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# A Predictor Analysis Framework for Surface Radiation Budget Reprocessing Using Design of Experiments

Patricia Allison Quigley  
*Old Dominion University*

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**A PREDICTOR ANALYSIS FRAMEWORK FOR SURFACE RADIATION BUDGET  
REPROCESSING USING DESIGN OF EXPERIMENTS**

by

Patricia Allison Quigley  
B.S. April 2007, Strayer University  
M.S. August 2012, Old Dominion University

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Committee Members:

Dr. Resit Unal (Director)

Dr. Steven T. Cotter (Member)

Dr. C.B. Daniels (Member)

Dr. Paul W. Stackhouse, Jr. (Member)

Dr. Stephen J. Cox (Member)

## **ABSTRACT**

### **A PREDICTOR ANALYSIS FRAMEWORK FOR SURFACE RADIATION BUDGET REPROCESSING USING DESIGN OF EXPERIMENTS**

Patricia Quigley  
Old Dominion University, 2017  
Director: Dr. Resit Unal

Earth's Radiation Budget (ERB) is an accounting of all incoming energy from the sun and outgoing energy reflected and radiated to space by earth's surface and atmosphere. The National Aeronautics and Space Administration (NASA)/Global Energy and Water Cycle Experiment (GEWEX) Surface Radiation Budget (SRB) project produces and archives long-term datasets representative of this energy exchange system on a global scale. The data are comprised of the longwave and shortwave radiative components of the system and is algorithmically derived from satellite and atmospheric assimilation products, and acquired atmospheric data. It is stored as 3-hourly, daily, monthly/3-hourly, and monthly averages of  $1^{\circ} \times 1^{\circ}$  grid cells.

Input parameters used by the algorithms are a key source of variability in the resulting output data sets. Sensitivity studies have been conducted to estimate the effects this variability has on the output data sets using linear techniques. This entails varying one input parameter at a time while keeping all others constant or by increasing all input parameters by equal random percentages, in effect changing input values for every cell for every three hour period and for every day in each month. This equates to almost 11 million independent changes without ever taking into consideration the interactions or dependencies among the input parameters. A more comprehensive method is proposed here for the evaluating the shortwave algorithm to identify both the input parameters and parameter interactions that most significantly affect the output

data. This research utilized designed experiments that systematically and simultaneously varied all of the input parameters of the shortwave algorithm. A D-Optimal design of experiments (DOE) was chosen to accommodate the 14 types of atmospheric properties computed by the algorithm and to reduce the number of trials required by a full factorial study from millions to 128.

A modified version of the algorithm was made available for testing such that global calculations of the algorithm were tuned to accept information for a single temporal and spatial point and for one month of averaged data. The points were from each of four atmospherically distinct regions to include the Amazon Rainforest, Sahara Desert, Indian Ocean and Mt. Everest. The same design was used for all of the regions. Least squares multiple regression analysis of the results of the modified algorithm identified those parameters and parameter interactions that most significantly affected the output products.

It was found that Cosine solar zenith angle was the strongest influence on the output data in all four regions. The interaction of Cosine Solar Zenith Angle and Cloud Fraction had the strongest influence on the output data in the Amazon, Sahara Desert and Mt. Everest Regions, while the interaction of Cloud Fraction and Cloudy Shortwave Radiance most significantly affected output data in the Indian Ocean region.

Second order response models were built using the resulting regression coefficients. A Monte Carlo simulation of each model extended the probability distribution beyond the initial design trials to quantify variability in the modeled output data.

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This dissertation is dedicated to my parents

Alfred and Barbara Visciarelli

with love and appreciation for encouraging me to achieve my dreams,

and to my beautiful children

Renee, Jennifer and Sara

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Dr. Steven Cotter from Old Dominion University inspired me to appreciate statistical analysis when I took his course in engineering design. I have so much admiration for his vast knowledge in this field, and I thank him for all of the time he dedicated to ensure that my analysis was sound.

I would also like to thank Dr. Charles Daniels for reviewing several drafts of this paper and for advising me on the cohesiveness of the chapters. I also appreciate his assistance with structuring my presentation so that I would adequately convey the background, purpose and results of this work to my audience.

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The views expressed in this dissertation are those of the author and do not reflect the official policy or position of NASA or the U.S. Government.



**NOMENCLATURE**

|       |  |
|-------|--|
| BSRN  | Baseline Surface Radiation Network                   |
| CERES | Clouds and the Earth's Radiant Energy System         |
| ECMWF | European Center for Medium range Weather Forecasting |
| GCM   | General Circulation Model                            |
| GEOS  | Goddard Earth Observing System data                  |
| GEWEX | Global Energy and Water Cycle Experiment             |
| GISS  | Goddard Institute for Space Studies                  |
| GMAO  | Global Modeling and Assimilation Office              |
| ISCCP | International Satellite Cloud Climatology Project    |
| LPLA  | Langley Parameterized Longwave Algorithm             |
| LPSA  | Langley Parameterized Shortwave Algorithm            |
| NASA  | National Aeronautics and Space Administration        |
| NCDC  | National Climatic Data Center                        |
| NCEP  | National Centers for Environmental Prediction        |
| NCAR  | National Center for Atmospheric Research             |
| PAR   | Photosynthetically Active Radiation                  |
| RSM   | Response Surface Methodology                         |
| SMOBA | Stratospheric Monitoring Ozone Blended Analyses      |
| SRB   | Surface Radiation Budget                             |
| TOA   | Top of Atmosphere                                    |
| TOMS  | Total Ozone Mapping Spectrometer                     |

TOVS                      TIROS Operational Vertical Sounder

WMO                      World Meteorological Organization

## METEOROLOGICAL AND STATISTICAL DEFINITIONS

|                          |  |
|--------------------------|--|
| Albedo                   | Fractional reflectance calculated at the surface or top of the atmosphere.   |
| Anisotropy               | Property of being directionally dependent.   |
| Climatology              | Weather conditions over a period of time.  |
| Degrees of Freedom       | The number of ways a system can be varied without violating constraints in the design space.                         |
| D-Optimal Design         | Determinant Optimal Experimental Design.   |
| Emissivity               | A measure of thermal energy emitted by the surface of the earth as a fraction of the theoretical black-body maximum. |
| Nadir                    | Directly beneath.  |
| Solar Zenith Angle       | The angle of the sun away from vertical.   |
| Radiative Transfer Model | Calculates transmittance, absorbance and scattering of electromagnetic radiation.                                    |

## ALGORITHM PARAMETER DEFINITIONS (PREDICTOR VARIABLES)

| Predictor Variables              | Definition   |
|----------------------------------|--|
| aerosol optical depth            | Measure of column aerosol concentration in dimensionless unit related to the attenuation of radiation stream through the column.                                       |
| aerosol single scattering albedo | Measure of proportion of radiation attenuated by aerosol which is scattered rather than absorbed.  |
| aerosol asymmetry parameter      | Measure of directionality of radiation scattered by aerosol.   |
| azimuth angle                    | Measurement of the angle formed between an observer, a reference point, and a position in the sky.   |
| cosine solar zenith angle        | Cosine of the measured angle from zenith (i.e., overhead) to the center of the sun; varies from the sun on the horizon (= 0) to sun overhead (= 1.0).                  |
| cosine satellite zenith angle    | Cosine of the measured angle from zenith (i.e., overhead) to the center of the satellite that varies from satellite on the horizon (= 0) to satellite overhead (=1.0). |
| cloud fraction                   | Fraction of the grid cell covered by clouds (varies from 0 to 1).  |
| cloud phase                      | Unitless reference to cloud properties where liquid is 1 and ice is 2.   |
| cloudy radiance                  | Mean narrowband scaled radiance from cloudy pixels measured in reflectance units.  |
| clear sky radiance               | Narrowband scaled radiance from clear pixels measured in radiance units.   |
| clear sky composite radiance     | A statistical measure of recent clear sky radiance at a location meant to approximate a background value.  |
| latitude                         | Angular distance north or south of the equator.  |
| longitude                        | Angular distance east or west of the equator.  |
| ozone                            | Gas consisting of three oxygen atoms; measurement of the amount integrated from the upper atmosphere to the earth's surface.   |
| satellite id                     | Unit to identify a named man-made satellite.   |
| snow/ice flag                    | Unitless reference to presence of snow/ice. Present = 1, not present =0.   |
| total column precipitable water  | Measurement in mm of the depth of water in a column of air.  |

## ALGORITHM OUTPUT PARAMETER DEFINITIONS (DEPENDENT VARIABLES)

| Dependent Variables                                  | Definition   |
|--|--|
| TOA shortwave downward flux (toadwn)                 | Total (shortwave) energy received by the earth from the sun at the top of the atmosphere.  |
| TOA shortwave upward flux (toaup)                    | Shortwave (0.2 – 4 $\mu\text{m}$ ) energy leaving the top of the atmosphere based on the amount of energy reflected by the surface/atmosphere system.                        |
| Surface downward flux (srfdownflx)                   | Shortwave energy reaching the surface.   |
| Surface downward diffuse flux (srfdowndiff)          | Shortwave energy reaching the surface outside of the direct beam.  |
| Surface upward flux (srfupflx)                       | Shortwave energy reflected by the surface of the earth.  |
| Surface downward diffuse PAR<br>(srfdowndifpar)      | Shortwave energy reaching the surface between 400nm and 700nm outside of the direct beam.  |
| Surface downward PAR (srfdownpar)                    | Shortwave energy reaching the surface between 400nm and 700nm (photosynthesis) wavelengths.  |
| TOA shortwave upward clear sky flux<br>(toaupclrsky) | Shortwave energy leaving the top of the atmosphere based on the amount of energy reflected by the surface/atmosphere system for clear sky (no clouds) part of the grid cell. |
| Surface downward clear sky flux<br>(srfdownclrsky)   | Shortwave energy reaching the surface for only the clear sky parts of the grid cell.   |
| Surface upward clear sky flux (srfupclrflx)          | Shortwave energy reflected by the surface of the earth for the clear sky part of the grid cell.  |
| Output aerosol optical depth (oaod)                  | Calculated column aerosol concentration.   |
| Output cloud optical depth (ocod)                    | Calculated optical depth of cloud field.   |
| Surface downward pristine sky flux<br>(srfdownprs)   | Theoretical measure of what the surface downward flux would be in a pristine sky with no clouds or aerosols.   |
| TOA upward pristine sky flux (toaupprs)              | Theoretical measure of what the TOA upward flux would be in a pristine sky.  |

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## CHAPTER 1. INTRODUCTION

### 1.1 Research Objective

The NASA/Global Energy and Water Cycle Experiment (GEWEX) Surface Radiation Budget (SRB) global surface and top-of-atmosphere (TOA) shortwave radiative flux data products are estimates of incoming radiation from the sun, as well as estimates of radiation that is absorbed and reflected back to space by the Earth and the atmosphere. The project produces and archives long-term global longwave and shortwave datasets representative of these energy exchanges. The goal of this project is to produce reliable, globally derived atmospheric products that overcome the spatial limitations posed by ground site measurements over enough years to establish a trend.

This work supports the SRB vision to provide a complete long-term global picture of solar irradiance. Ground sites are capable of obtaining direct measurements of all of the components of the SRB, but since it is not practical to cover the entire globe, including ocean, with a dense network of sites, it is desirable to use satellites to acquire this information. The challenge is that surface irradiance cannot be directly measured from the top of the atmosphere by satellites, so it must be derived or modeled from a variety of satellite and atmospheric assimilation products and acquired atmospheric data. This is done using flux retrieval algorithms and methods such as radiative transfer theory (Stackhouse et al., 2011).

Research indicates that input product uncertainty is an important source of variability of the output data; therefore the objective of this study was to identify those input parameters and parameter interactions that most significantly affect the output data of the SRB algorithm and to quantify this variability.

## 1.2 Surface Radiation Budget Project

The SRB data are derived from a variety of satellite and atmospheric assimilation products and acquired atmospheric data. Three major releases of the data have been published. The next release will offer a substantial refinement of the previous version with increased spatial resolution and improved input products. Spatial resolution will increase from  $1^\circ \times 1^\circ$  nested grid with 44016 cells to  $0.5^\circ \times 0.5^\circ$  global grid comprising 165,018 equal area cells.. Each of the cells has unique solar and atmospheric characteristics that affect the solar energy exchange. A partial list of such characteristics include angle of the sun, viewing angle of the satellite, gaseous constituents such as ozone and water vapor, atmospheric particulates such as clouds and aerosols, and surface reflectance using reprocessed mnHIRS, HX and GMAO GEOS data. These characteristics serve as input parameters to the SRB algorithm. Version 4.0 of the shortwave surface radiation component of the SRB offers 14 data sets over an unprecedented continuous 30-year temporal range.

## 1.3 SRB Data Significance

Knowledge of atmospheric properties and their fluxes is beneficial to many areas of research, space and planetary exploration and can have sustained benefits to industries from airlines to farming. With respect to SRB products, the data set supports the validation of data assimilation and climate models (Stackhouse et. al., 2002). Additionally, the NASA/GEWEX SRB project determines surface, top-of-atmosphere (TOA), and atmospheric shortwave (SW) and longwave (LW) radiative fluxes and is used in many meteorology applications to predict climate trends (NASA GEWEX, 2014). It is used in many meteorology applications.

The Surface Solar Energy project provides parameters from the data to aid with sizing and pointing or tilting of solar panels and for thermal applications. It also is used for determining size of batteries and other energy storage systems.

#### 1.4 Surface Radiation Budget Product Applications

Many initiatives based on solar radiation information have benefited third world countries by providing cooking and water sanitation solutions. The data have also benefited the farming and transportation industries, lighting and home appliances, heating, cooling, renewable energy initiatives, academia, transportation, space exploration and climate prediction. The Prediction of Worldwide Energy Resources (POWER)/ Surface Solar Energy (SSE) project team processes SRB parameters for renewable energy, sustainable buildings and agroclimatology projects. The refinement of the SRB algorithm will provide even more reliable surface radiation data, strengthening and improving work in the fields that rely on it.

#### 1.5 Surface Radiation Budget History

Regional studies of atmospheric data by ground observation stations, ships and telemetry instruments installed in weather balloons called radiosondes are longstanding, but being geographically constrained, do not represent the complete global picture. Aircraft have also proven to be good platforms for data retrieval, but are spatially limited to flight paths and are bounded by flying time and the cost of aircrews and fuel. Current technology offers satellites as the only method of contiguous atmospheric data retrieval on the global scale.

The first attempts at satellite retrieval of atmospheric data began with the inflatable Echo 1 Satellite, conceived by William J. O'Sullivan and launched on August 12, 1960 for the purpose of studying air density in the upper atmosphere to support design specifications of aircraft,



missiles and space vehicles (NASA, 2014a). The mission was not successful, but it paved the way for the era of satellites and the possibility of capturing atmospheric data from every grid point on the globe (Ellis, et al., 1978). The finding by Fritz (1963) that reflected solar flux at the top of the atmosphere observed by satellites correlated well with ground site observations inspired work that led to the current SRB studies. These led to other studies assessing the relationships between the reflected visible radiance from satellite and the surface solar flux (or short wavelength radiation from the sun called shortwave) measured at the surface of the Earth (i.e. Mosher and Raschke, 1984). Development at NASA LaRC led to Darnell et al., (1992) providing one of the first shortwave (SW) and thermal infrared (LW) climatology from satellite.

The Darnell et al., (1992) research was also unique because it not only incorporated imager data but also but also top-of-atmosphere radiative flux information from the Earth Radiation Budget Experiment (ERBE). ERBE was built and flown on the Earth Radiation Budget Satellite (ERBS) NASA dedicated satellite launched in 1984 by the Space Shuttle, Challenger, and on two National Oceanic and Atmospheric Administration (NOAA) satellites (NOAA-9 and NOAA-10). “The ERBE instruments on board the NOAA-9 and NOAA-10 satellites provide global spatial coverage, while the scanner instruments on board the ERBS provides coverage between 67.5 degrees north and south latitude and the nonscanner instruments on board the ERBS provide coverage between 60 degrees north and south latitude. Because ERBS is in a precessing (57-degree) orbit, the ERBE instruments on board this satellite provide diurnal sampling” (EOSWEB, 2016a). The campaign was successful in providing top-of-atmosphere global albedo, fluxes, and solar incidence measurements, but the combined limited spatial and temporal coverage of these satellites were restrictive.

Shortwave satellite algorithms to estimate radiation at the surface of the earth were first tested in 1986 using field experiment data by the World Climate Research Program (WCRP) at NASA Langley Research Center (Whitlock, et al, 1994, 1995). The first estimation of surface shortwave radiation modeled from satellite data was completed in 1994 and yielded a globally complete data product associated with atmospheric components of the SRB. The data set used as input satellite visible data as collected, calibrated and processed by the International Satellite Cloud Climatology Project (ISCCP, Rossow and Gardner, 1993a, 1993b). At the completion of the project, a collection of 52 shortwave parameters representing a 280 x 280 km equal area grid of global coverage were computed and compared with ground truth data. The *First Global WCRP Shortwave Surface Radiation Budget Dataset*, SRB Version 1.1, presented with minimal coverage deficiency as compared with ground site capabilities and rendered finer spatial resolution over smaller time periods (Whitlock, et al., 1994).

To diversify the approach to SRB estimation, the Pinker/Lazlo primary shortwave algorithm (Pinker & Lazlo, 1992) and another algorithm developed by W. F. Staylor at NASA Langley Research Center (Darnell, et al., 1992) were used to generate and compare data for the SRB version 1.1 (Whitlock et al., 1995) and the Pinker models have been improved and extended. This particular Surface Radiation Budget effort is now affiliated with the Global Energy and Water Cycle Exchange Program (GEWEX) of the World Climate Research Programme (WCRP). The current SW algorithm is based upon the Pinker and Lazlo model framework, but now uses the Fu-Liou radiative transfer model to compute monochromatic radiative fluxes that are integrated to the total SW spectrum (Cox et al., 2016; Fu & Liou, 1997). The model also uses scaled radiance, cloud amount, precipitable water, and ozone as input parameters with satellite calibration from the ISCCP data.

Table 1 (ASDC, 2014b) summarizes the evolution of the publically released versions of the SRB shortwave dataset since the origin of the NASA/WCRP-GEWEX/SRB project and provides a short description of product improvement for each version. A complete list of available SRB output products and versions is available at (GEWEX, 2015b).

As evidence of the importance of deriving the radiation fluxes at the TOA and surface of the atmosphere, co-incident with the advancements of surface radiation from imagers are the advancements in top-of-atmosphere radiative fluxes from the Clouds and the Earth's Radiant Energy System (CERES) extended the ERBE project with instruments launched in 1997 on the Tropical Rainfall Measuring Mission (TRMM) satellite and again on satellites EOS-TERRA and EOS-AQUA in 1999 and 2000 respectively. The newest CERES instrument orbits on board the Suomi National Polar-orbiting Satellite (Suomi NPP) that was launched in 2011. The data provided by these instruments help in understanding clouds and energy cycles from the top of the atmosphere to the surface of the earth with data compiled to show solar-reflected and earth-emitted radiation (CERES, 2016). Besides providing the most accurate TOA radiative flux information to date (Loeb et al., 2009; Wielicki et al., 1995), the CERES mission also includes a comprehensive effort to estimate the long-term variation in the surface radiation components with a suite of the data products (Kato et al., 2012; Rutan et al., 2015). These produces at the 1x1 degree resolution provide excellent validation relative to surface measurements and an important benchmark for assessment of GEWEX SRB data products. This speaks to the importance to accurately determining the TOA and surface radiative flux components.

| SRB SHORTWAVE DATASET VERSION HISTORY |  |
|---------------------------------------|--|
| VERSION                               | DESCRIPTION  |
| LaRC 1.0                              | 8 year dataset (July 1983-June 1991) on 2.5 degree equal area grid using ISCCP C1 and ERBE data for both the SW and LW (Darnell et al., 1992).   |
| WCRP SW SRB 1.1                       | 4 year WCRP SW only data set (March 1985 – Dec. 1988) on 280x280 km equal area grid using ISCCP C1 data and both the SW algorithm of Darnell et al., 1992 and the WCRP selected Pinker et al., 1989 (Whitlock et al., 1995).   |
| GEWEX SRB 2.0                         | 12 year SW and LW SRB dataset (July 1983-October 1995), on 1°x1° equal angle based nested grid using ISCCP DX pixel data. (Stackhouse et al., 2000)  |
| GEWEX SRB 2.81                        | As cited from the eosweb.larc.nasa.gov webpage, (EOSWEB, 2016b), “Atmospheric transmissivity/reflectivity lookup tables extended to cosine solar zenith angles as low as 0.01. Revamping of the methodology used to fill data gaps. These changes allowed data to be computed for locations with low sun angles the entire month (polar twilight areas).” And “Improvement of the TOA insolation calculation. Previously each January 1 the Earth began in the same orbital point. Leap years were handled by making day 366 a duplicate of day 1. The new scheme was a Julian day based approach from the Astronomical Almanac.” and “The effective solar constant was increased to 1367 W/m <sup>2</sup> from 1359 W/m <sup>2</sup> , for consistency with other products. The Pinker/Laszlo algorithm computes radiation in the range from 0.2-4.0 microns. That does not cover the full range of solar output, which extends past 4 microns. The extra energy was placed in the 0.7-4.0 micron band. |
| GEWEX SRB 3.0                         | As cited from the eosweb.larc.nasa.gov webpage, (EOSWEB, 2016c), “Replacement of simple climatological aerosol optical depth based on surface type with full monthly climatology based on MATCH aerosols. Improved treatment of clear vs. cloudy skies over bright surfaces” (personal correspondence Dr. Stephen Cox). Improved gap filling. Temporal coverage of Release 3.0 is extended to December 2007.   |
| GEWEX 4.0                             | Increase of spectral band numbers from 5 to 18. ISCCP HXS cloud and radiance inputs at higher resolution than DX. Full treatment of aerosol optical properties in lookup tables, with inputs coming from Max-Planck Aerosol Climatology. New water vapor from nnHIRS.  |

Table 1 Publicly Released Version History of Global Shortwave SRB Dataset.

## 1.6 Surface Radiation Budget Reprocessing

Reprocessing of the shortwave data for Version 4.0 uses the latest version of the ISCCP HXS full calibrated data set. The 10km satellite pixels for the ISCCP DX and HXS data, but only the ISCCP DX are subsampled to 30 km. Clear, cloudy radiances and cloud fraction are processed for each grid box prior to code execution from geosynchronous satellites with VIS/IR imagers and polar orbiting satellite with AVHRR from 1983 to near real time (Stackhouse, 2016). Version 4.0 will provide for a higher resolution of  $0.5^\circ \times 0.5^\circ$  over previous  $1^\circ \times 1^\circ$  in order to provide better local coverage to resolve more local features. This also improves accuracy as the uncertainty of atmospheric information is greatly dependent on box size as shown by (Jethva, et al., 2013). The data span a time record of 30 years as compared with 22 years in the 3.0 version series (Stackhouse, 2014). Upon completion, this data set will meet the climatological standard normal as defined by the World Meteorological Association (WMO) publication in recognition of long term climate flux (WMO, 2007). A valid time period refers to the most recent 30 year time record of available data. The input data for SRB Version 4.0 use a temporal resolution of three hours as for previous versions. All of the ancillary products, their sources and subsystems are shown in Table 2 modified from SRB Release 4.0 Baseline Processing System Inputs (NASA/GEWEX, 2012).

Referencing Table 2 below, the nnHIRS data product is acquired by measurements of the global distributions of temperature and relative humidity varied temporally (NOAA, 2016a).

