

# Performance and Usage Analytics for NCAR's Climate Model

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# Overview

1. **Background on Community Earth System Model (CESM)**
2. **Model's configuration**
3. **Data preparation and analysis**
4. **Key findings**
5. **Conclusion and future work**

# Goal

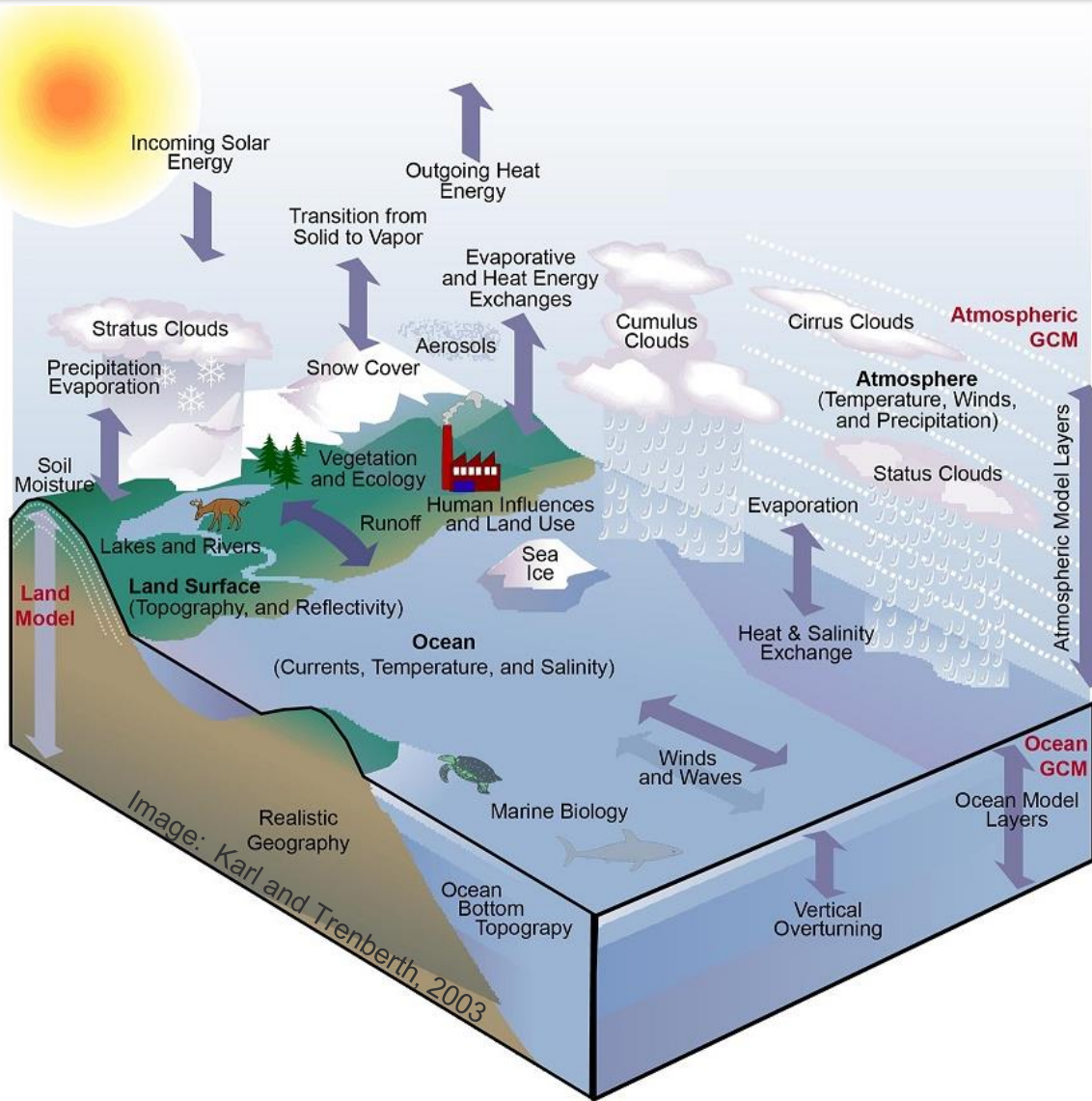


**Analyze CESM  
performance  
metadata**

- ☐ **Establish basic metrics**
- ☐ **Effect of a system upgrade on performance**



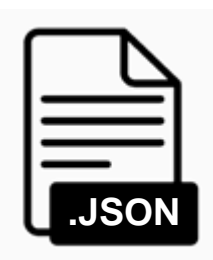
# CESM Climate Model



- **Virtual laboratory**
- **Freely available**
- **Components:**
  - **Atmosphere**
  - **Land**
  - **Ocean**
  - **River**
  - **Sea and Land Ice**
  - **Wave**

**CESM = Community Earth System Model**

# Method



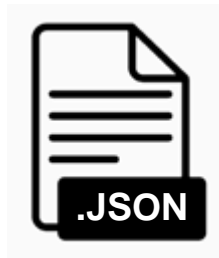
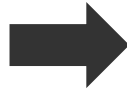
## Data Engineering

- Acquiring
- Saving

```
----- TIMING PROFILE -----
Case      : b.e21.BHIST.f09_g17.CMIP6-historical.001
LID       : 2979765.chadmin1.181015-050236
User      : cmip6
Curr Date : Mon Oct 15 10:01:22 2018
grid      :
a%0.9x1.25_l%0.9x1.25_o!%gx1v7_r%r05_g%gland4_w%ww3a_m%gx1v7
compset   : HIST_CAM60_CLM50%BGC-CROP_CICE_POP2%ECO%ABIO-
           : DIC MOSART CISM2%NOEVOLVE WW3 BGC%BDRD
run_type  : hybrid, continue_run = TRUE (inittype = FALSE)
stop_option : nyears, stop_n = 5
run_length : 1825 days (1825.0 for ocean)

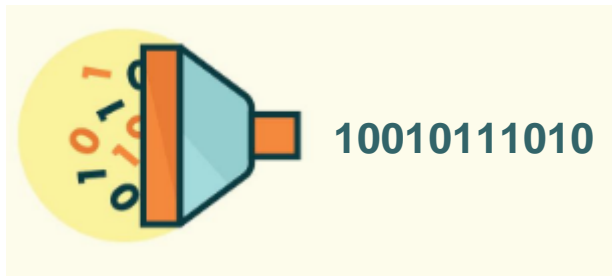
Init Time : 63.817 seconds
Run Time  : 17837.627 seconds          9.774 seconds/day
Final Time : 0.057 seconds
```

# Method



## Data Engineering

- Acquiring
- Saving



## Data Wrangling

- Reindexing
- More parsing
- Set data types
- Intuitive columns
- Calculations

# Data Wrangling

## Parse Run\_Length

3650 days (3650.0 for ocean)

```
▶ #1. Strip everything after "days" in run_length column
df['run_length_temp'] = df['run_length'].str.split('(').str[0]

#Confirm every run_length contains the same units of days
substr = 'days'
print ("Rows in df:", len(df))
print ("Rows with units of days:", df.run_length_temp.str.count(substr).sum())
```

Rows in df: 5160

Rows with units of days: 5160

```
▶ #2. Strip "days" in run_length column
df['run_length_days'] = df['run_length_temp'].str.split('d').str[0]
df.run_length_days.unique()

array(['3650 ', '365 ', '730 ', '2 ', '31 ', '1825 ', '2189 ', '1095 ',
       '5840 ', '5475 ', '1460 ', '2190 ', '5 ', '1 ', '10950 ', '7300 ',
       '4014 ', '426 ', '90 ', '4379 '], dtype=object)
```

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▶ #Convert necessary columns to numeric format
for col in df.columns:
    if 'length_days' in col:
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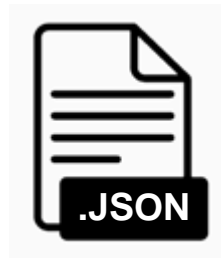
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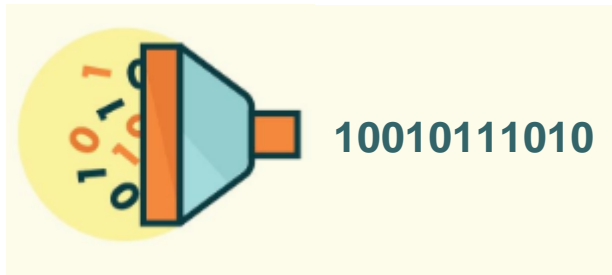


