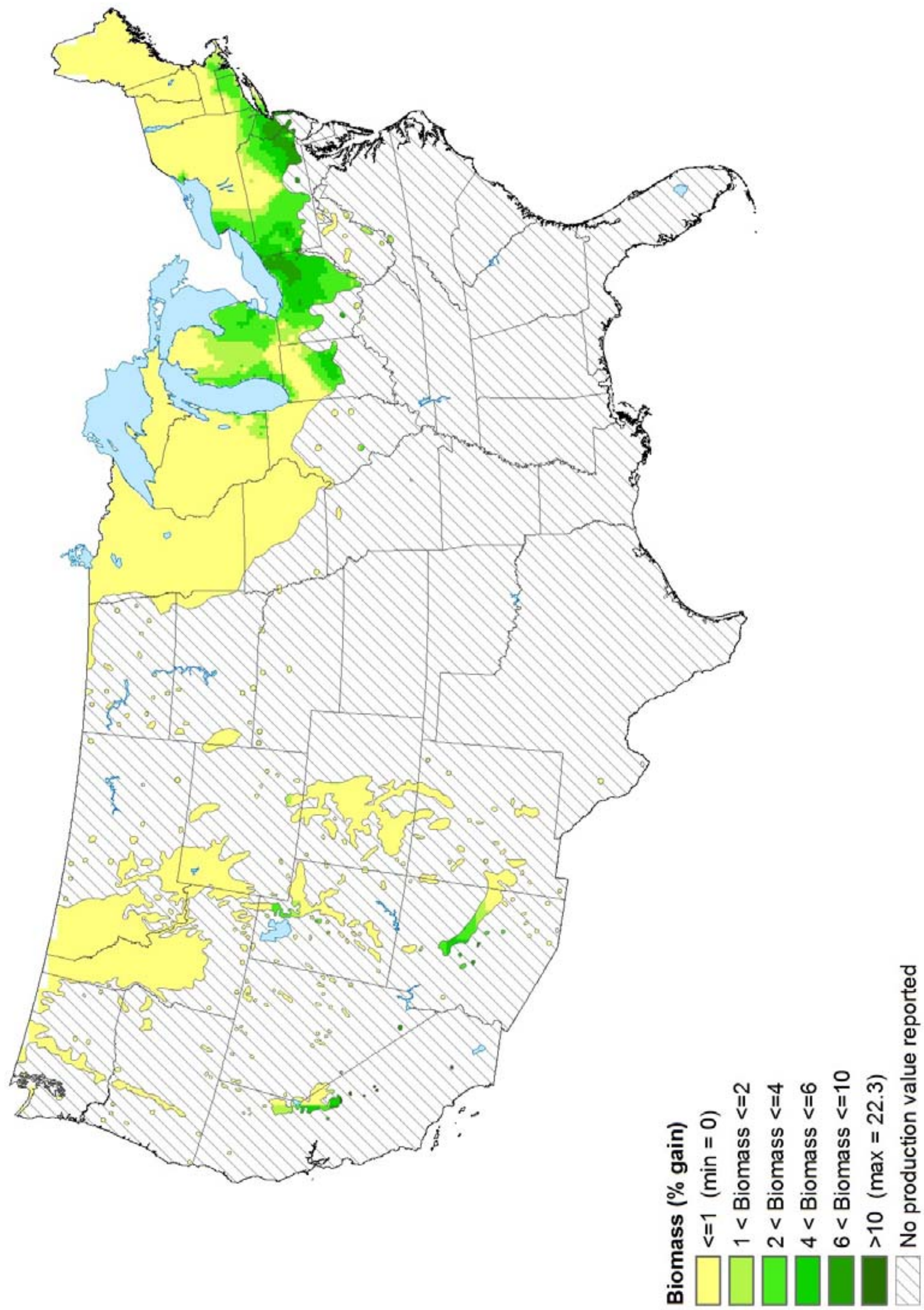
Map H-18: Biomass Gain from Baseline for Aspen. Quadratic Rollback 3-month SUM06 to 25 ppm-hour (unreduced W126).



Map H-19: Biomass Gain from Baseline for Aspen. Quadratic Rollback 3-month SUM06 to 15 ppm-hour (unreduced W126).



Map H-20: Biomass Gain from Baseline for Aspen. Quadratic Rollback W126 to 21 ppm-hour (unreduced W126).



Map H-21: Biomass Gain from Baseline for Aspen. Quadratic Rollback W126 to 13 ppm-hour (unreduced W126).

Appendix I AGSIM© Model Specifications

AGSIM© is an econometric-simulation model that is based on a large set of statistically estimated demand and supply equations for agricultural commodities produced in the United States. This model has been peer-reviewed and utilized in many pesticide and other major agricultural policy evaluations (Taylor et al., 1993). The present version of the model includes supply and utilization of corn, sorghum, barley, oats, wheat, soybeans, cotton, all hay, rice, peanuts, fresh and processed peaches, walnuts, fresh and processed apples, lettuce, onions, fresh and processed berries, fresh and processed oranges, fresh and processed grapes, and fresh and processed tomatoes. Supply of the major field crops is regionalized for the nine USDA production regions. Demand for each commodity is separated into various components, including stocks. Imports and exports are modeled separately.

The model is capable of analyzing the effects of changes in policies that affect crop yields or production costs. This is achieved by estimating how farmers will adjust crop acreage between commodities when relative profitability changes as a result of policy-induced crop yield and/or production cost changes[53]. Acreage and yield changes from various scenarios will affect total production of crops, which simultaneously affects both commodity prices and consumption. Commodity price changes, in turn, affect profitability and cropping patterns in subsequent years. Federal farm program and conservation reserve effects are also incorporated into the model.

Model Specification

AGSIM© is based on a set of dynamic supply and demand equations for major crops. Commodities are generally linked on both the supply side and demand side of markets. The simulation component of the model finds the set of prices for all commodities endogenous to the model that simultaneously clear all markets in each year over the simulation period. Dynamics are incorporated into the econometric specification and thus incorporated into the simulation model. All equations in the model were econometrically estimated, except a few policy equations that were based on legislated formula.

Supply Components

The crop supply component of AGSIM© is based on a set of supply equations for the major field crops produced in the United States. Effects of farm programs, specifically the 1985 Food Security Act (FSA), the 1990 Food Agricultural Conservation and Trade Act (FACTA), and the 1996 Federal Agricultural Improvement and Reform Act (FAIR), are reflected in the econometric specification of the supply component of the model, and thus are included in the simulation model.

Ex ante simulation of environmental policy will likely involve an assumption of continuation of the 1996 FAIR Act indefinitely. However, since most of the historical observations on which supply equations were econometrically estimated occurred under different programs, it is important to consider how historical equations reflect the 1996 FAIR Act. The basic philosophy that guided inclusion of farm program features into the supply component of the model follow. First, beginning with the 1985 FSA, continuing with the 1990 FACTA, and now with the 1996 FAIR Act, North American Free Trade Agreement (NAFTA) and the General Agreement on Tariffs and Trade (GATT), farm and international trade policy has moved U.S. agriculture to a market orientation. Although the 1985 FSA and the 1990

[53] To the extent that the Rule increases diesel prices, shipping prices for some agricultural products may increase, and may cause some farmers to change their production decisions. The magnitude of such an impact is likely to be small. Time and resources did not permit modeling this possible impact on their decision-making.

FACTA had price support and acreage diversion features, they embodied a strong market orientation. For all major program crops (in AGSIM©), the acreage devoted to the crop exceeded the acreage under government programs. Thus, *at the margin,* market prices (and not support prices) influenced crop acreage. Another way of looking at this is that farm programs have influenced crops at the intra-margin, while the market has influenced crops at the margin. Thus, after accounting for acreage diverted under farm programs, expected prices determine acreage. For these reasons, AGSIM© should be valid for simulating agricultural markets under the market conditions established under the 1996 FAIR Act.

Sets of equations that comprise the supply component of the current version of the model include: (1) acreage planted to each crop, (2) acreage harvested of each crop, (3) acreage in annual set-aside or acreage reduction programs (ARP) by crop, (4) acreage in cultivated summer fallow, (5) crop yields per harvested acre, (6) rate of participation in Federal farm programs by crop, and (7) annual set-aside rates by crop under past farm programs, as related to stock levels (historically legislated) and thus related to market price. Identities in the model are: (a) production is the product of acreage harvested and yield per harvested acre, and (b) the quantity supplied equals the quantity demanded for each commodity (market clearing). Specification of each of these sets of equations follows.

Acreage Planted Equations. Acreage planted is the key behavioral relationship in the supply component of the model. Acreage planted of a particular crop depends on expected per-acre net returns for that crop, expected per-acre net returns for competing crops, and farm program variables. In algebraic (and Fortran) form, the acreage planted equation is:

(1) acresp(ic,it,irun) = bc(ic) + bap(ic)*acresp(ic,it-1,irun) + bcrp(ic)*acrp(ic,it,irun) + bdiv(ic)*acrediv + brm(ic)*rerntm(ic,it,irun) + ber(ic)*rerentnp(it,irun) + byr(ic)*time(it) + bd83(ic)*dumb83(it)

where:

acresp(ic,it,irun)	=	acreage planted to the ic^{th} crop in the it^{th} year and in simulation “irun”,
acrp(ic,it,irun)	=	acreage of crop “ic” that was placed in the conservation reserve program,
acrediv	=	acreage diverted under annual set-aside programs,
rerentm(ic,it,irun)	=	real expected per acre returns over variable costs for the ic^{th} crop,
rerentnp(it,irun)	=	real expected per acre returns over variables costs computed as a weighted average[54] of rerentm(ic,it,irun) over all endogenous crops,
time(it)	=	a time-trend variable, and
dumb83(it)	=	a binary dummy variable to account for the PIK program in crop year 1983.

The remaining variables in equation (1) represent estimated coefficients. A single run of AGSIM© involves two simulations, one for the baseline (irun=0) and one for the policy scenario (irun=1). These two simulations are then compared to estimate the economic impacts of the policy scenario.

[54] Weights used in computing a composite expected return variable were the acreage harvested of each crop the previous year divided by total acreage harvested the previous year.

Expected returns over variable costs, rerentm(ic,it,irun), is defined as:

(1a) rerntm(ic,it,irun) = rp(ic,it-1,irun)*ey(ic,it,irun) - rcost(ic,it,irun)

where:

rp(ic,it-1,irun) = real price the previous crop year (actual or simulated, depending on the time period),
ey(ic,it,irun) = expected crop yield, and
rcost(ic,it,irun) = real variable production cost.

Expected yield is based on trend-line regressions:

(1b) ey(ic,it,irun) = [cint(ic) + by(ic)*time(it)]

where:

cint(ic) and by(ic) are estimated coefficients.

In the policy run, expected yield is adjusted for exogenously specified percentage yield changes ("dyld"):

(1c) ey(ic,it,irun) = [cint(ic) + by(ic)*time(it)]*(1.0 + dyld(ic,it)/100.)

Changes in real variable costs of production can also be exogenously specified for the policy simulation run. Thus, yield and cost changes directly impact acreage planted through equation (1), and indirectly impact acreage planted because of the resulting impact on prices in equation (1a) and thus in equation (1).

Given signs and magnitudes of estimated coefficients in equation (1), an increase in expected returns of the ic^{th} crop will increase acreage planted of that crop, while an increase in expected returns of other endogenous crops will decrease acreage of the ic^{th} crop. The estimated coefficient on lagged acreage planted in equation (1) is positive and less than one in value for all crops, which means that acreage planted is dynamically stable. The estimated coefficient on the set-aside acreage is negative and less than one in absolute value for all crops except oats, which reflects acreage slippage in the ARP program. Oats were typically planted to set-aside acreage, thus the estimated coefficient on set-aside acreage is positive in the oats equation, as expected. Further comments will be made on the acreage diverted effects on planted acreage after participation rate and acreage diverted equations, which are endogenous, are presented below.

Acreage Harvested Equations. Acreage harvested depends primarily on acreage planted:

(2) acresh(ic,it,irun) = bch(ic) + baph(ic)*acresp(ic,it,irun) + byrh(ic)*time(it) + bdvh(ic)*acrediv

where:

acresh(ic,it,irun) = the acreage harvested of the ic^{th} crop in the it^{th} year and in simulation "irun",

and other variables are as defined previously.

The estimated coefficient baph(ic) is positive and less than one, indicating that not all planted acreage is harvested, as expected. The coefficient bdvh(ic) on the acreage diverted variable is non-zero for oats only, in which case it is negative. This adjusts oat acreage harvested for the complexity of oats being planted (but not harvested) on ARP acreage. A time-trend variable for corn and grain sorghum, but not other crops shows how harvested acreage as a percentage of planted acreage has been increasing slightly over time.

Participation Rate in Farm Programs. Participation rates in the annual set-aside programs under the 1985 FSA and the 1990 FACTA were endogenized in the model with the set of equations:

(3) part(ic,it,irun) = bcp(ic) + brmp(ic)*rerntm(ic,it,irun) + brpp(ic)*rerntp(ic,it,irun) + byr(ic)*time(ic) + bpart(ic)*part(ic,it-1,irun) + bedpp(ic)*redp(ic,it,irun) + bd83p(ic)*dumb83(it)

where:

part(ic,it,irun)	=	the participation rate in the farm program for the icth crop in the itth year and in simulation "irun",
rerntp(ic,it,irun)	=	real expected returns over variable costs based on the support (target) price for that crop,
redp(ic,it,irun)	=	real effective acreage diversion payment rate,

and other variables are as defined previously.

Estimated coefficients brpp(ic) are non-negative, indicating that an increase in expected returns based on support price will increase participation, while estimated coefficients brmp(ic) are non-positive, indicating that an increase in expected returns based on expected market price will decrease participation. Lagged participation rate in equation (3) shows strong dynamics with respect to farm program participation.

Acreage Diverted under Farm Programs. Acreage diverted under annual set-aside (or ARP) programs is modeled as:

(4) adiv(ic,it,irun) = bcd(ic) + bd83d(ic)*dumb83(it) + bedpd(ic)*redp(ic,it,irun) + byrd(ic)*time(it) + bpsa(ic)*sa(ic,it,irun)*part(ic,it,irun)

where:

adiv(ic,it,irun)	=	acreage diverted under annual diversion programs for the icth crop in the itth year and in simulation "irun",
sa(ic,it,irun)	=	the set-aside rate specified by the Secretary of Agriculture under 1985 FSA and 1990 FACTA,

and other variables are as defined previously.

Acreage slippage (with respect to historical set-aside) in farm programs is implicit in the model specification, and results from the complex simultaneity of farm program variables in sets of equations (1), (3), and (4).