“The Goddard Earth Observing System Model, Version 5 (GEOS-5) is a system of models integrated using the Earth System Modeling Framework (ESMF). The GEOS-5 DAS integrates the GEOS-5 AGCM with the Gridpoint Statistical Interpolation (GSI) atmospheric analysis developed jointly with NOAA/NCEP/EMC. The GEOS-5 systems are being developed in the

GMAO to support NASA's earth science research in data analysis, observing system modeling and design, climate and weather prediction, and basic research” (GMAO, 2016). As previously mentioned, the ISCCP HXS is similar to ISCCP DX data using all of the pixels within each grid cell for each satellite with no sub-sampling to produce clear and cloudy radiances and cloud fraction before running the algorithm. Blended ozone is produced using data from the total ozone mapping spectrometer (TOMS), TIROS Operational Vertical Sounder (TOVS), an ensemble of three instruments including a High Resolution Infrared Radiation Sounder (HIRS), a Microwave Sounding Unit (MSU) and a Stratospheric Sounding Unit (SSU), (NOAA, 2016b), a 3-D daily global ozone analysis, and a Stratosphere Monitoring Ozone Blended Analysis (SMOBA) using SBUV/2 and HIRS/TOVS in the polar- night regions (NOAA, 2016c). All of the instruments are flown on earth orbiting satellites identified in their respective references. The vegetation map obtained from the International Geosphere Biosphere Programme provides satellite images of the earth for use in identifying regional climate characteristics. The CO<sub>2</sub> Global Marine product contains CO<sub>2</sub> trends as measured from air sampling sites distributed globally (NOAA, 2016). Tropical aerosols are represented by the Max-Planck-Institute Aerosol Climatology version 1 (MAC-v1). Albedo is a measurement of the fraction of radiation that is reflected by the surface of the earth. Surface albedo for the shortwave products was estimated at five different spectral wavelengths. Column ozone is a measurement of the total ozone at each cell location. Column ozone is calculated as derived in the Langley Parameterized Shortwave Algorithm (LPSA) (Gupta, et al., 2001).

| <b>Input Data</b>           | <b>Source</b>  | <b>Parameters</b>  |
|-----------------------------|--|--|
| ISCCP HXS                   | GISS/NCEI<br><a href="http://www.ncei.noaa.gov">http://www.ncei.noaa.gov</a>           | Satellite radiances, cloud properties, surface reflectance |
| ISCCP nnHIRS                | NOAA/CREST   | Column Water vapor   |
| MAC-v1                      | Max Planck Institute Aerosol Climatology   | Aerosol optical properties                                 |
| ISCCP Blended Ozone product | GISS<br><a href="http://isccp.giss.nasa.gov">http://isccp.giss.nasa.gov</a>            | Column Ozone   |
| Surface Type Map            | IGBP<br><a href="http://igbp.net">http://igbp.net</a>                                  | Code identifying land/water/ice/vegetation                 |
| Surface Elevation Map       | GTOPO30<br><a href="http://lta.cr.usgs.gov/GTOPO30">http://lta.cr.usgs.gov/GTOPO30</a> | Mean altitude for each grid box                            |
| Spectral Surface Albedoes   | Computed for each surface type   | 18 band albedo by surface types                            |

Table 2 SRB GSW Rel 4 Planned ancillary inputs, sources and parameters.

## 2. LITERATURE REVIEW

### 2.1 SRB Data Collection and Integrity

There are currently two ways to obtain a value for solar irradiance over a given location. It can be measured from the ground or derived from satellite data. Ground site positioning is problematic as placement is limited and not evenly distributed. Figure 1 serves to illustrate the sparse sampling of available sites and the impracticality of use for global assessment.

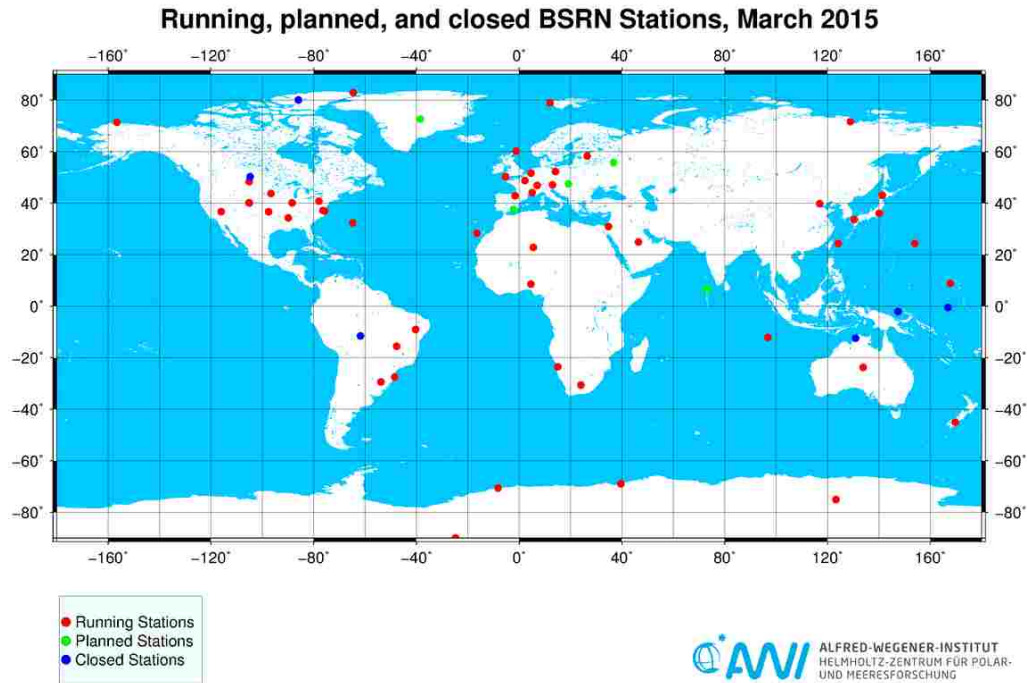


Figure 1 BSRN Site Network (BSRN, 2015)

Satellite coverage overcomes the challenges of ground site positioning, providing an opportunity for obtaining a global estimate. It should be noted that data from one ground site are assumed to be representative of the entire cell where satellite data covers every latitude and longitude point within a cell. While some variation is expected, comparison studies from 1950 to present indicate that satellite derived estimates on the global scale detect the same trends as ground station data with solar irradiance increasing and decreasing over the same time record, and provide extensive validation of the data. Table 3 and Figure 2 summarize these previous studies as culled from (Hinkelman et al., 2009) and highlight the trends.



| <b>Researchers</b>  | <b>Finding</b>  | <b>Year</b>           | <b>Data Source</b>                                  |
|---|---|-----------------------|---|
| Russak, 1990  | Decrease in downwelling solar irradiance.   | 1955-1986             | Ground Stations<br>Satellite                        |
| Liepert et al., 1994  | Decrease in downwelling solar irradiance.   | 1961 -1990            | Ground Stations                                     |
| Dutton et al., 2006   | Decrease in downwelling solar irradiance.   | 1977 -2004            | Ground Stations                                     |
| Stanhill & Moreshet 1992  | Decrease in insolation.   | 1958,1965, 1975, 1985 | Ground Stations                                     |
| Gilgen et al. 1998  | Decrease over large portions of the Earth.<br>Increase restricted to a few small regions. | 1950 -1990            | Ground Stations (GEBA)                              |
| Stanhill and Cohen, 2001  | A worldwide spatially variable reduction in [surface insolation].                         | 1950 -1990            | Ground Stations                                     |
| Wild et al.,2005  | Increase at many locations beginning around 1990.   | 1950 -1994            | Ground Stations (GEBA) and (BSRN)                   |
| Ohmura, 2006  | Increase at many locations beginning around 1990.   | 1950 -1994            | Ground Stations (GEBA) and (BSRN)                   |
| Pinker et al. , 2005  | Increase in global mean insolation from 1983 to 2001.                                     | 1983 -2001            | Satellite surface flux records and Ground Stations. |
| Hinkelman et al., 2009  | Decrease Global SRB SW flux.  | 1983 -1991            | Satellite   |
| Hinkelman et al., 2009  | Increase Global SRB SW flux.  | 1991 -1999            | Satellite   |
| Hinkelman et al., 2009  | Decrease Global SRB SW flux.  | 1999 -2004            | Satellite   |
| Gilgen et al., 1998;<br>Stanhill & Cohen, 2001;<br>Liepert,2002 | Decrease in surface SW irradiance from the 1950s until about 1990.                        | 1950 -1990            | Ground Stations                                     |
| Wild et al., 2005;<br>Ohmura, 2006.                             | Increase at the majority of these locations.  | 1980 -2005            | Ground Stations                                     |
| Dutton et al.,2006<br>Hatzianastassiou et al. 2005              | Decrease in solar downwelling fluxes.   | 1977 -2004            | NOAA observations                                   |
| Loeb, 2008  | Increase in global mean insolation.   | 2000 +                | CERES data  |

Table 3 Tabular Comparison of SW Flux Estimation Studies

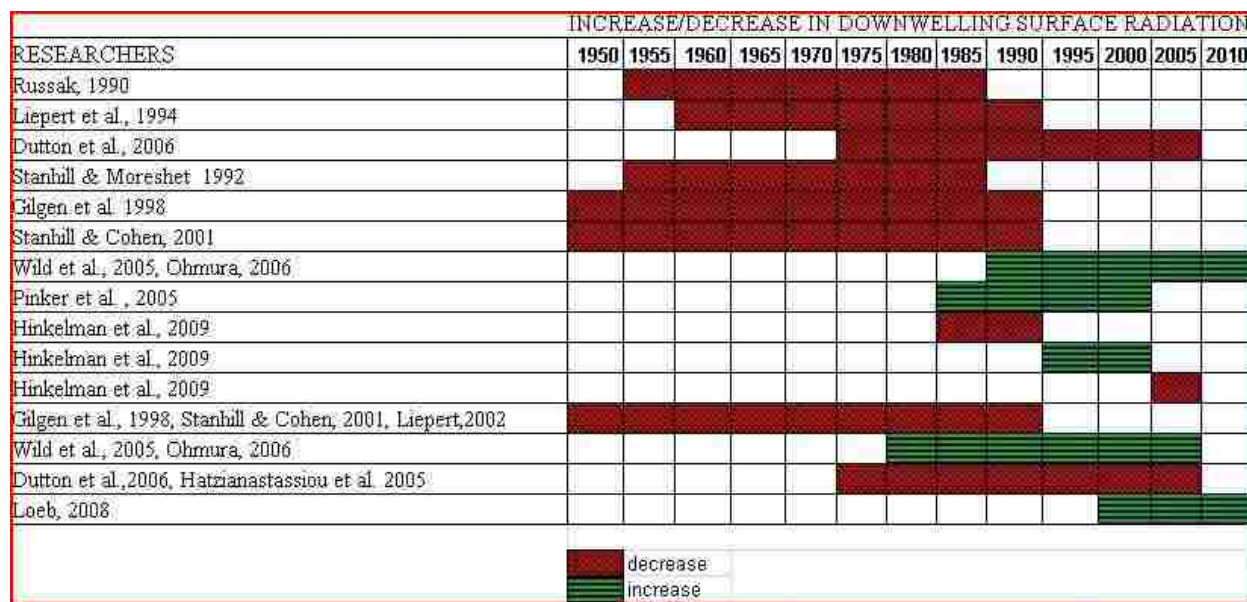


Figure 2 Graphical Representation of SW Flux Estimation Studies

## 2.2 Algorithm Viability

The SRB shortwave algorithm has undergone many changes and improvements since Version 1.0. Methods for improving solar energy output data sets include checking instrument calibration and geostationary satellite viewing angles (Hinkelman, et al., 2009) along with traceability of the inputs, and adherence to a more analytical framework for computations in a later work (Gupta et al., 2001). In a previous shortwave radiance study (Pinker et al., 1992) the physics of a solar irradiance model produced earlier (Pinker et al., 1985) was improved and adapted for use with global data. Several sensitivity studies on algorithm input parameters were conducted (Rossow, et al., 1995) and (Zhang, et al., 1995) and the results applied to calculations in subsequent studies. For example, the ocean albedo algorithm was reformulated and aerosol forcing was applied to a constraint algorithm in order to reduce uncertainty in key parameters (Rose, et al., 1997). Aerosol scattering changes solar energy distribution and is

accounted for in solar radiation algorithms. The computation for aerosol attenuation was therefore addressed in (Gupta, et al., 1999) and improved over (Darnell et al., 1992) using standard aerosols in climatological data with radiative parameters tailored to regional conditions, and albedos from ERBE measurements. When newly measured data became available from the Global Energy Balance Archive (GEBA) and the Baseline Surface Radiation Network (BSRN), it was used for analysis for quantifying errors in shortwave radiation estimates. Four radiation schemes were studied to show cause for errors over temperature and humidity profile inputs used to calculate radiance in layers of the atmosphere of varying scattering and absorption incidences, commonly known as a radiative transfer models (Wild, et al., 2001). As a result, improved cloud products and ancillary data sets were used in advanced radiative transfer models in order to reduce errors in input data. This did not completely eliminate uncertainties in the output data sets and the problematic input parameters (Zhang, et al., 2004). Input data and specific cloud parameters were also identified as error sources when long-term climatological data from ISCCP, NCEP/NCAR and ECMWF were used in a radiative transfer model (Hatzianastassiou, et al., 2005). Discrepancies were found in input parameters when surface flux calculations were computed using various global data sources (Zhang et al., 2006). Data sources were also varied to test uncertainties in the input parameters (Stephens, et al., 2011). Input parameters persisted as sources of errors (Stephens, et al., 2012). In an uncertainty estimate study by (Kato, et al., 2012) it was found that cloud and aerosol properties derived by satellite products cause uncertainty in temperature and precipitable water measurements that propagate to both surface downward longwave and shortwave irradiance uncertainties. While studies identified different input parameters, there was enough evidence to suggest that all of the inputs should be evaluated. "Larger errors were found where there are larger uncertainties in the input data such as over

snow/ice covered surfaces and where the site data did not represent the entire grid box. Larger errors in downward SW flux were also found over African and South American locations where aerosols from biomass burning are not accounted for in the SW model” (Konzelman et al., 1995). While independent research persisted in evaluating clouds and aerosols as the key source of uncertainty (Kato, et al., 2011), a quantitative evaluation of data sources used to calculate surface radiative flux (Zhang et al., 2006) had previously revealed that surface downward longwave flux was most influenced by input factors such as surface air temperature and humidity causing uncertainty and notable error propagation among various global datasets. Other input factors such precipitable water presented bias in model outputs, (Hinkelman, 2009) and (Kato, et al., 2012), supporting (Zhang, et al., 2007) that input parameters and broadband emissivity should be improved as they are a leading contributor to the errors in both longwave and shortwave products. In general it was found that surface albedo, cloud optical depth, aerosol optical depth, cloud fraction, surface temperature and precipitable water were most commonly tagged for further investigation with instrument calibration, sampling space and satellite viewing angles as key sources of instability (Hinkelman, 2009).

All of these studies influenced improvements to subsequent versions of the SRB algorithm and resulting datasets. Progress has been generally good with regard to reducing errors in retrieval methods, instrument failures, data product anomalies, satellite degradation and calibration, and inspection of spectral channels, all of which can never be eliminated (McDonald, 2011). Nonetheless, improvements to the algorithm has reduced the potential for error propagation and resulted in superior performance and sustained interest by the GEWEX/SRB and the Clouds and the Earth’s Radiant Energy System (CERES) projects (Gupta, 2011).

### 2.3 SRB Uncertainty Quantification (Historical)

The literature shows that the greatest cause of uncertainty is associated with the input data. Uncertainty is a result of variability, and variability in the SRB input data is still not well understood (Kato et al., 2012; Stephens et al., 2012). Uncertainty analysis methods have not varied significantly over time beyond a few trusted approaches discussed here. The review included irradiance estimate analyses for both longwave and shortwave products that were constrained either globally or regionally and were sourced from a variety of data products and instruments.

One of the commonly used methods used in conducting uncertainty and sensitivity analyses for satellite derived data products is the comparison of model outputs with ground site measurements. It has been shown that ground site data are reliable and useful for algorithm comparisons and for validation of the final results of satellite data analysis (Hinkelman, et. al., 2009). This uncertainty method has been used in many studies and typically involves a delta comparison of the quadratic mean, root mean squared (RMS), of the ground site (observed) and satellite (modeled) surface irradiances. Parameter perturbation is another method that uses estimated uncertainties as inputs to the algorithm (Ramanathan, 2008; Kato, 2012). In one study, two irradiance models were evaluated against each other and the combined uncertainties were evaluated against surface observations with the largest uncertainties observed in the input parameters of near-surface air temperature and precipitable water (Kato et al., 2012). Recent validation of SRB Version 3.0 shortwave and longwave flux was done by comparing quality controlled BSRN sites measurements with model output (Zhang et al., 2013, 2015). The bias/RMS for the monthly mean shortwave fluxes when compared with BSRN measurements are  $-5.2/23.3 \text{ W m}^{-2}$  under all-sky conditions (Zhang et al., 2013). These values are improved over

(Whitlock et al., 1994) where bias between satellite and surface measurements was calculated between  $10 - 25 \text{ W m}^{-2}$ .

### **3. LITERATURE GAP ANALYSIS**

#### **3.1 Uncertainty Studies**

Methods used to identify key input parameters most responsible for causing variability in satellite estimation data products were found through a literature review of several uncertainty and sensitivity analyses. A gap was identified in the analyses that could be filled to both identify key input parameters and quantify variability using multivariate input factor analysis. The past uncertainty and sensitivity analyses found in literature are summarized in the literature review summary, Table 5, to illustrate this gap. All of the referenced work focused on irradiance estimated in terms of longwave and shortwave, and constrained either globally or regionally from a variety of data products and instruments. The following keys in Table 4 reconcile with corresponding references in the literature review summary shown in Table 5.

| Irradiance Uncertainty and Sensitivity Methods Key |  |
|--|--|
| Key  | Description  |
| M1   | Compared satellite estimation model results with the results of existing satellite estimation models.  |
| M2   | Compared satellite estimation model results with ground station measurements.  |
| M3   | Assigned nominal values to select input parameters and compare results to previous results.  |
| M4   | Changed one input parameter at a time and computed and compared the bias of the resulting output datasets.   |
| M5   | All parameters, parameter interactions and squared terms (measuring the parameter against itself) were evaluated by experimental design over a scientifically prescribed distribution range at three distinct levels. A second-order approximation model was constructed from the results of least squares regression analysis. A Monte Carlo simulation of the model output extended the probability distribution beyond the initial design trials to expose variability in the modeled data. |
| M6   | Quantify uncertainty of different global data sets.  |
| M7   | Compare satellite estimation models with satellite observations.   |
| M8   | Compare inputs from various sources.   |
| M9   | Analyze irradiance differences   |
| M10  | Variations are represented by first-, second-, and third-degree polynomials and a sinusoidal fit.  |
| M11  | Comparison of two algorithms with each other and against site measured data.   |

Table 4 Uncertainty Methods Key

| Researchers                   | Irradiance Uncertainty and Sensitivity Quantification Methods |    |    |    |    |    |    |    |    |     |     |
|-------------------------------|---|----|----|----|----|----|----|----|----|-----|-----|
|                               | M1  | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | M11 |
| Whitlock et al., 1994         | *   | *  |    |    |    |    |    |    |    |     |     |
| Hinkelman et al., 2009        | *   | *  |    |    |    |    |    |    |    |     |     |
| Zhang et al., 2007            |   |    |    |    |    | *  |    |    |    |     |     |
| Kandel et al., 2010           | *   |    |    |    |    |    |    |    |    |     |     |
| Hatzianastassiou et al., 2005 | *   | *  |    |    |    |    |    |    |    |     |     |
| Pinker et al., 1992           |   | *  |    |    |    |    |    |    |    |     |     |
| Rose et al., 1997             | *   |    |    |    |    |    | *  |    |    |     |     |
| Gupta et al., 1999            |   | *  |    |    |    |    |    |    |    |     |     |
| Kato et al., 2012             | *   | *  |    |    |    |    |    |    |    |     |     |
| Zhang et al., 1995            |   |    | *  |    |    |    |    |    |    |     |     |
| Rossow et al., 1995           |   |    |    |    |    |    | *  |    |    |     |     |
| Stephens et al., 2011         | *   | *  |    |    |    |    |    |    |    |     |     |
| Wild et al., 2001             |   | *  |    |    |    |    |    |    |    |     |     |
| Zhang et al., 2004            |   | *  |    |    |    |    | *  |    |    |     |     |
| Zhang et al., 2006            |   |    |    |    |    |    |    | *  |    |     |     |
| Darnell et al., 1985          |   | *  |    |    |    |    |    |    |    |     |     |
| Darnell et al., 1988          |   |    | *  |    |    |    |    |    |    |     |     |
| Ellis et al., 1978            |   | *  |    |    |    |    |    |    |    |     |     |
| Darnell et al., 1992          |   | *  |    |    |    |    |    |    |    |     |     |
| Gupta et al., 1987            |   |    | *  |    |    |    |    |    |    |     |     |
| Gupta et al., 1992            | *   |    |    |    |    |    |    |    |    |     |     |
| Konzelmann et al., 1995       |   | *  |    |    |    |    |    |    |    |     |     |
| Kato et al., 2013             |   |    |    |    |    |    |    |    | *  |     |     |
| Dutton et al, 2005            |   | *  |    |    |    |    |    |    |    | *   |     |
| Cox (unpublished)             |   |    |    | *  |    |    |    |    |    |     |     |
| <b>Quigley, 2017</b>          |   |    |    |    | *  |    |    |    |    |     |     |
| Zhang, et al., 2013           |   | *  |    |    |    |    |    |    |    |     |     |
| Zhang, et al, 2015            |   | *  |    |    |    |    |    |    |    |     | *   |

Table 5 Literature Review Summary Table



### 3.2 Research Gap Solution

Methods to quantify variability in satellite estimation data products were reviewed through literature and a gap was found that was filled by multivariate input factor analysis overcoming the limitations of one factor at a time analysis. This included linear experiments that evaluated the output data when one input parameter at a time was increased or decreased or where all of the input factors were changed by equal percentages. This could result in millions of experiments without taking parameter interactions into account.

A sensitivity analysis of the input products has not yet been conducted at the interactive and multivariate level where input parameters are systematically and simultaneously varied in succession. An augmented D-Optimal design was constructed to enable this level of experimentation. The experimental design consisted of 128 trials constructed with the 13 SRB algorithm input parameters studied at three levels of two-factor interactions and squared terms to establish non-linearity.

## **4. RESEARCH PROTOCOL**

### 4.1 SRB Input Data

The input data used for the SRB Version 4.0 algorithm were obtained from various sources. Cosine solar zenith angle, cosine satellite zenith angle and azimuth angle were obtained from an angular distribution model. Cloud fraction, cloudy shortwave radiance, clear shortwave radiance and clear sky composite shortwave radiance are ISCCP products. Precipitable water, column ozone and aerosol asymmetry parameters are meteorological measurements and first guess aerosol optical depth and aerosol single scattering albedo are estimates. All of these products have been refined over the SRB versioning process. Ongoing issues include satellite

calibration shifts due to orbital drift, small discontinuities during satellite transitions and changes to the TOVS algorithm (GEWEX, 2015a).

The resulting datasets of previous SRB versions have undergone extensive testing and validation to include comparison studies among researchers and against ground site measurements obtained from the Baseline Surface Radiation Network (BSRN), the Swiss Federal Institute of Technology's Global Energy Balance Archive (GEBA) and NOAA's Climate Monitoring and Diagnostics Laboratory (CMDL) to justify that while error exists, the input values are within acceptable limits. With respect to trend analysis and integrity, literature proves that the data record of 30 years meets the climatological standard normal for establishing a trend as defined by the World Meteorological Association (WMO, 2007).