# Method



## Data Engineering

- Acquiring
- Saving



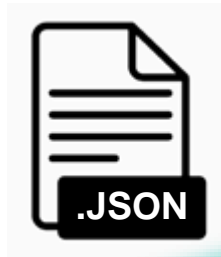
## Data Wrangling

- Reindexing
- More parsing
- Set data types
- Intuitive columns
- Calculations



## Data Storage

# Method



## Data Engineering

- Acquiring

**USABLE  
DATA!!**

ling

data types

- Intuitive columns
- Calculations



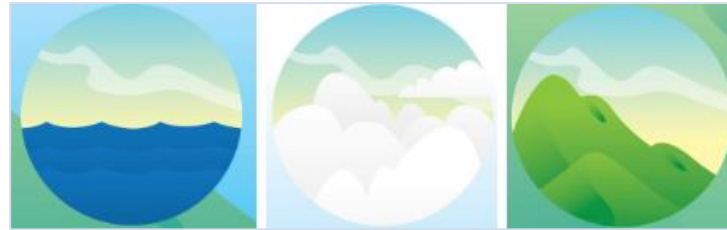
## Data Storage

# Method



4

## Exploratory Data Analysis



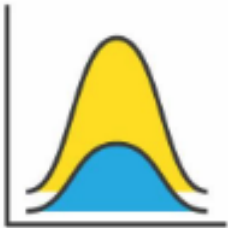
**52 unique  
component configurations**

# Method



4

**Exploratory Data Analysis**



5

**Statistical Analysis**

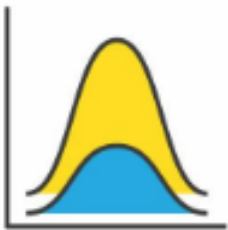
**Pandas**  
**Numpy**  
**Scipy Stats**  
**StatsModels**

# Method



4

**Exploratory Data Analysis**



5

**Statistical Analysis**



6

**Visualization**

**Matplotlib**  
**Seaborn**  
**Plotly**



# Analysis: Dataset Totals

**416 Days**

**948**  
Unique  
Cases



**21,785**  
Simulated  
Years

**137,112,802**  
CPU Hours

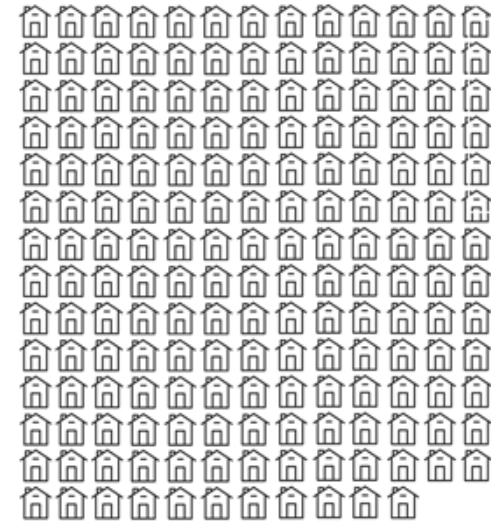
# Power Equivalence

**137,112,802  
CPU Hours**



**218 trips  
around the  
equator in a  
Nissan Leaf**

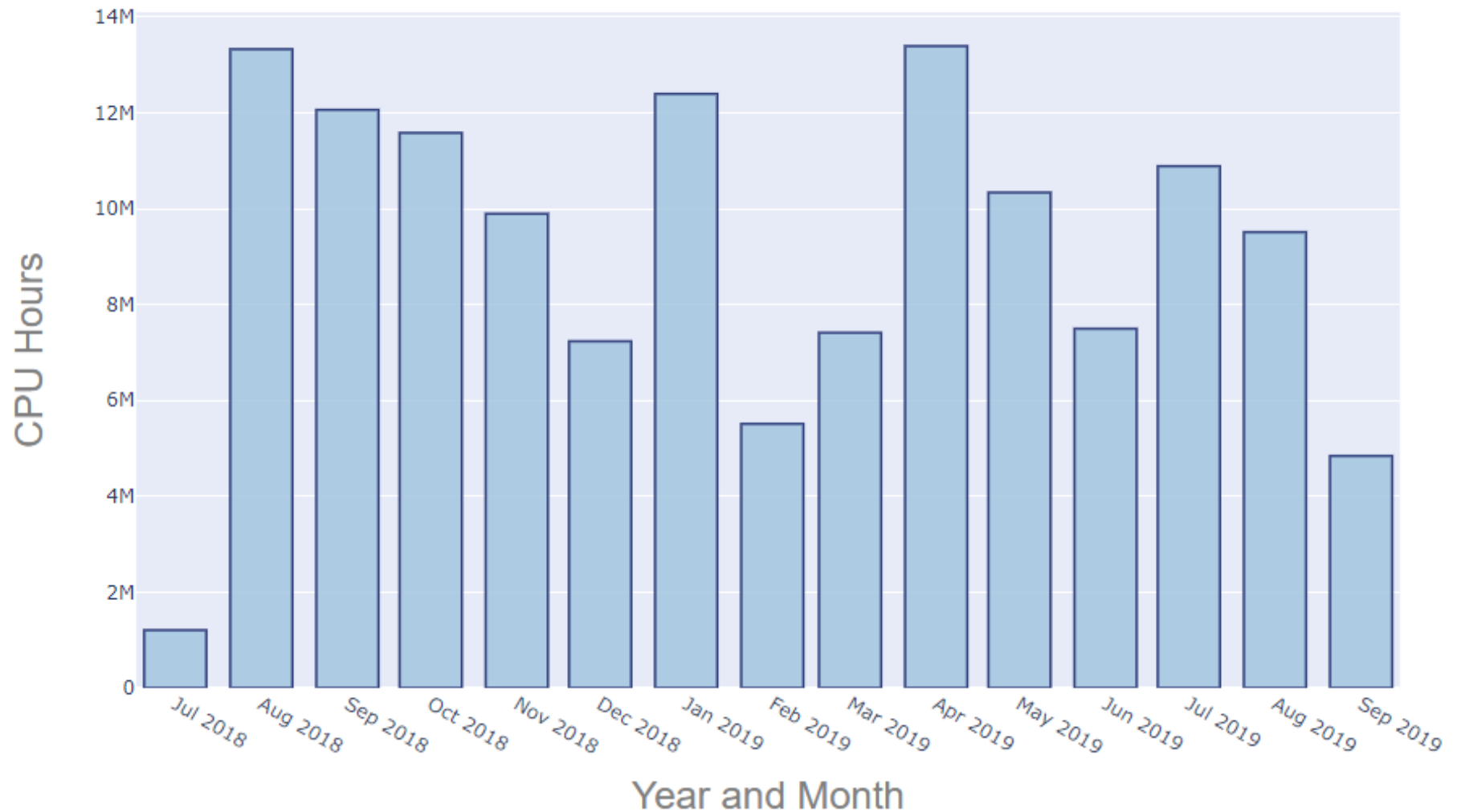
**or**



**Annual power  
for 180  
Colorado homes**

# Analysis: Monthly Totals

## CPU Hours by Month



# Analysis: Grouping Atmospheric Configurations

**Component string = compset**

'1850\_CAM60%1PCT\_CLM50%BGC-CROP\_CICE%CMIP6\_POP2%ECO\_MOSART\_CISM2%EVOLVE\_WW3\_BGC%BDRD'

The diagram illustrates the grouping of components in the component string into 9 categories. Brackets are drawn below the string to group the components as follows:

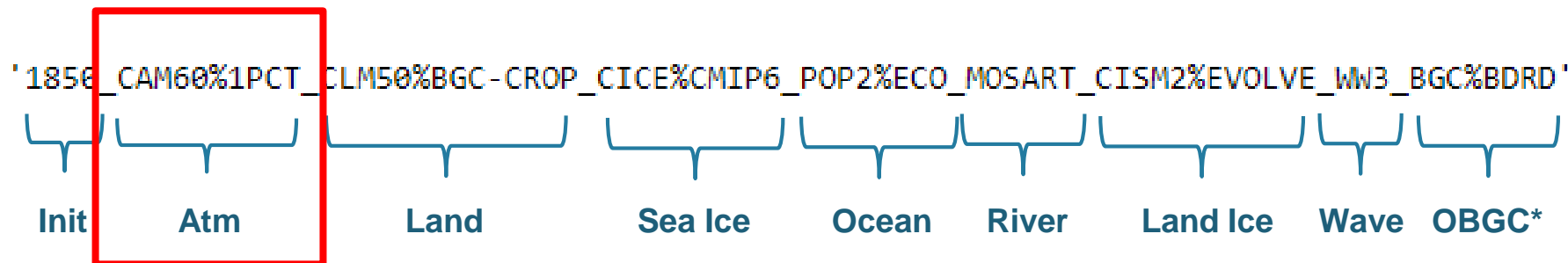
- Init**: 1850\_
- Atm**: CAM60%
- Land**: 1PCT\_CLM50%
- Sea Ice**: BGC-CROP\_CICE%
- Ocean**: CMIP6\_POP2%
- River**: ECO\_MOSART\_
- Land Ice**: CISM2%
- Wave**: EVOLVE\_WW3\_
- OBGC\***: BGC%BDRD'