Acreage in Cultivated Summer Fallow. Acreage in cultivated summer fallow is modeled by the equation:

(5) afl(it,irun) = bcfl + bafl*afl(it-1,irun) + berfl*rerentnp(it,irun) + byrfl*time(it) + bd83fl*dumb83(it)

where:

afl(it,irun)	=	acreage fallowed in year it in simulation run "irun".

Although the acreage in cultivated summer fallow is highly inelastic, this equation shows that an increase in expected returns based on expected market price results in a small decrease in acreage fallowed.

Fruit & Vegetable Supply. Fruit and vegetable supply in AGSIM© is modeled as a set of linear supply response equations. Supply depends on expected per acre returns, including dynamics.

Demand Components

The crop demand component of AGSIM© is based on a set of demand equations for each crop for utilization categories of (a) imports, (b) exports,(c) livestock feed, (d) food, fiber, ethanol production and other domestic uses, (e) ending stocks, and (f) residual use. Each demand component depends on current market price for that commodity and, where relevant, prices of other commodities. The model specification of each utilization category follows.

Imports. Imports of agricultural commodities are modeled by the set of equations:

$$\text{(6)} \quad qd(ic,it,irun,1) = bim(1,ic) + bim(2,ic)*rp(ic,it,irun)*xrate(ic,it-1,irun) + bim(3,ic)*qd(ic,it-1,irun,1) + bim(4,ic)*time(it) + bim(5,ic)*uspop(it,irun)$$

where:

qd(ic,it,irun,1)	=	the quantity of crop ic imported in year it in simulation run "irun",
rp(ic,it,irun)	=	real market price,
xrate(ic,it-1,irun)	=	the real trade-weighted exchange rate,
uspop(it,irun)	=	the United States population,

and bim(j,ic) are estimated coefficients. Lagged imports in equation (6) reflects dynamic adjustments.

Exports. Exports of agricultural commodities are modeled by the set of equations:

$$\text{(7)} \quad qd(ic,it,irun,2) = bex(1,ic) + bex(2,ic)*rp(ic,it,irun)*xrate(ic,it-1,irun) + bex(3,ic)*qd(ic,it-1,irun,2) + bex(4,ic)*time(it) + bex(5,ic)*wpop(it,irun)$$

where:

qd(ic,it,irun,2)	=	the quantity of crop ic exported in year it in simulation run "irun", and
wpop(it,irun)	=	world population.

Feed, Fiber and Crushing Use. Domestic utilization of crops for feed, fiber or crushing (depending on the crop) is modeled by the set of equations:

$$\text{(8)} \quad qd(ic,it,irun,3) = bfd(1,ic) + \sum_{jc} bfdcross(ic,jc)*rp(jc,it,irun) + bfd(2,ic)*qd(ic,it-1,irun,3) + bfd(3,ic)*time(it)$$

where:

qd(ic,it,irun,3) = utilization for feed, fiber or crushing.

Note that cross-price effects are incorporated into this set of equations through the set of estimated coefficients bfdcross(ic,jc). Symmetry of cross-price effects, consistent with microeconomic theory, was imposed on estimation so that bfdcross(ic,jc) = bfdcross(jc,ic) for ic $\neq$ jc. Own-price effects are all negative, as expected.

Domestic Food Use. The set of equations to represent domestic food use is:

(9) qd(ic,it,irun,4) = bfo(1,ic) + bfo(2,ic)*rp(ic,it,irun) + bfo(3,ic)*qd(ic,it-1,irun,4) + bfo(4,ic)*time(it) + bfo(5,ic)*uspop(it,irun) + bfo(6,ic)*rdincome(it,irun)

where:

rdincome(it,irun) = real per-capita disposable income in the United States,

and other variables are as defined previously. In the case of peanuts, the real market price is replaced by the fixed quota price that applies to all domestically consumed peanuts. This quota price for peanuts applies to the 1985 FSA, the 1990 FACTA, and continues with the 1996 FAIR Act.

Ending Stocks. Ending stocks are viewed as another component of demand. Although commodities are often held to maintain pipeline inventories, commodities are also held for speculative purposes. Thus, stock levels respond strongly to prices, so the stock relationships were specified and estimated as

(10) qd(ic,it,irun,5) = bst(1,ic) + bst(2,ic)*rp(ic,it,irun) + bst(3,ic)*qd(ic,it-1,irun,5) + bst(4,ic)*time(it)

where qd(ic,it,irun,5) is ending stocks in year t.

Residual Use. For some crops (rice, peanuts, and cottonseed), supply and utilization data show a residual category, which is modeled as,

(11) qd(ic,it,irun,6) = brs(1,ic) + brs(2,ic)*rp(ic,it,irun) + brs(3,ic)*time(it)

where:

qd(ic,it,irun,6) = residual use.

Although quantities in this residual use category are never used, the level of the residual does respond negatively to the real price, and is thus viewed as another utilization (demand) category.

Market Clearing Identities

In supply and demand specification outlined above, supply generally depends on past prices, while demand depends on current prices. In simulating these econometrically estimated equations into the future, simulated prices are solved by simultaneously solving the market clearing identities

(12) qs(ic,it,irun) +qd(ic,it-1,irun,5) = qd(ic,it,irun,1) + qd(ic,it,irun,2) + qd(ic,it,irun,3) + qd(ic,it,irun,4) + qd(ic,it,irun,5) + qd(ic,it,irun,6)

where:

qs(ic,it,irun) = the quantity produced of crop ic in year it in simulation “irun”.

Production is defined to be qs(ic,it,irun) = acresh(ic,it,irun)*ey(ic,it,irun). The left hand side of the equal sign in (12) gives total supply (production plus beginning stocks), while the right-hand side of (12) gives total utilization, including ending stocks.

In the simulation model this set of simultaneous equations are numerically solved to get the market clearing prices in a given year. This process is continued, considering the dynamics of the model, indefinitely into the future.

Historical Observation Period

Many econometric relationships in the model were estimated with data for the 1975-1995 time period. However, where structural change was apparent, such as with stock holding behavior and international trade, some of the early years were dropped from statistical analysis so that the simulation model would better reflect the future.

Alternative Specifications Considered

Many different specifications of how farm programs influence crop acreage have been considered in the evolution of AGSIM©, including: (a) acreage depends on support price, (b) acreage depends on the maximum of expected market price and support price, (c) acreage depends on a weighted average of support and expected market prices, with weights based on program and non-program acreage of the crop, and (d) acreage depends on expected market price. Models for expected market price have considered complex distributed lags that go back several years in time, to a simple model that expected market price is actual price the previous year.

Acreage equations have also been specified to depend on expected returns of: (1) all competing individual crops with no parameter restrictions, (2) all competing individual crops with full symmetry of cross-effects imposed on estimation, (3) major competing individual crops, and (4) a weighted average of all expected returns for all other crops. Many different ways of incorporating participation rates and acreage diverted into the model have also been considered. Several alternative functional forms (linear, log-linear, nonlinear share equations, asymptotic) have also been considered.

Theoretical specifications considered have ranged from *ad hoc* models to very tightly specified and detailed theoretical economic models based on complex assumptions. The present model draws from economic theory (e.g. symmetry of cross-price effects in demand and homogeneity of degree zero of all supply and demand equations with respect to prices), but does not specify the model so tightly with untested assumptions and functional forms that empirical data has almost no role in the resulting estimates. Alternative estimation techniques, ranging from simultaneous equations techniques, to Zellner's seemingly unrelated regressions, to ordinary least squares regression have been used. The current version of AGSIM© reflects a degree of subjective judgment of what best reflects supply and demand of agricultural commodities based on microeconomic theory, traditional statistical criteria, and substantive direct contact with farmers and ranchers in most regions of the United States.

Baseline

The current version of AGSIM© is designed to estimate changes in the agricultural sector resulting from pesticide or other policy. Changes in economic variables are computed by comparing a policy simulation of the model with a baseline simulation of the model. For *ex post* (retrospective) evaluations, the baseline reflects actual farm programs, prices, acreages, etc. However, for *ex ante* evaluations, AGSIM© is calibrated to an external baseline. The calibration is done by comparing an internally generated baseline to the external baseline and computing adjusted intercepts for all of the relevant demand and supply relationships in AGSIM©**.**

For the 1999 version of AGSIM© the externally specified year 2010 baseline is forecasted from the 2007 baseline reported by USDA (1988b). A few endogenous variables in AGSIM© were not included in the USDA baseline. In those cases, the 1997 FAPRI baseline was used (FAPRI, 1997).

It should be noted that the baseline is not especially critical to estimates of *changes* in the agricultural sector, except for the case of price support policy, which is not relevant here. That is, sensitivity analyses with previous versions of AGSIM© have shown that estimates of *changes* in variables are not very sensitive to baseline absolute values of variables. Use of the USDA baseline to the extent possible assures consistency with other governmental mandated agricultural policy analyses.

A USDA baseline was not available for specific fruit and vegetable commodities included in the present version of the model. For commodities for which there was no USDA baseline, an internally generated linear trend line based on historical values of the endogenous variables was used as a baseline. This internally generated baseline for fruit and vegetables is included as part of the output from AGSIM©.

Regional Effects Sub-Model

AGSIM© subroutines are also available to combine AGSIM© output with production cost information to estimate net farm income impacts for the policy scenario at the regional level (or farm, representative farm, area or state level). Required information for this type of evaluation includes for each farm or area: (a) yield and cost changes (which often differ from the national yield and cost changes for the policy scenario), (b) baseline production costs, and(c) acreages of each crop. This information is combined with price impacts estimated with AGSIM©, and regional supply elasticities from a prior version of AGSIM© (or from other sources) to estimate net farm income changes for the farms or areas considered.

The conceptual foundation for regional evaluation in this version of AGSIM© begins with a net farm income formula,

(13) $$\Pi_{ir} = \sum_{ic} A_{ic,ir} R_{ic,ir}$$

where:

Π_{ir} = net farm income in region ir,
Aic,ir = acreage harvested of the ic^{th} crop in that region, and
$R_{ic,ir}$ = per-acre net return in that region.

Based on equation (13), it can be shown that the theoretically appropriate formula for computing net farm income *changes* for different regional situations is:

(14) $$\frac{\Delta\Pi_{ir}}{\Delta Z} \cong \sum_{ic} R_{ic,ir} \sum_{jc} \frac{\Delta A_{ic,ir}}{\Delta R_{jc,ir}} \frac{\Delta R_{jc,ir}}{\Delta Z} + \sum_{ic} A_{ic,ir} \sum_{jc} \frac{\Delta R_{ic,ir}}{\Delta Z}$$

where:

Δ represents a discrete change,
ΔZ represents the discrete policy change,
ic and jc are crop indices,

and other variables are as previously defined.

Equation (14) can be expressed in acreage elasticity (with respect to per-acre income) form,

(15) $$\frac{\Delta\Pi_{ir}}{\Delta Z} \cong \sum_{ic} R_{ic,ir} \sum_{jc} \varepsilon_{ic,ij,ir} \frac{R_{ic,ir}}{A_{jc,ir}} \frac{\Delta R_{jc,ir}}{\Delta Z} + \sum_{ic} A_{ic,ir} \sum_{jc} \frac{\Delta R_{ic,ir}}{\Delta Z}$$

where:

$\varepsilon_{ic,ij,ir}$ = elasticity of acreage of the ic^{th} crop in the ir^{th} region with respect to per-acre income of the jc^{th} crop in that region.

The term $\Delta R_{ic,ij}/\Delta Z$ in equations (14) and (15) can be further expanded to give

(16) $\frac{\Delta R_{ic,ir}}{\Delta Z} \cong P_{ic} \Delta Y_{ic,ir} + Y_{ic,ir} \Delta P_{ic} - \Delta C_{ic,ir}$

Formula (15) along with (16) can be empirically implemented to estimate the change in regional (or farm, representative farm, area or state level) farm income with the following information for each region: (a) crop budgets, (b) the change in yield and cost associated with the policy in question, price impacts estimated with AGSIM©, and externally specified (from an older version of AGSIM©, from subjective estimates, or from the literature) elasticities.

The first term on the right-hand side of (14) and (15) represents the change in net income resulting from increased or decreased acreage, while the last term on the right-hand side of (14) and (15) represents the change in net farm income on existing acreage of crops in the region. Since acreage response is generally inelastic, the last term on the right-hand side of (14) and (15) dominates the change in net farm income in a region; thus, elasticities generally will not have a major impact on regional net farm income changes estimated with the above approach.

AGSIM© Output

The major outputs from AGSIM© are changes in crop acreage, production, price, income, foreign consumer benefits, domestic consumer benefits, and farm program costs. The traditional method of economic welfare analysis (which is based on the concept of economic surplus) of policy changes is used to compute the sum of changes in producer surplus (net farm income) plus changes to all consumers (changes in consumers surplus) plus any changes in farm program payments (zero under 1996 FAIR). To avoid the possibility of inappropriately comparing a baseline with a policy scenario that was actually based on another baseline, a single run of AGSIM© produces both the baseline tables and the policy scenario tables, then computes economic surplus and price changes based on these two runs of the model.

Output from each run of the model includes two sets of tables for each crop; one set of tables for supply variables and another set of tables for supply and utilization variables. Each table includes historical statistics as well as simulations into the future. These tables are constructed for the baseline and the policy scenario.

Uncertainty

From a theoretical viewpoint, the types of uncertainty about results from an econometric-simulation model like AGSIM© run the full gamut from specification bias to estimation bias to measurement bias to functional form bias. Since these potential biases are covered extensively in econometrics texts, they are not be repeated here. From a practical standpoint, much of the uncertainty about estimated economic impacts can be viewed in terms of uncertainty about estimated demand and supply elasticities. Generally, the demand and supply elasticities in the present version of AGSIM© are within the range of elasticities reported in the literature for the same commodities. Furthermore, estimated elasticities (or estimated coefficients on which elasticities are based) are generally highly significant.
The AGSIM© simulation model is keyed to the USDA baseline. Although the USDA gives point estimates of relevant endogenous and exogenous variables, there is nevertheless some uncertainty about these future values. This uncertainty about the baseline has not, to our knowledge, been quantified. Thus, uncertainty about the baseline cannot be quantitatively translated into uncertainty about economic impacts estimated with AGSIM©. Qualitatively, however, the estimated economic impacts are not highly sensitive to the baseline because they are computed as changes in economic variables.

Theoretically one could compute an overall goodness of fit statistic for the model, but such a statistic would be essentially meaningless since the statistical properties would be largely unknown. More importantly, while one can theoretically compute such statistics for large-scale models, they cannot be compared for different models due to fundamental differences in the structure of alternative large-scale models and due to different sets of endogenous variables from model to model.