#### 4.2 SRB Output Data

The SRB shortwave algorithm has produced reliable data since its inception in 1994 and has been successfully used in science and industry. The output data sets for this study were produced using a modified version of the same code running the Pinker/Laszlo algorithm, a modified version of an earlier physical model that derives surface solar irradiance from satellite observations (Pinker et al., 1991) and comprised of atmospheric properties calculations with radiative transfer. Where this code produces yearly global data averaged from several points within a cell, the modified software operates on a single latitude and longitude point and uses an average of one month of daily data. It produces 14 output parameters as shown in Table 6.

| Output Parameter Information                                       |                  |
|--|------------------|
| Parameter  | Units            |
| TOA downward flux  | W/m <sup>2</sup> |
| TOA upward flux  | W/m <sup>2</sup> |
| Surface downward flux  | W/m <sup>2</sup> |
| Surface downward diffuse flux                                      | W/m <sup>2</sup> |
| Surface upward flux  | W/m <sup>2</sup> |
| Surface downward diffuse photosynthetically active radiation (PAR) | W/m <sup>2</sup> |
| Surface downward PAR   | W/m <sup>2</sup> |
| TOA upward clear sky flux  | W/m <sup>2</sup> |
| Surface downward clear sky flux                                    | W/m <sup>2</sup> |
| Surface upward clear sky flux                                      | W/m <sup>2</sup> |
| Output Aerosol Optical Depth                                       | unitless         |
| Output Cloud Optical Depth   | unitless         |
| Surface downward pristine sky flux                                 | W/m <sup>2</sup> |
| TOA upward pristine sky flux                                       | W/m <sup>2</sup> |

Table 6 SRB Algorithm Output Parameters

#### 4.3 Input Predictor Bounds

The ranges of predictor values used for the DOE, and subsequently to be used as input parameters to the SRB algorithm, were scientifically prescribed by geographic region. All predictors, predictor interactions and predictor squared terms (measuring the predictor against itself) were evaluated by the experimental design over the distribution range at three levels in order to construct a second-order approximation model such as done in (Unal, et al., 2015). Three levels are used to model the non-linearity of the output data, and squared terms are included to determine all possible two-factor interactions.

#### 4.4 Experimental Design

Designed experiments have proven to be extremely useful in identifying the predictors and their interactions that are influencing the characteristics of systems and processes for the purpose of identifying variability in the dependent variables. They are also a robust means of

gaining information about these variations using the minimum number of experiments necessary to gain precision while reducing experimental cost (Unal, 2006). Experiments increase exponentially as more predictors and levels are studied requiring considerable computing power and an unreasonable amount of time.

Methods have been developed to reduce the number of experiments while maintaining the integrity and accuracy of the analysis. In 1926, Ronald A. Fisher described and proved the value of Design of Experiments (DOE) methodology for optimization of system performance with designed experiments. These formed the basis and justification for modern experimental design methodologies (Bell et al., 2013; Marengo et al., 1995). His premise was that even small effects due to changes can be revealed (Ek, 2005) and his goal was to identify variables that contribute to optimum processing proving using smaller polls and maintaining superior sampling (Ek, 2005). DOE also ensures that the design space is efficiently sampled to determine any dependencies among the predictors, and the magnitude and relative importance of the predictors and predictor interactions to the dependent variables. George E.P. Box effectively deployed experimental design techniques on process improvement (Box, et al., 1951) and his work is still the foundation of designed experimentation. Least squares regression serves to identify predictors and predictor interactions that significantly influence the dependent variables.

## **5. PROBLEM ANALYSIS**

### **5.1 Hypothesis Scope**

This study focused on one latitude and longitude point in each of four atmospherically distinct regions, so one hypothesis was proposed to test predictor and predictor interaction significance for each region and another to test commonality of predictor significance among the

regions. Significance among regions may be useful for assessing the global SRB algorithm.

The following hypotheses describe the problem:

### 5.2 Significance by Region

H1o (NULL): There is no statistically significant predictor variable or predictor interaction influencing any dependent variable in a given region.

$$\beta_{a_r} = \beta_{b_r} = \beta_{c_r} = \beta_{d_r} = \beta_{e_r} = \beta_{f_r} = \beta_{g_r} = \beta_{h_r} = \beta_{i_r} = \beta_{j_r} = \beta_{k_r} = \beta_{l_r} = \beta_{m_r} = 0$$

H1a: There is at least one statistically significant predictor variable or predictor interaction influencing any dependent variable in a given region.

$$\beta_{a_r} = \beta_{b_r} = \beta_{c_r} = \beta_{d_r} = \beta_{e_r} = \beta_{f_r} = \beta_{g_r} = \beta_{h_r} = \beta_{i_r} = \beta_{j_r} = \beta_{k_r} = \beta_{l_r} = \beta_{m_r} \neq 0$$

### 5.3 Significance among Regions

H2o (NULL): There are no globally common statistically significant predictor variables among regions.

$$\beta_{a_r} = \beta_{b_r} = \beta_{c_r} = \beta_{d_r} = \beta_{e_r} = \beta_{f_r} = \beta_{g_r} = \beta_{h_r} = \beta_{i_r} = \beta_{j_r} = \beta_{k_r} = \beta_{l_r} = \beta_{m_r} = 0$$

H2a: There is at least one globally common statistically significant predictor variables among regions.

$$\beta_{a_r} = \beta_{b_r} = \beta_{c_r} = \beta_{d_r} = \beta_{e_r} = \beta_{f_r} = \beta_{g_r} = \beta_{h_r} = \beta_{i_r} = \beta_{j_r} = \beta_{k_r} = \beta_{l_r} = \beta_{m_r} \neq 0$$

## 6. EXPERIMENTAL DESIGN

### 6.1 Design Structure

The research approach involves a sequence of procedures in order to identify the strong predictor and predictor interactions that most significantly affect the output data of the SRB algorithm and also to quantify variability in the dependent variable output values. Minimizing the design space to four regions enabled screening of the process and offered inference about the

results that could be obtained from a global sampling. The methodology described in this section describes sample space selection, construction of a DOE, development of software tools to handle thousands of SRB algorithm transactions, regression analysis, beta testing evaluation, second order quadratic model equation construction for each dependent variable in each region and the application of a sensitivity analysis of these models to quantify variability using Monte Carlo simulation.

## 6.2 Methodology

### *Define the sample space*

Four global regions were selected for study to include heavy foliage, pelagic, desert and mountainous in order to represent unique reciprocity to atmospheric conditions and to correlate some latitude and longitude points with ground site locations (BSRN sites and PMEL buoys) as shown in Table 7. Future studies could use the results from this study for comparison with measurements obtained from these locations. There is no ground site located at the highest point of Mt. Everest. This point was selected to endorse and illustrate the advantage of satellite derived data. Satellites pass over the geographic coordinates for locations where measuring equipment positioning is not possible.

| REGION              | LOCATION                      | LAT    | LON    | GROUND SITE     |
|---------------------|-------------------------------|--------|--------|-----------------|
| Amazon Rain Forrest | Rolim de Moura, Brazil        | -11.58 | 298.22 | BSRN 73         |
| Sahara Desert       | Gobabeb, Namib Desert, Africa | 23.56  | 15.04  | BSRN 20         |
| Indian Ocean        | Indian Ocean                  | -7.97  | 67.00  | BOUY RBJ        |
| Mt Everest          | Highest Point                 | 27.59  | 273.45 | Not Represented |

Table 7 Correlation of Regions with Ground Sites

### *Design the experiments*

There are 13 input parameters, each having a defined range of values. The ranges were studied at three levels (low, medium and high), with the mean of the range representing the medium value. JMP® Statistical Software was used to construct an orthogonal array matrix of 105 rows using coded values -1, 0, or 1 for the three levels. The design was then augmented with an additional 23 rows to allow for regression statistic computation. Figure 3 shows a view of the coded design used for each of the four regions.

| Trial | colza | catza | azi | cldfrc | cldrad | clrrad | cmprad | pwater | ozone |
|-------|-------|-------|-----|--------|--------|--------|--------|--------|-------|
| 1     | 1     | 1     | -1  | -1     | -1     | 1      | 1      | 1      | 1     |
| 2     | -1    | 0     | -1  | -1     | 1      | -1     | 1      | 1      | 1     |
| 3     | 1     | 0     | -1  | 1      | -1     | 0      | -1     | 1      | 0     |
| 4     | -1    | 1     | -1  | 1      | 0      | 1      | -1     | -1     | 1     |
| 5     | -1    | -1    | 0   | 1      | 1      | 0      | 1      | -1     | 1     |
| 6     | -1    | -1    | 1   | -1     | -1     | -1     | 1      | -1     | 1     |
| 7     | -1    | 1     | -1  | -1     | 1      | 1      | 1      | -1     | 0     |
| 8     | 1     | -1    | -1  | -1     | -1     | -1     | -1     | 1      | -1    |
| 9     | 1     | 1     | -1  | -1     | 1      | -1     | -1     | -1     | 1     |
| 10    | 1     | -1    | 1   | -1     | -1     | 1      | -1     | -1     | -1    |
| *     | *     | *     | *   | *      | *      | *      | *      | *      | *     |
| *     | *     | *     | *   | *      | *      | *      | *      | *      | *     |
| *     | *     | *     | *   | *      | *      | *      | *      | *      | *     |
| 121   | 0     | 1     | 1   | 0      | -1     | -1     | 1      | -1     | -1    |
| 122   | 1     | -1    | -1  | -1     | 0      | 0      | 0      | 1      | 1     |
| 123   | 1     | 1     | 1   | 1      | 0      | 1      | 1      | 1      | 1     |
| 124   | -1    | -1    | -1  | -1     | -1     | 1      | -1     | 0      | -1    |
| 125   | 1     | 1     | -1  | 1      | -1     | 1      | -1     | -1     | -1    |
| 126   | 1     | -1    | 1   | 1      | -1     | -1     | -1     | 1      | 1     |
| 127   | 0     | 0     | 1   | -1     | 1      | -1     | -1     | 0      | -1    |
| 128   | -1    | -1    | 1   | 0      | 1      | 1      | 0      | -1     | -1    |

Figure 3 D-Optimal Design with Coded Values

The input parameters for the SRB algorithm displayed in Figure 3 are the predictors of the SRB output data and the design responses. These parameters and their short names are listed in Table 8. Table 8 also includes the full range of values for each parameter and their data sources.

| Algorithm Input Variables |  |  |                            |
|---------------------------|--|--|----------------------------|
| Parameter Assignment      | Description                            | Full Range   | Source                     |
| colza                     | Cosine solar zenith angle              | 0.0(sun on horizon) - 1.0(sun overhead)              | Angular Distribution Model |
| catza                     | Cosine satellite zenith angle          | 0.0 (satellite on horizon)- 1.0(satellite over cell) | Angular Distribution Model |
| azi                       | Azimuth angle                          | 0.0 - 180.0  | Angular Distribution Model |
| cldfrc                    | Cloud fraction                         | 0.0 - 1.0  | ISCCP                      |
| cldrad                    | Cloudy shortwave radiance              | 0.0 - 1.11   | ISCCP                      |
| clrrad                    | Clear shortwave radiance               | 0.0 - 1.11   | ISCCP                      |
| cmprad                    | Clear sky composite shortwave radiance | 0.0 - 1.11   | ISCCP                      |
| pwater                    | Precipitable water                     | 1.0 - 50.0   | Meteorological             |
| ozone                     | Column ozone                           | 5.0 - 50.0   | Meteorological             |
| psheld                    | Phase of the cloud                     | 1 = liquid<br>2 = ice                                | ISCCP                      |
| aertau                    | First guess aerosol optical depth      | 0.0 - 1.0  | Estimate                   |
| aerssa                    | Aerosol single scattering albedo       | 0.9 - 1.0  | Estimate                   |
| aerasy                    | Aerosol asymmetry parameter            | 0.5 - 1.0  | Meteorological             |

Table 8 Predictor Names and Descriptions

The coded values (-1, 0 and 1) in each row of the D-Optimal design were then converted to actual values within the ranges for each parameter shown in Table 8. Figure 4 shows the partial design for the Amazon Region. Each of the 128 rows of the design represents a different combination of the SRB input parameters. Values labeled as VAR will be discussed in Step 3. Figures 10, 11, 12 and 13 in Appendices A through D, show the partial designs for each of the four regions.



| TRIAL | colza | catza | azi    | cldfrc | cldrad | clrrad | cmprad | pwater | ozone | phscld | aertau | aerssa | aerasy |
|-------|-------|-------|--------|--------|--------|--------|--------|--------|-------|--------|--------|--------|--------|
|       | 0.20  | 0.32  | 0.01   | 0.00   | 0.07   | 0.05   | 0.05   | 13.48  | 24.21 | 1      | 0.07   | 0.89   | 0.58   |
|       | 0.58  | 0.66  | 89.51  | 0.50   | VAR    | VAR    | VAR    | 36.86  | 26.09 | n/a    | 0.41   | 0.93   | 0.61   |
|       | 0.96  | 0.99  | 179.00 | 1.00   | 0.60   | 0.36   | 0.33   | 60.25  | 27.96 | 2      | 0.76   | 0.97   | 0.64   |
| 1     | 0.96  | 0.99  | 0.01   | 0.00   | 0.20   | 0.36   | 0.33   | 60.25  | 27.96 | 2      | 0.76   | 0.97   | 0.61   |
| 2     | 0.20  | 0.66  | 0.01   | 0.00   | 0.20   | 0.05   | 0.12   | 60.25  | 27.96 | 1      | 0.07   | 0.97   | 0.64   |
| 3     | 0.96  | 0.66  | 0.01   | 1.00   | 0.20   | 0.30   | 0.24   | 60.25  | 26.09 | 1      | 0.07   | 0.97   | 0.64   |
| 4     | 0.20  | 0.99  | 0.01   | 1.00   | 0.14   | 0.13   | 0.05   | 13.48  | 27.96 | 1      | 0.07   | 0.97   | 0.64   |
| 5     | 0.20  | 0.32  | 89.51  | 1.00   | 0.20   | 0.09   | 0.12   | 13.48  | 27.96 | 2      | 0.07   | 0.89   | 0.58   |
| 6     | 0.20  | 0.32  | 179.00 | 0.00   | 0.07   | 0.05   | 0.12   | 13.48  | 27.96 | 1      | 0.07   | 0.97   | 0.58   |
| 7     | 0.20  | 0.99  | 0.01   | 0.00   | 0.20   | 0.13   | 0.12   | 13.48  | 26.09 | 2      | 0.07   | 0.97   | 0.58   |
| 8     | 0.96  | 0.32  | 0.01   | 0.00   | 0.20   | 0.24   | 0.24   | 60.25  | 24.21 | 2      | 0.76   | 0.89   | 0.64   |
| 9     | 0.96  | 0.99  | 0.01   | 0.00   | 0.60   | 0.24   | 0.24   | 13.48  | 27.96 | 1      | 0.07   | 0.97   | 0.58   |
| 10    | 0.96  | 0.32  | 179.00 | 0.00   | 0.20   | 0.36   | 0.24   | 13.48  | 24.21 | 1      | 0.76   | 0.97   | 0.64   |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| 118   | 0.20  | 0.66  | 0.01   | 1.00   | 0.20   | 0.09   | 0.12   | 60.25  | 24.21 | 2      | 0.07   | 0.89   | 0.61   |
| 119   | 0.20  | 0.66  | 179.00 | 1.00   | 0.14   | 0.13   | 0.12   | 36.86  | 24.21 | 1      | 0.07   | 0.89   | 0.58   |
| 120   | 0.20  | 0.32  | 89.51  | 0.00   | 0.20   | 0.05   | 0.12   | 13.48  | 24.21 | 2      | 0.76   | 0.97   | 0.61   |
| 121   | 0.58  | 0.99  | 179.00 | 0.50   | 0.16   | 0.14   | 0.26   | 13.48  | 24.21 | 1      | 0.41   | 0.89   | 0.61   |
| 122   | 0.96  | 0.32  | 0.01   | 0.00   | 0.40   | 0.30   | 0.29   | 60.25  | 27.96 | 2      | 0.07   | 0.97   | 0.58   |
| 123   | 0.96  | 0.99  | 179.00 | 1.00   | 0.40   | 0.36   | 0.33   | 60.25  | 27.96 | 2      | 0.07   | 0.89   | 0.64   |
| 124   | 0.20  | 0.32  | 10.00  | 0.00   | 0.07   | 0.13   | 0.10   | 36.86  | 24.21 | 2      | 0.41   | 0.97   | 0.58   |
| 125   | 0.96  | 0.99  | 0.01   | 1.00   | 0.20   | 0.36   | 0.24   | 13.48  | 24.21 | 1      | 0.76   | 0.93   | 0.58   |
| 126   | 0.96  | 0.32  | 179.00 | 1.00   | 0.20   | 0.24   | 0.24   | 60.25  | 27.96 | 2      | 0.07   | 0.97   | 0.61   |
| 127   | 0.58  | 0.66  | 179.00 | 0.00   | 0.60   | 0.14   | 0.14   | 36.86  | 24.21 | 1      | 0.76   | 0.89   | 0.64   |
| 128   | 0.20  | 0.32  | 159.00 | 0.50   | 0.20   | 0.13   | 0.10   | 13.48  | 24.21 | 2      | 0.76   | 0.93   | 0.58   |

Figure 4 D-Optimal Design for Amazon Rainforest with Actual Values

The SRB algorithm also takes as input 6 additional static parameters. Spatial inputs such as latitude and longitude are set for each region. One month of a year was chosen for the temporal values for all regions to establish a fixed distance from the earth to the sun. The satellite position ID was set to 1 for all regions and was predefined based on orbital paths. For this study, atmospheric and space weather observations were obtained from the NOAA-9 sun-synchronous satellite, launched on December 12, 1984 (OSCAR, 2015). The snow/ice unit was set to 0 for all of the regions except for the Mt. Everest Region. The snow/ice value is determined by region. The values for the static parameters are shown in Table 9.

| Algorithm Static Input Variables |       |      |          |           |                       |          |
|----------------------------------|-------|------|----------|-----------|-----------------------|----------|
| REGION                           | MONTH | YEAR | LATITUDE | LONGITUDE | SATELLITE POSITION ID | SNOW/ICE |
| Amazon Rainforest                | JUL   | 2007 | -11.58   | 298.23    | 1                     | 0        |
| Indian Ocean                     | JUL   | 2007 | -7.97    | 67.00     | 1                     | 0        |
| Mt. Everest                      | JUL   | 2007 | 27.59    | 273.45    | 1                     | 1        |
| Sahara Desert                    | JUL   | 2007 | 23.56    | 15.04     | 1                     | 0        |

Table 9 Static Input Values for the SRB Algorithm

*Execute the SRB algorithm to conduct the experiments*

For each region, the DOE was programmatically parsed to extract and pass one row of inputs to the SRB algorithm software. This process is represented in Figure 5. Executing and compiling the results was automated for efficiency, speed, scalability and reuse. A utility script created 128 NAMELIST files that contained a value for each of the 13 varied input parameters and the 6 static input parameters. After the SRB algorithm processed all of the 128 NAMELIST files, the utility script created a table of all of the output parameters to be used as dependent variables for the regression analysis. This was done for each of the four regions equating to  $4 \times 14 \times 128 = 7,168$  experiments.

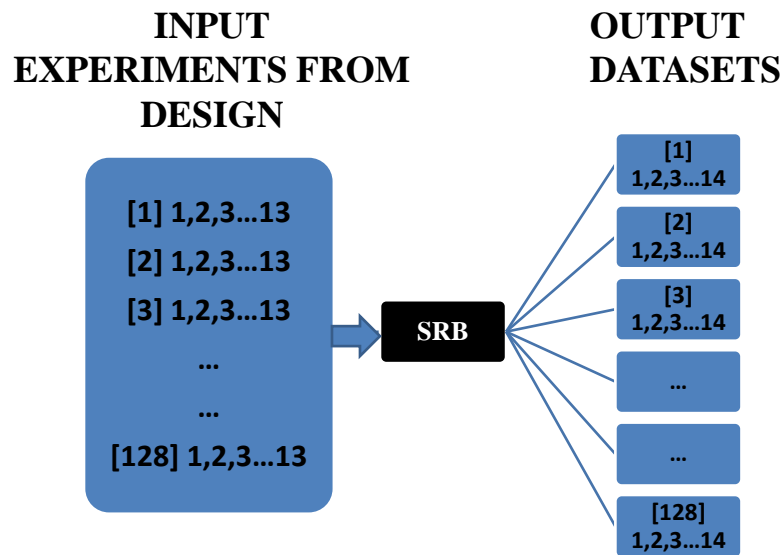


Figure 5 Surface Radiation Budget Algorithm Processing

*Evaluate the results of the output data*

The Amazon Rainforest region was selected for beta testing. Analysis of the output data sets indicated that input parameter ranges should be more finely tuned as some produced infeasible solutions. This was due to codependency among cosine of the solar zenith angle with clear sky radiance (clrrad), cloudy sky radiance (cldrad) and clear sky composite shortwave radiance (cmprad). These predictor values cannot extend to the limits of range during conditions of low sun and low satellite angles. The values were then set depending on the value of the cosine of the solar zenith angle (colza) and correlated well with the atmospheric profile of each region. Table 10 shows the adjustment of the predictors in the Amazon region as the cosine of the solar zenith angle varied from 0.2 to 0.58 to 0.96. Infeasible solutions were managed for the other three regions as well.

|       |        |        |        |        |        |        |        |        |        |
|-------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| colza | 0.2    |        |        | 0.58   |        |        | 0.96   |        |        |
|       | clrrad | cldrad | cmprad | clrrad | cldrad | cmprad | clrrad | cldrad | cmprad |
| low   | 0.05   | 0.07   | 0.05   | 0.14   | 0.16   | 0.14   | 0.24   | 0.20   | 0.24   |
| med   | 0.09   | 0.135  | 0.085  | 0.205  | 0.38   | 0.20   | 0.30   | 0.40   | 0.285  |
| high  | 0.13   | 0.20   | 0.12   | 0.27   | 0.60   | 0.26   | 0.36   | 0.60   | 0.33   |

Table 10 Adjusted Predictor Value Bounds for Amazon Region

*Perform a regression analysis for each dependent variable*

To measure the goodness of the model, a least squares regression analysis was performed for each dependent variable in each region to obtain a minimum generalized variance of the estimates of the model coefficients and to show the correlation among predictors. JMP® Statistical Software was prescribed for this effort and was commercially available. The response surface Fit Model regression included all of the predictors, predictor interactions and squared terms. A separate regression was done for every dependent variable in all four regions.

The model specification results of the regression analysis included P value statistics and regression coefficients that were used to determine the significant predictors and predictor interactions. P value analyses serve as a standard for identifying influential predictors and predictor interactions that were significantly impacting the dependent variables, and provided evidence for rejecting or not rejecting the null hypothesis. For this study, the predictors with P values that were approximately within the 90% confidence range were considered significant in order to include more predictors in the model. Specifically, this was where  $P \leq 0.11$ . The P value statistic for 56 (14 dependent variable sets of 128 x 4 regions) individual analyses was examined. Figure 6 shows the P value statistics for TOAUP in the Amazon Rainforest region.

| AMAZON TOAUP     |                |
|------------------|----------------|
| <i>Predictor</i> | <i>P-Value</i> |
| colza            | 0              |
| cldfrc*cldrad    | 0              |
| cldrad           | 0              |
| cldfrc           | 0              |
| colza*cldrad     | 0              |
| colza*cldfrc     | 0.00003        |
| azi*azi          | 0.00018        |
| colza*catza      | 0.00036        |
| pwater*pshcld    | 0.00188        |
| colza*colza      | 0.00384        |
| azi*pwater       | 0.00644        |
| catza            | 0.00979        |
| pwater           | 0.02555        |
| cmprad*aerasy    | 0.03931        |
| catza*aertau     | 0.04264        |
| aertau*aerssa    | 0.04434        |
| clrrad*clrrad    | 0.06447        |
| azi*pshcld       | 0.06861        |
| clrrad           | 0.07346        |
| cmprad           | 0.0842         |
| colza*clrrad     | 0.08601        |
| cldfrc*aerasy    | 0.08618        |
| colza*aertau     | 0.09291        |
| cldfrc*aertau    | 0.10158        |
| colza*azi        | 0.10652        |

Figure 6 P Value Statistics for TOAUP in Amazon Region

### *Construct model equations*

A second order math model, approximating the relationship between the dependent variables and each of the predictor variables (Unal, 2015) in each of the four regions, was built for each dependent variable using the significant predictors and predictor interactions as determined by the P value analysis. The equation was generated using the coefficients of each dependent variable where predictors and predictor interactions satisfied the P value criteria of P

$\leq$  to .11. The purpose of this model was to create an equation that could be used in a Monte Carlo simulation to extend the capabilities of the design and show variability of the output data as the inputs changed. The model equation is in the form  $Y = b_0 + \sum b_i x_i + \sum \sum b_{ij} x_{ij} + \sum b_{ii} x_i^2$  where  $b_0$  is the Y intercept, Y is the dependent variable value, lower case  $b_i$  represents the coefficients from the regression analysis and x's represent one of the three possible levels of the predictors. Lower case i and j represent the experiment numbers where  $i=1-n$  and  $j=1-n$ . Software was developed in order to rapidly build the 56 model equations for each of the 14 dependent variable values in each of the four regions.