**14 unique atmospheric components**

**\*OBGC = Ocean Bio-geo-chemistry**

# Analysis: Grouping Atmospheric Configurations

Component string = compset



14 unique atmospheric components

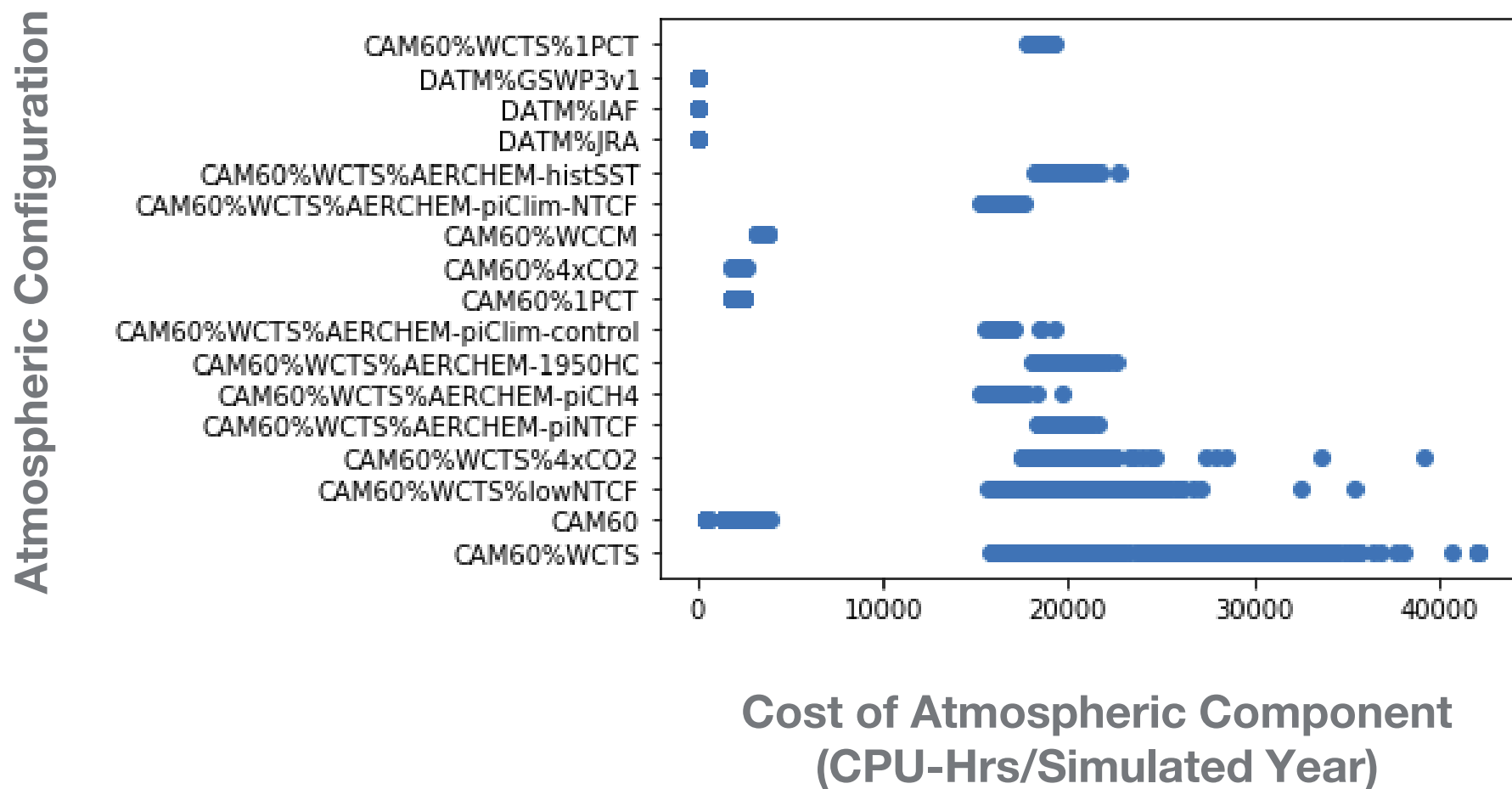
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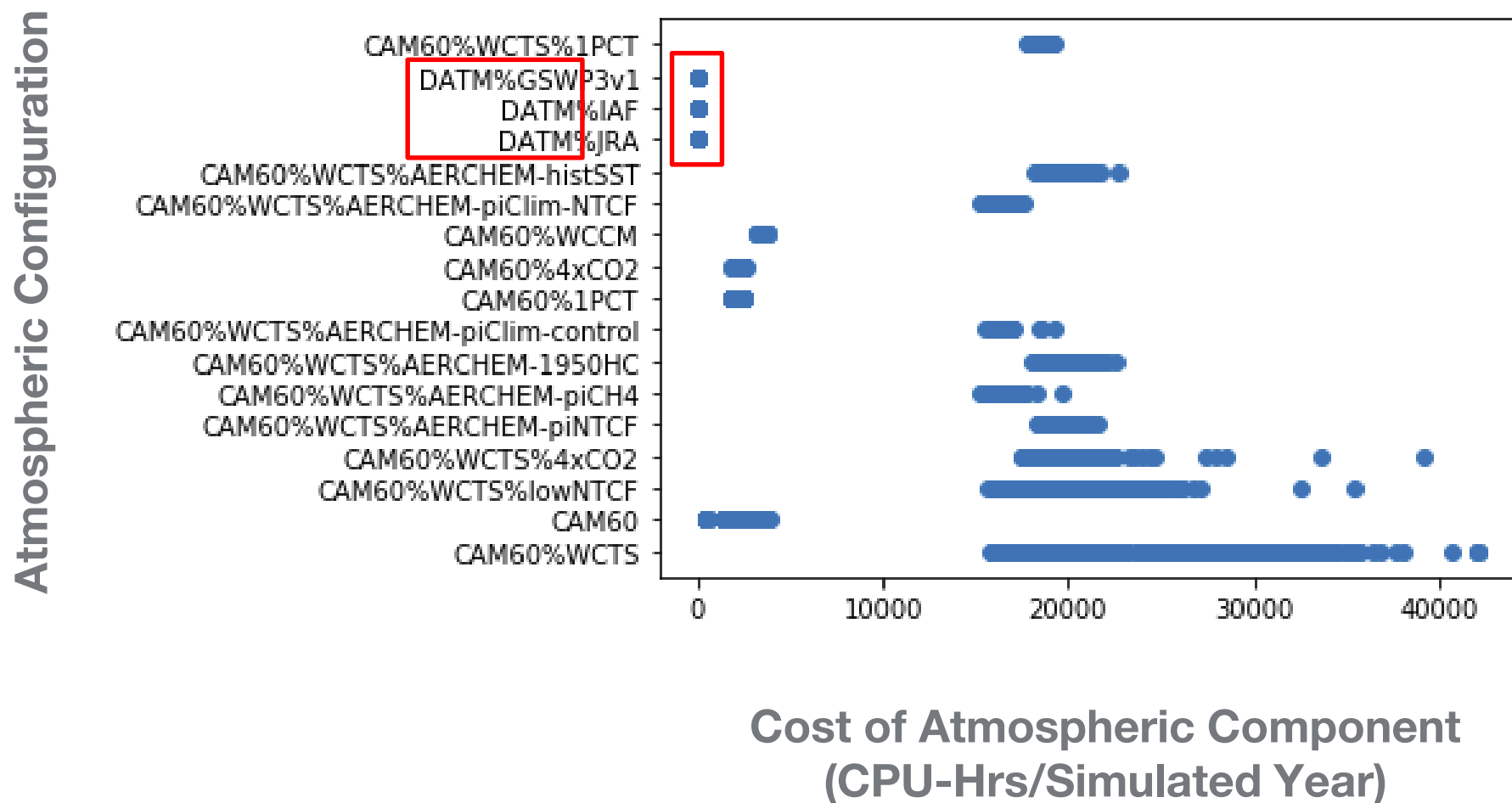
# Analysis: Grouping Atmospheric Configurations