Another unresolved theoretical issue pertains to the combined effects of uncertainty about AGSIM© and uncertainty about yield and cost estimates provided by others. This is a very messy and complicated issue, particularly when one appropriately considers non-zero covariances between economic variables and crop yield variables.

Yet another source of uncertainty relates to implications of massive consolidation and integration of the agricultural sector that has occurred in the past two decades. AGSIM© implicitly assumes competition; to the extent that imperfect competition exists, the econometric results are somewhat biased as is the theoretical interpretation of economic surplus.

At best, we can only subjectively assess uncertainty about quantitative results from a large-scale model like AGSIM©. Based on over 30 years of developing and applying large-scale models including national programming models and econometric-simulation, our subjective assessment is that there is a modest amount of uncertainty about the AGSIM© results *given* changes in yield and cost. Overall, our subjective estimate is that estimated changes in economic surplus are within 50% of their true values, but estimated effects are more uncertain for some commodities and less uncertain for others.

Appendix J TREGRO simulations of red maple and yellow poplar trees under scenarios of reduced ozone exposure at two locations in the southern Appalachian Mountains

REPORT TO ABT ASSOCIATES, INC.

D. A. Weinstein, Ph.D.

May 18, 2006

The response of total tree growth of two species, red maple and yellow (or tulip) poplar was simulated in each of two locations in the southern Appalachian Mountains to five scenarios of ozone (O_3) reduction provided by Abt Associates. These simulations were done using the computer model, TREGRO (Weinstein et al. 1991). This report provides the details of the methodology and results from this examination.

Procedure

1. The TREGRO model was used to simulate the growth of a single mature yellow poplar (Liriodendron tulipifera L.) tree over three years under climate conditions characteristic of the cove hardwood forests (USDA Forest Type, Hansen et al., 1992) of the Cranberry region of North Carolina, east of Great Smoky Mountains National Park (Table 1) and the cove hardwood forests of the Shenandoah National Park region of Virginia. Yellow poplar was chosen for analysis because controlled studies and previous analysis indicated a sensitivity to ozone (O_3) (Cannon et al. 1993). These sites were selected, in consultation with personnel at Abt and EPA, because previous analysis indicated yellow poplar growing at those sites was sensitive to O_3 exposure (Weinstein et al. 2002). The cove hardwood stands are widely viewed as some of our most treasured forests because their protected, rich, and moist set of conditions historically permits trees to grow to magnificent size with very high growth rates. Yellow poplar is one of the most abundant species in the southern Appalachian forest, and comprises approximately 10% of the cove forest (unpublished data from USFS FIA Eastwide Database, Hansen et al. 1992). The simulations were done using a parameter set established previously based on the following method:

The parameterization for yellow poplar (tulip poplar; (*Liriodendron tulipifera* L.)) was originally reported in Weinstein et al. 2001. Parameters were established to permit TREGRO to simulate the growth of a mature yellow-poplar tree of approximately 30 m in height, 40 cm in diameter, and 50 years old (Beck 1990, Clark and Schroeder 1977). Initial biomass of individual tree components (foliage, branch, stem, and coarse and fine root) was calculated using diameter at breast height (dbh)-based allometric equations derived by Clark and Schroeder (1977). Biomass of branch, stem and coarse roots was divided into structure (living) and wood (dead) according to Panshin and de Zeeuw (1980). This distinction is important because wood cannot be used to store reserve carbon that can be drawn on to meet plant needs when the supply of newly fixed carbon coming from photosynthesis falls to insufficient levels. The reserve carbon, or total nonstructural carbohydrate (TNC), was assumed to represent 30% of structural mass in the stem, branch, and roots, and 20% of structure in the foliage based on reported starch concentrations in roots (Jensen and Patton 1990) and TNC concentrations in foliage (Wullschleger et al. 1992). This percentage in the structural tissue, therefore, establishes an upper limit of the quantity of reserve carbon the tree can maintain.

Leaf growth was set to be initiated on April 7th and last until May 7th (Britton 1878, Kienholz 1941, Lamb 1915) at which point height and radial growth were started (Kienholz 1941, Morrow and McKee 1963, Mowbray and Oosting 1968), continuing until approximately September 10th (Lieth and Radford 1971, Morrow and McKee 1963). Leaf fall was set to occur at the end of the second week in October (Lamb 1915). Maximum net carbon assimilation rate was set at 0.01718 gC•gC $leaf^{-1}$•hr^{-1} (7.67 umol•m^{-2}•s^{-1}) (Cannon et al. 1993, Chappelka et al. 1988, Gunderson et al. 1993, Neufeld et al. 1985, Norby and O'Neill 1991, Tjoelker and Luxmoore 1992, Wullschleger et al. 1992) to approximate the conditions found on a midsummer day (PPFD > 1500 umol•m^{-2}•s^{-1}; ambient air temperature 25 - 30° C). Leaf respiration rate was set to approximate a respiration-to-net photosynthesis ratio of 0.2215 (mean value from Cannon et al. 1993 and Wullschleger et al. 1992) and finalized at 0.04% of net carbon assimilation rate. Both flushes of leaves produced in a given year were assumed to have identical photosynthetic and respiratory rates.

Trees of this dbh typically exhibit an annual dbh increment of 0.30 cm yr^{-1} and a height increment of 23 cm yr^{-1} under the environmental conditions that existed on average from 1940 to 1990 (Beck 1990). Calculating the expected size of tissues from the previously described allometric relationships, the amount of growth expected by each type of tissue was estimated by subtracting their estimated initial size before this three year growth period. The maximum potential rate of growth of each tissue was then adjusted until the simulated tree predicted the appropriate growth for each type of tissue, with the proportion of TNC, structure, and wood in each of the tree components remaining unchanged. The fine root senescence was set at the maximum rate possible given excess available carbon.

2. The TREGRO model was used to simulate the growth of a single mature red maple (Acer rubrum L.) tree over three years under climate conditions characteristic of the mixed central hardwood forests (USDA Forest Type, Hansen et al., 1992) of the Cranberry region of North Carolina, east of Great Smoky Mountains National Park (Table 1) and the mixed central hardwood forests of the Shenandoah National Park region of Virginia. Red maple was chosen for analysis because controlled studies and previous analysis indicated a sensitivity to O_3 (Samuelson 1994). These sites were selected, in consultation with personnel at Abt and EPA, because previous analysis indicated red maple at these locations was sensitive to O_3 exposure (Weinstein et al. 2002). Red maple is one of the most abundant species in the eastern forest, comprising between 10% and 20% of the forests studied (unpublished data from USFS FIA Eastwide Database, Hansen et al. 1992). The simulations were done using a parameter set established previously based on the following method:

The parameterization for red maple (*Acer rubrum* L.) was originally reported in Weinstein et al. 2001. Parameters were established to permit TREGRO to simulate a mature red maple tree based on the diameter at breast height (dbh = 26 cm) of dominant and codominant trees measured by Erdmann et al. (1985) in upper Michigan as part of a crown release study of red maple. The age of a tree at this dbh is approximately 50 years old (Erdmann et al. 1985), with a height of approximately 19 m (Erdmann et al. 1985), and mean crown radius of 3.34 m (Gilman 1988).

Initial biomass of individual tree components (foliage, branch, stem, and coarse and fine root) was calculated using dbh-based allometric equations derived from red maple trees originally growing in Maine and New Hampshire (Young et al. 1980, Hocker and Early 1983). In the absence of available data, the proportion of wood in the initial tree's stem, branches, and coarse (woody) roots was set to be 20% based on a value determined for the stem of sugar maple by Chapman and Gower (1991). The remainder of the initial biomass was split between structure and TNC using the assumption that TNC was 30% of structure in the stem, branch, and roots and TNC was 20% of structure in the foliage, using the same assumption reported above for yellow poplar (Jensen and Patton 1990; Wullschleger et al. 1992).

Seasonal development of red maple was set to begin in the late winter/early spring (approximately March 1st – May 1st) with flower bud swell and bloom, with foliage bud break and foliage flush occurring in the early spring (approximately May 1st – May 22nd), and with height and radial growth beginning soon after foliage bud break and continuing until approximately July 15th (Walters and Yauney 1990). Foliage senescence occurred in mid-October (approximately October 15th) (Lamb 1915). Net carbon assimilation under high light conditions (1000 µE m^{-2} s^{-1}; 25 - 30 C, midsummer day, day-of-year 200-210) was set to approximately 0.00776 gC•gC $leaf^{-1}$•hr^{-1} based on values recorded by Reich et al. (1991). Leaf respiration was set at 14% of gross carbon assimilation based on values recorded by Kloeppel et al. (1993).

Red maple trees of this dbh typically exhibit diameter growth of 3.6 cm in seven years in the absence of O_3 (Erdmann et al. 1985). Calculating the expected size of tissues from allometric relationships, the amount of growth expected by each type of tissue was estimated by subtracting their estimated initial size. The maximum potential rate of growth of each tissue was then adjusted until the simulated tree predicted the appropriate growth for each type of tissue, with the proportion of TNC, structure, and wood in each of the tree components remaining unchanged. The fine root senescence was set at the maximum rate possible given excess available carbon.

3. An O_3 response was established for both species. The TREGRO model calculates the hourly uptake of O_3 through the stomata as a function of stomatal conductance and cumulative uptake over the leaf's lifespan. In the model, the potential maximum rate of photosynthesis during any given hour is reduced in direct proportion to the cumulative uptake of O_3 over the course of the growing season, based on work by Hansen et al. (1994). Although O_3 does not accumulate in the leaf tissue, the effect of cumulative O_3 uptake is proportional to the sum of the hourly O_3 concentration (exposure) multiplied by the foliar rate of O_3 stomatal conductance. The slope of the described response was set so that the simulated reduction in photosynthesis matched the photosynthesis reduction and cumulative O_3 exposure observed at the end of an open-top chamber exposure experiment.

The red maple response to O_3 was based on the work of Samuelson (1994), who reported a reduction in current leaf net photosynthesis of seedlings of 25% relative to charcoal filtered air after a total cumulative O_3 exposure of 175,000 ppb•hrs (a simulated uptake of 0.0138 g O_3 g^{-1} leaf C), which amounted to a 14.3% drop in photosynthesis for every 100 ppm-hrs O_3 exposure. The yellow-poplar response to O_3 was set to match the results reported by Cannon et al. (1993), who measured a reduction in net photosynthesis of seedlings of 10% relative to charcoal-filtered air after a total cumulative O_3 exposure of 75,600 ppb•hrs (a simulated uptake of 0.0044 g O_3 g^{-1} leaf C), a 13.2% drop in photosynthesis for every 100 ppm-hrs O_3 exposure. It was assumed that all trees of a given species would experience the same average reduction in photosynthesis in response to O_3 as was reported in the aforementioned studies.

Mature trees were assumed to have the same O_3 exposure responses as those measured in experiments with seedlings. Experiments by Samuelson and Edwards (1993) and by Hanson et al. (1994) have demonstrated that mature red oak tree leaves are more sensitive to O_3 than seedlings. However, no data from controlled exposures of mature yellow poplar or red maple were available. Consequently, the data of Samuelson (1994) and Cannon et al. (1993) were the only relevant studies on which to draw. At worst, the use of this data to represent mature tree responses gives a conservative estimate of the actual tree response.

4. Meteorology input for TREGRO consisted of base files for the hourly conditions of the period 1993-1995.

5. Air quality input for TREGRO consisted of O_3 scenarios provided by Abt Associates, which represented rollbacks of hourly O_3 values for 1993-1995 to meet current and alternative standards. Growth of each tree species was simulated for three years to account for the accumulative effect of repeated injury. For some of the scenarios O_3 levels did not exceed the defined standard for each year; therefore, theoretically the trees were not injured during every year of the analysis. The hourly O_3 values in each scenario were used in place of the O_3 values in the original base meteorology data. Therefore, the simulations were run with weather variables for 1993-1995 and O_3 values from each of the scenarios.

6. TREGRO simulations were run for each scenario of O_3 reduction supplied by Abt Associates:

1) Scenario 1. Rolled back hourly O_3 values for 1993-1995 to the current EPA O_3 standard (as expressed in western TREGRO analysis) as 4th highest daily maximum 8-hour average, not to exceed 0.085 ppm). The 8-hour mean of 0.085 ppm was exceeded only at the Big Meadows site in Shenandoah National Park, Virginia, and only for the years 1993 and 1995; therefore, the quadratic rollback (Rizzo 2006) was only performed on this site for these two site-years.

2) Scenario 2. Rolled back hourly O_3 values for 1993-1995 to a SUM06 of 25 ppm-hours cumulated over a consecutive 3-month period during the 12 (8:00 am to 8:00 pm) daylight hours.

3) Scenario 3. Rolled back hourly O_3 values for 1993-1995 to the 1st highest daily maximum 8-hour average, not to exceed 0.070 ppm.

4) Scenario 4. Rolled back hourly O_3 values for 1993-1995 to the 4th highest daily maximum 8-hour average, not to exceed 0.070 ppm.

5) Scenario 5. Rolled back hourly O_3 values for 1993-1995 to a SUM06 of 15 ppm-hours cumulated over a consecutive 3-month period during the 12 (8:00 am to 8:00 pm) daylight hours.

Results

The simulations produced a prediction of average annual total tree growth over the 3-year period for each scenario. These results were compared to the base scenario, which consisted of a prediction of growth under the hourly meteorology and O_3 conditions for the period 1993-1995.

The predictions indicated substantial increases in 3-year total tree growth increments with reduction of O_3 exposure, particularly under Scenario 3, a rollback to conform to the standard of the 1st highest maximum 8-hour average being no greater than 0.070 ppm. Yellow poplar had nearly a twenty percent increase in growth in response to this scenario, an average annual increase of 6.5%.