The model equation for the dependent variable TOAUP in the Amazon Rainforest region is shown on the far right in Figure 7. It was built using the coefficients from the regression analysis as shown in the table in the center of Figure 7 where significant predictors and predictor interactions are listed with their corresponding coefficient value. For this equation, Y is the dependent variable. The alpha character 'A' followed by a number is a cell in a spreadsheet that represents the high, medium or low value for each predictor as illustrated by the table on the left in Figure 7. These were varied using appropriate probability distributions for the sensitivity analysis. Two predictor interactions and squared terms are multiplied as denoted by the asterisks.

| TOAP |        |       | MODEL EQUATION |            |
|------|--------|-------|----------------|------------|
|      |        |       | Amazon Region  |            |
|      |        |       | Predictor      | coeff      |
|      |        |       | Intercept      | 316.505385 |
| A3   | colza  | H,M,L | colza          | 154.111742 |
| A4   | catza  | H,M,L | cldfrc*cldrad  | 54.064277  |
| A5   | azi    | H,M,L | cldrad         | 65.568597  |
| A6   | cldfrc | H,M,L | cldfrc         | 60.5750548 |
| A7   | cldrad | H,M,L | colza*cldrad   | 43.0150125 |
| A8   | clrrad | H,M,L | colza*cldfrc   | 24.2120005 |
| A9   | cmprad | H,M,L | azi*azi        | -65.674031 |
| A10  | pwater | H,M,L | colza*catza    | -19.861128 |
| A11  | ozone  | H,M,L | pwater*pshcld  | -31.34222  |
| A12  | pshcld | H,M,L | colza*colza    | -54.421118 |
| A13  | aertau | H,M,L | azi*pwater     | -15.360723 |
| A14  | aerssa | H,M,L | catza          | 17.5129775 |
| A15  | aerasy | H,M,L | pwater         | 15.0105291 |
|      |        |       | cmprad*aerasy  | -9.7826131 |
|      |        |       | catza*aertau   | -10.073629 |
|      |        |       | aertau*aerssa  | 10.3136588 |
|      |        |       | clrrad*clrrad  | 29.6186082 |
|      |        |       | azi*pshcld     | -17.40929  |
|      |        |       | clrrad         | 12.0928359 |
|      |        |       | cmprad         | 11.6893114 |
|      |        |       | colza*clrrad   | 8.94938664 |
|      |        |       | cldfrc*aerasy  | -8.7228263 |
|      |        |       | colza*aertau   | -8.0108616 |
|      |        |       | cldfrc*aertau  | -8.3427717 |
|      |        |       | colza*azi      | 8.14932366 |

### MODEL EQUATION Amazon Region

$$\begin{aligned}
 Y = & 316.505385 + 154.1117419 * A3 + 54.06427701 * A6 * A7 + 65.56859697 * A7 + 60.5750548 \\
 & 05477 * A6 + 43.0150125 * A3 * A7 + 24.21200051 * A3 * A6 + -65.6740312 * A5 * A5 + \\
 & 19.86112823 * A3 * A4 + -31.34222036 * A10 * A12 + \\
 & 54.42111832 * A3 * A3 + 15.3607226 * A5 * A10 + 17.51297749 * A4 + \\
 & 15.01052909 * A10 + 9.782613058 * A9 * A15 + \\
 & 10.07362949 * A4 * A13 + 10.31365884 * A13 * A14 + 29.61860823 * A8 * A8 + \\
 & 17.40928998 * A5 * A12 + 12.09283592 * A8 + 11.68931142 * A9 + 8.94938664 * A3 * A8 + \\
 & 8.72282627 * A6 * A15 + 8.010861627 * A3 * A13 + \\
 & 8.342771651 * A6 * A13 + 8.149323664 * A3 * A5
 \end{aligned}$$

Figure 7 P Values and Coefficients Summary

### Sensitivity Analysis

To determine the variability in the output data for each dependent variable, a Monte Carlo simulation using @Risk® commercial software. This enabled more variations of predictor levels beyond the designed experiment to be evaluated. Setup entailed using the dependent variable as the risk output and the predictor values varied by three levels as the input. Triangular distributions that can model skewness were used. The parameters of these distributions were determined by using expert judgment. To avoid correlation of the predictor values in the equation, the high, medium and low actual values for each predictor were normalized by coding the actual values back to 1, 0 and -1 respectively. The simulation varied all of the input parameters in the model equation about their normalized distribution ranges 10,000 times for each dependent variable and for each region.

### 6.3 Tool Development

Software tools were created to assist with the following tasks for customization and automation of the SRB algorithm execution, construction of tables for the regression analysis and the model equations:

1. Histogram files containing the ranges for each of the predictors were provided by the scientist. A program was written to extract the high and low values for the parameters and compute the medium values from the histogram text files. These values were then used to convert the coded predictor values of the computer generated D-Optimal DOE to actual predictor values in a spreadsheet with a simple Excel function.
2. After porting the DOE to the directory where the SRB algorithm is stored, it was parsed with a script to create 128 NAMELIST files for each region. The NAMELIST files are used as input to the SRB algorithm.
3. A utility script successively passed each NAMELIST file to the SRB algorithm for processing. The algorithm created 128 output datasets for each of the 14 output data sets. These were then programmatically combined into a matrix of 128 rows and 14 columns. The values in the 14 columns became the dependent variables.
4. JMP<sup>®</sup> Statistical Software was used to do a regression analysis for each output parameter. The summary effects and P-value results for each regression were ported into tables. A script extracted P-values and coefficients from the regressions that were used to determine the strong predictors and predictor interactions and test H1o and H1a.
5. Second order quadratic equations were programmatically constructed using the coefficients from the regression for use in the Monte Carlo simulation.



6. A script was used to compare and report the significant predictors and predictor interactions among all of the regions to test H2o and H2a.

A report file was written containing detailed instructions for accomplishing all of the tasks. A README file containing instructions for executing code for sequential SRB processing is also available.

## 7. DATA ANALYSIS

### 7.1 Predictor Analysis Results

It was found by identifying predictors and predictor interactions having the lowest P value in each region that there were predictors and predictor interactions that very strongly influenced the dependent variables. These are shown in Table 11.

| REGION            | PREDICTOR | PREDICTOR INTERACTIONS     |
|-------------------|-----------|----------------------------|
| Amazon Rainforest | colza     | colza*cldfrc               |
| Sahara Desert     | colza     | colza*cldfrc,cldfrc*cldrad |
| Mt. Everest       | colza     | colza*cldfrc               |
| Indian Ocean      | colza     | cldfrc*cldrad              |

Table 11 Strongest Predictor and Predictor Interactions by Region

Statistics were also analyzed to identify the dependent variables that had the most predictors and predictor interactions with P-values less than 0.11. These are shown in Table 12.

| REGION            | DEPENDENT VARIABLE<br>(P-value < 0.11) |
|-------------------|--|
| Amazon Rainforest | SRFDWNFLX                              |
| Sahara Desert     | SRFDWNPRS                              |
| Mt Everest        | SRFDWNFLX                              |
| Indian Ocean      | SRFDWNPAR                              |

Table 12 Dependent Variables with Highest Number of Influential Predictors and Predictor Interactions by Region

An analysis was performed to determine if there were significant predictors and predictor interactions that were common among the regions. A comparison of all of the strong predictor and predictor interactions tables sorted by dependent variable was conducted. The results are shown in Table 13. For each dependent variable in the first column of Table 13, a predictor or predictor interactions that were found in all four regions are listed in the second column.

| Dependent Variable | Predictors and Predictor Interactions   |
|--------------------|---|
| OAOD               | clrrad  |
| OCOD               | colza, catza*cldrad   |
| SRFDWNCLRSKY       | colza, clrrad   |
| SRFDWNDIFF         | colza, cldfr*cldrad   |
| SRFDWNIFPAR        | colza   |
| SRFDWNFLX          | cldfr*cldrad, cldfr, colza, cldrad, cldfr*pshcld, colza*cldfr   |
| SRFDWNPAR          | cldrad, colza, cldfr*cldrad, cldfr*pshcld, colza*cldfr  |
| SRFDWNPRS          | pshcld*aerasy, cldfr*ozone, catza, pwater*pwater, colza, colza*catza, ozone*aertau, cmprad, aerasy, cldfr*pshcld, colza*colza, pwater, cmprad*aerssa, ozone, colza*pwater |
| SRFUPCLRFLX        | colza   |
| SRFUPFLX           | colza*catza, cldrad, cldfr  |
| TOAUP              | pwater*pshcld, azi*pwater, cldfr*cldrad, cldfr, cldrad, colza, colza*cldrad, catza*aertau, azi*pshcld, azi*azi, clrrad*clrrad, colza*cldfr, clrrad                        |
| TOAUPCLRSKY        | cmprad, colza, colza*catza, catza*azi   |
| TOAUPPRS           | cmprad, colza, colza*catza, colza*cmprad  |

Table 13 Common Significant Predictors for Dependent Variables among Regions

## 7.2 Sensitivity Analysis Results

The second objective was to quantify variability of the output data sets as the input values changed. The Monte Carlo simulation varied the normalized values of all of the input parameters in the model about their normalized distribution ranges 10,000 times for each dependent variable and for each region. The resulting distribution curve of three standard deviations for each simulation along with statistical output quantified the variability. Figure 8 shows the approximated variability for each dependent variable by region.

| <b>Dependent Variable</b> | <b>VARIABILITY</b> |               |                   |                     |
|---------------------------|--------------------|---------------|-------------------|---------------------|
|                           | <b>Amazon</b>      | <b>Sahara</b> | <b>Mt Everest</b> | <b>Indian Ocean</b> |
| <b>TOAUP</b>              | 254                | 202.5         | 319               | 306                 |
| <b>SRFDWNFLX</b>          | 548                | 447           | 720               | 492                 |
| <b>SRFDWNDIFF</b>         | 221.5              | 277           | 116.2             | 317                 |
| <b>SRFUPFLX</b>           | 190.3              | 125.3         | 43.4              | 74.1                |
| <b>SRFDWNDIFFPAR</b>      | 55.8               | 155.1         | 60.5              | 158.1               |
| <b>SRFDWNPAR</b>          | 258                | 211.5         | 272               | 242                 |
| <b>TOAUPCLRSKY</b>        | 174.3              | 114.8         | 43.9              | 87                  |
| <b>SRFDWNCLRSKY</b>       | 586                | 586           | 630               | 525                 |
| <b>SRFUPCLRFLX</b>        | 205.7              | 142.6         | 49.3              | 61.4                |
| <b>OAOD</b>               | 0.488              | 0.977         | 0.057             | 0.613               |
| <b>OCOD</b>               | 146.7              | 146.3         | 130.2             | 140.2               |
| <b>SRFDWNPRS</b>          | 604                | 655           | 628               | 599                 |
| <b>TOAUPPRS</b>           | 199.5              | 139.7         | 52.1              | 160.3               |

Figure 8 Results of Sensitivity Analysis ( $\text{W m}^{-2}$ )

Figure 8 shows the graphical representation of the analysis statistics for the dependent variable TOAUP in the Amazon Rainforest region to include the coefficient table, a graph of the coefficient table and the variability histogram produced by @Risk® software. A complete collection of the graphical representations for each dependent variable in each region is shown in Figures 14 through 65.

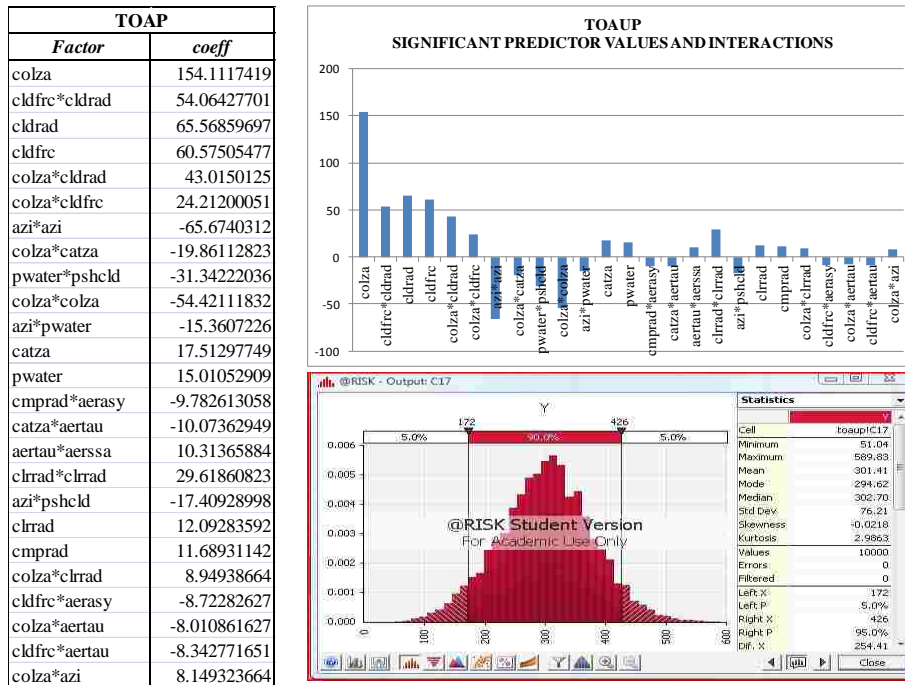


Figure 9 Amazon Region Sensitivity Analysis - TOAUP

Model equations were not constructed for TOADWN for any of the regions. This variable represents the sunlight coming into the earth's atmosphere and is not affected by surface or atmospheric properties; therefore the only significant input was cosine of the solar zenith angle (colza).

### 7.3 Resolution of Research Objectives

The first objective was to identify significant input parameters and parameter interactions that significantly affected the output data sets of the SRB algorithm. This was accomplished by analysis of the regression statistics.

H1a: There is at least one statistically significant predictor variable or predictor interaction influencing any dependent variable in a given region.

$$\beta_{a_r} = \beta_{b_r} = \beta_{c_r} = \beta_{d_r} = \beta_{e_r} = \beta_{f_r} = \beta_{g_r} = \beta_{h_r} = \beta_{i_r} = \beta_{j_r} = \beta_{k_r} = \beta_{l_r} = \beta_{m_r} \neq 0$$

P value analysis showed that the NULL hypothesis H1o should be rejected because each dependent variable in all four regions was significantly influenced by at least one predictor and/or predictor interaction.

The results showed that the null hypothesis H2o can be rejected. There is at least one globally common statistically significant predictor variable among regions.

H2a: There is at least one globally common statistically significant predictor variables among regions.

$$\beta_{a_r} = \beta_{b_r} = \beta_{c_r} = \beta_{d_r} = \beta_{e_r} = \beta_{f_r} = \beta_{g_r} = \beta_{h_r} = \beta_{i_r} = \beta_{j_r} = \beta_{k_r} = \beta_{l_r} = \beta_{m_r} \neq 0$$

## 8. SUMMARY

### 8.1 Statistical Approach to Predictor Analysis

An analytical and statistical framework was developed to determine significant predictors and predictor interactions that influenced the output products of the SRB algorithm and quantified the variation in the resulting output data sets. This was accomplished using DOE, regression analysis and Monte Carlo simulation. Predictor variables and second order interactions that strongly influenced the dependent variables were determined. The influence of predictors and predictor interactions varied among the dependent variables and among regions, but that there was some commonality with the cosine of the solar zenith angle having the strongest influence on the output data in all four regions. The interaction of Cosine Solar Zenith Angle and Cloud Fraction had the strongest influence on output data in the Amazon Rainforest, Sahara Desert and Mt. Everest Regions, and the interaction of Cloud Fraction and Cloudy Shortwave Radiance most significantly affected output data in the Indian Ocean region. Tools

were developed to simplify and automate the processes and to make the analyses much more efficient.

## 8.2 Summary of Results

Methods to identify influential input parameters and quantify variability in satellite estimation data products were reviewed through literature. A gap in analytic methods was identified and filled by multivariate input factor analysis. A D-Optimal design of 128 experiments was constructed to enable many combinations of the input data to be evaluated simultaneously. Key predictor and predictor interactions were identified and the variability of the output data was quantified. Tools were built to automate and streamline processes.

The SRB algorithm requires 13 input parameters and 6 static parameters to complete execution and delivers 14 output parameters each time it runs. Changing the values of the input parameters changes the values of the output parameters. The research problem was to identify those input parameters that caused the most significant influence on the output parameters and to quantify the impact. In the past, these were tested by changing one input parameter at a time. In order to address this problem more efficiently, both input parameters and input parameter interactions were studied as two factor interactions and squared terms. This was accomplished using a D-Optimal experimental design. The design provided 128 variations of the inputs that were then processed by the SRB algorithm. The result was 128 different responses for each output parameter. This was done for each of the four atmospherically distinct regions using a modified configuration of the SRB algorithm.

A regression analysis was conducted using the design matrix of 128 rows and 13 columns as the predictor variables and each output parameter set of 128 experiments as the dependent variables. The regression included all of the predictor values and all possible interactions of the

predictor values. Square terms of each predictor value were also included. Summary statistics were provided after each regression to include P-values. This enabled the significance of each predictor variable and the relationships among the predictor variables to be measured. Predictor and predictor interactions with P-values  $< 0.11$  were flagged as significant and presented as tables and graphs. There were several significant predictors and predictor interactions influencing the dependent variables, so the null hypothesis H10 was rejected.

In addition, it was found by identifying predictors and predictor interactions having the lowest P-value in each region that there were predictors and predictor interactions that very strongly influenced the dependent variables. These were shown in Table 11. Statistics were also analyzed to identify the dependent variables that had the most predictors and predictor interactions with P-values less than 0.11. These were shown in Table 12.

Commonality of strong predictors and predictor interactions was the basis of hypotheses H20 and H2a. Tables containing the strong predictors and predictor interactions for each dependent variable for all four regions were programmatically parsed and compared. H20 was rejected as the results of the comparison showed that there was at least one significant predictor and/or predictor interaction common to all of the regions. These were shown in Table 13.

The dependent variable SRFDWNPRS was most strongly affected in every region by colza, colza\*colza, colza\*pwater, colza, pwater and pwater\*pwater. The only difference was that SRFDWNPRS in the Mt. Everest region was also strongly affected by ozone. It was found that Cosine solar zenith angle was the strongest influence on the output data in all four regions. The interaction of Cosine Solar Zenith Angle and Cloud Fraction had the strongest influence on the output data in the Amazon, Sahara Desert and Mt. Everest Regions, while the interaction of

Cloud Fraction and Cloudy Shortwave Radiance most significantly affected output data in the Indian Ocean region.

In order to quantify the impact that the significant predictors and predictor interactions had on the dependent variables, a second order quadratic equation was constructed for each dependent variable using the coefficients for each of its significant predictor and predictor interactions from the regression analysis. Monte Carlo simulation extended the capability of the DOE by varying the predictor values for each dependent variable 10,000 times. The results showed the range for the possible outcomes and quantified the variability of the output data. These are shown for each dependent variable in each region in figures 14 - 65.

## **9. RESEARCH CONTRIBUTIONS**

### **9.1 Contribution to Atmospheric Science Analysis Method**

A D-Optimal design was constructed to enable many combinations of the input data to be evaluated simultaneously, overcoming the limitations of one value at a time analysis (OVAT) by evaluating the interactions of the inputs as well as the main effects. The design consists of 128 trials constructed to handle the large number of input parameters and dependent variables needed to run the experiments. This is a software-generated, minimum point design with additional experiments added for greater degrees of freedom. Codependency of the cosine of the solar zenith angle with cloudy radiance, clear radiance and clear sky composite shortwave radiance due to incidences of low sun and satellite angles at certain zenith angles was quickly managed using software to add scientifically prescribed values as the bounds when infeasible outputs occurred.



## 9.2 Contribution to Atmospheric Science Computing Process

The research approach enabled input values to be programmatically extracted from the design, formatted as required by the algorithm and then passed into the algorithm as arguments allowing for automatic rapid and repeated execution of the design trials. This also served to eliminate the task of manually entering input values into the NAMELIST files. A software tool for building quadratic math models from regression analysis output was developed to reduce the level of effort in building second order quadratic models with multiple parameter inputs and parameter interactions.

## 10. LIMITATIONS AND ADVANTAGES

### 10.1 Limitations

It is not yet known if the variability at the regional level applies to the global signal, but it was found that there is at least one globally common statistically significant predictor variables among regions (cosine of the solar zenith angle) and the interaction of cosine of the solar zenith angle and cloud fraction was significant in the Amazon, Mt. Everest and Sahara regions. The results in this analysis are based on a point in one cell out of 44016 possible cells with many points and should be extended to other regions in order to get a global picture. The SRB algorithm produces an approximation to the value of the dependent variable so the regression results may not be an accurate representation of the actual site measured values. The relative significance of the predictors and their interactions would not be expected to change. Similarly, the Monte Carlo simulation provided a good indication of relative variability, but results may not be accurate as the model equation is an approximation of an algorithm that is also an approximation.

## 10.2 Advantages

Input parameters used by the SRB algorithm are notably a key source of variability in the resulting output data sets. The relative significance of these parameters and their interactions would not be expected to change. Previous studies included linear techniques such as varying one input parameter at a time while keeping all others constant or by increasing all input parameters by equal random percentages. This research used D-Optimal DOE and reduced the number of trials required by full factorial designs or by linear analyses from millions to 128. Second order quadratic model equations constructed from the results of least squares multiple regressions were used in Monte Carlo simulations. This provided further indication of relative uncertainty. Another advantage over one variable at a time (OVAT) analyses is that parameter interactions were determined. These can be stronger than main effects as seen in the results of this study. The result of this framework enabled an efficient and structured analysis approach to identify those parameters and parameter interactions that most significantly affected the SRB output products.

## 11. CONCLUSIONS AND FUTURE RESEARCH

There is much potential for further study of SRB output data at the regional level. This work provided a very small sampling of the globe where there are a total of 44016 candidate cells that could also be studied. Studying more cells may further identify commonality of strong predictor and predictor interactions on the global scale. Ground site comparison studies showed good correlation of the modeled SRB data to measured values so studies should be done using to model optimization techniques where the dependent variable values are constrained to site measurements. Strong predictors and predictor interactions were common among certain

dependent variables. Scientific analysis of this finding is suggested and may result in testing input parameters outside of the ranges used in this study.

A power analysis using information from the current design and scientific reasoning can be used to optimize future designs. This is done by computing the signal to noise ratio where the signal is equal to the desired delta in the response (not predicted in this study), and the noise is the standard deviation computed for the dependent variables that were calculated in this study.

This sensitivity analysis modeled a triangular distribution of the input ranges. Future studies could use a skewed distribution with orthogonal polynomials. Model and validate prior covariance distributions and then using a Bayesian hierarchical approach to regression modeling in addition to the current model.

Finally, taking known uncertainties of the input parameters into consideration, establish an error profile for each of the output parameters so that uncertainty can be established on a global scale.