## Atmospheric Configuration vs. Cost



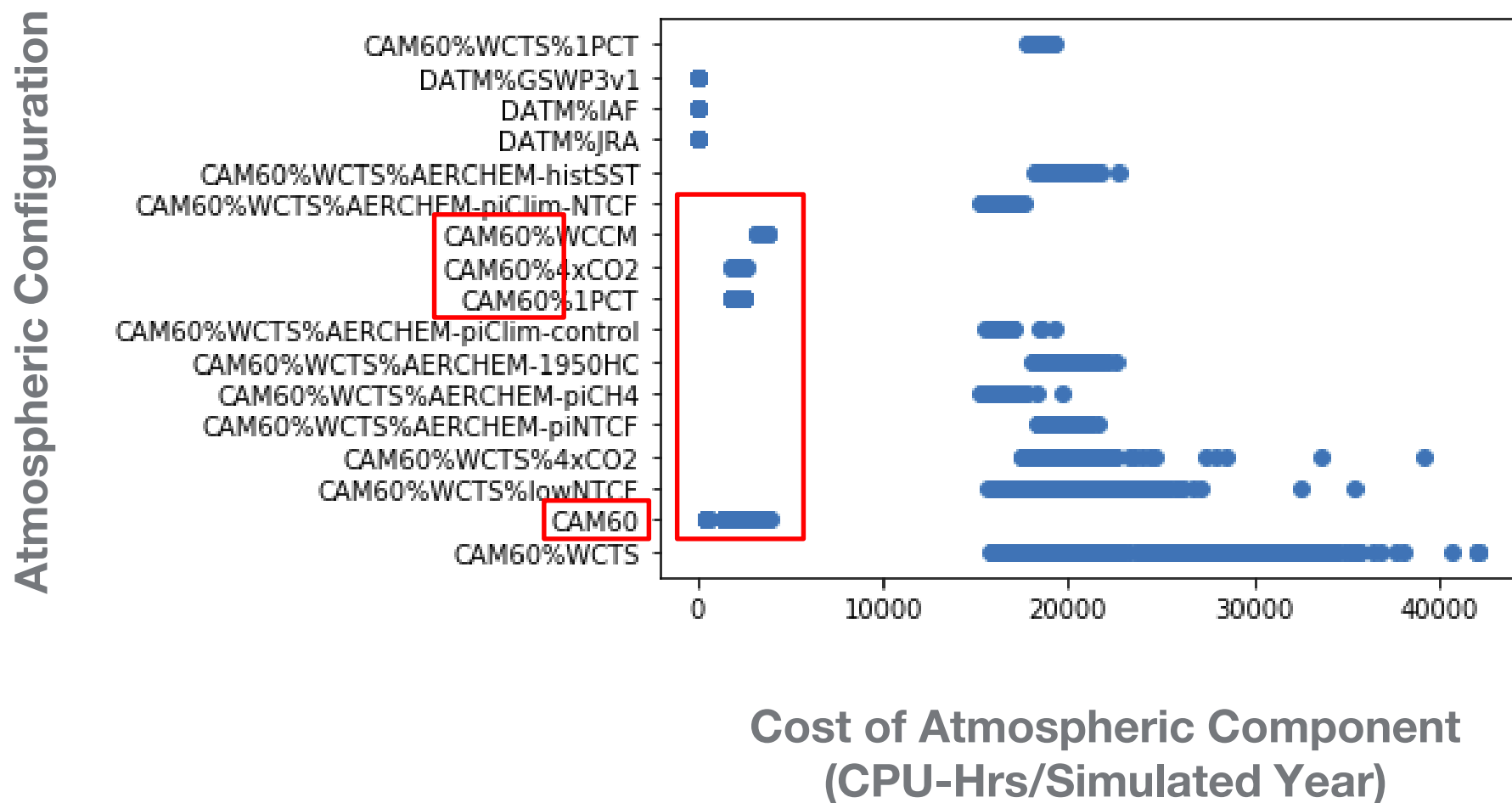
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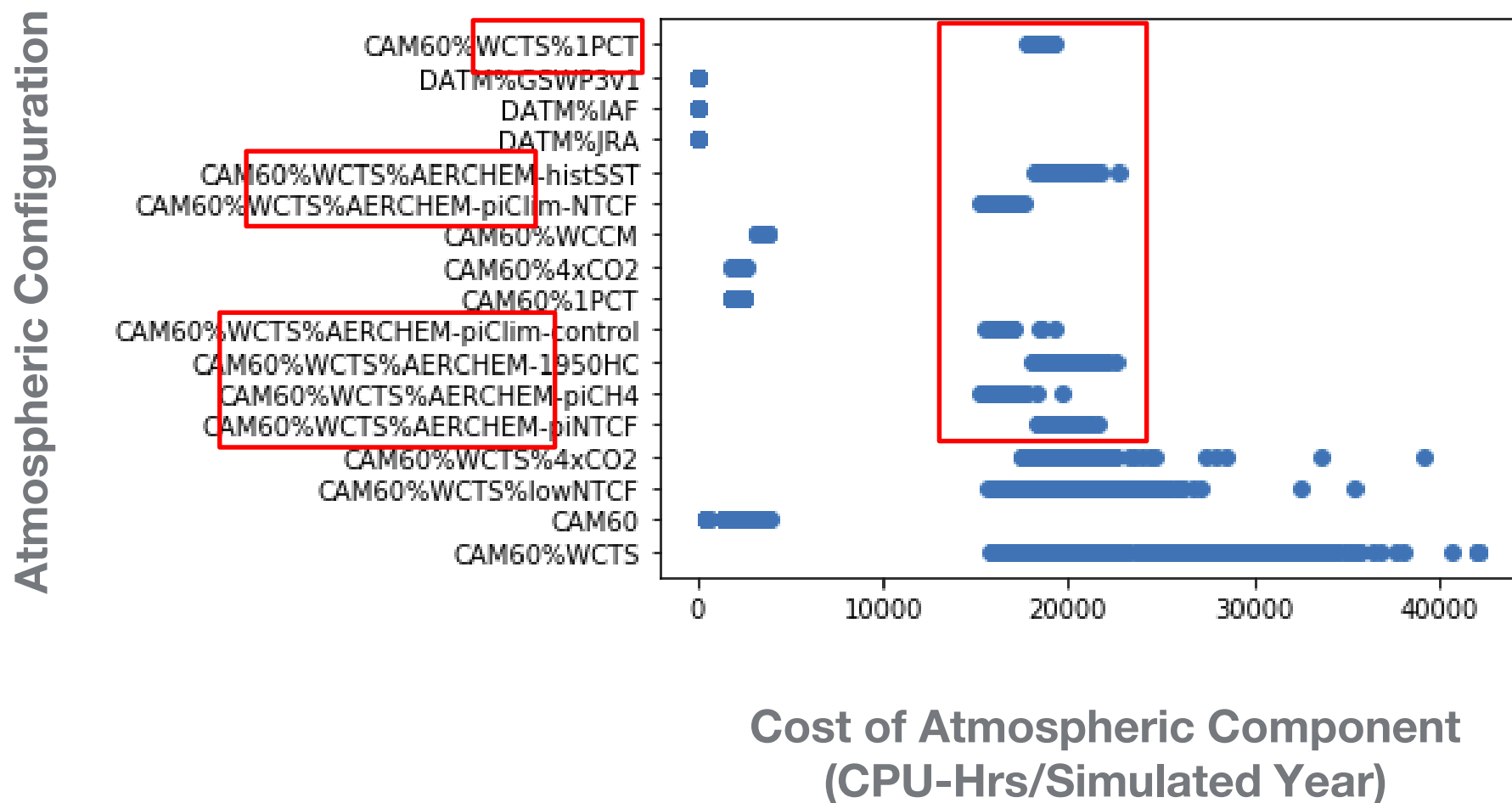
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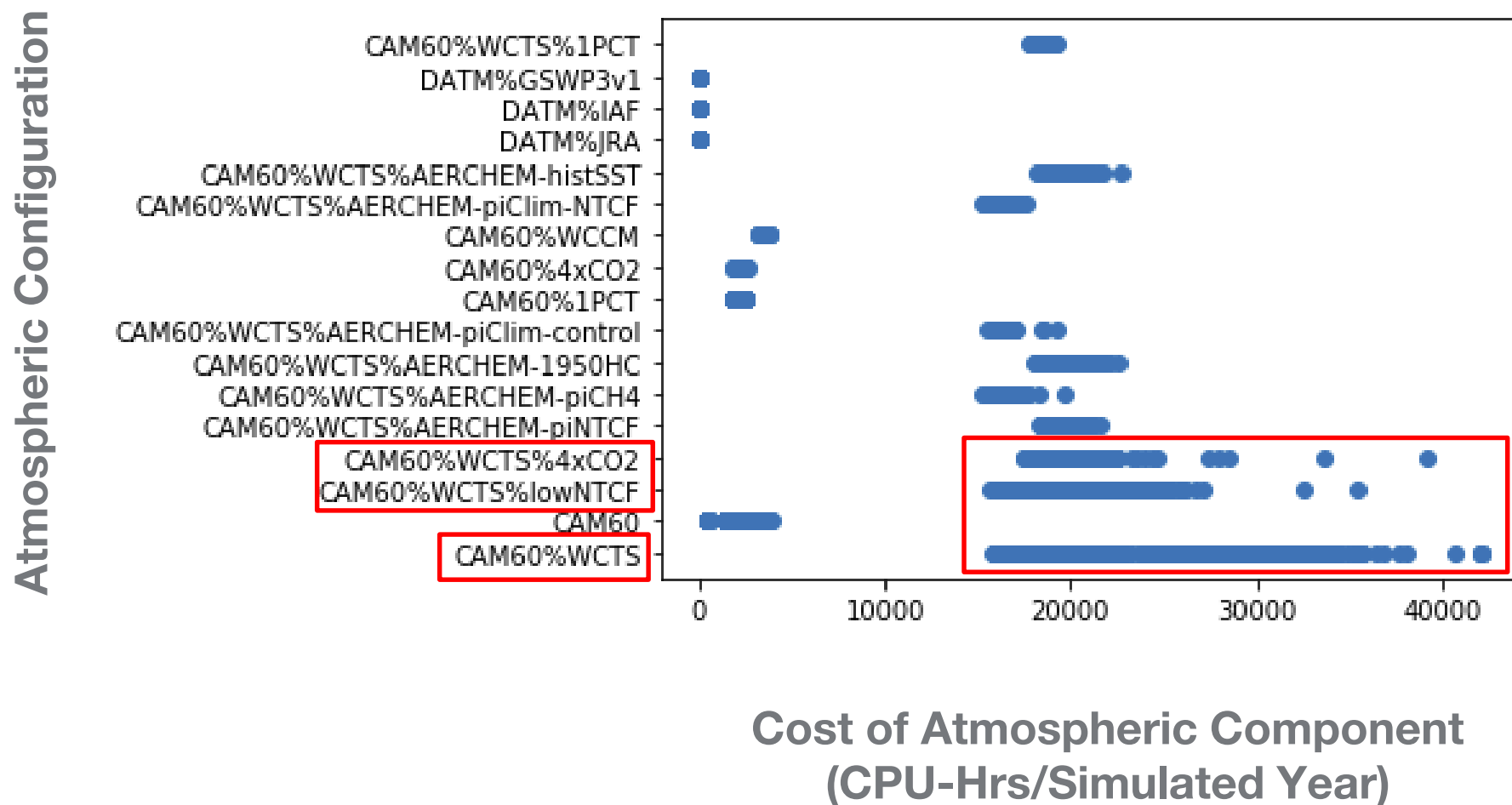
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## Atmospheric Configuration vs. Cost