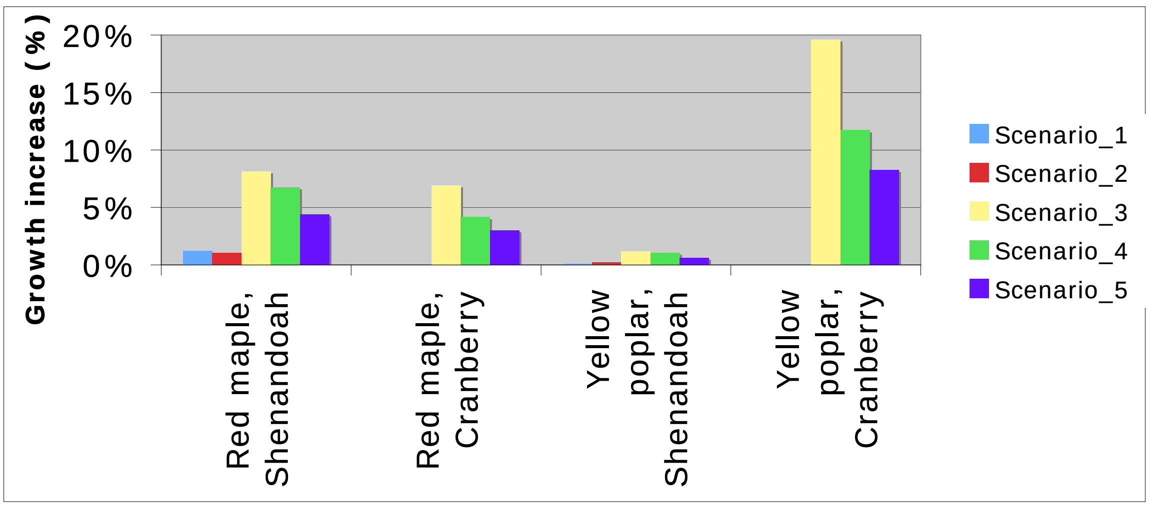
Table J-1 Predicted percent increases in total tree growth over a 3-year period under the 4 ozone (O_3) reduction scenarios.

	Red maple, Shenandoah	Red maple, Cranberry	Yellow poplar, Shenandoah	Yellow poplar, Cranberry

Scenario_1	1.22%		0.08%	
Scenario_2	1.02%		0.20%	
Scenario_3	8.14%	6.92%	1.15%	19.61%
Scenario_4	6.72%	4.15%	1.03%	11.73%
Scenario_5	4.49%	2.99%	0.60%	8.26%

Scenario 1: Rollback current EPA standard 4th highest max. 8-hr avg. 0.085 ppm
Scenario 2: Rollback SUM06 25 ppm-hr
Scenario 3: Rollback 1st highest max. 8-hr avg. 0.070 ppm
Scenario 4: Rollback 4th highest max. 8-hr avg. 0.070 ppm
Scenario 5: Rollback SUM06 15ppm-hr

Figure J-1 Tree growth response of red maple and yellow poplar in forests of Shenandoah National Park, Virginia and Cranberry, North Carolina to ozone (O_3) reduction scenarios.



Red maple was simulated to have a similar response to Scenario 3 in Shenandoah and in Cranberry. However, it had nearly twice the increase to Scenario 4 at Shenandoah as it did at Cranberry. The response to Scenario 5 was slightly less than Scenario 4 for red maple and for yellow poplar in both Shenandoah and Cranberry. The response of yellow poplar at Cranberry to Scenario 5 was still very large, with growth projected to increase more than 8% under this level of O_3 reduction.

Yellow poplar had a very different response to O_3 reduction at Shenandoah compared to Cranberry. The temperatures at Cranberry are more in the middle of the range of temperatures over which yellow poplar is found than are the cool temperatures of Shenandoah, making conditions at Cranberry more ideal for growth. Higher growth rates may cause greater sensitivity to O_3. Red maple has a much larger geographical distribution, so that the temperature differences between Shenandoah and Cranberry are less likely to affect the growth response. This phenomenon was reflected in the simulations.

Finally, Scenarios 1 and 2 produced very little growth response in either species. These scenarios produced no change in the predicted O_3 exposure at Cranberry, so they were not even simulated. At Shenandoah, the change in O_3 exposure to Scenarios 1 and 2 was very slight.

Uncertainty

Any simulation result is dependent on the accuracy with which the parameters used in the model can be estimated. In a model with as many parameters as TREGRO, it is nearly impossible to conduct a comprehensive uncertainty analysis, in which each parameter is allowed to vary throughout it's potential distribution to assess the impact of different values on the model's predictions. Despite the absence of an uncertainty analysis, it is also incorrect to assume that in a deterministic model such as TREGRO (with no stochastic elements) all parameters were correctly estimated and therefore the prediction is the only one possible. Two trees of the same species, identical size, and growing under the same conditions can vary in growth rate considerably.

The predictions of the response to O_3 are dependent on the relationship used in the model between cumulative exposure and photosynthesis reduction. This relationship, established in a controlled chamber experiment, had only a small amount of variability surrounding it caused by within experiment variability. The amount the relationship might vary when environmental conditions are changed from those of the experiment to those of the Cranberry or Shenandoah forests is unknown. However, the relationship does not seem to be very sensitive to these types of shifts in environmental variables. The principle variable that appears to affect the responsiveness of growth of a tree to O_3 is the historical growth of that tree under a given set of environmental conditions. The TREGRO model explicitly incorporates this effect by calculating the energy and carbon balance of the tree. A tree with a poorer energy balance, i.e. one where energy demands do not greatly exceed energy supplies, has proven to be more susceptible to injury from O_3 in TREGRO (Weinstein et al. 2001), and this appears to mirror patterns observed in real forests.

The effect of O_3 changes as a tree continues to be exposed over a succession of years. TREGRO attempts to account for some of this effect by simulating over three consecutive years. However, as stated above, the effect of O_3 is larger in a tree that is in a poorer energy balance, and a year of significant O_3 exposure will place a tree into a poorer energy balance for the next year. Therefore, if O_3 levels remain high for many years in a row, the effect of a given level of O_3 will increase with each year. The choice of three years attempts to capture the nature of this effect, but simulating five or ten successive years of high O_3 exposure would lead to a prediction of higher average annual effects. Historically, the variability in year-to-year O_3 exposure has made it unlikely that there would be a period of high O_3 this lengthy without intervening years of lower O_3.

Appendix K Report from the Preliminary Evaluation of O_3 Interpolation Approaches using 53 monitored dropout sites

This appendix contains the full text of a memorandum delivered by to EPA by Abt Associates on 4-25-06, detailing the preliminary investigation of 10 interpolation approaches being considered. Since this early investigation was redone in greater depth for the writing of the current report, much of the material in this appendix appears earlier in the body of this report. Specifically, material coming before section K.2.4 has already appeared in the body of this report.

K.1. Introduction

During the last review of the ozone (O_3) NAAQS, as part of the development of the 1996 O_3 Staff Paper (SP), EPA conducted analyses that assessed national O_3 air quality, vegetation exposures and risk, and impacts to economic benefits. At the time of the last review, large rural sections of the country had little or no monitor coverage, including important growing regions for agricultural crops and forested ecosystems. Since O_3 monitor coverage in agricultural and rural/remote sites has changed little since the last review, EPA must again rely on generated O_3 air quality in non-monitored areas to provide national O_3 exposure coverage. Given a number of recent air quality related developments, including the refinement of the Community Multiscale Air Quality (CMAQ) model, inclusion of a spatial interpolation tool in EPA's Environmental Benefits Mapping and Analysis Program (BenMAP), and updated monitored air quality, EPA has decided to use a different method to generate a national exposure surface in this review.

In this memorandum we evaluate approaches for generating a national O_3 surface, based on their ability to make predictions for sites where we have O_3 monitoring data. To test these approaches, we chose a number of “dropout” monitors across the country (see section K.2.4 for details), removed them from our data set, and used each of the approaches to make O_3 predictions for the dropout locations using the remaining data. We then compared these predictions to the actual data from the dropout monitors to evaluate the effectiveness of the different approaches.

The approaches we considered are summarized in Section K.3. Our results suggest that enhanced Voronoi Neighbor Averaging (eVNA) offers substantial improvements over the CMAQ modeling data, and in certain cases, substantial improvements over the traditional VNA approach (as used in BenMAP) as well. In the results section (Section K.3) we provide a range of quantitative measures that underlie our evaluation.

K.2 Methods

Below we describe the data that we used in our analysis, how we processed the data, and finally the approach that we used to evaluate our results.

K.2.1 Monitor Data

The monitor data used in this analysis was taken from the Air Quality System (AQS) and Clean Air Status and Trends Network (CASTNet) for the year 2001. AQS O_3 data was taken from the file RD_501_44201_2001.zip, and information on the monitors was taken from the file AMP500_1994_FEB05.zip. Both are available at http://www.epa.gov/ttn/airs/airsaqs/detaildata/downloadaqsdata.htm. CASTNet O_3 data was taken from www.epa.gov/camdis01/prepack/ozone_2001.zip, and information on CASTNet monitors can be found at http://cfpub.epa.gov/gdm/index.cfm.

Completeness Criteria

Data from a given monitor was only used if the monitor was deemed "complete", i.e. if it had valid O_3 values for at least 50 percent[s] of the hours during its region's O_3 season. Note that O_3 seasons vary by geography and range from year-round (in California) to periods as short as June-September (Montana). In all states except Texas, O_3 regions follow state boundaries. Texas is unique in that it contains parts of 2 different O_3 regions, each with its own O_3 season. To simplify matters, we have applied the shorter of these seasons to the entirety of Texas.

Definition of O_3 Metrics (SUM06 and Annual 4th Highest Daily Maximum 8-hour Average)

For hourly O_3 data, we considered two O_3 metrics (SUM06 and 8-hour maximum average) that can be calculated on the daily-level ("SUM06" and "daily 8-hour maximum average") or the yearly-level ("annual maximum 3-month SUM06" and "annual 4th highest daily maximum 8-hour average").

The daily SUM06 metric is the sum of all O_3 values greater than or equal to 0.06 parts per million (ppm) observed from 8am-8pm. In order for a day to have a valid SUM06 value, 75 percent of the hours from 8am-8pm must be valid. To adjust for missing hourly O_3 values, we scale SUM06 by the ratio of (number of possible hourly O_3 values) / (number of valid hourly O_3 values).[t]

The yearly SUM06 metric is the annual maximum 3-month SUM06. To compute it, we calculate the sum of all daily SUM06 values over all possible 3-month periods. And then to adjust for missing days, we scale each monthly SUM06 value by the ratio of (number of days in the month) / (number of valid days).[u] The greatest of these 3-month SUM06 values is the annual maximum 3-month SUM06. In order for a 3-month period to have a valid "3-month SUM06" value, each month in the 3-month period must have at least 75 percent valid days. In order for a year to have a valid yearly SUM06 value (annual maximum 3-month SUM06), it must have at least one 3-month period with a valid 3-month SUM06 value.

[s] For example, if the ozone season were May-September, then a valid monitor would have to have at least 1,836 hourly observations out of a potential total of 3762 (= 153 days x 24 hours). Out of 1,194 monitors, all but two of them have at least 50 percent valid readings during their O_3 season. We are considering raising this threshold to 75 percent. This would eliminate an additional 79 monitors, leaving about 93 percent of the original monitors remaining.

[t] When interpolating hourly ozone values (as opposed to daily ozone metrics), we do not follow this exact method. Instead, we apply a scaling factor at the monthly level (valid observations during the month) / (12hours x number of days in the month). This simplifies the process and does not alter the quantitative analysis in any meaningful way. For further explanation, see subsection in Section 2.3, Interpolating Hourly Data vs. Metrics.

[u] This is done when interpolating metrics, but not when interpolating hours. See previous footnote for details.

The daily 8-hour maximum is calculated from rolling 8-hour averages of hourly O_3 data, where a valid 8-hour average must have 75 percent of a potential of eight hours in any given 8-hour period (i.e., at least six hours out of eight).[v] The daily 8-hour maximum is the greatest of the day's 8-hour averages. Note that for a daily maximum to be considered valid, the day must have at least 75 percent of the potential 8-hour averages (i.e., 18 out of a potential of 24).[w]

The yearly metric associated with the 8-hour maximum is the annual 4th highest daily maximum 8-hour average. This is defined to be the 4th highest value amongst all of the valid daily 8-hour maximums throughout the year.

K.2.2 Model Data

We used two CMAQ modeling datasets, one with a resolution of 12km x 12km, the other with a resolution of 36km x 36km. The 12-km CMAQ grid consists of 188 x 213 cells covering the eastern U.S. (bounded approximately on the west by the 99° line of longitude) excluding the northernmost parts of Maine, Wisconsin, Minnesota, and South Dakota, and the southernmost parts of Florida and eastern Texas. The 36-km CMAQ grid consists of 112 x 148 cells covering the entire continental US. Each dataset gives hourly O_3 values for each cell.[x]

K.2.3 Interpolation Approaches

We used two interpolation approaches: Voronoi Neighbor Averaging (VNA) and enhanced Voronoi Neighbor Averaging (eVNA). The former is based only on monitor data, and the latter uses both monitoring and modeling data. We describe each below; in addition, Appendix C (above) provides a detailed numerical example.

Voronoi Neighbor Averaging (VNA)

VNA uses distance-weighted averages of neighboring monitor data to arrive at predictions for a dropout site. It identifies neighboring monitors for each dropout site using a Voronoi Neighbor Algorithm, and takes an inverse-distance-weighted average of each neighbor's value for the data point in question (hourly O_3 value, daily metric, etc) to arrive at a prediction for that data point corresponding to the dropout site in question.

Enhanced Voronoi Neighbor Averaging (eVNA)

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[v] When there are six or seven hours in any given 8-hour period, we sum the available hourly measurements and then divide by the number of available measurements (as opposed to always dividing by eight).

[w] There are 24 possible 8-hour measurements in a day, starting with 12:00 midnight to 7:59 am, and going through 11:00 pm to 6:59pm. This allows 8-hour measurements to straddle days, following the approach in the Federal Register (40 CFR, Part 58). We consider an 8-hour measurement to be part of a day if it starts during that day. So 11pm[day1]-6am[day2] is part of day1.

[x] All of the CMAQ data was provided by EPA in netCDF (Network Common Data Form) format. Steve Howard from EPA provided a program to convert from netCDF to text.

The eVNA approach attempts to improve the accuracy of VNA predictions by taking into consideration modeling predictions for the areas involved. To illustrate the rationale behind eVNA, we consider a simple fictional example.

Suppose we wish to predict the O_3 level at a hypothetical monitor at location X for a given hour. Location X has two equidistant neighboring monitors, monitor A and monitor B. Monitor A reports 32 ppb, and monitor B reports 20 ppb. A simple VNA approach would calculate the O_3 at location X to be 26 ppb (the average of 32 and 20, with equal weights given to the two equidistant neighbors).

Suppose, however, that CMAQ modeling data shows O_3 levels at location X to be about twice that of O_3 levels at either location A or location B. For example, suppose the average CMAQ O_3 values for locations A and B are 15 ppb, whereas average CMAQ O_3 values for location X are 30 ppb. If CMAQ accurately captures the relationship between locations A, B, and X, then we would expect the O_3 value to be twice as high at X, compared to A and B. That is we would expect a value closer to 52 ppb – the weighted-distance average of 2*32 ppb and 2*20 ppb. The eVNA approach formalizes this technique over large and more complicated sets of data.