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## APPENDICES

## A. Design Matrix for Amazon Rainforest

| TRIAL | colza | catza | azi    | cldfrc | cldrad | clrrad | cmprad | pwater | ozone | phscld | aertau | aerssa | aerasy |
|-------|-------|-------|--------|--------|--------|--------|--------|--------|-------|--------|--------|--------|--------|
|       | 0.20  | 0.32  | 0.01   | 0.00   | 0.07   | 0.05   | 0.05   | 13.48  | 24.21 | 1      | 0.07   | 0.89   | 0.58   |
|       | 0.58  | 0.66  | 89.51  | 0.50   | VAR    | VAR    | VAR    | 36.86  | 26.09 | n/a    | 0.41   | 0.93   | 0.61   |
|       | 0.96  | 0.99  | 179.00 | 1.00   | 0.60   | 0.36   | 0.33   | 60.25  | 27.96 | 2      | 0.76   | 0.97   | 0.64   |
| 1     | 0.96  | 0.99  | 0.01   | 0.00   | 0.20   | 0.36   | 0.33   | 60.25  | 27.96 | 2      | 0.76   | 0.97   | 0.61   |
| 2     | 0.20  | 0.66  | 0.01   | 0.00   | 0.20   | 0.05   | 0.12   | 60.25  | 27.96 | 1      | 0.07   | 0.97   | 0.64   |
| 3     | 0.96  | 0.66  | 0.01   | 1.00   | 0.20   | 0.30   | 0.24   | 60.25  | 26.09 | 1      | 0.07   | 0.97   | 0.64   |
| 4     | 0.20  | 0.99  | 0.01   | 1.00   | 0.14   | 0.13   | 0.05   | 13.48  | 27.96 | 1      | 0.07   | 0.97   | 0.64   |
| 5     | 0.20  | 0.32  | 89.51  | 1.00   | 0.20   | 0.09   | 0.12   | 13.48  | 27.96 | 2      | 0.07   | 0.89   | 0.58   |
| 6     | 0.20  | 0.32  | 179.00 | 0.00   | 0.07   | 0.05   | 0.12   | 13.48  | 27.96 | 1      | 0.07   | 0.97   | 0.58   |
| 7     | 0.20  | 0.99  | 0.01   | 0.00   | 0.20   | 0.13   | 0.12   | 13.48  | 26.09 | 2      | 0.07   | 0.97   | 0.58   |
| 8     | 0.96  | 0.32  | 0.01   | 0.00   | 0.20   | 0.24   | 0.24   | 60.25  | 24.21 | 2      | 0.76   | 0.89   | 0.64   |
| 9     | 0.96  | 0.99  | 0.01   | 0.00   | 0.60   | 0.24   | 0.24   | 13.48  | 27.96 | 1      | 0.07   | 0.97   | 0.58   |
| 10    | 0.96  | 0.32  | 179.00 | 0.00   | 0.20   | 0.36   | 0.24   | 13.48  | 24.21 | 1      | 0.76   | 0.97   | 0.64   |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| 118   | 0.20  | 0.66  | 0.01   | 1.00   | 0.20   | 0.09   | 0.12   | 60.25  | 24.21 | 2      | 0.07   | 0.89   | 0.61   |
| 119   | 0.20  | 0.66  | 179.00 | 1.00   | 0.14   | 0.13   | 0.12   | 36.86  | 24.21 | 1      | 0.07   | 0.89   | 0.58   |
| 120   | 0.20  | 0.32  | 89.51  | 0.00   | 0.20   | 0.05   | 0.12   | 13.48  | 24.21 | 2      | 0.76   | 0.97   | 0.61   |
| 121   | 0.58  | 0.99  | 179.00 | 0.50   | 0.16   | 0.14   | 0.26   | 13.48  | 24.21 | 1      | 0.41   | 0.89   | 0.61   |
| 122   | 0.96  | 0.32  | 0.01   | 0.00   | 0.40   | 0.30   | 0.29   | 60.25  | 27.96 | 2      | 0.07   | 0.97   | 0.58   |
| 123   | 0.96  | 0.99  | 179.00 | 1.00   | 0.40   | 0.36   | 0.33   | 60.25  | 27.96 | 2      | 0.07   | 0.89   | 0.64   |
| 124   | 0.20  | 0.32  | 10.00  | 0.00   | 0.07   | 0.13   | 0.10   | 36.86  | 24.21 | 2      | 0.41   | 0.97   | 0.58   |
| 125   | 0.96  | 0.99  | 0.01   | 1.00   | 0.20   | 0.36   | 0.24   | 13.48  | 24.21 | 1      | 0.76   | 0.93   | 0.58   |
| 126   | 0.96  | 0.32  | 179.00 | 1.00   | 0.20   | 0.24   | 0.24   | 60.25  | 27.96 | 2      | 0.07   | 0.97   | 0.61   |
| 127   | 0.58  | 0.66  | 179.00 | 0.00   | 0.60   | 0.14   | 0.14   | 36.86  | 24.21 | 1      | 0.76   | 0.89   | 0.64   |
| 128   | 0.20  | 0.32  | 159.00 | 0.50   | 0.20   | 0.13   | 0.10   | 13.48  | 24.21 | 2      | 0.76   | 0.93   | 0.58   |

Figure 10. Design Matrix for Amazon Rainforest



## B. Design Matrix for Sahara Desert

| TRIAL | colza | catza | azi    | cldfrc | cldrad | clrrad | cmprad | pwater | ozone | phscld | aertau | aerssa | aerasy |
|-------|-------|-------|--------|--------|--------|--------|--------|--------|-------|--------|--------|--------|--------|
|       | 0.20  | 0.44  | 0.00   | 0.00   | 0.07   | 0.05   | 0.07   | 2.02   | 24.01 | 1      | 0.12   | 0.93   | 0.66   |
|       | 0.60  | 0.71  | 89.50  | 0.50   | 0.31   | 0.20   | 0.22   | 19.32  | 27.41 | n/a    | 0.37   | 0.94   | 0.69   |
|       | 0.99  | 0.99  | 179.00 | 1.00   | 0.55   | 0.35   | 0.33   | 36.62  | 30.81 | 2      | 0.61   | 0.95   | 0.72   |
| 1     | 0.99  | 0.99  | 0.00   | 0.00   | 0.07   | 0.35   | 0.33   | 36.62  | 30.81 | 2      | 0.61   | 0.95   | 0.69   |
| 2     | 0.20  | 0.71  | 0.00   | 0.00   | 0.55   | 0.05   | 0.33   | 36.62  | 30.81 | 1      | 0.12   | 0.95   | 0.72   |
| 3     | 0.99  | 0.71  | 0.00   | 1.00   | 0.07   | 0.20   | 0.07   | 36.62  | 27.41 | 1      | 0.12   | 0.95   | 0.72   |
| 4     | 0.20  | 0.99  | 0.00   | 1.00   | 0.31   | 0.35   | 0.07   | 2.02   | 30.81 | 1      | 0.12   | 0.95   | 0.72   |
| 5     | 0.20  | 0.44  | 89.50  | 1.00   | 0.55   | 0.20   | 0.33   | 2.02   | 30.81 | 2      | 0.12   | 0.93   | 0.66   |
| 6     | 0.20  | 0.44  | 179.00 | 0.00   | 0.07   | 0.05   | 0.33   | 2.02   | 30.81 | 1      | 0.12   | 0.95   | 0.66   |
| 7     | 0.20  | 0.99  | 0.00   | 0.00   | 0.55   | 0.35   | 0.33   | 2.02   | 27.41 | 2      | 0.12   | 0.95   | 0.66   |
| 8     | 0.99  | 0.44  | 0.00   | 0.00   | 0.07   | 0.05   | 0.07   | 36.62  | 24.01 | 2      | 0.61   | 0.93   | 0.72   |
| 9     | 0.99  | 0.99  | 0.00   | 0.00   | 0.55   | 0.05   | 0.07   | 2.02   | 30.81 | 1      | 0.12   | 0.95   | 0.66   |
| 10    | 0.99  | 0.44  | 179.00 | 0.00   | 0.07   | 0.35   | 0.07   | 2.02   | 24.01 | 1      | 0.61   | 0.95   | 0.72   |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| 118   | 0.20  | 0.71  | 0.00   | 1.00   | 0.55   | 0.20   | 0.33   | 36.62  | 24.01 | 2      | 0.12   | 0.93   | 0.69   |
| 119   | 0.20  | 0.71  | 179.00 | 1.00   | 0.31   | 0.35   | 0.33   | 19.32  | 24.01 | 1      | 0.12   | 0.93   | 0.66   |
| 120   | 0.20  | 0.44  | 89.50  | 0.00   | 0.55   | 0.05   | 0.33   | 2.02   | 24.01 | 2      | 0.61   | 0.95   | 0.69   |
| 121   | 0.60  | 0.99  | 179.00 | 0.50   | 0.07   | 0.05   | 0.33   | 2.02   | 24.01 | 1      | 0.37   | 0.93   | 0.69   |
| 122   | 0.99  | 0.44  | 0.00   | 0.00   | 0.31   | 0.20   | 0.22   | 36.62  | 30.81 | 2      | 0.12   | 0.95   | 0.66   |
| 123   | 0.99  | 0.99  | 179.00 | 1.00   | 0.31   | 0.35   | 0.33   | 36.62  | 30.81 | 2      | 0.12   | 0.93   | 0.72   |
| 124   | 0.20  | 0.44  | 0.00   | 0.00   | 0.07   | 0.35   | 0.07   | 19.32  | 24.01 | 2      | 0.37   | 0.95   | 0.66   |
| 125   | 0.99  | 0.99  | 0.00   | 1.00   | 0.07   | 0.35   | 0.07   | 2.02   | 24.01 | 1      | 0.61   | 0.94   | 0.66   |
| 126   | 0.99  | 0.44  | 179.00 | 1.00   | 0.07   | 0.05   | 0.07   | 36.62  | 30.81 | 2      | 0.12   | 0.95   | 0.69   |
| 127   | 0.60  | 0.71  | 179.00 | 0.00   | 0.55   | 0.05   | 0.07   | 19.32  | 24.01 | 1      | 0.61   | 0.93   | 0.72   |
| 128   | 0.20  | 0.44  | 179.00 | 0.50   | 0.55   | 0.35   | 0.22   | 2.02   | 24.01 | 2      | 0.61   | 0.94   | 0.66   |

Figure 11. Design Matrix for Sahara Desert

## C. Design Matrix for Indian Ocean

| TRIAL | colza | catza | azi    | cldfrc | cldrad | clrrad | cmprad | pwater | ozone | phscld | aertau | aerssa | aerasy |
|-------|-------|-------|--------|--------|--------|--------|--------|--------|-------|--------|--------|--------|--------|
|       | 0.20  | 0.40  | 0.00   | 0.00   | 0.01   | 0.00   | 0.18   | 25.98  | 23.83 | 1      | 0.05   | 0.96   | 0.64   |
|       | 0.58  | 0.69  | 84.50  | 0.50   | 0.47   | 0.05   | 0.21   | 44.93  | 25.56 | n/a    | 0.08   | 0.98   | 0.67   |
|       | 0.96  | 0.99  | 169.00 | 1.00   | 0.93   | 0.11   | 0.26   | 63.88  | 27.29 | 2      | 0.11   | 0.99   | 0.71   |
| 1     | 0.96  | 0.99  | 0.00   | 0.00   | 0.01   | 0.11   | 0.26   | 63.88  | 27.29 | 2      | 0.11   | 0.99   | 0.67   |
| 2     | 0.20  | 0.69  | 0.00   | 0.00   | 0.93   | 0.00   | 0.26   | 63.88  | 27.29 | 1      | 0.05   | 0.99   | 0.71   |
| 3     | 0.96  | 0.69  | 0.00   | 1.00   | 0.01   | 0.05   | 0.18   | 63.88  | 25.56 | 1      | 0.05   | 0.99   | 0.71   |
| 4     | 0.20  | 0.99  | 0.00   | 1.00   | 0.47   | 0.11   | 0.18   | 25.98  | 27.29 | 1      | 0.05   | 0.99   | 0.71   |
| 5     | 0.20  | 0.40  | 84.50  | 1.00   | 0.93   | 0.05   | 0.26   | 25.98  | 27.29 | 2      | 0.05   | 0.96   | 0.64   |
| 6     | 0.20  | 0.40  | 169.00 | 0.00   | 0.01   | 0.00   | 0.26   | 25.98  | 27.29 | 1      | 0.05   | 0.99   | 0.64   |
| 7     | 0.20  | 0.99  | 0.00   | 0.00   | 0.93   | 0.11   | 0.26   | 25.98  | 25.56 | 2      | 0.05   | 0.99   | 0.64   |
| 8     | 0.96  | 0.40  | 0.00   | 0.00   | 0.01   | 0.00   | 0.18   | 63.88  | 23.83 | 2      | 0.11   | 0.96   | 0.71   |
| 9     | 0.96  | 0.99  | 0.00   | 0.00   | 0.93   | 0.00   | 0.18   | 25.98  | 27.29 | 1      | 0.05   | 0.99   | 0.64   |
| 10    | 0.96  | 0.40  | 169.00 | 0.00   | 0.01   | 0.11   | 0.18   | 25.98  | 23.83 | 1      | 0.11   | 0.99   | 0.71   |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| 118   | 0.20  | 0.69  | 0.00   | 1.00   | 0.93   | 0.05   | 0.26   | 63.88  | 23.83 | 2      | 0.05   | 0.96   | 0.67   |
| 119   | 0.20  | 0.69  | 169.00 | 1.00   | 0.47   | 0.11   | 0.26   | 44.93  | 23.83 | 1      | 0.05   | 0.96   | 0.64   |
| 120   | 0.20  | 0.40  | 84.50  | 0.00   | 0.93   | 0.00   | 0.26   | 25.98  | 23.83 | 2      | 0.11   | 0.99   | 0.67   |
| 121   | 0.58  | 0.99  | 169.00 | 0.50   | 0.01   | 0.00   | 0.26   | 25.98  | 23.83 | 1      | 0.08   | 0.96   | 0.67   |
| 122   | 0.96  | 0.40  | 0.00   | 0.00   | 0.47   | 0.05   | 0.21   | 63.88  | 27.29 | 2      | 0.05   | 0.99   | 0.64   |
| 123   | 0.96  | 0.99  | 169.00 | 1.00   | 0.47   | 0.11   | 0.26   | 63.88  | 27.29 | 2      | 0.05   | 0.96   | 0.71   |
| 124   | 0.20  | 0.40  | 0.00   | 0.00   | 0.01   | 0.11   | 0.18   | 44.93  | 23.83 | 2      | 0.08   | 0.99   | 0.64   |
| 125   | 0.96  | 0.99  | 0.00   | 1.00   | 0.01   | 0.11   | 0.18   | 25.98  | 23.83 | 1      | 0.11   | 0.98   | 0.64   |
| 126   | 0.96  | 0.40  | 169.00 | 1.00   | 0.01   | 0.00   | 0.18   | 63.88  | 27.29 | 2      | 0.05   | 0.99   | 0.67   |
| 127   | 0.58  | 0.69  | 169.00 | 0.00   | 0.93   | 0.00   | 0.18   | 44.93  | 23.83 | 1      | 0.11   | 0.96   | 0.71   |
| 128   | 0.20  | 0.40  | 169.00 | 0.50   | 0.93   | 0.11   | 0.21   | 25.98  | 23.83 | 2      | 0.11   | 0.98   | 0.64   |

Figure 12. Design Matrix for Indian Ocean

## D. Design Matrix for Mt Everest

| TRIAL | colza | catza | azi    | cldfrc | cldrad | clrrad | cmprad | pwater | ozone | phscld | aertau | aerssa | aerasy |
|-------|-------|-------|--------|--------|--------|--------|--------|--------|-------|--------|--------|--------|--------|
|       | 0.20  | 0.45  | 3.99   | 0.00   | 0.00   | 0.00   | 0.07   | 12.76  | 23.21 | 1      | 0.09   | 0.95   | 0.62   |
|       | 0.60  | 0.72  | 80.07  | 0.50   | 0.45   | 0.05   | 0.09   | 35.80  | 28.69 | n/a    | 0.14   | 0.96   | 0.65   |
|       | 0.99  | 0.99  | 156.14 | 1.00   | 0.89   | 0.10   | 0.13   | 58.85  | 34.17 | 2      | 0.18   | 0.98   | 0.67   |
| 1     | 0.99  | 0.99  | 3.99   | 0.00   | 0.00   | 0.10   | 0.13   | 58.85  | 34.17 | 2      | 0.18   | 0.98   | 0.65   |
| 2     | 0.20  | 0.72  | 3.99   | 0.00   | 0.89   | 0.00   | 0.13   | 58.85  | 34.17 | 1      | 0.09   | 0.98   | 0.67   |
| 3     | 0.99  | 0.72  | 3.99   | 1.00   | 0.00   | 0.05   | 0.07   | 58.85  | 28.69 | 1      | 0.09   | 0.98   | 0.67   |
| 4     | 0.20  | 0.99  | 3.99   | 1.00   | 0.45   | 0.10   | 0.07   | 12.76  | 34.17 | 1      | 0.09   | 0.98   | 0.67   |
| 5     | 0.20  | 0.45  | 80.07  | 1.00   | 0.89   | 0.05   | 0.13   | 12.76  | 34.17 | 2      | 0.09   | 0.95   | 0.62   |
| 6     | 0.20  | 0.45  | 156.14 | 0.00   | 0.00   | 0.00   | 0.13   | 12.76  | 34.17 | 1      | 0.09   | 0.98   | 0.62   |
| 7     | 0.20  | 0.99  | 3.99   | 0.00   | 0.89   | 0.10   | 0.13   | 12.76  | 28.69 | 2      | 0.09   | 0.98   | 0.62   |
| 8     | 0.99  | 0.45  | 3.99   | 0.00   | 0.00   | 0.00   | 0.07   | 58.85  | 23.21 | 2      | 0.18   | 0.95   | 0.67   |
| 9     | 0.99  | 0.99  | 3.99   | 0.00   | 0.89   | 0.00   | 0.07   | 12.76  | 34.17 | 1      | 0.09   | 0.98   | 0.62   |
| 10    | 0.99  | 0.45  | 156.14 | 0.00   | 0.00   | 0.10   | 0.07   | 12.76  | 23.21 | 1      | 0.18   | 0.98   | 0.67   |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| *     | *     | *     | *      | *      | *      | *      | *      | *      | *     | *      | *      | *      | *      |
| 118   | 0.20  | 0.72  | 3.99   | 1.00   | 0.89   | 0.05   | 0.13   | 58.85  | 23.21 | 2      | 0.09   | 0.95   | 0.65   |
| 119   | 0.20  | 0.72  | 156.14 | 1.00   | 0.45   | 0.10   | 0.13   | 35.80  | 23.21 | 1      | 0.09   | 0.95   | 0.62   |
| 120   | 0.20  | 0.45  | 80.07  | 0.00   | 0.89   | 0.00   | 0.13   | 12.76  | 23.21 | 2      | 0.18   | 0.98   | 0.65   |
| 121   | 0.60  | 0.99  | 156.14 | 0.50   | 0.00   | 0.00   | 0.13   | 12.76  | 23.21 | 1      | 0.14   | 0.95   | 0.65   |
| 122   | 0.99  | 0.45  | 3.99   | 0.00   | 0.45   | 0.05   | 0.09   | 58.85  | 34.17 | 2      | 0.09   | 0.98   | 0.62   |
| 123   | 0.99  | 0.99  | 156.14 | 1.00   | 0.45   | 0.10   | 0.13   | 58.85  | 34.17 | 2      | 0.09   | 0.95   | 0.67   |
| 124   | 0.20  | 0.45  | 3.99   | 0.00   | 0.00   | 0.10   | 0.07   | 35.80  | 23.21 | 2      | 0.14   | 0.98   | 0.62   |
| 125   | 0.99  | 0.99  | 3.99   | 1.00   | 0.00   | 0.10   | 0.07   | 12.76  | 23.21 | 1      | 0.18   | 0.96   | 0.62   |
| 126   | 0.99  | 0.45  | 156.14 | 1.00   | 0.00   | 0.00   | 0.07   | 58.85  | 34.17 | 2      | 0.09   | 0.98   | 0.65   |
| 127   | 0.60  | 0.72  | 156.14 | 0.00   | 0.89   | 0.00   | 0.07   | 35.80  | 23.21 | 1      | 0.18   | 0.95   | 0.67   |
| 128   | 0.20  | 0.45  | 156.14 | 0.50   | 0.89   | 0.10   | 0.09   | 12.76  | 23.21 | 2      | 0.18   | 0.96   | 0.62   |

Figure 13. Design Matrix for Mt Everest

### Amazon Region Uncertainty Analysis - TOAUP

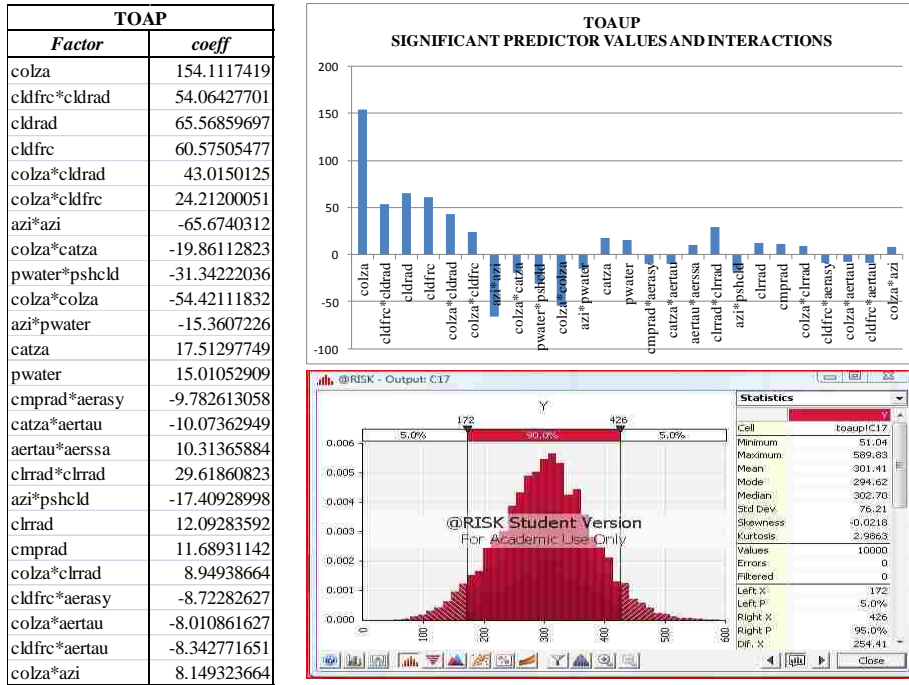


Figure 14. Amazon Region Uncertainty Analysis - TOAUP

### Amazon Region Uncertainty Analysis – SRFDWNFLX

| SRFDWNFLX     |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza         | 382.9461164  |
| colza*cldfrc  | -90.63405531 |
| pwater*pschld | 108.9176169  |
| cldfrc*pschld | -104.0961336 |
| colza*pschld  | -96.54917188 |
| cldfrc*cldrad | -53.24440353 |
| cmprad*ozone  | 46.54944911  |
| cldrad        | -54.02676806 |
| azi*aerasy    | 41.60918266  |
| cmprad*aertau | 38.89942004  |
| cldrad*aerssa | -36.44564153 |
| cldfrc*cmprad | -37.02796033 |
| pwater        | -44.26567483 |
| colza*aerssa  | -33.65453932 |
| cldfrc        | -45.10353722 |
| catza*aerssa  | -32.19221218 |
| cldfrc*pwater | 30.68786027  |
| ozone*pschld  | 52.66211027  |
| cldrad*aerasy | 24.6052091   |
| colza*colza   | 93.0791078   |
| aertau*aerasy | -23.0985605  |
| colza*cmprad  | -23.61064069 |
| colza*pwater  | 23.57226813  |
| pschld*aertau | 45.2910791   |
| cldfrc*cldrad | -24.08195858 |
| cldrad*ozone  | 21.51405464  |
| ozone*aertau  | -21.73255895 |
| cmprad*pwater | 22.39020449  |
| aertau        | -30.59768048 |
| azi*cldrad    | 20.81361175  |
| cmprad        | -29.35991234 |

