The Pennsylvania State University
College of Earth and Mineral Sciences
Department of Geosciences

Risk Analysis of Sea Level Rise Around the Port of L.A.

A Senior Thesis in Earth Sciences

by

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of the Requirements
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We approve this thesis:

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Abstract:
The goal of this study is to analyze the probabilities of different sea level heights at different years in the future. Data collected close to the Port of Los Angeles are used to create an empirical model to assess future sea level risks. The analysis shows that there is a non-linear increase in flooding probability in this century towards the end of the analysis. Also, for the 99 percentiles of sea level rise, the flooding probabilities in this century are greater than 90% for two meters and greater than 50% for three meters.
Introduction:

Sea level rise is increasingly an issue for areas of the world located in coastal regions (Bromirski et al., 2007). Sea level rise has been tracked for decades and has been rising over the last century at a rate of approximately 20cm/century (Bromirski et al., 2007). Models are showing that increases in sea level could potentially occur at greater rates in the future, due to a major process occurring in the Earth (Bromirski et al., 2007).

The major process affecting sea level rise is the increase in greenhouse gas emissions which is creating a temperature increase (Lempert et al., 2012). The temperature increases drive sea level rise mainly due to oceanic expansion, melting of glaciers, from the melting of the polar ice caps (Lempert et al., 2012). Also, changes in atmospheric and oceanic circulation can lead to local sea-level changes (Lempert et al., 2012).

The goal of this analysis is to assess flooding probability risks due to sea level change. Data collected close to the Port of Los Angeles are used to create an empirical model to assess future sea level risks.
**Background:**

Sea level rise has been measured since the late 1800’s (Tide Gauge Sea Level, 2011). The tools used for measuring sea level in the past were tidal gauges (Tide Gauge Sea Level, 2011). These tools worked by measuring the sea level height relative to a natural landmark (Tide Gauge Sea Level, 2011). Uncertainty in past data resulted because the tidal gauges can move vertically (Tide Gauge Sea Level, 2011). Even though the past data is not accurate, it is still used in many models for predicting future sea level rise (Tide Gauge Sea Level, 2011).

As technology improved, the measuring of sea levels became more accurate with the use of satellite imagery (Milne et al., 2009). Since 1992, satellite images have provided near complete maps of global sea level, in periods of ten days; allowing for accurate data to be compiled (Milne et al., 2009). GRACE, Gravity Recovery And Climate Experiment, is a collection of satellites used to measure the global gravity field every month (Milne et al., 2009). The gravity field is highly dependent on the motion of water around the Earth and the GRACE system can measure the changes in gravity (Milne et al., 2009). Along with satellites, there are floats that sink and rise in the oceans (Milne et al., 2009). Specifically, the Argo Network, measures the temperature and salinity within the top one to two kilometers of the oceans (Milne et al., 2009). Since 2000, the network has grown to more than 3000 floats. (Milne et al., 2009). These two systems can separate out the differences of events that contribute to sea level rise and give very accurate data of how sea level rise is occurring (Milne et al., 2009).

With data continuously being collected, different computer models are being used to project future sea levels (Sarokin, 2012). The two different types of models used are mechanistic and empirical models (Sarokin, 2012). Mechanistic models are based on an understanding of the behavior of a system’s components (Sarokin, 2012). In the case of modeling sea level rise, mechanistic models would use the different components of sea level rise, such as the emission
of greenhouse gasses and the melting of polar ice sheets, to make projections (Sarokin, 2012). Empirical models can be mechanistically motivated, but usually are constrained with different parameters based on the data that is available (Sarokin, 2012). An empirical model is based on direct observations and the collection of data and the statistical relationships of the data to make projections into the future (Sarokin, 2012).

Despite the collection of data, there is still much uncertainty about the future of global sea levels because models are difficult to create, and it is very hard to account for all the different variables within one model (Douglas, 1991). Some of the current predictions on sea level rise estimate that sea level rise has occurred at a rate of about 20cm/century, but within the next century could rise as much as one to two meters (Bromirski et al., 2007).