Unlike VNA, which averages the "raw" monitor predictions, eVNA first "adjusts" the individual monitor predictions, multiplying by an adjustment factor that reflects the relationship between the neighbor's and the dropout location's O_3 levels, as determined by modeling data. For example, if the modeling data suggested that O_3 levels at neighbor A were generally twice as high as at the dropout location, and that O_3 levels at neighbor B were generally half as high as the dropout location, we would multiply neighbor A's O_3 value by ½ and multiply neighbor B's O_3 value by 2 before proceeding to take a distance weighted average over the two neighbors.

Four Approaches to Condition-Specific Adjustment Factors

The eVNA approach, as we have described it thus far, is imperfect in that it assumes the O_3-level relationship between two locations to be constant throughout the year. In fact, the relationship may vary with the season, or with the time of day, or with numerous other factors. To take this into account, we have added an additional layer of complexity. Rather than condensing a year's worth of model data into a single relationship between the O_3 levels of two locations (and thus a single adjustment factor for each neighbor-dropout pair), we determine the relationship for a number of different conditions. This allows us to tailor our adjustments to the conditions at hand.

If we are adjusting a monitor value in January, we can use an adjustment factor that specifically reflects the modeled relationship between the locations at hand *during the month of January*. Similarly, if we are adjusting an O_3 value that is particularly high, we can use an adjustment factor that describes the general modeled relationship between the locations in question *when O_3 levels are high*.

One can imagine many such ways to divide the data into subsets that reflect the particular conditions of the data in question. We have chosen four such divisions, herein referred to as "approaches", which we outline below. Each approach represents a separate and distinct effort to generate an O_3 surface; i.e. each of these four approaches can each be applied separately to the data to yield a different set of O_3 predictions.

Month-Decile

We first sort CMAQ modeled hourly values into 12 groups by month. In each month-group we split evenly the ordered hourly values into ten rank-ordered deciles. This gives us 120 groups of hourly O_3 values (for every CMAQ grid cell). We calculate the average of the hourly values in each gridcell-month-decile combination, and use this average as the "representative value" of that

CMAQ grid cell for that month-decile. In order to adjust a neighboring monitor value to reflect the modeled relationship to the unmonitored or dropout site, the appropriate month-decile adjustment factor must be used. For example, to adjust a monitor value that falls into the 10^{th} decile of January monitor values, we multiply by the ratio of [the representative value of the dropout's gridcell for the 10^{th} decile of January] over [the representative value of the neighbor's gridcell for the 10^{th} decile of January].

$$adjusted\ monitor\ value = monitor\_value_{neighbor} * \frac{representativeCMAQ_{dropout\_gridcell,month,decile}}{representativeCMAQ_{neighbor\_gridcell,month,decile}}$$

Season-Decile

We first sort CMAQ modeled hourly values into four groups by season (Jan-Mar, Apr-Jun, July-Sep, Oct-Dec). In each season-group we split evenly the ordered hourly values into ten rank-ordered deciles. This gives us 40 groups of hourly O_3 values (for every CMAQ grid cell). We calculate the average of the hourly values in each gridcell-season-decile combination, and use this average as the representative value of that CMAQ gridcell for that season-decile. In order to adjust a neighboring monitor value to reflect the modeled relationship to the unmonitored or dropout site, the appropriate season-decile adjustment factor must be used. For example, to adjust a monitor value that falls into the 10^{th} decile of the Jan-Mar monitor values, we multiply by the ratio of [the representative value of the dropout's modeled O_3 data for the 10^{th} decile of Jan-Mar] over [the representative value of the neighbor's modeled O_3 data for the 10^{th} decile of Jan-March].

Month-Hour

We first sort CMAQ modeled hourly values into 12 groups by month. In each month-group we split evenly the ordered hourly values into 24 groups by time of day. This gives us 288 groups of hourly O_3 values (for every CMAQ grid cell). We calculate the average of the hourly values in each gridcell-month-hour combination, and use this average as the representative value of that CMAQ grid cell for that month-hour. In order to adjust a neighboring monitor value to reflect the modeled relationship to the unmonitored or dropout site, the appropriate month-hour adjustment factor must be used. For example, to adjust a monitor value from 9am in the month of January, we multiply by the ratio of [the representative value of the dropout's gridcell for the 9am hour in January] over [the representative value of the neighbor's gridcell for the 9am hour in January].

Season-Hour

We first sort CMAQ modeled hourly values into four groups by season. In each season-group we split evenly the ordered hourly values into 24 groups by time of day. This gives us 96 groups of hourly O_3 values (for every CMAQ grid cell). We calculate the average of the hourly values in each gridcell-season-hour combination, and use this average as the representative value of that CMAQ grid cell for that month-hour. In order to adjust a neighboring monitor value to reflect the modeled relationship to the unmonitored or dropout site, the appropriate season-hour adjustment factor must be used. For example, to adjust a monitor value from 9am in the Jan-Mar season, we multiply by the ratio of [the representative value of the dropout's gridcell for the 9am hour in the Jan-Mar season] over [the representative value of the neighbor's gridcell for the 9am hour in the Jan-Mar season].

Interpolating Hourly Data vs. Metrics

So far we have been speaking only of interpolating hourly O_3 values from neighbor sites to a dropout location. In principle, the exact same techniques can be used to interpolate daily (or even yearly) metrics from neighbors to dropout.

For example, suppose we had a day's worth of hourly O_3 values for monitor A and monitor B. We wanted to predict the daily SUM06 value for location X, situated at the midpoint between monitors A and B. We have two options. We can use eVNA to generate *hourly* O_3 predictions for location X, then calculate the daily SUM06 from these hourly predictions. Alternately, we can calculate daily SUM06 at each of the neighbor sites, and then interpolate *daily* SUM06 values using eVNA.

Our work examines both of these methods. For each of the four eVNA approaches outlined above, we generate a set of predictions based on interpolating hourly O_3 values, and a set of predictions based on interpolating daily metrics.

To interpolate daily metrics, we class hourly data according to some approach (month-decile, month-hour, season-decile, season-hour). As with hourly-techniques, we adjust neighboring monitor values at the hourly level (scale by a ratio of representative CMAQ values). However, before taking a distance-weighted average over the set of neighbors, we compute daily metrics (SUM06 and 8-hour maximum average) from the adjusted hourly neighbor data. These metrics are then distance-weight averaged to produce daily metric predictions at the dropout site.

K.2.4 Choice of Dropout Monitor Sites

To test the validity of the different approaches, we dropped some monitors from our monitor sample, and then used the remaining O_3 monitors to predict O_3 levels at these "out-of-sample" monitor sites. We chose monitor sites for our out-of-sample testing that are isolated from other monitors and that appear to be in relatively rural areas (Figures K-1 and K-2). There are fewer monitors in the western United States (i.e., west of 99 degrees longitude) than in the East, and the monitors tend to be a greater distance from each other, with the exception of California, which has a large number of closely located monitors. As a result, we chose fewer dropout sites in the West (12) than in the East (41).

Figure K-1 Location of "Dropout" Monitor Sites (Triangle = West; Pentagon = East)

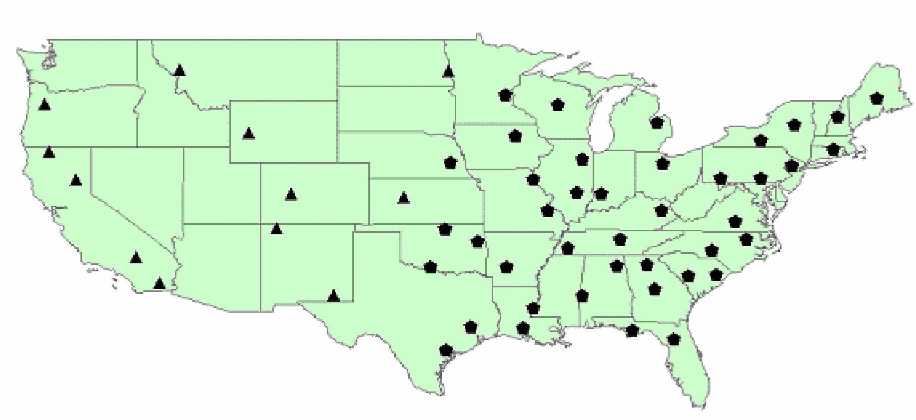
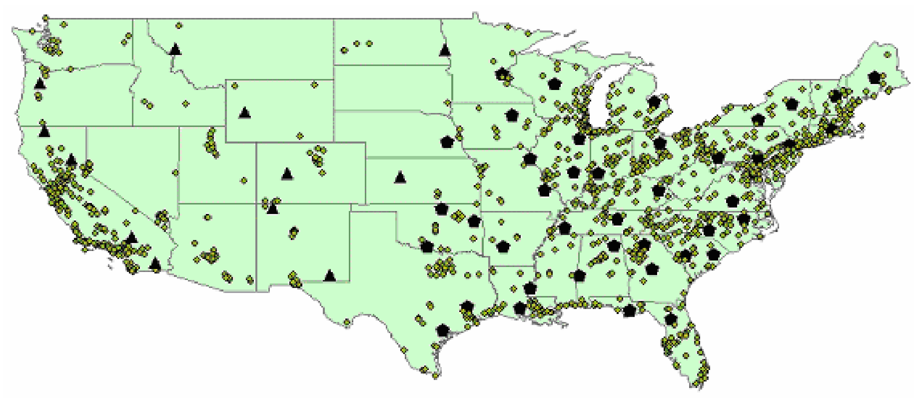


Figure K-2 Location of "Dropout" Monitor Sites and Other AQS and CASTNet Monitor Sites



K.2.5 Evaluation Criteria

In evaluating the different options for generating an O_3 surface, we used two summary statistics (normalized bias and normalized error) for both the annual maximum 3-month SUM06 and the annual 4th highest daily maximum 8-hour average.[y] We define mean normalized bias and mean normalized error formulaically for annual maximum 3-month SUM06. (The definitions of mean normalized bias and mean normalized error for the annual 4th highest daily maximum 8-hour average follow the same principles, so we have not presented them here.)

$$Mean\ SUM06\ normalized\ bias = average_{i \in dropouts}\left(100 * \frac{predictedSUM06_i - actualSUM06_i}{actualSUM06_i}\right)$$

$$Mean\ SUM06\ normalized\ error = average_{i \in dropouts}\left(100 * \frac{\left|predictedSUM06_i - actualSUM06_i\right|}{actualSUM06_i}\right)$$

[y] See the discussion on the definition of model performance statistics starting on page 6 of the recent analysis by EPA: *CMAQ Performance Evaluation for 2001: Updated March 2005*.

The mean normalized bias gives an average of the signed error of each dropout prediction. The mean normalized error gives an average of the absolute error of each dropout prediction. A negative mean normalized bias indicates predictions that tend to underestimate the actual values. A positive mean normalized bias indicates predictions that tend to overestimate the actual values. All mean normalized errors are positive. Their magnitude grows with the inaccuracy of the predictions.

To clarify these statistics, we give the following example dataset. Note that individual normalized biases and errors differ only in sign. However, when averages are taken over normalized biases and normalized errors, the results differ in magnitude as well as sign. A normalized error and a normalized bias which are equal in absolute value indicate that predictions consistently underestimate (or overestimate, depending on the sign) actual values:

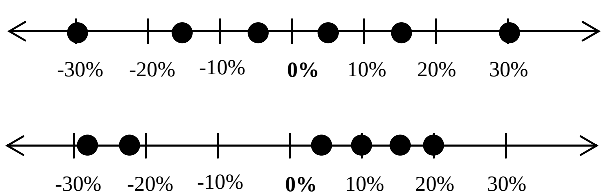
eVNA value	monitor value	bias	error	normalized bias	normalized error
5	7	-2	2	-29%	29%
9	8	1	1	13%	13%
3	5	-2	2	-40%	40%
6	5	1	1	20%	20%

mean normalized bias	-9%
mean normalized error	25%

It is erroneous to say that either mean normalized bias or mean normalized error is more “important” or “meaningful” than another. Rather, they work in conjunction to tell a particular story. The error (from here forward, we use bias and error to refer to mean normalized bias and mean normalized error) describes the general level of accuracy of its corresponding set of predictions. The bias then indicates the general distribution of this inaccuracy between under-predictions and over-predictions.

In choosing approaches for generating a POES, it is preferable to have low error (and thus more reliable predictions), but the bias must play a role in the decision as well. For example, if one is attempting to establish a lower bound on crop damage estimates, it is unwise to choose an approach with positive bias – as this may overestimate O_3 pollution.

It is worth noting, however, that bias and error cannot paint a complete picture of the results. Observe below:



Both scenarios yield the same error and bias (16.7 percent error, 0 percent bias), even though the distribution of predictions is quite different. This suggests that in addition to comparing the bias and error, it may be useful to look at the distribution of the results themselves. To this end, we have included individual prediction data for the hourly approaches in Section K.3.3 below.

K.3. Results

The approaches we considered are summarized in Table K-1, and ranked on a subjective scale of good / fair / poor. The "good" ranking is assigned to the top-performing approaches. Often several approaches receive a "good" ranking, because one performs slightly better in terms of error, and the other performs slightly better in terms of bias. Approaches that perform almost as well as "good" approaches (but generally yield slightly less accurate results) receive a "fair" rating. The "poor" rating is given to approaches that perform *significantly* worse than "good" approaches. Bear in mind that in this subjective analysis, more weight was given to small variations in error than small variations in bias. However, significant biases factored in strongly when compared to smaller variations in error. Sections K.3.1 and K.3.2 provide a range of quantitative measures that underlie our evaluation. Section K.3.3 presents the raw data on which these quantitative measures are based.

Table K-1 Summary of O_3 Prediction Accuracy by Region and Metric

Approach	What gets interpolated	SUM 06 -- Eastern Dropouts (12km model Grid) SUM06	8-hour Maximum -- Eastern Dropouts (12km model grid)	SUM 06 -- Western Dropouts (36km model grid)	8-hour Maximum --Western Dropouts (36km model grid)
VNA	Hour	Fair	Fair	Poor	Poor
VNA	Metric	Poor	Good	Poor	Poor
Model		Poor	Poor	Poor	Poor
Month-Decile	Hour	Good	Fair	Poor	Poor
Month-Hour	Hour	Fair	Good	Poor	Poor
Season-Decile	Hour	Good	Fair	Poor	Poor
Season-Hour	Hour	Fair	Good	Poor	Poor
Month-Decile	Metric	Poor	Good	Poor	Poor
Month-Hour	Metric	Poor	Fair	Poor	Poor
Season-Decile	Metric	Poor	Good	Poor	Poor
Season-Hour	Metric	Poor	Fair	Poor	Poor

We observe generally that in the east (on a 12km grid), the hour-month-decile and hour-season-decile approach are best for predicting annual maximum 3-month SUM06 metrics, whereas the hour-month-hour approach is best for predicting annual 4th highest daily maximum 8-hour average metrics. The data further suggest (though they do not guarantee) that better predictions might be achieved through a blend of VNA and eVNA techniques; applying VNA to monitors within 100km distance of the location in question, and eVNA to monitors which are further away. We recommend further exploration of this mixed approach.