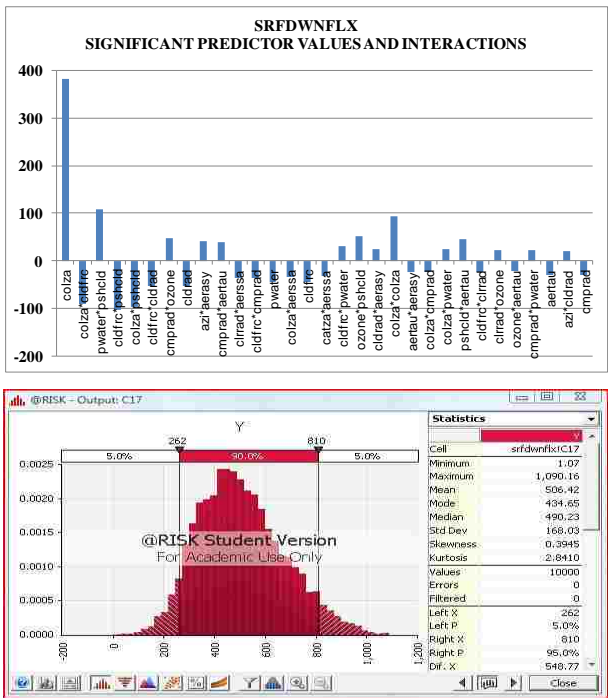


Figure 15. Amazon Region Uncertainty Analysis – SRFDWNFLX

Amazon Region Uncertainty Analysis – SRFDWNDIFF

| SRFDWNDIFF    |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza         | 140.6291315  |
| cldfrc*cldrad | 52.85939655  |
| clrrad*aertau | -43.16895246 |
| cmprad*aerasy | 37.95462644  |
| cldfrc*cldrad | 40.40664113  |
| colza*cldrad  | 40.45512973  |
| cldrad*pwat   | -36.4055498  |
| azi*cldrad    | -33.00641562 |
| cldfrc*aerssa | -30.44506    |
| aertau        | 45.61121845  |
| colza*cldrad  | -33.35983669 |
| cmprad        | 43.04506968  |
| clrrad*cmprad | -30.6144951  |
| colza*cmprad  | 30.90827792  |
| colza*catza   | 28.79746925  |
| catza*aerssa  | 27.82603932  |

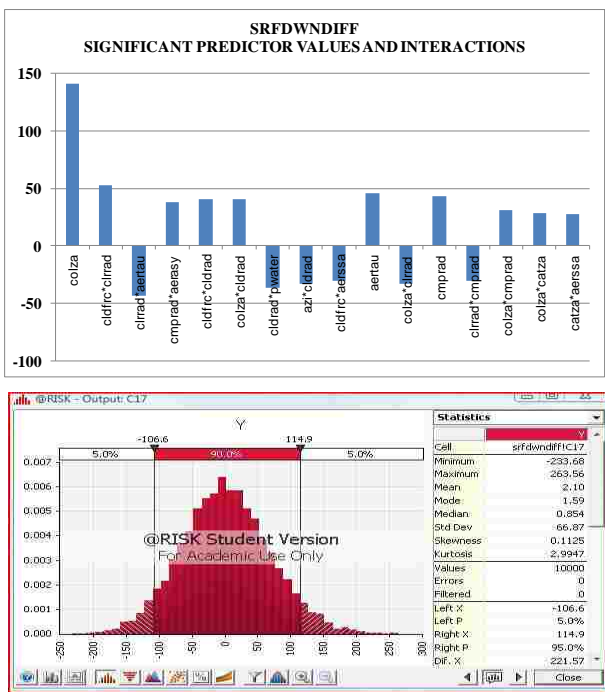


Figure 16. Amazon Region Uncertainty Analysis - SRFDWNDIFF

### Amazon Region Uncertainty Analysis - SRFUPFLX

| SRFUPFLX       |              |
|----------------|--------------|
| Factor         | Coeff        |
| colza          | 132.304397   |
| colza*cldfric  | -31.36328236 |
| colza*catza    | -21.13445332 |
| colza*pwater   | 19.71625229  |
| cmprad*ozone   | 19.09001726  |
| cldfric*cmprad | -18.36853157 |
| cldfric*pshcld | -32.44337933 |
| azi*aerasy     | 17.73329134  |
| cldfric*cldrad | -17.67275699 |
| pwater*pshcld  | 31.87459228  |
| colza*pshcld   | -29.89265634 |
| cldfric        | -21.6984442  |
| colza*aerssa   | -15.55891502 |
| clrrad*aerssa  | -14.56922056 |
| catza*aerssa   | -14.56429006 |
| cmprad*aertau  | 14.63020705  |
| catza*catza    | -45.87126499 |
| clrrad         | 15.78025572  |
| cldrad         | -14.87876133 |
| cmprad         | 15.20509837  |
| ozone*aertau   | -10.48787161 |
| cldfric*pwater | 10.98236064  |
| pwater*aerasy  | 10.51209738  |

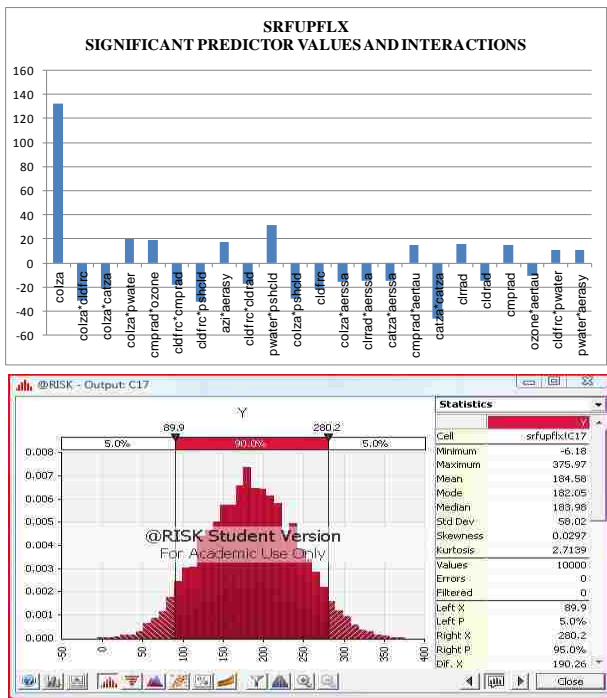


Figure 17. Amazon Region Uncertainty Analysis - SRFUPFLX

### Amazon Region Uncertainty Analysis - SRFDWNDIFPAR

| SRFDWNDIFPAR  |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza         | 68.50564991  |
| cldfrc*cldrad | 24.22765232  |
| clrad*aertau  | -20.06901209 |
| colza*cldrad  | 20.06921577  |
| cmprad*aerasy | 17.42519503  |
| cldfrc*cldrad | 18.23056897  |
| cldrad*pwater | -16.69790855 |
| azi*cldrad    | -15.82664449 |
| cldfrc*aerssa | -14.02151098 |
| aertau        | 20.61476343  |
| colza*clrad   | -15.24468961 |
| clrad*cmprad  | -13.89058232 |
| cmprad        | 19.22129042  |
| colza*catza   | 13.73947227  |
| colza*cmprad  | 13.61147964  |

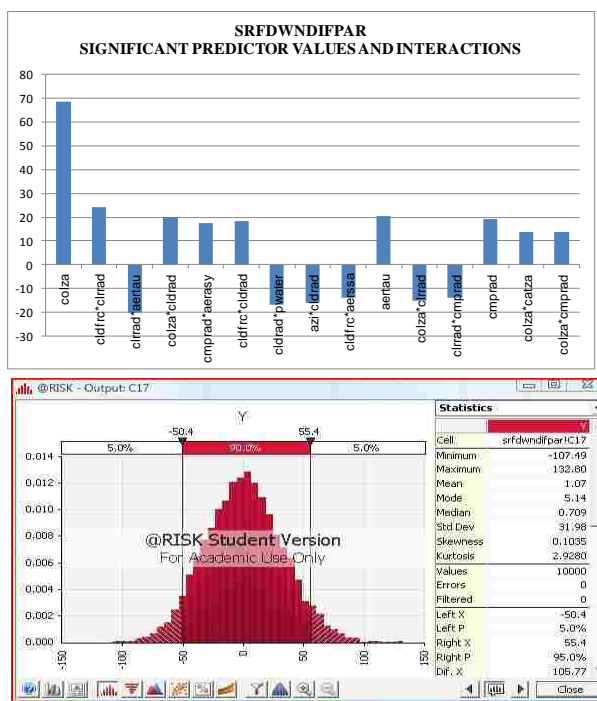


Figure 18. Amazon Region Uncertainty Analysis - SRFDWNDIFPAR



## Amazon Region Uncertainty Analysis - SRFDWNPAP

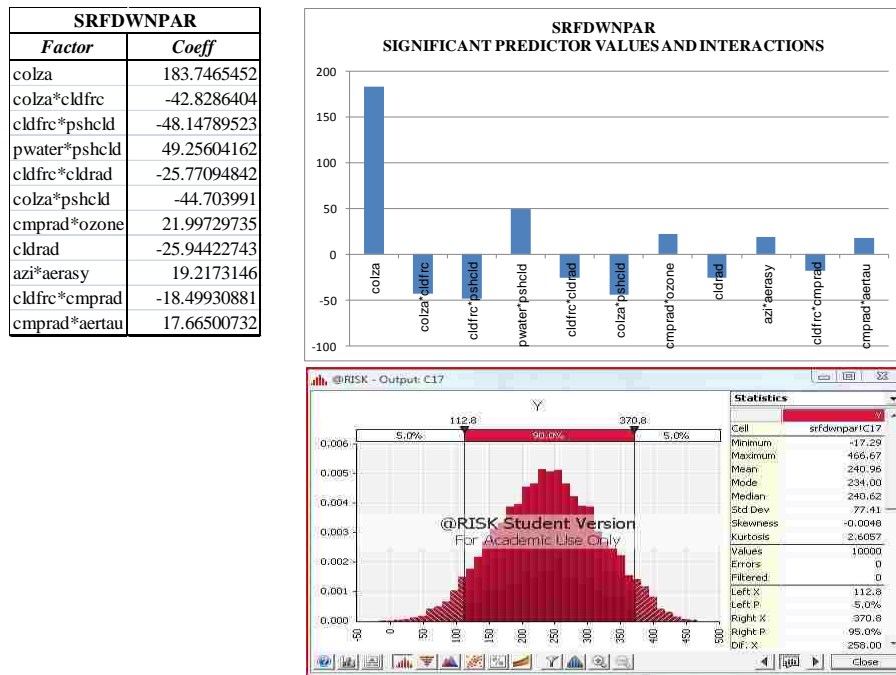


Figure 19. Amazon Region Uncertainty Analysis - SRFDWNPAP

## Amazon Region Uncertainty Analysis – TOAUPCLRSKY

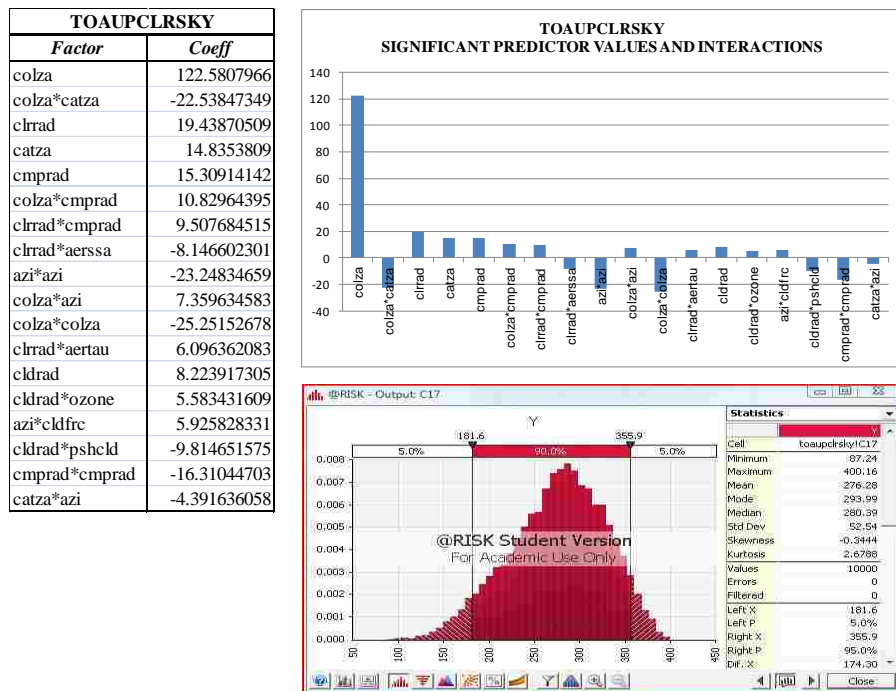


Figure 20. Amazon Region Uncertainty Analysis – TOAUPCLRSKY

### Amazon Region Uncertainty Analysis – SRFDWNCLRSKY

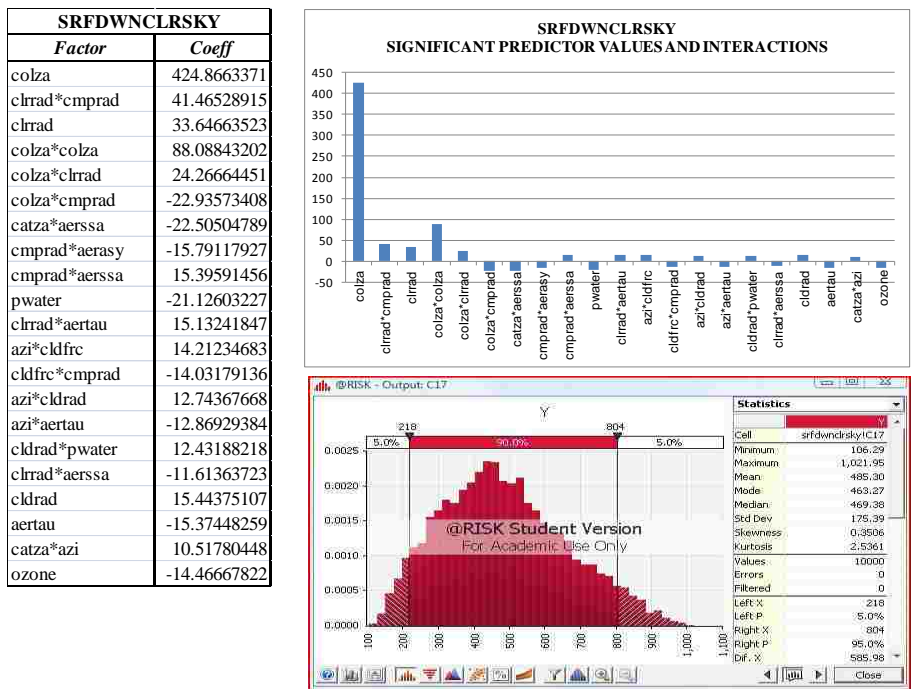


Figure 21. Amazon Region Uncertainty Analysis – SRFDWNCLRSKY

Amazon Region Uncertainty Analysis – SRFUPCLRFLX

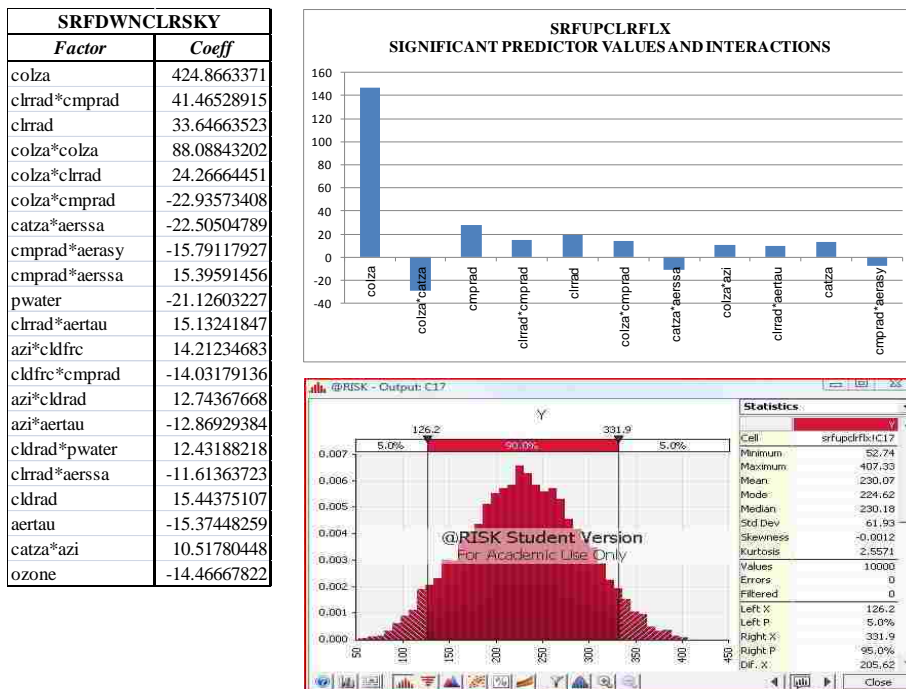


Figure 22. Amazon Region Uncertainty Analysis – SRFUPCLRFLX

### Amazon Region Uncertainty Analysis – OAO

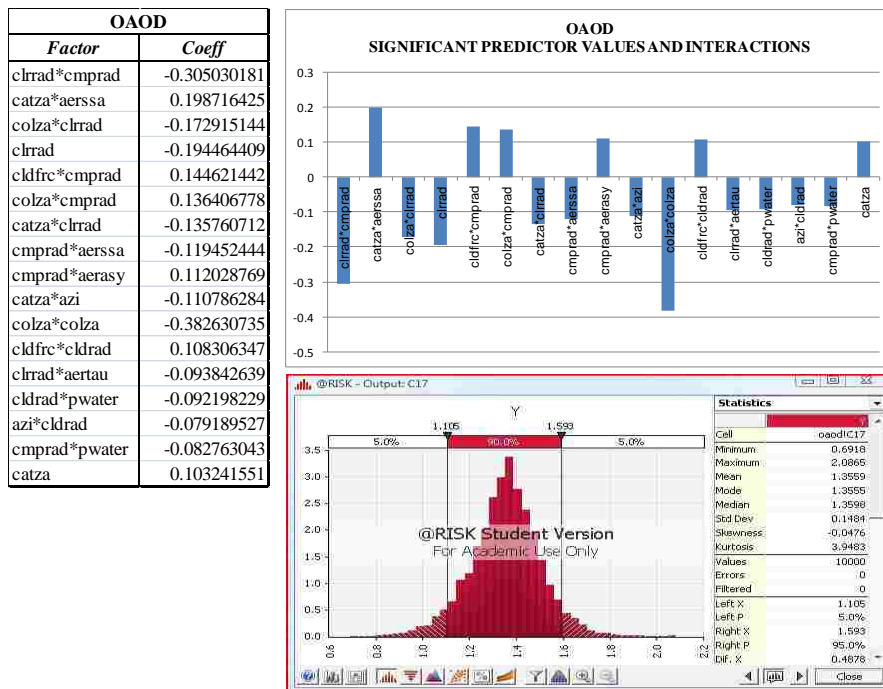


Figure 23. Amazon Region Uncertainty Analysis – OAO

### Amazon Region Uncertainty Analysis - OCOD

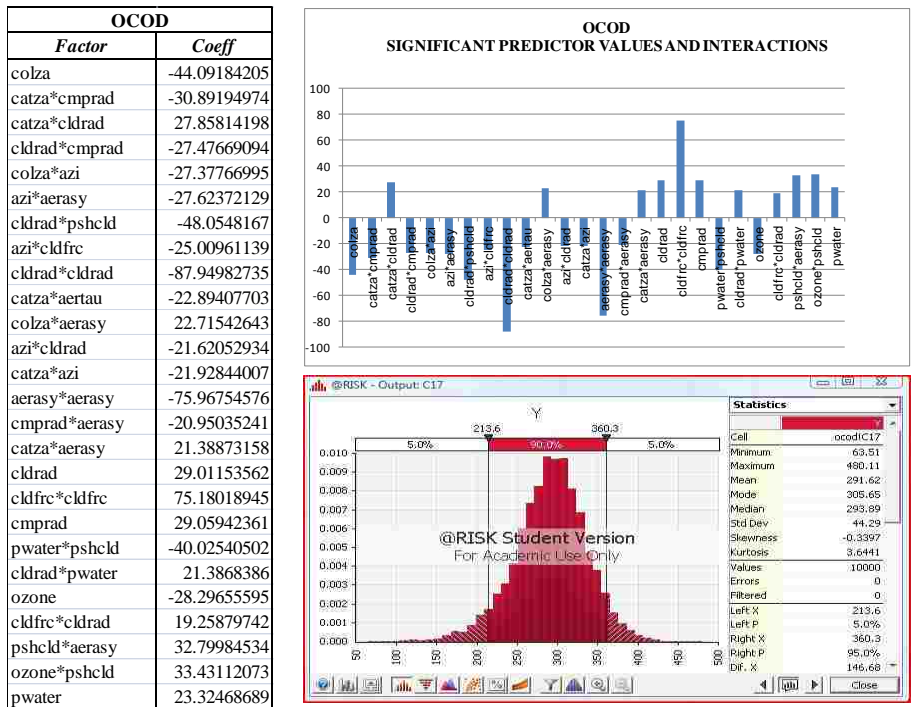


Figure 24. Amazon Region Uncertainty Analysis - OCOD

### Amazon Region Uncertainty Analysis - SRFDWNPRS

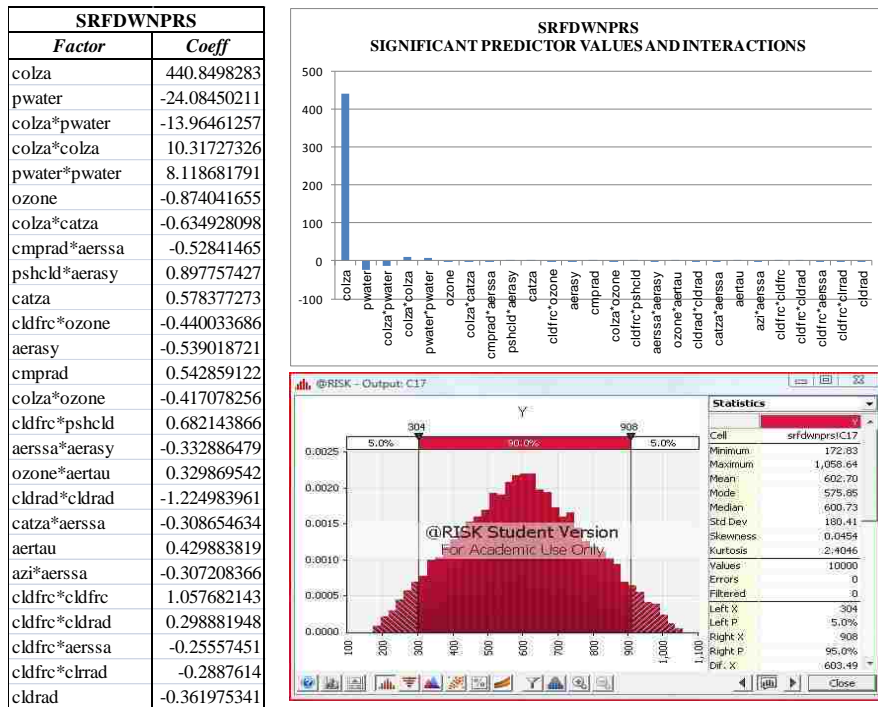


Figure 25. Amazon Region Uncertainty Analysis - SRFDWNPRS

## Amazon Region Uncertainty Analysis - TOAUPPRS

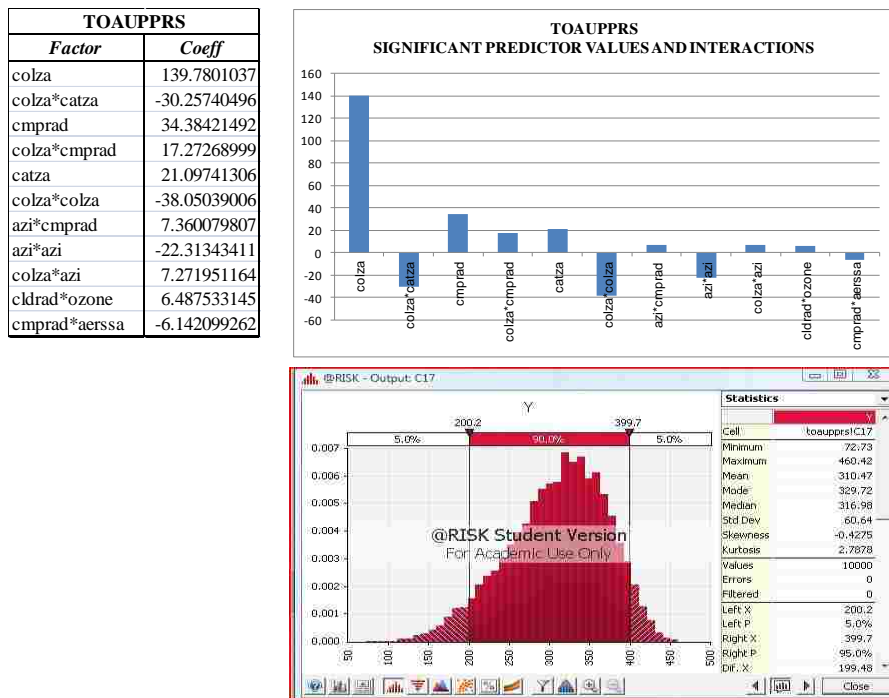


Figure 26. Amazon Region Uncertainty Analysis - TOAUPPRS



### Indian Ocean Uncertainty Analysis – TOAUP

| TOAP          |              |
|---------------|--------------|
| Factor        | coeff        |
| colza         | 136.8010444  |
| cldfrc*cldrad | 104.0002547  |
| cldrad        | 116.5962273  |
| colza*cldrad  | 86.67079813  |
| cldfrc        | 110.5761926  |
| colza*cldfrc  | 71.10861874  |
| azi*azi       | -72.74400195 |
| pwater*pshcld | -42.82584785 |
| azi*pwater    | -23.49847519 |
| clrrad        | 26.41172474  |
| pshcld*aerasy | -34.65641767 |
| clrrad*clrrad | 58.28573306  |
| catza*pshcld  | 34.21874438  |
| aerasy        | 22.30614197  |
| azi*pshcld    | -30.80916273 |
| azi*cldfrc    | 15.55271443  |
| pwater        | 20.58112627  |
| catza*cmprad  | -15.87217278 |
| catza*aertau  | -14.1143738  |