In this study, I will use a range of data and empirical models to assess flooding risks close to the Port of L.A. (similar to Lempert et al., 2012). The data for this experiment includes local, hourly sea level data from around the Port of L.A. and uses global data for future projections (Lempert et al., 2012). The infrastructure currently lies approximately 12 feet above sea level, with electrical wires underneath only being about 9 feet above sea level (Lempert et al., 2012). The terminals are relatively high compared to the mean sea level, but with future projections showing increases in sea level, it would be beneficial to upgrade the terminals to prevent frequent flooding in the future (Lempert et al., 2012).
Methods and Figures:

For this project, the hourly data was first used to make a histogram of the frequencies of the sea level anomalies. From the Figure 1, a probability density function, or pdf, (Figure 2) was created. The next plot that created was Figure 3 which is an empirical cumulative distribution function, or cdf, which shows the hourly sea level anomalies and the probabilities the anomalies will occur, between zero and one.

![Histogram of the sea level anomalies](image)

*Figure 1: Histogram of the sea level anomalies of the hourly data with respect to the annual mean.*
Figure 2: Probability density function of the hourly sea level anomalies with respect to the annual mean over the entire observation period of several decades.

Figure 3: Empirical cumulative density function of the hourly sea level anomalies with respect to the annual mean over the entire observation period of several decades.

With the empirical cdf, a gev fit, or generalized extreme value fit, was added to the cdf plot to create Figure 4. The gev fit is used to help better predict the extreme end cases in the
data. The plot was created by fitting parameters of $\xi$, $\mu$, and $\beta$ to the data and creating a line. These parameters represent the shape, location, and scale of the gev function, respectively.

![Empirical cumulative density function of the sea level anomalies shown in Figure 3 with the GEV fit.](image)

**Figure 4:** Empirical cumulative density function of the sea level anomalies shown in Figure 3 with the GEV fit.

From the empirical cdf plot, a survival plot in Figure 5 was then created which was used to better analyze the tails of the data. The survival plot is used to emphasize the extreme values from a cdf plot and used to then make future projections. The survival plot shows how the probability changes with respect to the sea-levels. The points from the cdf plot were stratified into percentiles and were subtracted from the value one. They were plotted on a log scale. A gev function was fitted to the data.
Figure 5: Survival plot of sea level anomalies shown in Figures 1, 2, and 3 with the generalized extreme value function model fit.

Published sea level anomalies (Lempert et al., 2012) from each decade of 2020 to 2100 in 20 year increments was then averaged, converted to mm, and superimposed to the hourly data. The hourly data stands for the year 2000 with no sea level rise. These five superimposed lines were added to illustrate the possible effects of sea level rise in Figure 6.
Figure 6: Survival plot of sea level anomalies with generalized extreme value fit and superimposed mean future projections.

Then the flooding probabilities of different heights of one, two, and three meter were found for all the years using the cumulative probability of the gev probability density function in Figure 7. The probability gev density function, pgev, allows for a numeric vector of probabilities of the gev function to be found at a given quantile. Using the pgev function, the average sea level rise anomaly for a given year was subtracted from the desired sea level rise height in mm to find the probability that flooding would occur, given the model assumptions. The probabilities of flooding to infrastructure heights of one, two, and three meter sea level rise were plotted against each year.
Finally, I compare flooding probabilities to infrastructure heights of two and three meter in Figures 8 and 9. The probabilities were then plotted.
Figure 9: Flooding probabilities for 1, 50, and 99 percentiles of the annual sea-level rise projections to an infrastructure height of three meter.
Discussion:
Figure 1 shows the frequencies of the hourly sea level anomalies with respect to the annual means. It has an approximately Gaussian shape. Figure 2 shows the probability of any sea level anomaly to occur within a range of probabilities. The sea level anomalies with higher frequencies have higher probabilities of occurring, compared to the sea level anomalies with lower frequencies.

Figure 3 shows the amount of sea level anomalies that are below a probability. This means that for extreme sea level anomalies of high values, the probability that sea levels will be below that are very likely. The probability that sea levels will be above very low extreme sea level anomalies is also very likely.

Figures 5 and 6 are used to focus on the tails of the cdf plots (Figures 3 and 4), which are the extreme events in the sea level anomalies. The extreme events are important because those are the times when infrequent flooding will occur. Each decade represented on the plot shows that more sea level rise is expected to occur as the data is shifted to the right in a positive direction. In Figure 7, the probability of flooding increases with time and decreases with infrastructure height.