# Analysis: Grouping Atmospheric Configurations

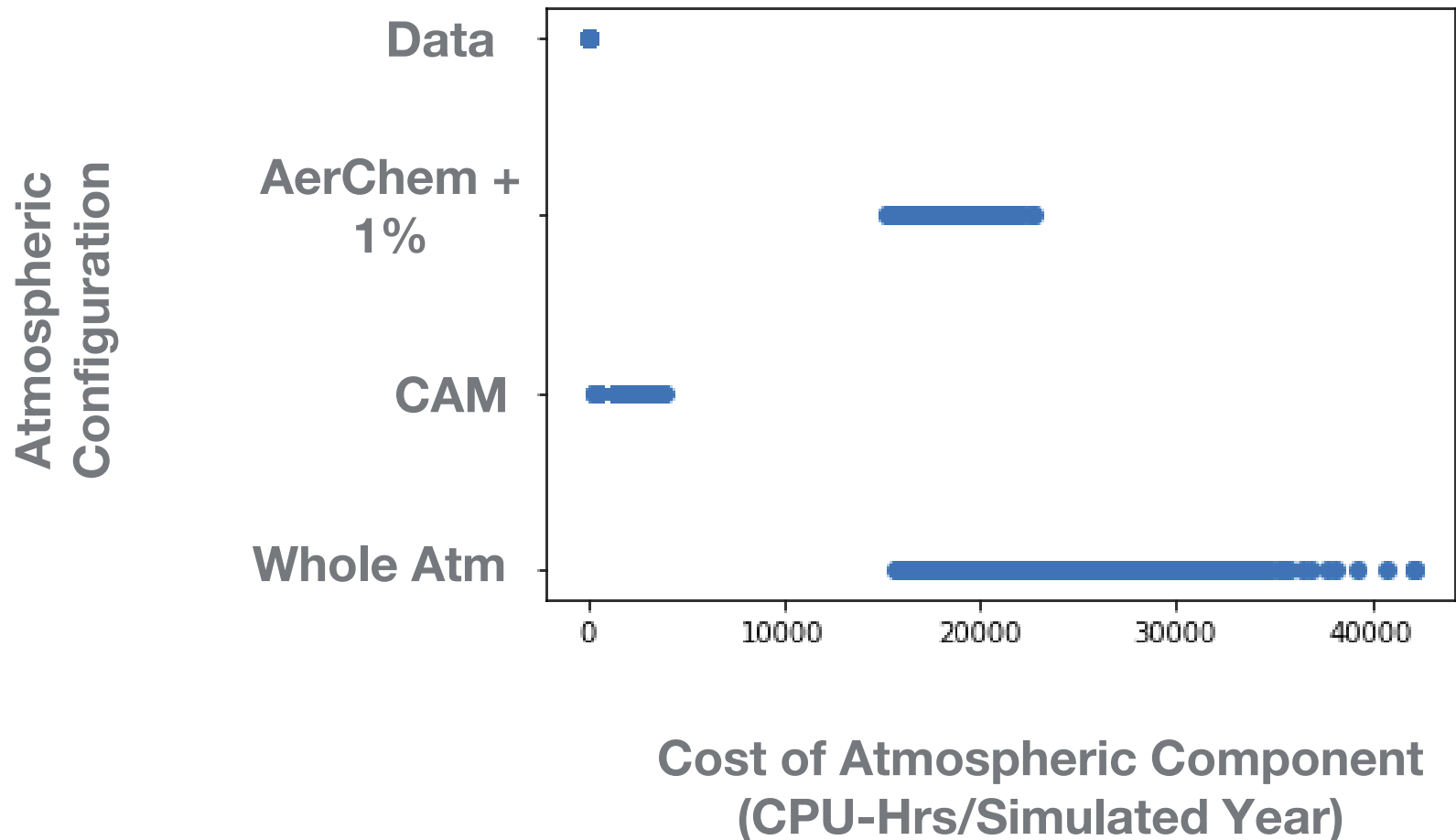
## Atmospheric Configuration vs. Cost





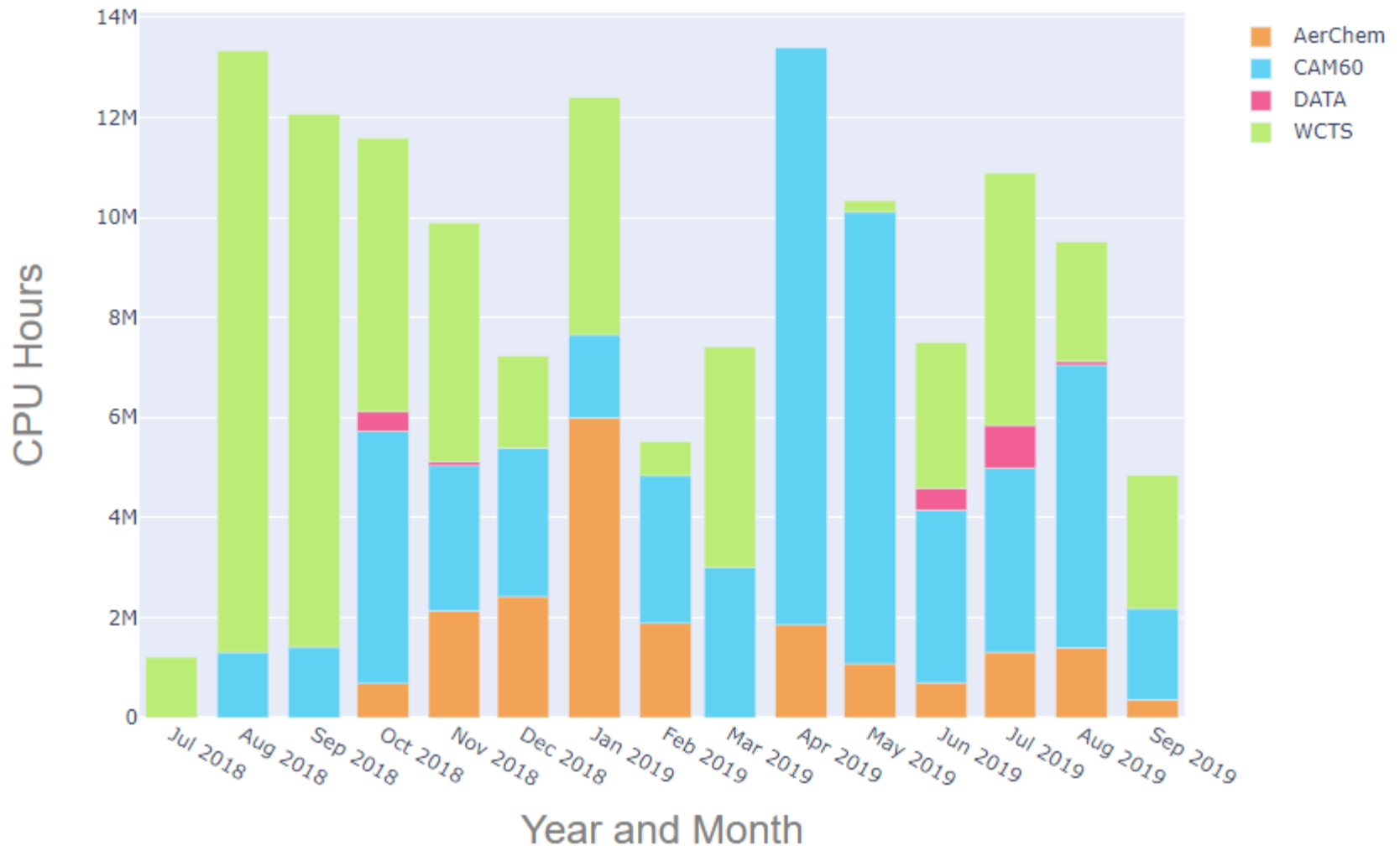
# Analysis: Grouping Atmospheric Configurations