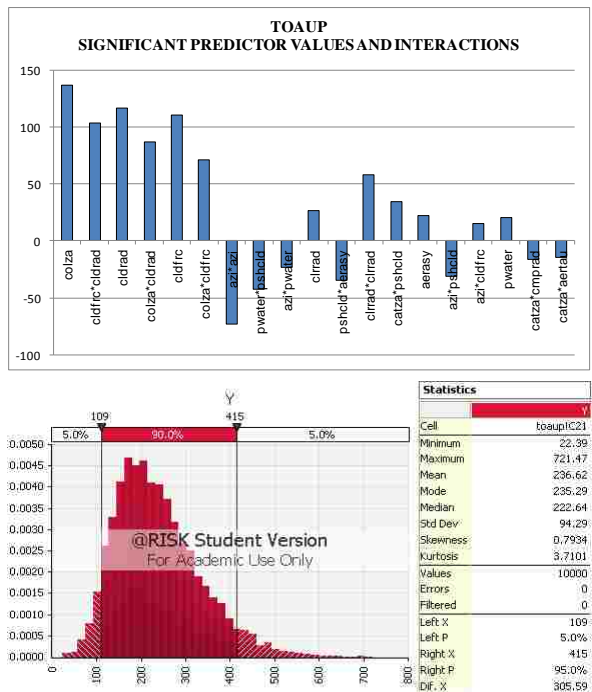


Figure 27. Indian Ocean Uncertainty Analysis – TOAUP

Indian Ocean Uncertainty Analysis – SRFDWNFLX

| SRFDWNFLX     |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza         | 302.285188   |
| cldfrc*cldrad | -101.6666469 |
| cldrad        | -119.3190072 |
| colza*cldrad  | -93.14457016 |
| cldfrc        | -116.6031614 |
| colza*cldfrc  | -80.36859665 |
| aerasy        | -36.88045573 |
| azi*cldfrc    | -28.28445273 |
| clrad*cldrad  | -88.02318041 |
| colza*colza   | 95.16322783  |
| colza*ozone   | -28.43461819 |
| clrad*pschld  | 50.92365042  |
| cmprad*pschld | 50.53093944  |
| pschld*aerasy | 44.12332711  |
| colza*azi     | -24.20124505 |
| cmprad        | -31.55044717 |
| clrad         | -30.86844942 |
| azi*pwater    | 24.56767643  |
| ozone*aerasy  | -21.24195338 |
| colza*pwater  | -20.35744395 |
| catza*aerasy  | -19.20616032 |
| cmprad*cmprad | -64.61146675 |
| cldfrc*pschld | -34.48805844 |
| colza*pschld  | -34.61188226 |
| cldrad*aerasy | 17.13321456  |
| azi*azi       | 56.31494111  |
| pschld*aertau | -34.96479976 |
| cldfrc*cldfrc | 62.2950832   |
| cldfrc*aerssa | 16.07377331  |
| catza*cldrad  | 16.9223221   |
| catza*pwater  | 16.41142705  |

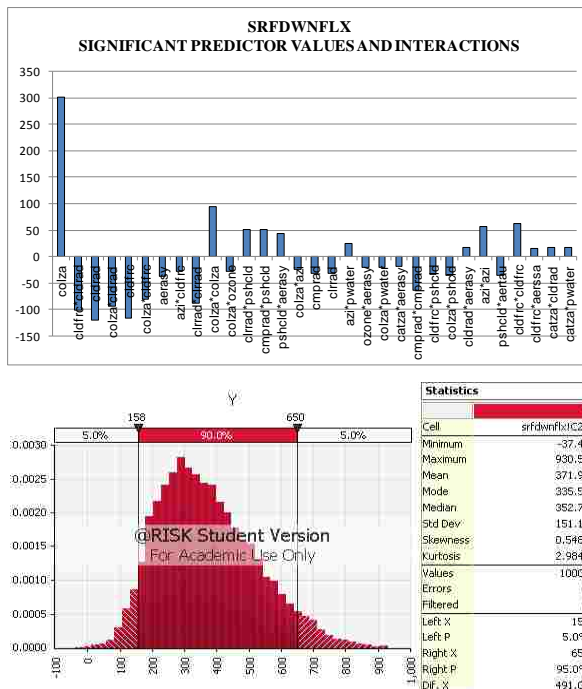


Figure 28. Indian Ocean Uncertainty Analysis – SRFDWNFLX

Indian Ocean Uncertainty Analysis – SRFDWNDIFF

| SRFDWNDIFF    |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza         | 197.6527599  |
| cldrad        | -79.90631736 |
| colza*cldfr   | -47.27573169 |
| cldfr*cldrad  | -48.89206639 |
| colza*pschld  | -64.15122246 |
| colza*cldrad  | -35.62309658 |
| cldfr*cmprad  | -30.38869746 |
| azi           | -40.90316228 |
| cldfr*pschld  | -52.76933685 |
| cldfr         | -38.48473557 |
| azi*cldrad    | 25.8346537   |
| cldrad*pschld | 50.79175872  |
| pschld*aerasy | 39.25167982  |
| azi*pschld    | 38.78534124  |
| cmprad*cmprad | -62.08583001 |
| aertau*aerssa | 18.50481267  |
| catza*aerasy  | -17.25072563 |
| colza*colza   | 61.44030884  |
| cldfr*aertau  | -17.26400668 |
| cldrad*cldrad | -62.03472154 |
| catza*cmprad  | 17.35405751  |
| clrrad*pwater | 17.13386905  |
| catza*pwater  | 16.8521054   |
| catza*aerssa  | -16.34788011 |
| ozone*aerssa  | -15.64990799 |
| azi*ozone     | 15.82204443  |
| catza*cldfr   | 15.10052392  |
| cldfr*aerasy  | -15.38867285 |
| pwater*aerasy | 14.96309904  |
| cldrad*aerasy | 14.05345666  |

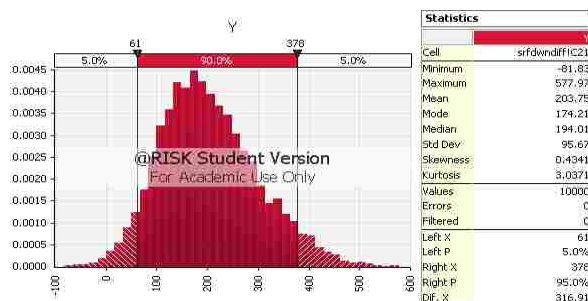
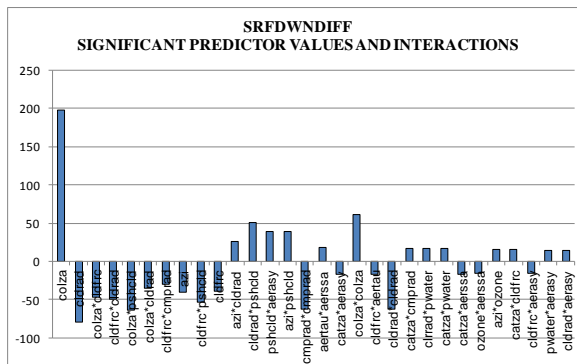


Figure 29. Indian Ocean Uncertainty Analysis – SRFDWNDIFF

### Indian Ocean Uncertainty Analysis - SRFUPFLX

| SRFUPFLX      |              |
|---------------|--------------|
| Factor        | Coeff        |
| cldfrc        | -35.48213199 |
| colza         | 27.49480954  |
| cldfrc*cldrad | -17.58364513 |
| colza*cldrad  | -17.77339543 |
| colza*crrad   | -10.71945244 |
| cldrad        | -12.77095662 |
| cldfrc*crrad  | -10.00634308 |
| catza*crrad   | 9.632513299  |
| pwater*ozone  | 8.856021539  |
| cldrad*cmprad | -8.291538634 |
| pwater*aertau | 8.73064827   |
| colza*catza   | -7.999176819 |
| catza*cldfrc  | -7.670966348 |
| cmprad*cmprad | -24.00095078 |
| aerasy        | -8.842818578 |
| colza*ozone   | -7.357600133 |
| cldfrc*cmprad | 6.886247618  |
| pwater*aerasy | -6.650113462 |
| catza*azi     | 6.495442323  |
| colza*cmprad  | 6.693554502  |
| crrad*aertau  | 6.308792779  |
| pwater*pschld | -11.93404116 |
| pschld*aertau | -12.26834616 |
| ozone*ozone   | -20.80386002 |
| colza*colza   | 22.13151739  |
| cmprad*pschld | 11.95571781  |
| crrad         | 8.110109011  |
| colza*aerssa  | 5.880480979  |
| cmprad*pwater | -5.67009006  |
| ozone*pschld  | -10.38368268 |

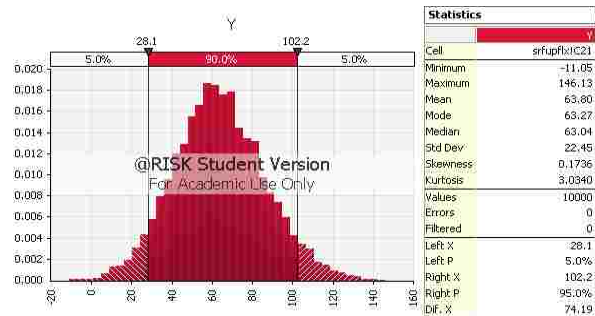
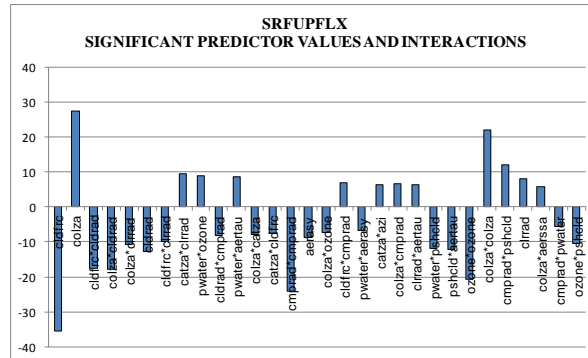


Figure 30. Indian Ocean Uncertainty Analysis - SRFUPFLX

### Indian Ocean Uncertainty Analysis - SRFDWNDIFPAR

| SRFDWNDIFPAR  |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza         | 99.68472914  |
| cldrad        | -38.20346895 |
| cldfrc*cldrad | -23.76095529 |
| colza*cldfrc  | -21.13627166 |
| colza*pschld  | -31.3788446  |
| colza*cldrad  | -16.60581513 |
| cldfrc*pschld | -26.32468271 |
| cldfrc*cmprad | -14.31476828 |
| azi           | -18.99697744 |
| cldfrc        | -18.3386321  |
| cldrad*pschld | 23.72107986  |
| azi*cldrad    | 11.89072436  |
| pschld*aerasy | 18.6169568   |
| azi*pschld    | 18.07641417  |
| colza*colza   | 31.07159078  |
| aertau*aerssa | 8.83489887   |
| cmprad*cmprad | -29.0438892  |
| catza*aerasy  | -8.231086639 |
| cldrad*cldrad | -31.57466677 |
| catza*pwater  | 8.499458038  |
| cldfrc*aertau | -8.373750572 |
| catza*aerssa  | -8.083806179 |
| catza*cmprad  | 8.382038344  |
| clrad*pwater  | 7.978029545  |
| azi*ozone     | 7.796013585  |
| ozone*aerssa  | -7.390819699 |
| cldrad*aerasy | 6.73135477   |
| catza*cldfrc  | 7.028984183  |

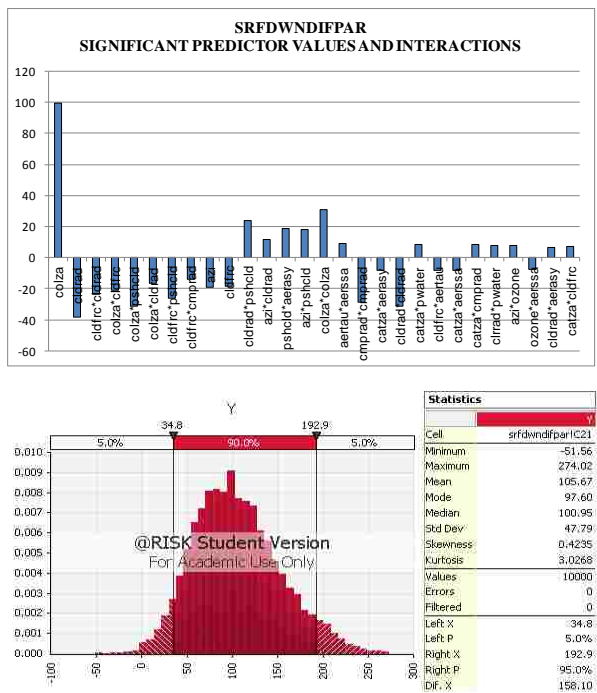


Figure 31. Indian Ocean Uncertainty Analysis - SRFDWNDIFPAR

### Indian Ocean Uncertainty Analysis – SRFDWNP

| SRFDWNP         |              |
|-----------------|--------------|
| Factor          | Coeff        |
| colza           | 151.0524943  |
| cldfric*cldrad  | -48.98385433 |
| cldrad          | -57.37255095 |
| colza*cldrad    | -43.97619625 |
| cldfric         | -54.70286742 |
| colza*cldfric   | -37.63316418 |
| aerasy          | -17.38388405 |
| azi*cldfric     | -13.42976524 |
| clrrad*clrrad   | -42.94853811 |
| clrrad*pschld   | 24.72091504  |
| colza*ozone     | -13.6519993  |
| cmprad*pschld   | 24.67279354  |
| colza*colza     | 44.41336576  |
| pschld*aerasy   | 20.93844783  |
| cmprad          | -15.27020893 |
| colza*azi       | -11.41071687 |
| clrrad          | -14.74576505 |
| ozone*aerasy    | -10.1301848  |
| azi*pwater      | 11.35797788  |
| cldfric*pschld  | -17.66946753 |
| catza*aerasy    | -9.28736525  |
| colza*pschld    | -17.72316881 |
| cldrad*aerasy   | 8.47904859   |
| cmprad*cmprad   | -30.35673906 |
| pschld*aertau   | -17.23913739 |
| cldfric*cldfric | 30.15757579  |
| azi*azi         | 26.1995602   |
| catza*cldrad    | 8.116255888  |
| cldfric*aersa   | 7.448936096  |
| catza*pwater    | 8.2464186    |
| cmprad*aerasy   | 7.390423291  |
| ozone*aertau    | -7.498459322 |
| catza*cmprad    | 7.937794854  |

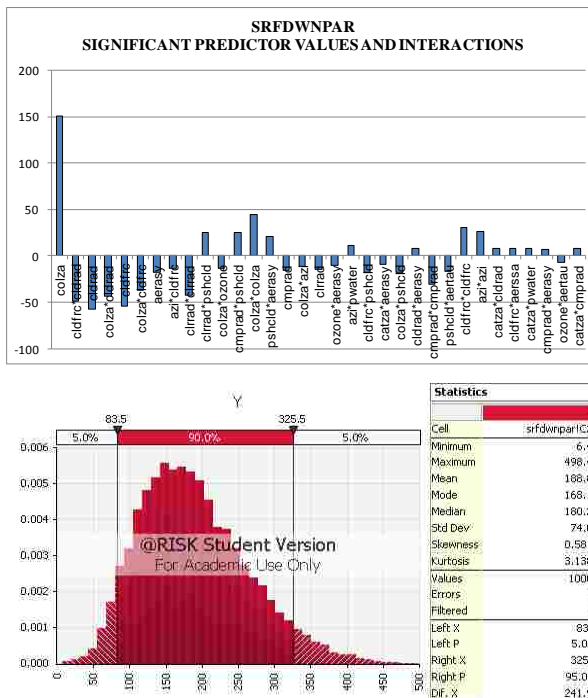


Figure 32. Indian Ocean Uncertainty Analysis – SRFDWNP

Indian Ocean Uncertainty Analysis – TOAUPCLRSKY

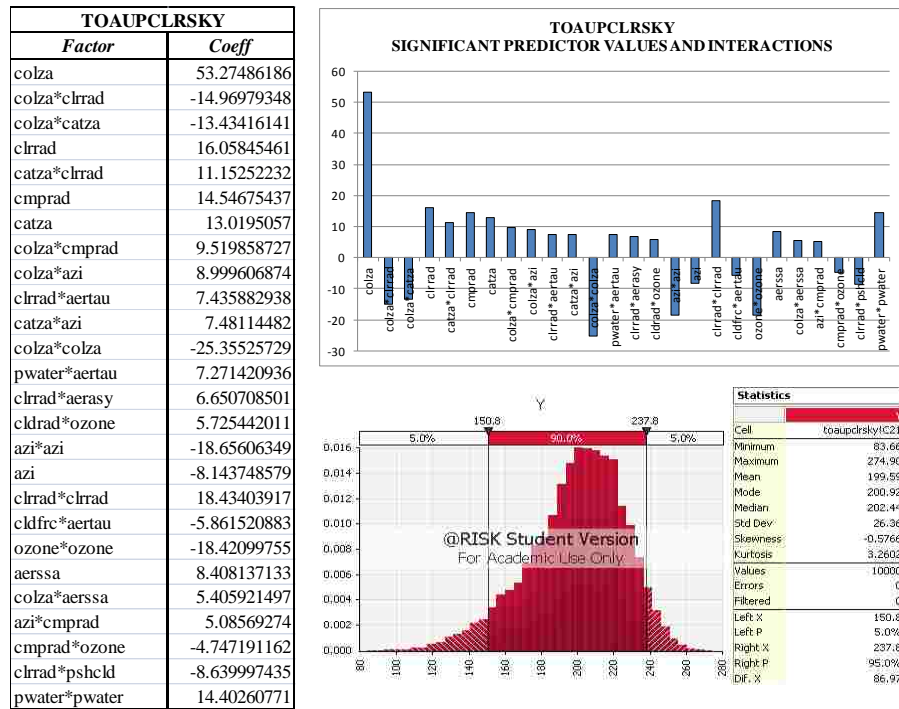


Figure 33. Indian Ocean Uncertainty Analysis – TOAUPCLRSKY

Indian Ocean Uncertainty Analysis – SRFDWNCLRSKY

| SRFDWNCLRSKY  |            |
|---------------|------------|
| Factor        | Coeff      |
| colza         | 381.709889 |
| cmprad        | -26.378844 |
| colza*cmprad  | -16.753786 |
| colza*colza   | 47.2747457 |
| cmprad*aerssa | 10.1851715 |
| pwater        | -12.827438 |
| colza*aerasy  | -9.6088951 |
| colza*azi     | -9.6416104 |
| colza*clrad   | -8.0418498 |
| azi           | 10.4130804 |
| clrad*aertau  | -7.1093995 |
| cldfrc*cldfrc | 23.7728968 |
| azi*pshcld    | -12.852417 |
| clrad         | 8.79498871 |
| azi*cmprad    | -6.4398671 |
| aerssa*aerssa | -21.562312 |
| azi*cldrad    | -6.0036885 |
| clrad*aerasy  | -6.2900644 |
| colza*pwater  | -5.9839559 |
| aertau*aerssa | -5.832602  |

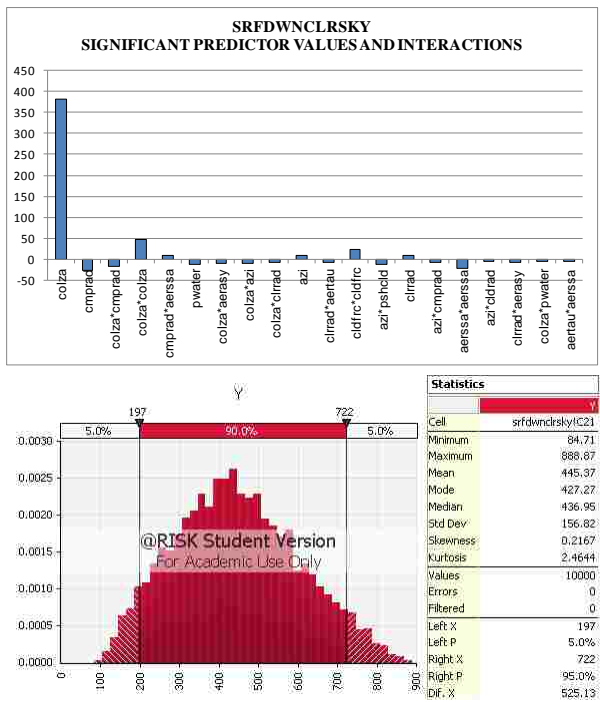


Figure 34. Indian Ocean Uncertainty Analysis – SRFDWNCLRSKY



Indian Ocean Uncertainty Analysis – SRFUPCLRFLX

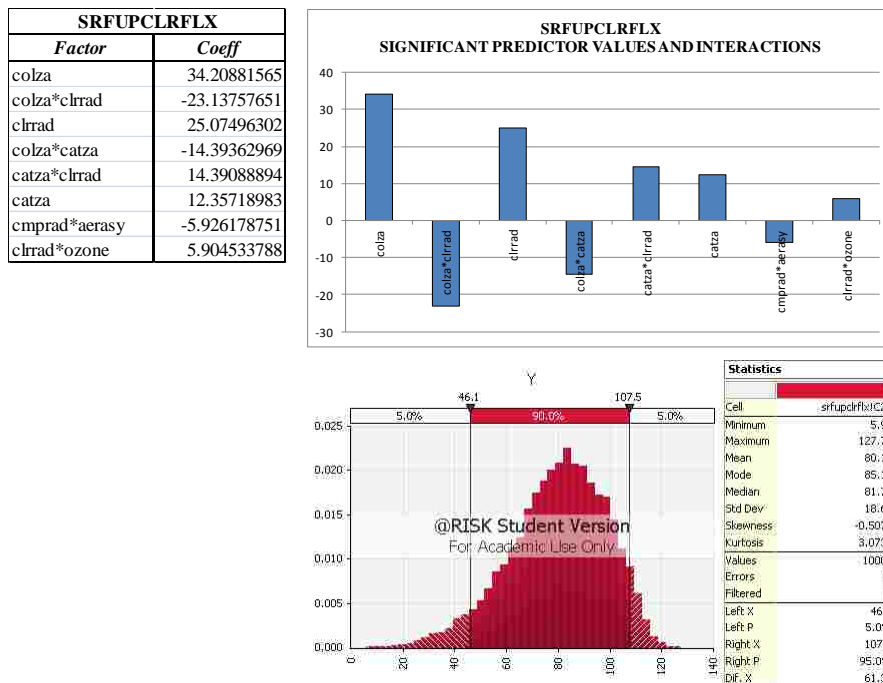


Figure 35. Indian Ocean Uncertainty Analysis – SRFUPCLRFLX

### Indian Ocean Uncertainty Analysis – OAO

| OAO           |            |
|---------------|------------|
| Factor        | Coeff      |
| colza         | 0.3383956  |
| cmprad        | 0.17790742 |
| colza*cmprad  | 0.09984941 |
| colza*aerasy  | 0.09585278 |
| colza*azi     | 0.08194952 |
| colza*clrrad  | 0.07635142 |
| colza*colza   | -0.259449  |
| azi           | -0.091098  |
| cmprad*aerssa | -0.0611575 |
| clrrad        | -0.0769373 |
| azi*cmprad    | 0.05438405 |
| clrrad*aertau | 0.05034663 |
| aertau*aerssa | 0.0470889  |
| aerssa*aerssa | 0.15632282 |
| azi*psfld     | 0.08758804 |
| cldfrc*cldfrc | -0.1606022 |
| aerasy        | 0.05734049 |
| azi*cldrad    | 0.04327788 |
| cmprad*aerasy | 0.03789615 |