The plots that were created for this risk analysis do project sea level rise in the future, but there is still uncertainty about the projections. Uncertainty comes from the fact that the data is from a limited time frame and the measuring of the data further in the past is not as accurate as the data gathered closer to the present day. Also, when running the model, the gev fits that were used were estimated based on the data, therefore they were not perfect fits. This uncertainty in the gev fits, leads to ambiguity in the future sea level rise projections because they are based off the original gev fit of the data.

This analysis, thus far focuses on the mean projection of sea level rise. However, future sea level rise projections carry considerable uncertainty (Lempert et al., 2012). I hence analyze
flooding probabilities for the 1, 50, and 99th percentile of annual mean sea level rise projections for infrastructure heights of two (Figure 8) and three (Figure 9) meter.
Conclusion:

The risk analysis does show that sea level rise is more likely to occur in the future based on the probabilities from the plots. This analysis shows that there is a non-linear flooding probability in this century as time persists. Also, for the 99 percentiles of sea level rise, the flooding probabilities in this century are greater than 90% for infrastructure heights of two meter and greater than 50% for infrastructure heights of three meter. This analysis is very simple and neglects many important factors and uncertainties. For example, using past observed hourly anomalies assumes a stationary distribution of intra-annual variability. Obviously, much more work needs to be done to refine this analysis.
Acknowledgments:

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References


http://smallbusiness.chron.com/mechanistic-model-12706.html
Appendix of Code:

#Creating Figures 1, 2, and 3
#Author: Andy Lowy
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#http://creativecommons.org/licenses/by-nc-sa/3.0/legalcode
#Data from (Lempert et al., 2012)

#reading and sorting out fill values in the data

data=hourly_data <-
read.table("C:/Users/Andy/Desktop/hourly_data.txt", quote="\"")

slr_data=data[,2]

slr=slr_data[slr_data!=9999]

#making the histogram of the SL data

hist(slr,main="",col="blue",
xlab="Hourly sea level anomaly [mm]", ylab="Frequency")
dev.copy2pdf(file = "Histogram of Sea Level Data.pdf")

#making the PDF of the SL data

d=density(slr)
plot(d,main="",xlab="Hourly sea level anomaly [mm]", ylab="Density",
xlim=c(500,3500),)
polygon(d, col="blue", border="black")
dev.copy2pdf(file="Empirical PDF of Sea Level Data.pdf")

#making the CDF of the SL data

cdf=ecdf(slr)
plot(cdf,main="",col="blue", xlab="Hourly sea level anomalies [mm]",
ylab="Probability",
xlim=c(500,3500))
dev.copy2pdf(file="Empirical CDF of Sea Level Data.pdf")
#Creating Figure 4
#Author: Andy Lowy
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#http://creativecommons.org/licenses/by-nc-sa/3.0/legalcode
#Data from (Lempert et al., 2012)

#read data into code
data=hourly_data 
read.table("C:/Users/Andy/Desktop/hourly_data.txt", quote="\"")
slr_data=data[,2]
slr=slr_data[slr_data!=9999]

ecdf_data=ecdf(slr) #creates empirical cdf
quant_data=ecdf_data(slr) #creates the quantiles of the data

#plots empirical cdf
pdf(file="Empirical CDF with GEV Fit of Sea Level Data 2.pdf")
plot(slr,quant_data,type="p",col="blue",
 ylab="Probability",
 xlab="Maximum hourly sea level anomaly [mm]",main="")
library(fExtremes)

fit=gevFit(slr, type="pwm") #estimates GEV parameters
#write(fit) #to get values below

q=seq(0,1,length.out=1000000)  # quantile array
fit_q=qgev(q, xi=-0.3376601, mu=1833.4000824, beta=526.2455781)

lines(fit_q, q, col="black", lwd=3) # add fitted model to plot for empirical cdf

#legend for empirical cdf
legend(x="topleft",
inset=c(0.1,0.1),
legend=c("Observations","GEV Fit"),
col=c("blue","black"),
lt=c("solid","solid"),
lwd=c(3,3)
)