The predictions in the west are much less accurate, which is not surprising given concerns expressed by EPA staff about the accuracy of western modeling results. Section K.3.1 presents quantitative results for the east; Section K.3.2 presents similar results for the west; Section K.3.3 presents the individual predicted and actual values for each of the 41 eastern monitors.

K.3.1 Eastern Dropout Results

Table K-2 through K-4 summarize the results of our predictions for the selected dropout sites and for each of the approaches. They used two summary statistics, (mean normalized) bias and (mean normalized) error for both the annual maximum 3-month SUM06 and the annual 4th highest daily maximum 8-hour average. For simplicity of presentation, these tables (and their discussion) use the terms SUM06 and 8-hour maximum (or 8hr) in lieu of annual maximum 3-month SUM06 and annual 4th highest daily maximum 8-hour average. Our results suggest that the best approach would be hour-season-hour.

Table K-2 summarizes the results from the entire set of 41 eastern dropouts for each of our 11 approaches. Based on our initial evaluation of the data, we observe the following:

- SUM06 predictions generally have greater bias and error compared to 8-hour.
- The model by itself predicts relatively poorly.
- Hourly VNA performs relatively well. However, some potentially significant gains in accuracy are still possible by including an eVNA approach.
- For SUM06, interpolating hourly values is more accurate than interpolating metrics. (Model predictions fall between these two approaches in terms of accuracy.)
- For the best overall performance on SUM06 (in the east), we would recommend the hour-month-decile approach or the hour-season-decile approach. Hour-month-decile has a slightly lower bias; hour-season-decile has a slightly lower error. The choice may depend on the specific application of the data (see section 2.5 for a more in-depth discussion of error and bias)
- For the best overall performance on 8-hour (in the east), we would recommend the hour-month-hour approach. Metric-month-decile may be appropriate in certain circumstances where its tendency towards underestimation is not a concern.

Table K-2 Evaluation Statistics for Eastern Dropout Monitors

Adjustment Method	What gets interpolated	SUM06 Bias	SUM06 Error	8-hour Bias	8-hour Error
model-predictions		37.59	69.22	-6.72	9.26
VNA (no adjustment)	hour	4.18	32.61	-2.42	6.23
VNA (no adjustment)	metric	116.69	118.89	-1.37	5.86
month-decile	hour	-4.67	27.60	-3.09	6.09
month-hour	hour	10.31	36.31	-0.64	6.17
season-decile	hour	-5.09	27.02	-3.14	5.92
season-hour	hour	14.33	39.05	-0.70	6.30
month-decile	metric	108.47	111.35	-1.96	5.80
month-hour	metric	115.06	117.02	1.33	7.02
season-decile	metric	109.30	111.98	-1.86	5.73
season-hour	metric	115.11	117.08	1.18	6.93

Table K-3 separates the data into subsets based on the distance between neighbor monitor and dropout site. To isolate distance as a variable, we must present the data at a pre-interpolation phase (interpolation combines data from several neighbors, each of varying distance). Interpolation significantly reduces error and bias; as a result, inaccuracies are significantly overstated in these data. We observe the following:

- Predictions generally become less accurate as distance increases. The one exception to this is the transition from 0-50km to 50-100km distance. Here, SUM06 errors increase slightly, but SUM06 biases decrease. 8-hour errors and biases both decrease.

- VNA outperforms eVNA between 0-50 km. VNA also does quite well from 50-100km, with very low relative error (though its bias is significantly higher than that of the month-decile and season-decile approaches).
- Above 100km, VNA's performance is significantly worse than that of eVNA. Season-decile performs the best at these distances, with month-decile as a close second.

Table K-3 Evaluation Statistics for Adjusted Neighbor Values At Eastern Dropout Monitors, by Distance from Neighbors

Adjustment Method	What gets interpolated	SUM06 Bias	SUM06 Error	8-hour Bias	8-hour Error
0-50 km					
vna	hour	8.18	29.65	1.39	7.32
month_decile	hour	10.32	31.48	1.40	8.11
month_hour	hour	13.71	33.60	4.35	8.84
season_decile	hour	11.04	33.26	1.78	7.55
season_hour	hour	16.05	36.62	4.78	9.28
50-100 km					
vna	hour	7.53	30.07	1.16	6.53
month_decile	hour	-2.71	32.75	-0.29	6.44
month_hour	hour	6.67	37.89	3.37	8.71
season_decile	hour	-1.06	33.81	-0.13	6.51
season_hour	hour	10.98	40.03	3.70	9.15
100-150 km					
vna	hour	33.81	56.32	3.15	7.29
month_decile	hour	23.28	47.81	1.66	6.94
month_hour	hour	29.41	52.50	5.02	9.44
season_decile	hour	18.81	44.37	1.55	6.49
season_hour	hour	31.09	53.69	4.91	9.17
150+ km					
vna	hour	149.45	180.71	5.93	13.30
month_decile	hour	106.31	141.00	6.12	10.48
month_hour	hour	147.25	173.95	11.82	16.86
season_decile	hour	106.36	140.24	5.21	10.67
season_hour	hour	145.41	173.24	11.21	16.93
COMBINED					
vna	hour	45.20	69.49	2.73	8.30
month_decile	hour	29.33	59.99	1.82	7.67
month_hour	hour	43.98	70.68	5.76	10.69
season_decile	hour	28.95	59.60	1.71	7.55
season_hour	hour	46.02	72.07	5.79	10.88

Note: To allow for distance-based comparison, the results from this table are calculated pre-interpolation, i.e. using the predicted O3 values at each neighbor site, rather than the interpolated value at the dropout site. Because interpolation eliminates a great deal of error, our actual results would be much more accurate than suggested in this exhibit. Compare the "Combined" results from this exhibit with the hour-based results from exhibit 3-2 for more a quantitative look at this phenomenon.

Table K-4 separates the monitors between those with a low O_3 concentration at the dropout site (as determined by the dropout monitor's SUM06 value), and those with a high O_3 concentration at the dropout site. It then gives the four statistics for each of subset. The split between "low" and "high" is made at the 50th percentile of SUM06 O_3 values. We observe the following:

All approaches (Model, VNA, and eVNA) tend to overestimate low SUM06 values and underestimate high SUM06 values, i.e. they reduce extremes. This trend is also generally observed for 8-hour values. The model's SUM06 predictions are more accurate in high-O_3 situations. In low O_3 situations they perform poorly.
VNA performs relatively poorly in low-O_3 conditions. It performs very well in high O_3 conditions – it is one of the better approaches for high-O_3 SUM06, and it performs relatively well on high-O_3 8-hour predictions.

Season-decile appears to be the best approach in low-O_3 conditions. Season-hour appears to be the best approach in high-O_3 conditions, with season-decile as a close second.

Table K-4 Evaluation Statistics for Eastern Dropout Monitors, by Low/High O_3 Levels

Adjustment Method	What gets interpolated	SUM06 Bias	SUM06 Error	8-hour Bias	8-hour Error
LOW					
Model		98.29	111.17	-2.99	8.19
vna	hour	26.66	46.33	0.92	6.49
month_decile	hour	11.92	33.33	0.15	5.48
month_hour	hour	39.48	53.79	3.41	6.93
season_decile	hour	11.58	31.50	-0.01	5.26
season_hour	hour	45.66	59.53	3.30	6.85
HIGH					
Model		-20.21	29.26	-10.28	10.28
vna	hour	-17.23	19.53	-5.61	5.98
month_decile	hour	-20.48	22.15	-6.18	6.66
month_hour	hour	-17.46	19.65	-4.50	5.44
season_decile	hour	-20.96	22.75	-6.13	6.55
season_hour	hour	-15.51	19.55	-4.50	5.77
COMBINED					
Model		37.59	69.22	-6.72	9.26
vna	hour	4.18	32.61	-2.42	6.23
month_decile	hour	-4.67	27.60	-3.09	6.09
month_hour	hour	10.31	36.31	-0.64	6.17
season_decile	hour	-5.09	27.02	-3.14	5.92
season_hour	hour	14.33	39.05	-0.70	6.30

K.3.2 Results of Western Monitors

Below we present data from the west that corresponds to the data from the east above. See section K.3.1 for explanatory text.

Table K-5 Evaluation Statistics for Western Dropout Monitors

Adjustment Method	What gets interpolated	SUM06 Bias	SUM06 Error	8-hour Bias	8-hour Error
model-predictions		143.03	149.98	22.23	22.81
VNA (no adjustments)	hour	-10.91	83.23	3.00	12.68
VNA (no adjustments)	metric	203.76	203.76	4.77	12.65
month-decile	hour	-18.97	73.49	1.95	11.78
month-hour	hour	-17.11	73.40	4.50	13.47
season-decile	hour	-19.50	71.62	1.69	12.03
season-hour	hour	-15.53	71.64	3.83	13.10
month-decile	metric	163.44	163.44	3.92	13.03
month-hour	metric	161.56	164.58	7.87	13.98
season-decile	metric	154.73	155.54	3.64	12.49
season-hour	metric	160.90	162.65	7.44	13.86

Table K-6 Evaluation Statistics for Adjusted Neighbor Values At Western Dropout Monitors, by Distance from Neighbors

Adjustment Method	What gets interpolated	SUM06 Bias	SUM06 Error	8-hour Bias	8-hour Error
0-50 km					
vna	hour	-42.41	57.13	-15.12	15.63
month_decile	hour	-36.12	62.94	-13.60	15.37
month_hour	hour	-32.18	67.35	-13.07	16.85
season_decile	hour	-36.96	62.58	-13.82	15.78
season_hour	hour	-33.52	66.02	-12.88	16.66
50-100 km					
vna	hour	195.88	214.91	17.40	21.02
month_decile	hour	174.62	190.13	17.73	21.08
month_hour	hour	166.77	179.62	26.63	29.83
season_decile	hour	169.45	183.58	17.44	21.09
season_hour	hour	170.27	183.12	25.66	29.04
100-150 km					
vna	hour	18.22	58.40	15.91	20.62
month_decile	hour	24.80	53.47	17.71	18.08
month_hour	hour	49.29	65.68	18.57	18.57
season_decile	hour	27.25	54.32	14.93	15.43
season_hour	hour	44.36	61.23	16.06	16.55
150+ km					
vna	hour	18.21	85.27	1.88	11.35
month_decile	hour	-6.60	62.25	1.68	9.89
month_hour	hour	-1.43	62.65	6.09	12.44
season_decile	hour	-9.38	62.38	1.21	9.86
season_hour	hour	0.23	63.17	5.49	12.00
COMBINED					
vna	hour	46.79	104.07	5.46	13.95
month_decile	hour	26.10	83.03	5.58	12.67
month_hour	hour	30.78	82.75	10.33	16.04
season_decile	hour	23.43	82.09	4.92	12.40
season_hour	hour	32.09	83.28	9.50	15.40

Table K-7 Evaluation Statistics for Western Dropout Monitors, by Low/High O_3 Levels

Adjustment Method	What gets interpolated	SUM06 Bias	SUM06 Error	8-hour Bias	8-hour Error
LOW					
Model		277.28	277.28	29.29	29.29
vna	hour	33.36	123.39	10.40	15.23
month_decile	hour	10.71	103.78	8.43	15.25
month_hour	hour	11.37	100.75	10.98	15.94
season_decile	hour	9.46	102.53	8.38	15.03
season_hour	hour	14.64	99.72	10.49	15.59
HIGH					
Model		31.15	43.90	11.37	12.54
vna	hour	-47.80	49.75	-7.34	8.57
month_decile	hour	-43.70	48.26	-7.38	7.88
month_hour	hour	-40.84	50.61	-4.84	10.41
season_decile	hour	-43.63	45.87	-7.87	8.25
season_hour	hour	-40.67	48.24	-5.68	9.93
COMBINED					
Model		143.03	149.98	20.33	20.92
vna	hour	-10.91	83.23	1.53	11.90
month_decile	hour	-18.97	73.49	0.52	11.56
month_hour	hour	-17.11	73.40	3.07	13.17
season_decile	hour	-19.50	71.62	0.26	11.64
season_hour	hour	-15.53	71.64	2.41	12.76

K.3.3 Monitor-Level Prediction Data

This section contains individual predictions for the 41 eastern dropout monitors and the associated error and bias values. We present this data for model predictions and all hour-based predictions. We have omitted the equivalent tables for the less accurate metric-based predictions. For SUM06 predictions an additional datum is given which specifies whether or not the 3-month period used to predict the annual SUM06 metric corresponds to the 3-month period used to calculate the actual annual SUM06 metric. Its value is 1 if the 3-month periods match, 0 otherwise.