## Atmospheric Configuration (Grouped) vs. Cost



# Analysis: Atmospheric Components

## CPU Hours by Month and Atm Component Group



# Analysis: System Upgrade

- **Cheyenne Supercomputer: 145,152 processors**
- **Upgrade: June 25-July 5, 2019**
- **Install SUSE Linux Enterprise Server Service Pack 4 to update security and support**

**Spoiler Alert!**  
**Name of new supercomputer!**



# Analysis: System Upgrade

More maniacal subsetting . . .

**By Case**

```
b.e21.B1850G.f09_g17_g14.CMIP6-1pctCO2to4x-withism.001
```

# Analysis: System Upgrade

More maniacal subsetting . . .

**By Case**

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**By Base**

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**By atmospheric component  
+ atmospheric processors  
+ oceanic processors**

	compset_atm	comp_pes_atm	comp_pes_ocn	total_submits
CAM60		576	144	10
CAM60		900	751	66
CAM60		1080	1080	912
CAM60%1PCT		1800	432	5
CAM60%1PCT		3456	1536	49
CAM60%WCCM		3456	432	98
CAM60%WCTS		1728	1728	41
CAM60%WCTS%4xCO2		3456	72	64
CAM60%WCTS%4xCO2		3456	108	168



# Analysis: System Upgrade

More maniacal subsetting . . .

**By Case (811 data points, 3445 sim years, 14 cases)**

b.e21.B1850G.f09\_g17\_g14.CMIP6-1pctCO2to4x-withism.001

**By Base (1206 data points, 4271 sim years, 14 bases)**

b.e21.B1850G.f09\_g17\_g14.CMIP6-1pctCO2to4x-withism.001

**By atmospheric component  
+ atmospheric processors  
+ oceanic processors**

(3113 data points,  
12,493 sim years,  
9 groups)

	compset_atm	comp_pes_atm	comp_pes_ocn	total_submits
CAM60		576	144	10
CAM60		900	751	66
CAM60		1080	1080	912
CAM60%1PCT		1800	432	5
CAM60%1PCT		3456	1536	49
CAM60%WCCM		3456	432	98
CAM60%WCTS		1728	1728	41
CAM60%WCTS%4xCO2		3456	72	64
CAM60%WCTS%4xCO2		3456	108	168

# Analysis: System Upgrade

## Tests for Normality

**All**

**All - normalized**

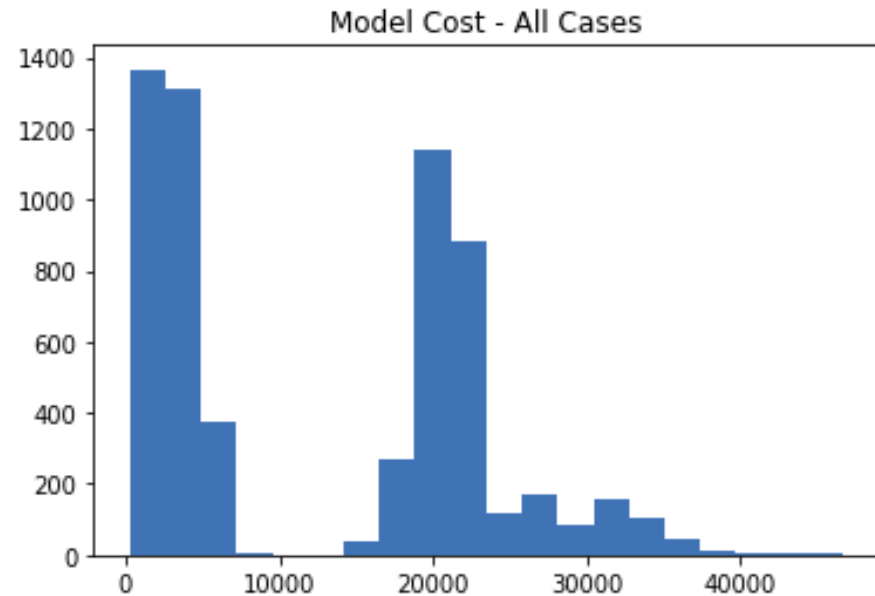
**All - before/after**

**By case**

**By base**

**By group:**

**(atm compset/atm + ocn processors)**



# Analysis: System Upgrade

## Tests for Normality

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**All - normalized**

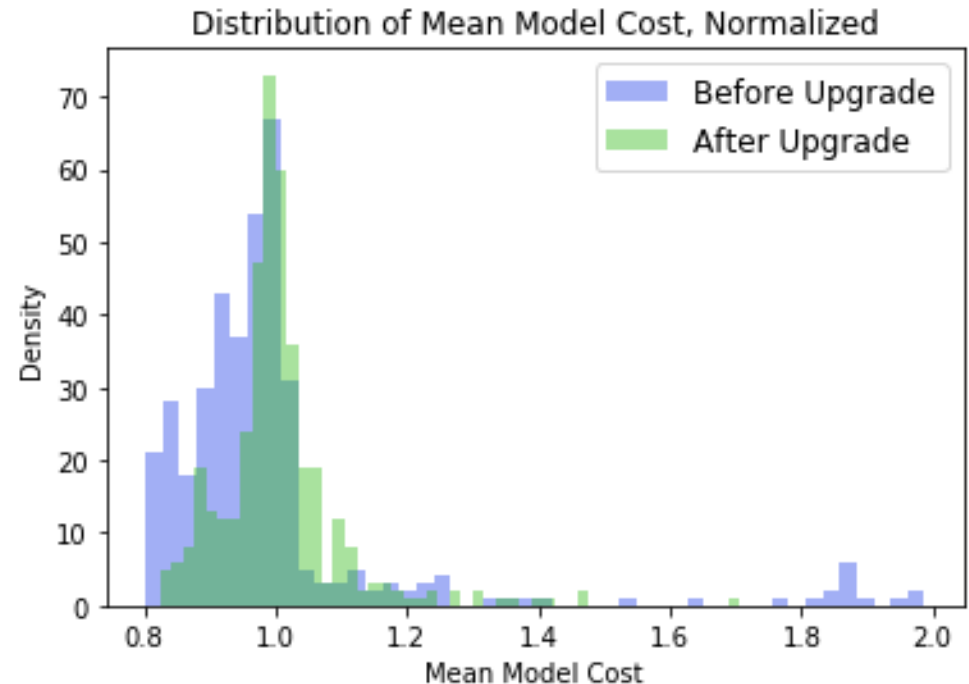
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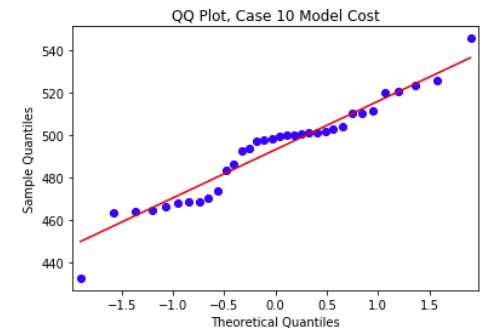
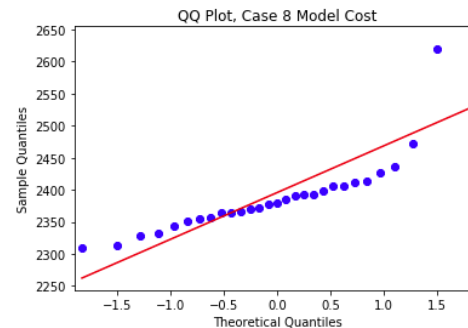
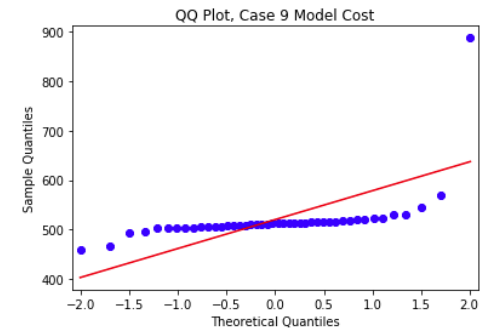
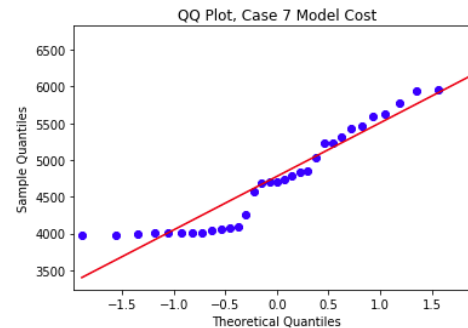
All - before/after