dev.off()
# Creating Figures 5, 6, and 7

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http://creativecommons.org/licenses/by-nc-sa/3.0/legalcode
Data from (Lempert et al., 2012)

```r
#data from format_sla <
read.table("C:/Users/Andy/Desktop/format_sla.txt", quote="\"")
slr_data=data[,1]
slr=slr_data[slr_data!=9999]
# sorting out the data for the survival plot

ecdf_data=ecdf(slr)
quant_data=ecdf_data(slr)
# creating quantiles to make the survival plot
library(fExtremes)
fit=gevFit(slr, type="pwm") # estimates GEV parameters
q=seq(0,1,length.out=1000000)  # quantile array
opt_q=qgev(q, xi = -0.3047, mu =-175.735, beta = 516.769)
# best fit line

plot(slr,1-quant_data,type="1",col="blue", cex=1.5,log="y",ylim=c(0.000001,1.), xlim=c(-2000,4000), ylab="log(1-cdf)",xlab="Maximum hourly sea level anomaly [mm]",main="")
# plotting the data alone for the survival plot
axis(2,at=c(1e-7,1e-6,1e-5,1e-4,1e-3,1e-2,1e-1,1), lab=c("","","","","","","",""))
# y-axis
lines(opt_q,1-q,type="1",col="red",lwd=4)
# plots opt_q line
legend(x="topright", inset=c(0.05,0.05), legend=c("Observations","GEV Fit"), col=c("blue","red"), lty=c("solid","solid"), lwd=c(3,3)

plot(slr,1-quant_data,type="1",col="red", cex=1.5,log="y",ylim=c(0.000001,1.), xlim=c(-2000,4000), ylab="log(1-cdf)",xlab="Maximum hourly sea level anomaly [mm]",main="")
```

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#plotting the data alone for the survival plot

axis(2, at=c(1e-7, 1e-6, 1e-5, 1e-4, 1e-3, 1e-2, 1e-1, 1),
     lab=c("", ",", ",", ",", ",", ",")
#y-axis

lines(opt_q, 1-q, type="l", col="blue", lwd=4)
#plots opt_q line

data <- read.table("C:/Users/Andy/Desktop/slr_decadal.txt", quote="\"")

slra20 = slra[,2]*10
slra40 = slra[,4]*10
slra60 = slra[,6]*10
slra80 = slra[,8]*10
slra100 = slra[,10]*10
#reading data for each decade
#converts to mm

avgslra20 = mean(slra20)
avgslra40 = mean(slra40)
avgslra60 = mean(slra60)
avgslra80 = mean(slra80)
avgslra100 = mean(slra100)
#averages slr in different decades

lines(opt_q+avgslra20, 1-q, type="l", col="orange", lwd=4)
lines(opt_q+avgslra40, 1-q, type="l", col="yellow", lwd=4)
lines(opt_q+avgslra60, 1-q, type="l", col="green", lwd=4)
lines(opt_q+avgslra80, 1-q, type="l", col="purple", lwd=4)
lines(opt_q+avgslra100, 1-q, type="l", col="brown", lwd=4)
#plots lines with added slr

legend(x="left",
cex=0.6,
inset=c(0.05, 0.05),
legend=c("Observations", "GEV Fit", "2020 Predictions", "2040 Predictions",
        "2060 Predictions", "2080 Predictions", "2100 Predictions"),
col=c("blue", "red", "orange", "yellow", "green", "purple", "brown"),

lty=c("solid", "solid", "solid", "solid", "solid", "solid", "solid"),
lwd=c(3, 3, 3, 3, 3, 3, 3)
)

###########################################################

opt_q2 = pgev(0, xi = -0.3047, mu = -175.735, beta = 516.769)

data <- read.table("C:/Users/Andy/Desktop/slr_decadal.txt", quote="\")

slra20 = slra[,2]*10
slra40 = slra[,4]*10
slra60 = slra[,6]*10
slra80 = slra[,8]*10
slra100 = slra[,10]*10
#reading data for each decade

avgslra20 = mean(slra20)
avgslra40 = mean(slra40)
avgslra60 = mean(slra60)
avgslra80 = mean(slra80)
avgslra100 = mean(slra100)
#averages slr in different decades

lines(opt_q+avgslra20, 1-q, type="l", col="orange", lwd=4)
lines(opt_q+avgslra40, 1-q, type="l", col="yellow", lwd=4)
lines(opt_q+avgslra60, 1-q, type="l", col="green", lwd=4)
lines(opt_q+avgslra80, 1-q, type="l", col="purple", lwd=4)
lines(opt_q+avgslra100, 1-q, type="l", col="brown", lwd=4)
#plots lines with added slr

legend(x="left",
cex=0.6,
inset=c(0.05, 0.05),
legend=c("Observations", "GEV Fit", "2020 Predictions", "2040 Predictions",
        "2060 Predictions", "2080 Predictions", "2100 Predictions"),
col=c("blue", "red", "orange", "yellow", "green", "purple", "brown"),

lty=c("solid", "solid", "solid", "solid", "solid", "solid", "solid"),
lwd=c(3, 3, 3, 3, 3, 3, 3)
)