Table K-8 Model Predictions

Monitor_ID	SUM06	Acutal SUM06	Correct First Month	Normalized Bias	Normalized Error	8hr max	Actual 8hr max	Normalized Bias	Normalized Error
0111900021	9.98	8.53	0	17.05	17.05	69.38	72.57	-4.39	4.39
1200130111	11.62	21.81	0	-46.74	46.74	68.19	79.00	-13.68	13.68
1302100121	19.04	20.74	1	-8.18	8.18	81.41	86.25	-5.62	5.62
1308500012	27.89	20.18	1	38.25	38.25	73.87	77.75	-5.00	5.00
1700100061	18.25	13.27	0	37.50	37.50	72.97	78.00	-6.45	6.45
1704910012	24.22	15.33	0	58.01	58.01	76.00	77.13	-1.46	1.46
1719710111	30.37	19.37	0	56.77	56.77	77.93	78.43	-0.64	0.64
1805500011	25.85	30.13	0	-14.20	14.20	77.87	85.75	-9.19	9.19
1901700111	21.25	12.31	0	72.59	72.59	71.48	69.88	2.30	2.30
2205500051	9.47	14.84	0	-36.21	36.21	72.25	77.25	-6.48	6.48
2302100031	4.65	5.14	1	-9.57	9.57	64.35	68.00	-5.37	5.37
2700310011	14.48	9.07	0	59.71	59.71	79.91	73.67	8.47	8.47
2800100041	13.78	14.16	1	-2.66	2.66	69.10	75.13	-8.03	8.03
2918600051	13.75	23.42	0	-41.29	41.29	75.00	75.13	-0.16	0.16
3110900161	15.80	0.92	1	1619.52	1619.52	70.52	51.50	36.94	36.94
3402730011	23.12	31.80	1	-27.28	27.28	81.06	101.13	-19.84	19.84
3604100051	14.22	12.84	0	10.78	10.78	71.75	82.38	-12.89	12.89
3706500991	19.30	27.27	1	-29.22	29.22	71.49	85.64	-16.52	16.52
4002190021	13.74	19.31	0	-28.84	28.84	71.31	75.00	-4.92	4.92
4006706711	18.87	29.79	0	-36.67	36.67	71.87	81.25	-11.55	11.55
4007190031	15.15	34.29	0	-55.83	55.83	69.47	81.88	-15.15	15.15
4213300081	24.72	35.09	0	-29.56	29.56	78.79	87.75	-10.22	10.22
4500300041	14.27	23.39	0	-38.97	38.97	70.37	79.88	-11.90	11.90
4508900012	14.24	8.38	1	70.02	70.02	69.45	67.88	2.31	2.31
4707500031	18.74	26.09	0	-28.17	28.17	72.88	81.50	-10.57	10.57
4833900891	20.14	18.15	0	10.95	10.95	77.96	90.63	-13.98	13.98
4846900031	4.00	8.58	0	-53.33	53.33	67.13	73.50	-8.66	8.66
5507300121	11.61	10.10	0	14.87	14.87	67.69	72.13	-6.15	6.15
ABT147	18.54	22.11	1	-16.14	16.14	86.13	106.00	-18.74	18.74
CAD150	13.40	13.95	0	-3.91	3.91	68.81	74.28	-7.35	7.35
CKT136	19.09	22.38	1	-14.70	14.70	69.93	76.69	-8.81	8.81
CND125	18.38	22.03	1	-16.57	16.57	73.17	80.08	-8.62	8.62
CTH110	15.32	16.49	0	-7.09	7.09	70.45	85.23	-17.33	17.33
ESP127	17.83	15.11	0	17.98	17.98	69.06	74.36	-7.13	7.13
LRL117	29.22	15.05	0	94.10	94.10	77.09	75.58	2.01	2.01
LYK123	25.14	30.63	0	-17.94	17.94	76.50	86.05	-11.09	11.09
PED108	19.89	22.64	1	-12.15	12.15	71.53	84.64	-15.48	15.48
SND152	18.62	29.17	0	-36.16	36.16	72.69	83.20	-12.64	12.64
SUM156	7.57	9.02	0	-16.07	16.07	67.03	68.51	-2.16	2.16
UVL124	16.38	20.70	0	-20.87	20.87	80.59	85.24	-5.45	5.45
WST109	9.31	8.35	1	11.52	11.52	66.68	69.39	-3.90	3.90

Table K-9 Hour-VNA Predictions

Monitor_ID	SUM06	Acutal SUM06	Correct First Month	Normalized Bias	Normalized Error	8hr max	Actual 8hr max	Normalized Bias	Normalized Error
0111900021	12.54	8.53	1	47.09	47.09	73.62	72.57	1.45	1.45
1200130111	10.09	21.81	0	-53.75	53.75	71.56	79.00	-9.42	9.42
1302100121	20.28	20.74	1	-2.20	2.20	80.07	86.25	-7.16	7.16
1308500012	15.81	20.18	1	-21.63	21.63	72.62	77.75	-6.59	6.59
1700100061	14.00	13.27	1	5.51	5.51	71.69	78.00	-8.09	8.09
1704910012	18.04	15.33	1	17.72	17.72	71.43	77.13	-7.38	7.38
1719710111	17.52	19.37	1	-9.55	9.55	75.16	78.43	-4.17	4.17
1805500011	20.02	30.13	1	-33.56	33.56	77.99	85.75	-9.05	9.05
1901700111	3.24	12.31	1	-73.67	73.67	62.41	69.88	-10.68	10.68
2205500051	7.82	14.84	0	-47.33	47.33	73.24	77.25	-5.19	5.19
2302100031	6.64	5.14	0	29.15	29.15	70.36	68.00	3.47	3.47
2700310011	9.28	9.07	1	2.28	2.28	72.28	73.67	-1.89	1.89
2800100041	9.64	14.16	0	-31.95	31.95	71.16	75.13	-5.27	5.27
2918600051	18.21	23.42	1	-22.28	22.28	73.06	75.13	-2.74	2.74
3110900161	4.13	0.92	0	349.67	349.67	65.11	51.50	26.43	26.43
3402730011	26.06	31.80	1	-18.04	18.04	92.79	101.13	-8.24	8.24
3604100051	11.78	12.84	1	-8.24	8.24	78.99	82.38	-4.10	4.10
3706500991	21.88	27.27	1	-19.79	19.79	75.03	85.64	-12.39	12.39
4002190021	10.16	19.31	0	-47.37	47.37	65.88	75.00	-12.16	12.16
4006706711	27.51	29.79	1	-7.65	7.65	79.61	81.25	-2.02	2.02
4007190031	35.23	34.29	1	2.73	2.73	81.86	81.88	-0.01	0.01
4213300081	32.77	35.09	1	-6.61	6.61	90.16	87.75	2.75	2.75
4500300041	18.85	23.39	1	-19.40	19.40	75.01	79.88	-6.09	6.09
4508900012	14.53	8.38	1	73.45	73.45	74.36	67.88	9.55	9.55
4707500031	25.83	26.09	1	-0.98	0.98	75.80	81.50	-6.99	6.99
4833900891	14.72	18.15	0	-18.89	18.89	85.76	90.63	-5.37	5.37
4846900031	11.59	8.58	0	35.03	35.03	80.22	73.50	9.15	9.15
5507300121	10.04	10.10	0	-0.61	0.61	72.66	72.13	0.75	0.75
ABT147	17.32	22.11	1	-21.66	21.66	93.67	106.00	-11.63	11.63
CAD150	16.81	13.95	1	20.52	20.52	72.61	74.28	-2.25	2.25
CKT136	13.18	22.38	1	-41.14	41.14	73.44	76.69	-4.23	4.23
CND125	26.20	22.03	0	18.94	18.94	80.98	80.08	1.13	1.13
CTH110	13.85	16.49	0	-16.05	16.05	80.59	85.23	-5.43	5.43
ESP127	25.09	15.11	1	66.02	66.02	75.69	74.36	1.79	1.79
LRL117	22.45	15.05	1	49.13	49.13	81.80	75.58	8.24	8.24
LYK123	24.83	30.63	1	-18.95	18.95	84.01	86.05	-2.37	2.37
PED108	21.56	22.64	1	-4.78	4.78	80.83	84.64	-4.50	4.50
SND152	18.48	29.17	1	-36.65	36.65	73.29	83.20	-11.91	11.91
SUM156	11.10	9.02	0	23.13	23.13	72.36	68.51	5.62	5.62
UVL124	21.22	20.70	1	2.49	2.49	85.30	85.24	0.08	0.08
WST109	9.29	8.35	0	11.26	11.26	74.67	69.39	7.61	7.61

Table K-10 Hour-Month-Decile Predictions

Monitor_ID	SUM06	Acutal SUM06	Correct First Month	Normalized Bias	Normalized Error	8hr max	Actual 8hr max	Normalized Bias	Normalized Error
0111900021	10.26	8.53	1	20.36	20.36	73.20	72.57	0.87	0.87
1200130111	9.59	21.81	0	-56.02	56.02	68.91	79.00	-12.77	12.77
1302100121	20.32	20.74	1	-2.00	2.00	81.79	86.25	-5.17	5.17
1308500012	16.01	20.18	1	-20.64	20.64	72.77	77.75	-6.41	6.41
1700100061	15.37	13.27	1	15.79	15.79	72.09	78.00	-7.58	7.58
1704910012	16.28	15.33	1	6.21	6.21	69.78	77.13	-9.53	9.53
1719710111	17.95	19.37	1	-7.33	7.33	75.43	78.43	-3.83	3.83
1805500011	19.79	30.13	1	-34.34	34.34	78.92	85.75	-7.97	7.97
1901700111	3.39	12.31	0	-72.50	72.50	62.66	69.88	-10.33	10.33
2205500051	7.02	14.84	0	-52.74	52.74	71.52	77.25	-7.42	7.42
2302100031	5.24	5.14	1	1.89	1.89	68.15	68.00	0.21	0.21
2700310011	12.66	9.07	1	39.62	39.62	76.76	73.67	4.20	4.20
2800100041	9.72	14.16	1	-31.39	31.39	72.24	75.13	-3.84	3.84
2918600051	13.66	23.42	1	-41.69	41.69	71.38	75.13	-4.99	4.99
3110900161	1.97	0.92	0	114.11	114.11	63.01	51.50	22.34	22.34
3402730011	32.39	31.80	1	1.85	1.85	95.82	101.13	-5.24	5.24
3604100051	12.80	12.84	1	-0.36	0.36	80.99	82.38	-1.68	1.68
3706500991	22.46	27.27	1	-17.65	17.65	76.01	85.64	-11.24	11.24
4002190021	2.77	19.31	0	-85.66	85.66	62.49	75.00	-16.67	16.67
4006706711	23.34	29.79	1	-21.65	21.65	78.17	81.25	-3.79	3.79
4007190031	33.88	34.29	1	-1.20	1.20	83.22	81.88	1.65	1.65
4213300081	31.26	35.09	1	-10.91	10.91	89.60	87.75	2.10	2.10
4500300041	18.14	23.39	1	-22.43	22.43	74.52	79.88	-6.70	6.70
4508900012	12.65	8.38	1	51.00	51.00	68.27	67.88	0.58	0.58
4707500031	26.15	26.09	1	0.24	0.24	77.57	81.50	-4.82	4.82
4833900891	24.46	18.15	0	34.79	34.79	93.59	90.63	3.27	3.27
4846900031	14.65	8.58	1	70.77	70.77	78.70	73.50	7.08	7.08
5507300121	10.70	10.10	0	5.91	5.91	71.73	72.13	-0.55	0.55
ABT147	18.44	22.11	1	-16.59	16.59	92.99	106.00	-12.27	12.27
CAD150	12.23	13.95	1	-12.32	12.32	70.61	74.28	-4.94	4.94
CKT136	15.21	22.38	1	-32.06	32.06	72.16	76.69	-5.90	5.90
CND125	25.43	22.03	1	15.45	15.45	77.62	80.08	-3.06	3.06
CTH110	12.92	16.49	0	-21.70	21.70	79.07	85.23	-7.23	7.23
ESP127	19.18	15.11	1	26.94	26.94	74.21	74.36	-0.20	0.20
LRL117	22.98	15.05	1	52.68	52.68	81.05	75.58	7.24	7.24
LYK123	26.21	30.63	0	-14.43	14.43	84.19	86.05	-2.16	2.16
PED108	19.67	22.64	1	-13.10	13.10	76.86	84.64	-9.19	9.19
SND152	15.92	29.17	1	-45.42	45.42	72.68	83.20	-12.65	12.65
SUM156	6.94	9.02	1	-23.05	23.05	69.98	68.51	2.14	2.14
UVL124	19.77	20.70	1	-4.50	4.50	86.42	85.24	1.38	1.38
WST109	9.39	8.35	0	12.46	12.46	75.24	69.39	8.43	8.43

Table K-11 Hour-Month-Hour Predictions

Monitor_ID	SUM06	Acutal SUM06	Correct First Month	Normalized Bias	Normalized Error	8hr max	Actual 8hr max	Normalized Bias	Normalized Error
0111900021	12.55	8.53	0	47.20	47.20	75.63	72.57	4.21	4.21
1200130111	9.42	21.81	1	-56.80	56.80	70.72	79.00	-10.48	10.48
1302100121	20.16	20.74	1	-2.77	2.77	80.61	86.25	-6.54	6.54
1308500012	17.41	20.18	1	-13.73	13.73	75.04	77.75	-3.48	3.48
1700100061	16.92	13.27	1	27.48	27.48	74.18	78.00	-4.90	4.90
1704910012	16.68	15.33	1	8.79	8.79	70.25	77.13	-8.91	8.91
1719710111	20.07	19.37	1	3.59	3.59	77.97	78.43	-0.59	0.59
1805500011	21.36	30.13	1	-29.09	29.09	79.53	85.75	-7.26	7.26
1901700111	3.87	12.31	0	-68.60	68.60	63.54	69.88	-9.06	9.06
2205500051	6.57	14.84	0	-55.76	55.76	70.95	77.25	-8.15	8.15
2302100031	5.64	5.14	0	9.63	9.63	68.85	68.00	1.25	1.25
2700310011	11.06	9.07	1	21.98	21.98	75.31	73.67	2.23	2.23
2800100041	13.51	14.16	1	-4.57	4.57	75.78	75.13	0.88	0.88
2918600051	15.00	23.42	1	-35.98	35.98	71.77	75.13	-4.46	4.46
3110900161	4.10	0.92	0	346.07	346.07	66.23	51.50	28.59	28.59
3402730011	33.94	31.80	1	6.73	6.73	101.91	101.13	0.77	0.77
3604100051	13.15	12.84	0	2.37	2.37	82.15	82.38	-0.27	0.27
3706500991	22.93	27.27	1	-15.90	15.90	76.19	85.64	-11.04	11.04
4002190021	3.88	19.31	0	-79.92	79.92	62.75	75.00	-16.33	16.33
4006706711	22.45	29.79	1	-24.64	24.64	81.11	81.25	-0.17	0.17
4007190031	33.97	34.29	1	-0.93	0.93	83.26	81.88	1.69	1.69
4213300081	30.01	35.09	1	-14.48	14.48	89.04	87.75	1.47	1.47
4500300041	17.82	23.39	1	-23.80	23.80	74.67	79.88	-6.51	6.51
4508900012	13.82	8.38	1	64.97	64.97	71.60	67.88	5.48	5.48
4707500031	25.95	26.09	1	-0.52	0.52	76.57	81.50	-6.05	6.05
4833900891	27.36	18.15	0	50.77	50.77	99.74	90.63	10.05	10.05
4846900031	22.41	8.58	1	161.21	161.21	88.58	73.50	20.52	20.52
5507300121	11.84	10.10	0	17.18	17.18	73.44	72.13	1.83	1.83
ABT147	19.39	22.11	1	-12.28	12.28	95.83	106.00	-9.59	9.59
CAD150	22.42	13.95	1	60.68	60.68	77.52	74.28	4.37	4.37
CKT136	16.87	22.38	1	-24.65	24.65	75.48	76.69	-1.58	1.58
CND125	24.82	22.03	0	12.69	12.69	77.69	80.08	-2.98	2.98
CTH110	14.38	16.49	0	-12.81	12.81	81.93	85.23	-3.86	3.86
ESP127	20.56	15.11	1	36.08	36.08	74.90	74.36	0.72	0.72
LRL117	24.67	15.05	1	63.88	63.88	83.25	75.58	10.16	10.16
LYK123	29.25	30.63	0	-4.52	4.52	90.82	86.05	5.55	5.55
PED108	20.56	22.64	1	-9.17	9.17	78.28	84.64	-7.52	7.52
SND152	17.76	29.17	1	-39.13	39.13	75.06	83.20	-9.78	9.78
SUM156	8.89	9.02	1	-1.45	1.45	71.37	68.51	4.17	4.17
UVL124	20.41	20.70	1	-1.41	1.41	85.61	85.24	0.43	0.43
WST109	9.55	8.35	0	14.42	14.42	75.58	69.39	8.92	8.92