By case

By base

By group:

(atm compset/atm + ocn processors)



## Statistical Tests for Normality:

- Kolmogorov-Smirnoff
- Shapiro-Wilk

# **Analysis: System Upgrade**

**Mean Model Cost Before Upgrade**

**vs.**

**Mean Model Cost After Upgrade**

**Calculated percent difference (% change) in means before and after the upgrade:**

- **By case**
- **By base**
- **By group**

**Determined whether there was statistical significance in the means using Kruskal Wallis test**

# Analysis: System Upgrade

## Cases that span the upgrade

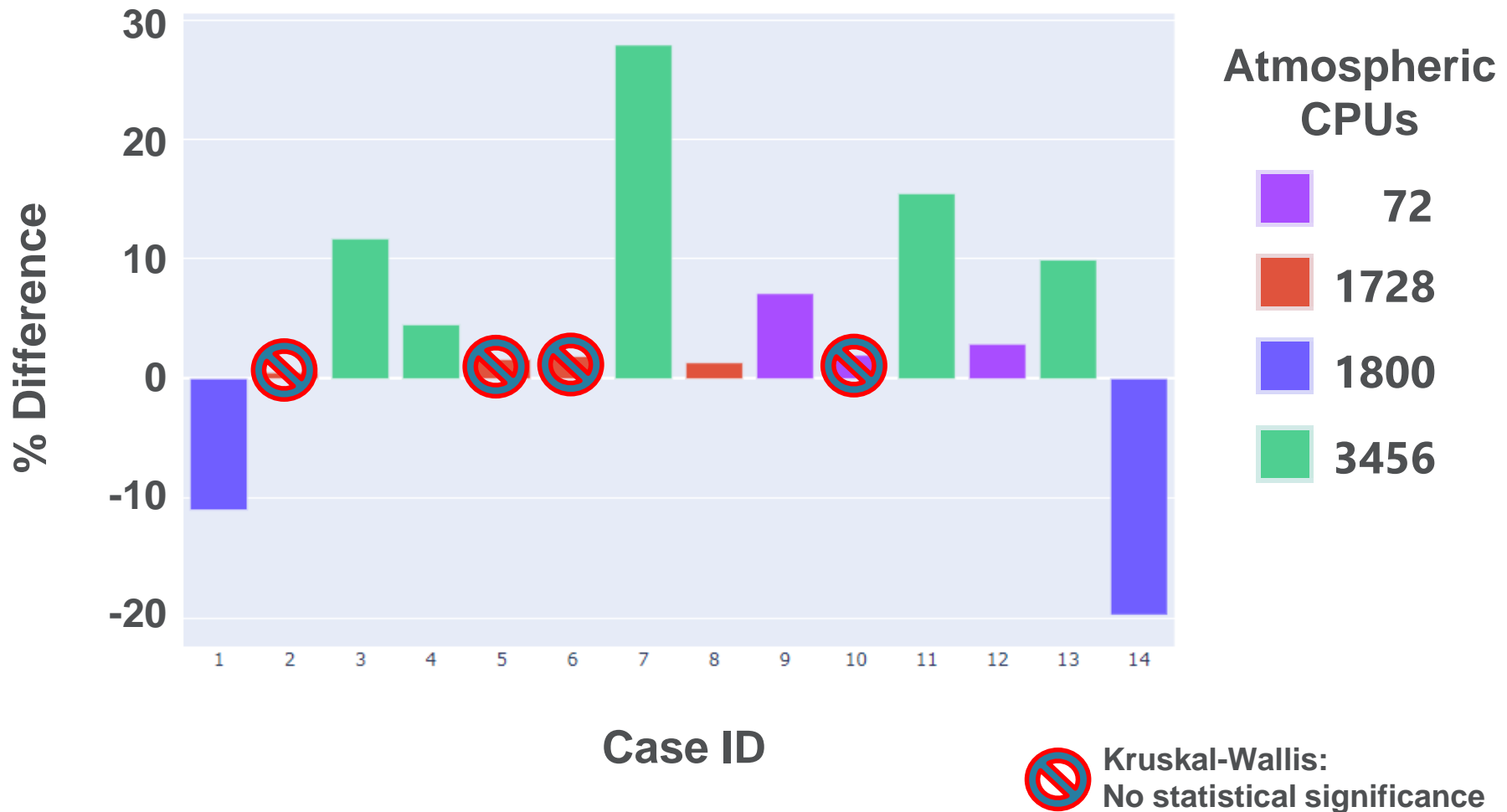
% Difference in Mean Model Cost



# Analysis: System Upgrade

## Cases that span the upgrade

% Difference in Mean Model Cost

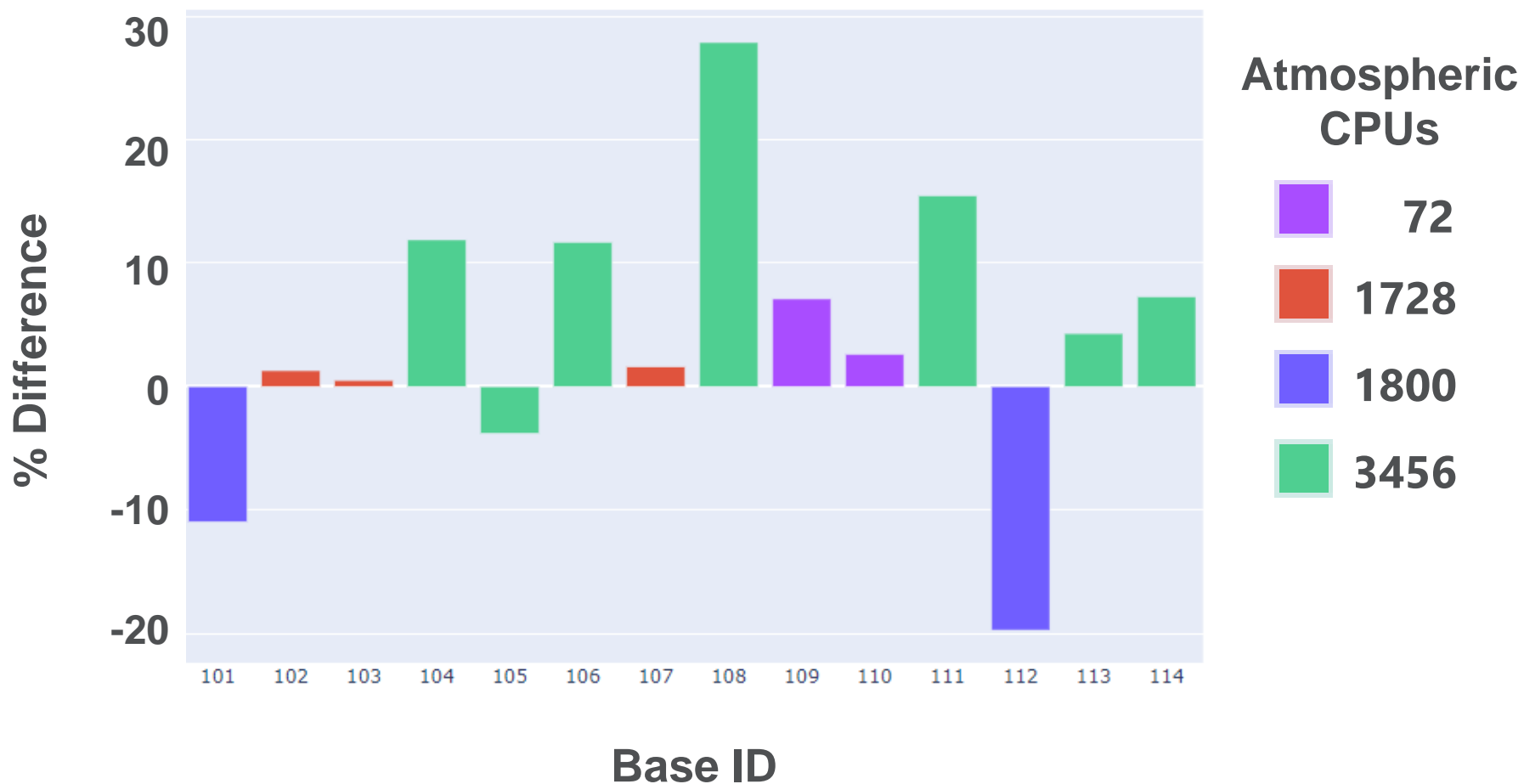




# Analysis: System Upgrade

## Bases that span the upgrade

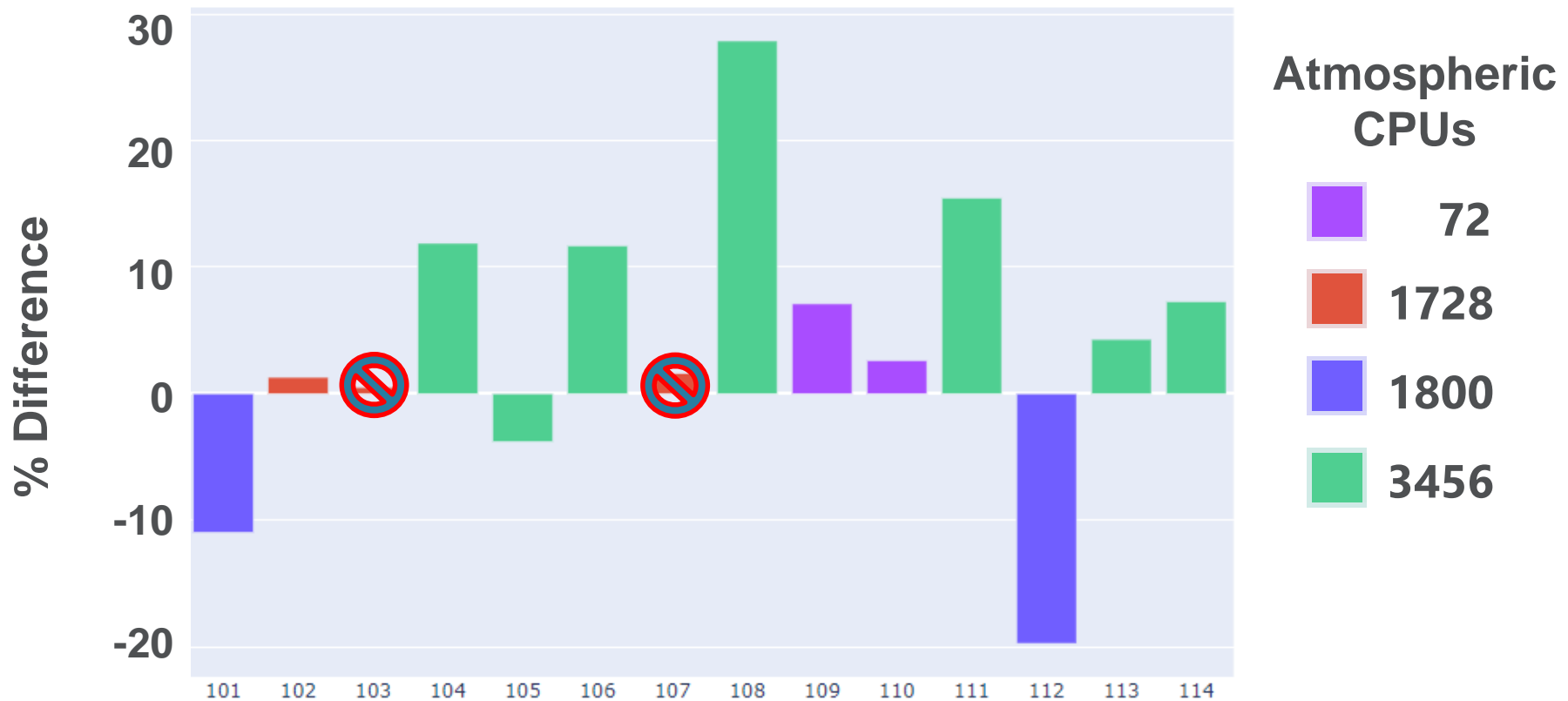
% Difference in Mean Model Cost



# Analysis: System Upgrade

## Bases that span the upgrade

% Difference in Mean Model Cost



Base ID

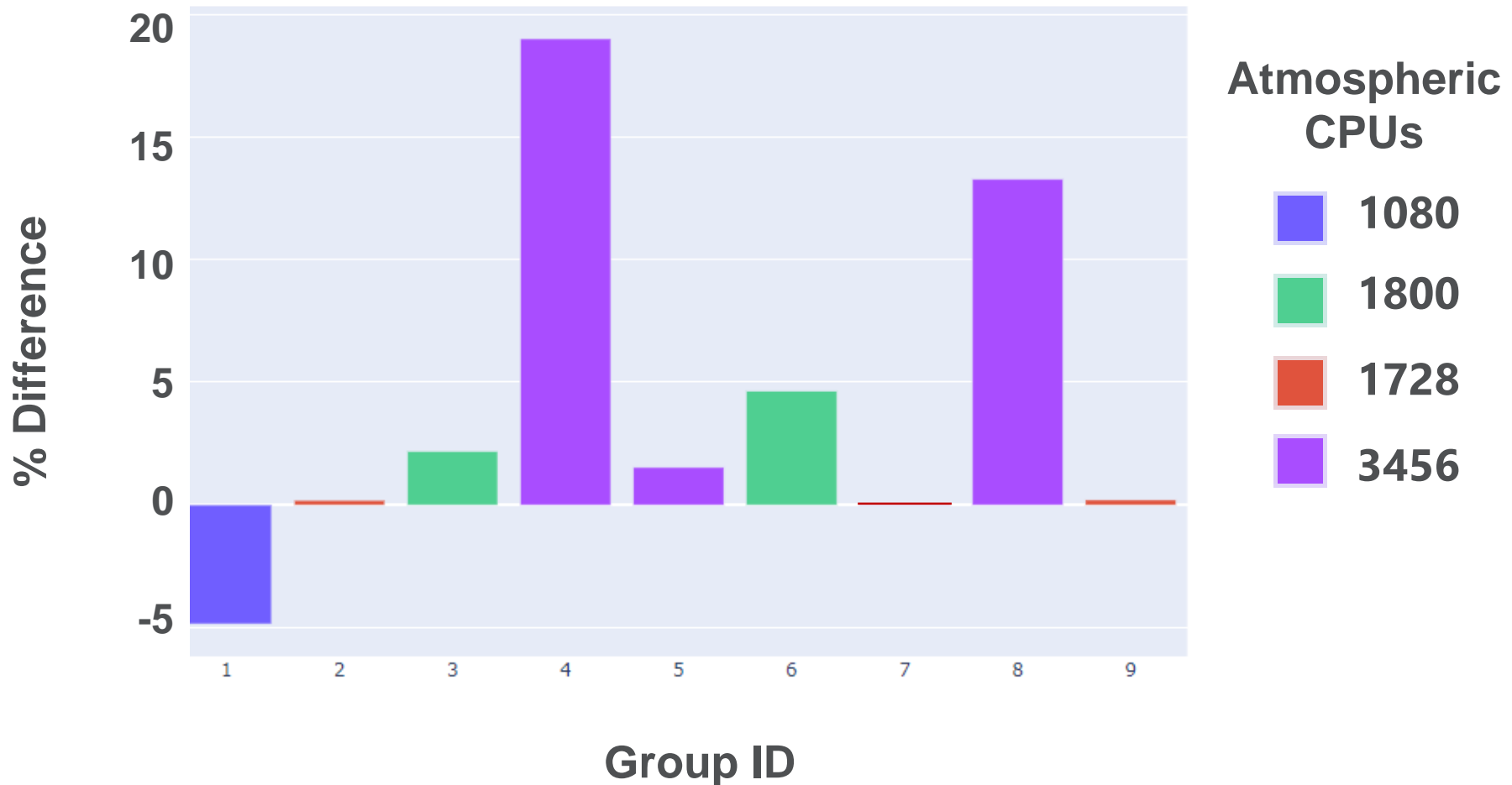


Kruskal-Wallis:  
No statistical significance

# Analysis: System Upgrade

## Groups that span the upgrade

% Difference in Mean Model Cost



# Analysis: System Upgrade

## Groups that span the upgrade

% Difference in Mean Model Cost

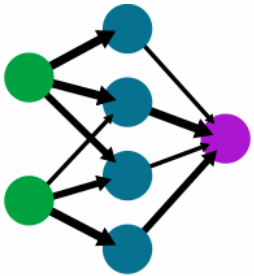


# Conclusion

- ✔ **More analysis in my Jupyter Notebook that points to performance degradation after the upgrade**
- ✔ **Enormous amounts of information to be sliced and diced by each component, physics module, number of processors, and other settings specific to parallel computing**
- ✔ **Answers lead to more questions**

# Future Work

## Machine Learning



- **Correlation Plots**
- **Feature Engineering**
- **Supervised Learning to Predict Performance (Model Cost)**
- **Unsupervised Learning (K-Means) to reveal patterns**

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## Images

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# Questions?

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