###########################################################

year<-c(2000,2020,2040,2060,2080,2100)
probability_1<-c(0.02047473,0.06336983,0.1658731,0.3954346,0.7302562,0.9570335)
probability_2<-c(0,0,0.2426368e-08,0.007088618,0.09540864,0.4168879)
```r
probability_3 <- c(0, 0, 0, 0, 0, 0.009065673)
plot(year, probability_1, col="red", pch=21, type="p", ylab="Probability"

  xlab="Year",
  main="")
lines(year, probability_2, col="blue", pch=22, type="p")
lines(year, probability_3, col="green", pch=24, type="p")

legend(x="topleft",
  cex=.75,
  inset=c(0.05, 0.05),
  legend=c("1M", "2M", "3M"),
  col=c("red", "blue", "green"),
  lty=c("solid", "solid", "solid"),
  lwd=c(3,3,3)
)
```
Data from (Lempert et al., 2012)

slra = slr_decadal <-
read.table("C:/Users/Andy/Desktop/slr_decadal.txt", quote=""")
slra20 = slra[,2]*10
slra40 = slra[,4]*10
slra60 = slra[,6]*10
slra80 = slra[,8]*10
slra100 = slra[,10]*10
# reads in slr data and converts to mm

data = format_sla <-
read.table("C:/Users/Andy/Desktop/format_sla.txt", quote=""")
slr_data = data[,1]
slr = slr_data[slr_data!=9999]
# this is the present data and edits out filler values

ecdf_data = ecdf(slr)
quant_data = ecdf_data(slr)
# makes present data to cdf

time = seq(0,1,.01)
quant_data00 <- quantile(quant_data, probs=time, names=FALSE)
quant_data20 <- quantile(slra20, probs=time, names=FALSE)
quant_data40 <- quantile(slra40, probs=time, names=FALSE)
quant_data60 <- quantile(slra60, probs=time, names=FALSE)
quant_data80 <- quantile(slra80, probs=time, names=FALSE)
quant_data100 <- quantile(slra100, probs=time, names=FALSE)
# creates quantiles of all data

year = c(2000,2020,2040,2060,2080,2100)
two_meter_99 = c(0,0,0.001584638,0.09551861,0.5839849,0.9804455)
two_meter_50 = c(0,0,1.189254e-08,0.006931031,0.09261243,0.4075595)
two_meter_01 = c(0,0,0,0,0,0)
# two meter height with quantiles of 1,50,99
# values come from evaluating pgev function by hand in R
# pgev(Height(mm) - quant_data(year)[quantile #], xi = -0.3047, mu = -175.735, beta = 516.769)
# example of how pgev function was evaluated in R

plot(year, two_meter_99, col="red", pch=21, type="p", ylab="Probability", xlab="Year", main="")
```r
lines(year,two_meter_50,col="blue",pch=22,type="p")
lines(year,two_meter_01,col="green",pch=24,type="p")
legend(x="topleft",
    inset=c(0.05,0.05),
    legend=c("1%","50%","99%"),
    col=c("green","blue","red"),
    lty=c("solid","solid","solid"),
    lwd=c(3,3,3)
)
#plots two meter height data

three_meter_99<-c(0,0,0,0,0.0379364,0.5431896)
three_meter_50<-c(0,0,0,0,0.008167676)
three_meter_01<-c(0,0,0,0,0,0)
#three meter height with quantiles of 1,50,99

plot(year,three_meter_99,col="red",pch=21,type="p",ylab="Probability ",
    xlab="Year",main="")
lines(year,three_meter_50,col="blue",pch=22,type="p")
lines(year,three_meter_01,col="green",pch=24,type="p")
legend(x="topleft",
    inset=c(0.05,0.05),
    legend=c("1%","50%","99%"),
    col=c("green","blue","red"),
    lty=c("solid","solid","solid"),
    lwd=c(3,3,3)
)
#plots three meter height data
```