Table K-12 Hour-Season-Decile Predictions

Monitor_ID	SUM06	Acutal SUM06	Correct First Month	Normalized Bias	Normalized Error	8hr max	Actual 8hr max	Normalized Bias	Normalized Error
0111900021	10.52	8.53	1	23.33	23.33	72.10	72.57	-0.66	0.66
1200130111	8.86	21.81	0	-59.39	59.39	70.44	79.00	-10.83	10.83
1302100121	19.19	20.74	1	-7.47	7.47	80.80	86.25	-6.32	6.32
1308500012	16.09	20.18	1	-20.26	20.26	72.17	77.75	-7.17	7.17
1700100061	14.68	13.27	1	10.65	10.65	72.47	78.00	-7.09	7.09
1704910012	16.57	15.33	1	8.07	8.07	70.91	77.13	-8.06	8.06
1719710111	17.49	19.37	1	-9.71	9.71	76.12	78.43	-2.94	2.94
1805500011	20.08	30.13	1	-33.37	33.37	78.72	85.75	-8.20	8.20
1901700111	3.40	12.31	0	-72.41	72.41	62.94	69.88	-9.93	9.93
2205500051	7.29	14.84	0	-50.90	50.90	72.93	77.25	-5.60	5.60
2302100031	5.13	5.14	0	-0.20	0.20	67.51	68.00	-0.71	0.71
2700310011	12.25	9.07	1	35.09	35.09	74.99	73.67	1.79	1.79
2800100041	10.09	14.16	1	-28.73	28.73	71.92	75.13	-4.26	4.26
2918600051	14.27	23.42	1	-39.09	39.09	70.61	75.13	-6.01	6.01
3110900161	2.09	0.92	0	127.35	127.35	63.12	51.50	22.57	22.57
3402730011	32.46	31.80	1	2.09	2.09	96.12	101.13	-4.95	4.95
3604100051	12.71	12.84	1	-0.99	0.99	80.17	82.38	-2.68	2.68
3706500991	22.44	27.27	1	-17.72	17.72	75.01	85.64	-12.41	12.41
4002190021	2.70	19.31	0	-86.00	86.00	62.32	75.00	-16.91	16.91
4006706711	23.12	29.79	1	-22.39	22.39	78.55	81.25	-3.33	3.33
4007190031	33.87	34.29	1	-1.23	1.23	81.82	81.88	-0.07	0.07
4213300081	31.13	35.09	1	-11.29	11.29	90.01	87.75	2.57	2.57
4500300041	18.35	23.39	1	-21.53	21.53	74.14	79.88	-7.19	7.19
4508900012	12.32	8.38	1	47.03	47.03	69.00	67.88	1.66	1.66
4707500031	25.98	26.09	1	-0.42	0.42	75.57	81.50	-7.28	7.28
4833900891	22.04	18.15	0	21.44	21.44	94.10	90.63	3.84	3.84
4846900031	12.84	8.58	1	49.65	49.65	76.55	73.50	4.15	4.15
5507300121	10.31	10.10	0	2.08	2.08	71.67	72.13	-0.63	0.63
ABT147	18.13	22.11	1	-18.00	18.00	94.17	106.00	-11.17	11.17
CAD150	14.81	13.95	1	6.16	6.16	70.82	74.28	-4.65	4.65
CKT136	14.66	22.38	1	-34.52	34.52	73.38	76.69	-4.32	4.32
CND125	25.71	22.03	0	16.70	16.70	78.90	80.08	-1.47	1.47
CTH110	12.96	16.49	1	-21.41	21.41	79.43	85.23	-6.80	6.80
ESP127	19.81	15.11	1	31.12	31.12	73.21	74.36	-1.55	1.55
LRL117	23.69	15.05	1	57.40	57.40	81.62	75.58	7.99	7.99
LYK123	26.67	30.63	0	-12.93	12.93	85.60	86.05	-0.52	0.52
PED108	19.50	22.64	1	-13.86	13.86	78.54	84.64	-7.20	7.20
SND152	16.04	29.17	1	-45.01	45.01	70.81	83.20	-14.89	14.89
SUM156	6.80	9.02	1	-24.56	24.56	70.27	68.51	2.57	2.57
UVL124	19.71	20.70	1	-4.81	4.81	86.77	85.24	1.80	1.80
WST109	9.30	8.35	0	11.48	11.48	74.89	69.39	7.93	7.93

Table K-13 Hour-Season-Hour Predictions

Monitor_ID	SUM06	Acutal SUM06	Correct First Month	Normalized Bias	Normalized Error	8hr max	Actual 8hr max	Normalized Bias	Normalized Error
0111900021	12.93	8.53	1	51.66	51.66	74.49	72.57	2.64	2.64
1200130111	8.88	21.81	0	-59.27	59.27	70.12	79.00	-11.24	11.24
1302100121	19.14	20.74	1	-7.68	7.68	79.31	86.25	-8.05	8.05
1308500012	17.65	20.18	1	-12.52	12.52	73.46	77.75	-5.52	5.52
1700100061	15.28	13.27	1	15.12	15.12	73.28	78.00	-6.05	6.05
1704910012	16.84	15.33	1	9.88	9.88	70.97	77.13	-7.98	7.98
1719710111	20.59	19.37	1	6.28	6.28	78.00	78.43	-0.55	0.55
1805500011	21.80	30.13	1	-27.64	27.64	79.32	85.75	-7.49	7.49
1901700111	4.16	12.31	1	-66.20	66.20	63.84	69.88	-8.63	8.63
2205500051	6.33	14.84	0	-57.34	57.34	70.71	77.25	-8.47	8.47
2302100031	5.71	5.14	0	11.09	11.09	68.25	68.00	0.37	0.37
2700310011	11.00	9.07	1	21.25	21.25	75.87	73.67	2.99	2.99
2800100041	15.20	14.16	0	7.31	7.31	76.89	75.13	2.35	2.35
2918600051	16.50	23.42	1	-29.57	29.57	71.23	75.13	-5.18	5.18
3110900161	5.04	0.92	0	448.65	448.65	66.31	51.50	28.76	28.76
3402730011	36.31	31.80	1	14.18	14.18	104.07	101.13	2.91	2.91
3604100051	13.14	12.84	1	2.31	2.31	81.88	82.38	-0.61	0.61
3706500991	22.88	27.27	1	-16.12	16.12	75.86	85.64	-11.41	11.41
4002190021	4.21	19.31	0	-78.19	78.19	63.78	75.00	-14.97	14.97
4006706711	24.85	29.79	1	-16.60	16.60	80.43	81.25	-1.01	1.01
4007190031	33.96	34.29	1	-0.97	0.97	81.87	81.88	-0.01	0.01
4213300081	29.95	35.09	1	-14.66	14.66	89.35	87.75	1.82	1.82
4500300041	18.39	23.39	1	-21.36	21.36	74.25	79.88	-7.05	7.05
4508900012	13.33	8.38	1	59.19	59.19	71.23	67.88	4.94	4.94
4707500031	26.78	26.09	1	2.65	2.65	75.19	81.50	-7.74	7.74
4833900891	25.03	18.15	0	37.94	37.94	98.01	90.63	8.15	8.15
4846900031	21.38	8.58	1	149.17	149.17	88.07	73.50	19.83	19.83
5507300121	11.37	10.10	0	12.49	12.49	72.74	72.13	0.85	0.85
ABT147	19.96	22.11	1	-9.72	9.72	96.28	106.00	-9.17	9.17
CAD150	26.56	13.95	1	90.42	90.42	78.99	74.28	6.35	6.35
CKT136	16.95	22.38	1	-24.28	24.28	76.34	76.69	-0.45	0.45
CND125	25.23	22.03	0	14.54	14.54	79.90	80.08	-0.22	0.22
CTH110	14.80	16.49	0	-10.28	10.28	82.43	85.23	-3.28	3.28
ESP127	21.26	15.11	1	40.66	40.66	74.03	74.36	-0.45	0.45
LRL117	26.66	15.05	1	77.07	77.07	83.83	75.58	10.92	10.92
LYK123	30.60	30.63	0	-0.12	0.12	90.93	86.05	5.67	5.67
PED108	20.09	22.64	1	-11.26	11.26	79.39	84.64	-6.20	6.20
SND152	18.02	29.17	1	-38.23	38.23	73.49	83.20	-11.67	11.67
SUM156	8.58	9.02	1	-4.84	4.84	71.52	68.51	4.39	4.39
UVL124	21.70	20.70	1	4.80	4.80	87.73	85.24	2.92	2.92
WST109	9.82	8.35	0	17.67	17.67	75.59	69.39	8.95	8.95

Appendix L Comparison of Hour and Metric Interpolation Approaches

This appendix offers an initial discussion of the tendency observed (In appendix K) of metric-based interpolation to over-predict SUM06, and hour-based interpolation to slightly under-predict SUM06 (here we once again use the terms SUM06 and 8-hour maximum to refer to the associated annual metrics).

- When interpolating metrics, any neighbor's O_3 value at or above 60 ppb will have a positive effect on the final SUM06 statistic, even if the rest of the neighbors do not show any O_3 levels greater than or equal to 60 ppb during the hour in question. This leads to a tendency to over-predict SUM06.

- When interpolating hours, neighboring O_3 values above 60 only have an effect on the final daily SUM06 statistic if the other neighbors have high enough O_3 values *in the exact hour* of the first neighbor's high value. This leads to lower values, as made clear in the examples that follow.

Note that the examples that we present below are only for SUM06. Similar arguments (not elaborated here) would seem to apply to the 8-hour maximum, and indeed suggest that the metric approach would give somewhat higher values than the hour approach. However, our reported results (e.g., Exhibit 3-1) show the reverse, with the metric approach predicting lower values than the hour approach. This suggests that the arguments presented here do *not* directly apply to the 8-hour maximum, or there are some errors in our reported results, or, perhaps, that there are some other issue that we have not yet identified that explain the results that we have presented. As a result, we need to view our conclusions as tentative, until we can better understand our results.

Example of Over-prediction in Metric-based SUM06 Interpolation

Suppose location X has 2 equidistant neighbors, monitor A, and monitor B.
Suppose monitor data looks like this:

Time	Monitor A	Monitor B
8am	0.01	0.01
9am	0.02	0.01
10am	0.03	0.01
11am	0.04	0.01
12pm	0.05	0.01
1pm	0.06	0.01
2pm	0.05	0.01
3pm	0.04	0.01
4pm	0.03	0.01
5pm	0.02	0.01
6pm	0.01	0.01
7pm	0.01	0.01

Under the hourly approach (using VNA), daily SUM06 is predicted to be 0:

Time	Hourly VNA Interpolation to Location X	
8am	0.01	
9am	0.015	
10am	0.02	
11am	0.025	
12pm	0.03	
1pm	0.035	
2pm	0.03	
3pm	0.025	
4pm	0.02	
5pm	0.015	
6pm	0.01	SUM06=0
7pm	0.01	

But under the Metric Approach, daily SUM06 is predicted to be .03:

SUM06 A	0.06
SUM06 B	0
Interpolation to SUM06 at Location X	0.03

An even more extreme example can be seen where a monitor reports an unlikely high value:

Time	Monitor A	Monitor B
8am	0.01	0.01
9am	0.02	0.01
10am	0.03	0.01
11am	0.04	0.01
12pm	0.05	0.01
1pm	0.06	0.01
2pm	0.05	0.01
3pm	0.04	0.01
4pm	0.03	0.01
5pm	0.02	0.01
6pm	0.01	**0.06**
7pm	0.01	0.01

This “fluke” .06 doesn’t have an effect on daily SUM06 in the hourly approach, since it doesn’t correlate with the data from monitor A very well:

Time	Hourly VNA Interpolation to Location X	
8am	0.01	
9am	0.015	
10am	0.02	
11am	0.025	
12pm	0.03	
1pm	0.035	
2pm	0.03	
3pm	0.025	
4pm	0.02	
5pm	0.015	
6pm	0.035	SUM06=0
7pm	0.01	

But in the metric approach, it has a large effect:

SUM06 A	0.06
SUM06 B	0.06
Interpolation to SUM06 at Location X	0.06

In this case, .06 seems to be an over-approximation for location X. This agrees with our findings that the metric approach tends to dramatically over predict SUM06 values.

An Example of Under-prediction in Hour-based SUM06 Interpolation

The hourly approach tends towards a slight underestimation of SUM06 values. We can understand this as follows:

Time	Monitor A	Monitor B	Dropout @ X
8am	0.01	0.01	0.01
9am	0.02	0.01	0.01
10am	0.03	0.01	0.02
11am	0.04	0.02	0.03
12pm	0.05	0.03	0.04
1pm	0.06	0.04	0.05
2pm	0.05	0.05	0.06
3pm	0.04	0.06	0.05
4pm	0.03	0.05	0.04
5pm	0.02	0.04	0.03
6pm	0.01	0.03	0.02
7pm	0.01	0.02	0.01

We could interpret this as a pocket of high O_3 levels moving across the terrain with the regional wind pattern. It reaches A first, then the dropout at X, then B.

In a case such as this, hourly interpolation would under-predict daily SUM06, due to the failure of the above-threshold O_3 values to fall in the same hour at the neighbor monitors:

Time	Hourly VNA Interpolation to Location X	Location X
8am	0.01	0.01
9am	0.015	0.01
10am	0.02	0.02
11am	0.03	0.03
12pm	0.04	0.04
1pm	0.05	0.05
2pm	0.05	0.06
3pm	0.05	0.05
4pm	0.04	0.04
5pm	0.03	0.03
6pm	0.02	0.02
7pm	0.15	0.01
SUM06	**0**	**0.06**

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