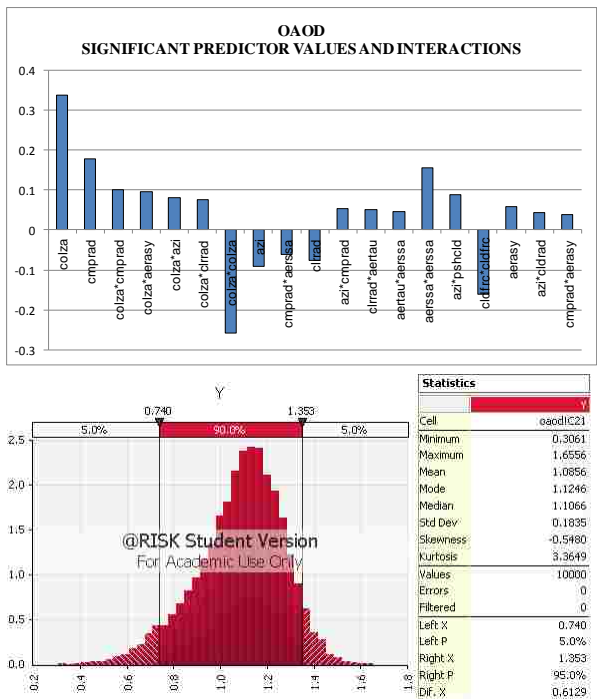


Figure 36. Indian Ocean Uncertainty Analysis – OAO

## Indian Ocean Uncertainty Analysis – OCOD

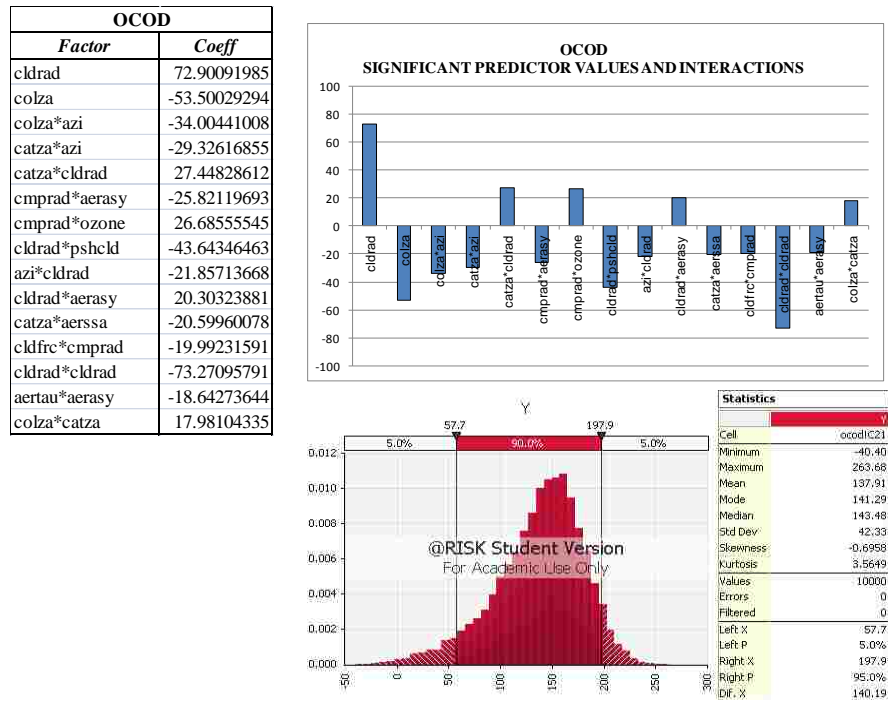


Figure 37. Indian Ocean Uncertainty Analysis – OCOD

### Indian Ocean Uncertainty Analysis - SRFDWNPRS

| SRFDWNPRS     |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza         | 438.8815077  |
| pwater        | -14.16375035 |
| colza*pwater  | -8.284500806 |
| pwater*pwater | 8.976069467  |
| colza*colza   | 6.108648484  |
| cmprad        | 1.417858848  |
| cmprad*aerssa | -0.980900575 |
| colza*cmprad  | 0.77663444   |
| catza         | 0.985820457  |
| pshcl* aerasy | 1.213982505  |
| cldfrc*ozone  | -0.647826788 |
| colza*azi     | 0.644991958  |
| clrrad*clrrad | 1.983058583  |
| cldrad*ozone  | 0.568015181  |
| catza*aerssa  | -0.58337155  |
| ozone         | -0.801743604 |
| aerasy        | -0.732407095 |
| clrrad*aertau | 0.553713411  |
| ozone*aerssa  | -0.540600705 |
| azi*cmprad    | 0.504973275  |
| cldfrc*pshcl  | 0.927331864  |
| azi           | -0.699672948 |
| ozone*ozone   | -1.661182693 |
| pwater*aerssa | 0.469325203  |
| ozone*aertau  | 0.438008361  |
| azi*cldrad    | 0.429066579  |
| catza*ozone   | 0.412627903  |
| colza*catza   | -0.42972842  |
| catza*azi     | 0.40766183   |

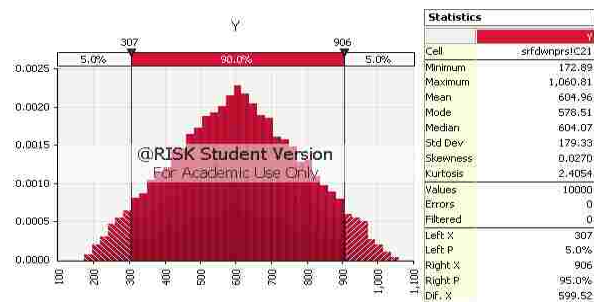
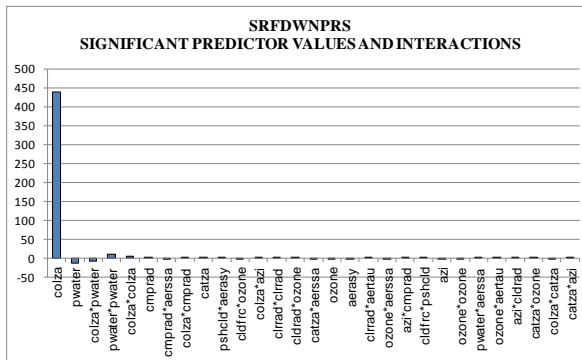


Figure 38. Indian Ocean Uncertainty Analysis - SRFDWNPRS

### Indian Ocean Uncertainty Analysis – TOAUPPRS

| TOAUPPRS      |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza         | 57.8239753   |
| colza*colza   | -156.7713221 |
| cmprad        | 39.44176545  |
| colza*cmprad  | 22.69109428  |
| colza*azi     | 21.27966364  |
| clrrad*aertau | 19.03390455  |
| catza         | 24.08496039  |
| cmprad*aerssa | -16.95676391 |
| azi*cmprad    | 17.61450268  |
| clldrad*ozone | 14.83392761  |
| azi           | -21.07423632 |
| colza*catza   | -14.08941446 |
| ozone*ozone   | -42.73224904 |
| clrrad*clrrad | 39.98296437  |
| pwater*pwater | 40.50629825  |
| cldfr*cldfr   | -42.87752274 |
| colza*aerssa  | 12.31044165  |
| ozone*aerssa  | -11.68380681 |
| catza*azi     | 11.50094512  |
| aerssa*aerssa | 39.57502171  |
| catza*aerssa  | -10.35429893 |
| azi*aerssa    | 10.00738144  |

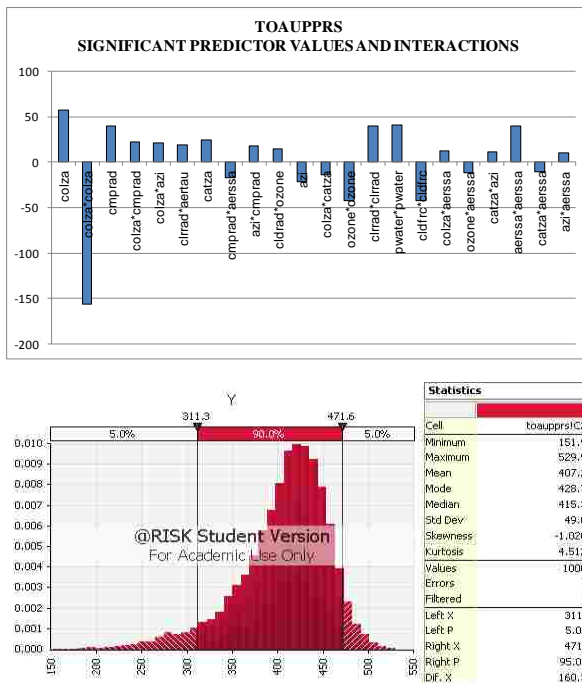


Figure 39. Indian Ocean Uncertainty Analysis – TOAUPPRS

Mt Everest Region Uncertainty Analysis – TOAUP

| TOAP          |              |
|---------------|--------------|
| Factor        | coeff        |
| cldfrc*cldrad | 115.2212428  |
| cldfrc        | 140.2430722  |
| colza*cldrad  | 107.7495571  |
| cldrad        | 130.5245471  |
| colza*cldfrc  | 87.93354856  |
| colza         | 98.42277257  |
| azi*azi       | -93.9618548  |
| azi*pwater    | -29.5821811  |
| aerasy        | 33.52102692  |
| pshcld*aerasy | -48.76786558 |
| azi*cldfrc    | 20.8863524   |
| cmprad*cmprad | 70.68902025  |
| cmprad        | 27.62602964  |
| colza*ozone   | 21.32667562  |
| clrad*clrad   | 62.49226464  |
| ozone*aerssa  | 19.12020808  |
| catza*aertau  | -18.22343993 |
| clrad         | 23.7189156   |
| catza*cmprad  | -18.45030038 |
| catza*pshcld  | 31.41133532  |
| pwater*pshcld | -31.09852347 |
| azi*pshcld    | -30.60353962 |

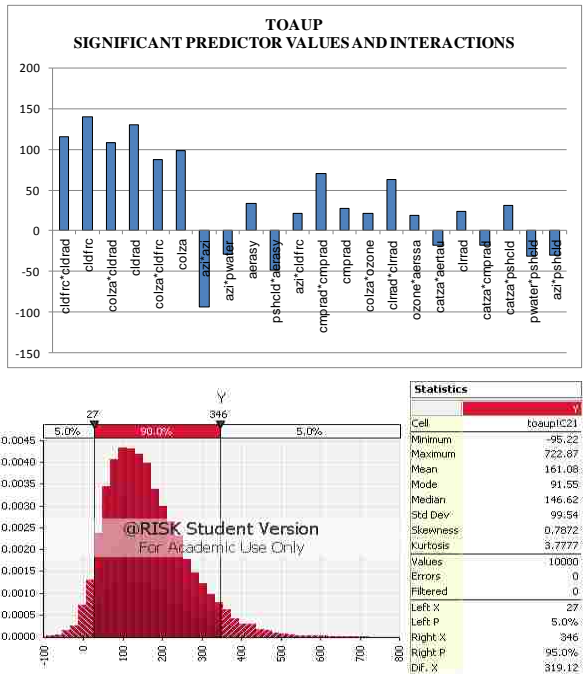


Figure 40. Mt Everest Region Uncertainty Analysis – TOAUP

Mt Everest Region Uncertainty Analysis - SRFDWNFLX

| SRFDWNFLX     |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza         | 344.8860811  |
| colza*cldfrc  | -151.5897099 |
| cldfrc        | -173.0218529 |
| cldfrc*cldrad | -83.05843004 |
| cldrad        | -85.95620817 |
| cldfrc*cmprad | -50.83706681 |
| colza*pschld  | -89.89451301 |
| colza*cldrad  | -49.74735537 |
| cmprad        | -60.76467344 |
| aertau*aerasy | -41.47535795 |
| colza*cmprad  | -43.14650501 |
| cldrad*cmprad | 39.24104553  |
| clrrad*clrrad | -120.8463259 |
| pwater*aertau | -39.48141655 |
| catza*cmprad  | 39.61599595  |
| cmprad*ozone  | 37.67947117  |
| clrrad*aerssa | -36.53837093 |
| azi*pschld    | 68.6776565   |
| pwater*pschld | 66.74464483  |
| aerasy        | -43.70927804 |
| ozone*pschld  | 63.33205619  |
| cmprad*aertau | 33.42633475  |
| cldfrc*pschld | -59.32248102 |
| catza*aerssa  | -31.4560949  |
| cldfrc*pwater | 27.72894644  |
| ozone         | -36.22776056 |
| catza*cldrad  | 24.15171079  |

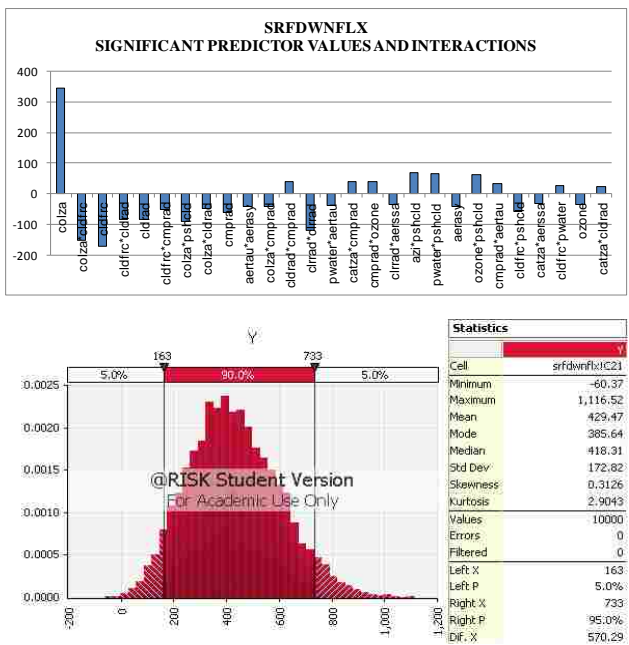


Figure 41. Mt Everest Region Uncertainty Analysis - SRFDWNFLX

Mt Everest Region Uncertainty Analysis – SRFDWNDIFF

| SRFDWNDIFF    |            |
|---------------|------------|
| Factor        | Coeff      |
| colza         | 48.6263565 |
| colza*cldfrc  | 29.1605612 |
| cldrad        | -28.917509 |
| cldfrc        | 27.2496631 |
| cmprad*ozone  | 19.5594086 |
| aertau        | 26.9456335 |
| cldrad*cldrad | -65.236849 |
| cldrad*aertau | -16.552705 |
| cldrad*pschld | 31.565315  |
| pwater*aertau | -17.229072 |
| azi*ozone     | 16.7157453 |
| pschld*aertau | -31.661779 |
| cldfrc*pschld | -28.144761 |
| colza*pschld  | -26.270815 |
| cldfrc*cldrad | -13.717458 |
| cldfrc*ozone  | -13.293412 |
| cmprad*cmprad | 44.0281975 |
| aertau*aerasy | -12.28914  |
| azi*aerasy    | 12.5356271 |
| catza*aertau  | 11.9471347 |
| aerasy*aerasy | 40.1197313 |
| cldrad*ozone  | 10.9388214 |
| azi*cmprad    | 11.4519199 |

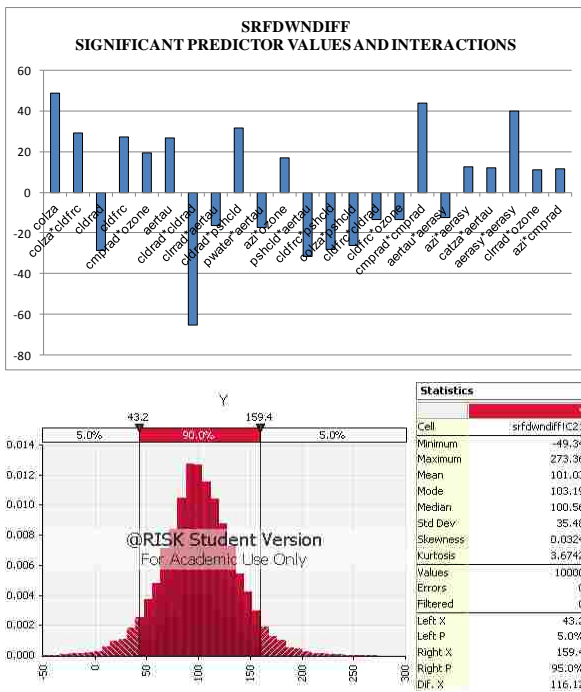


Figure 42. Mt Everest Region Uncertainty Analysis – SRFDWNDIFF



Mt Everest Uncertainty Analysis - SRFUPFLX

| SRFUPFLX      |             |
|---------------|-------------|
| Factor        | Coeff       |
| cldfrc        | -21.6070721 |
| cldfrc*cmprad | -15.5029048 |
| emprad        | 17.69790063 |
| cldfrc*cldrad | -8.46447637 |
| azi*azi       | -20.9371003 |
| azi*cldfrc    | 6.019967374 |
| colza*catza   | -5.30577716 |
| cldrad        | -6.35604331 |
| colza*pshcld  | -8.8530402  |
| colza*azi     | 4.604209765 |
| colza*cldrad  | 4.572046291 |
| emprad*ozone  | 4.292603585 |
| aertau*aerasy | -4.0327533  |
| pwater*ozone  | 3.882777449 |
| cldfrc*aerasy | -3.7087818  |
| pwater        | 4.657257864 |
| aertau*aerssa | 3.391866386 |

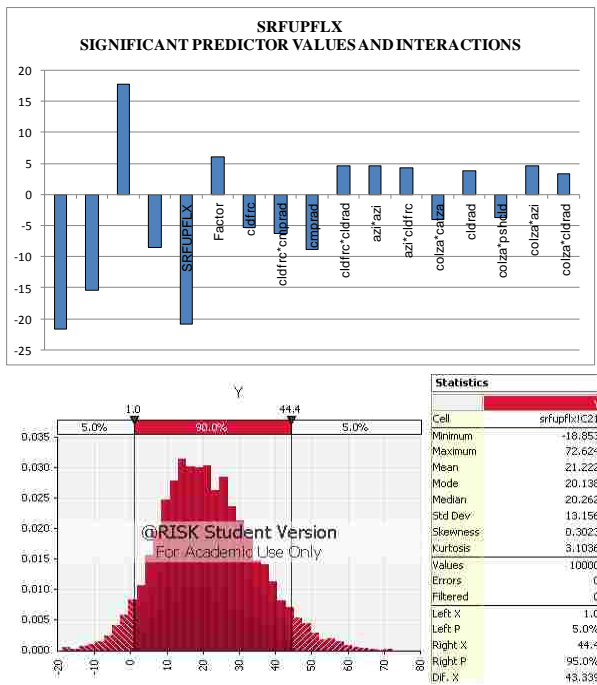


Figure 43. Mt Everest Uncertainty Analysis - SRFUPFLX

### Mt Everest Uncertainty Analysis - SRFDWNDIFPAR

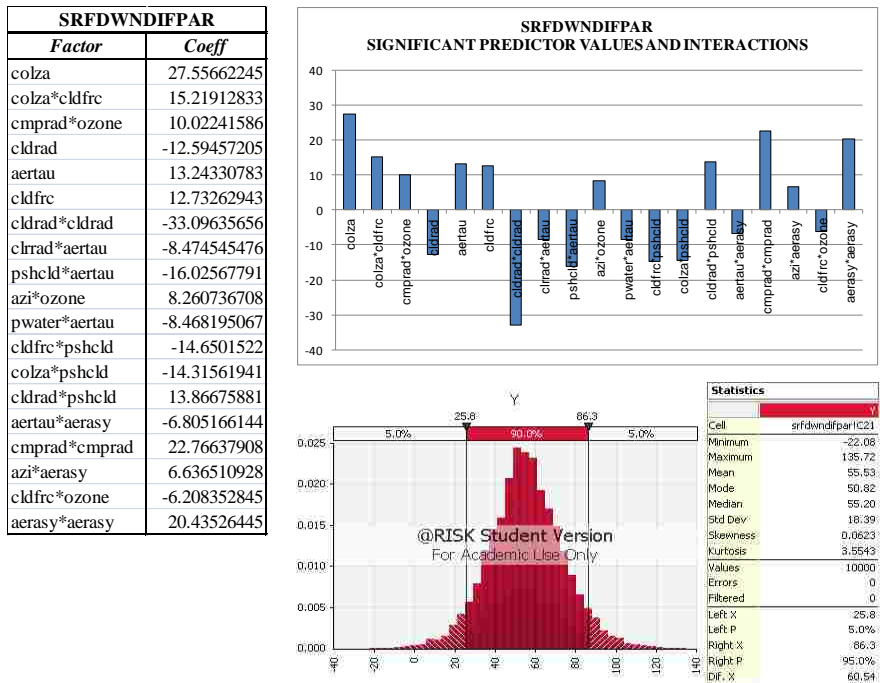


Figure 44. Mt Everest Uncertainty Analysis - SRFDWNDIFPAR

Mt Everest Uncertainty Analysis - SRFDWNP

| SRFDWNP       |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza         | 168.2567983  |
| colza*cldfrc  | -70.6303174  |
| cldfrc        | -80.28365813 |
| cldfrc*cldrad | -38.84459673 |
| cldrad        | -40.2989868  |
| cldfrc*cmprad | -24.46953308 |
| colza*pschld  | -42.90398893 |
| cmprad        | -28.37812168 |
| aertau*aerasy | -20.06630501 |
| colza*cldrad  | -21.91641512 |
| colza*cmprad  | -20.6462971  |
| cldrad*cmprad | 18.60545347  |
| pwater*aertau | -19.36941791 |
| catza*cmprad  | 19.36995387  |
| cmprad*ozone  | 18.18268416  |
| clrrad*clrrad | -56.68302705 |
| clrrad*aerssa | -16.55920075 |
| azi*pschld    | 31.62537898  |
| catza*aerssa  | -16.15327367 |
| ozone*pschld  | 30.11253716  |
| pwater*pschld | 29.72763399  |
| aerasy        | -19.81274577 |
| cldfrc*pschld | -28.69268379 |
| cmprad*aertau | 15.75480463  |
| ozone         | -17.24227806 |

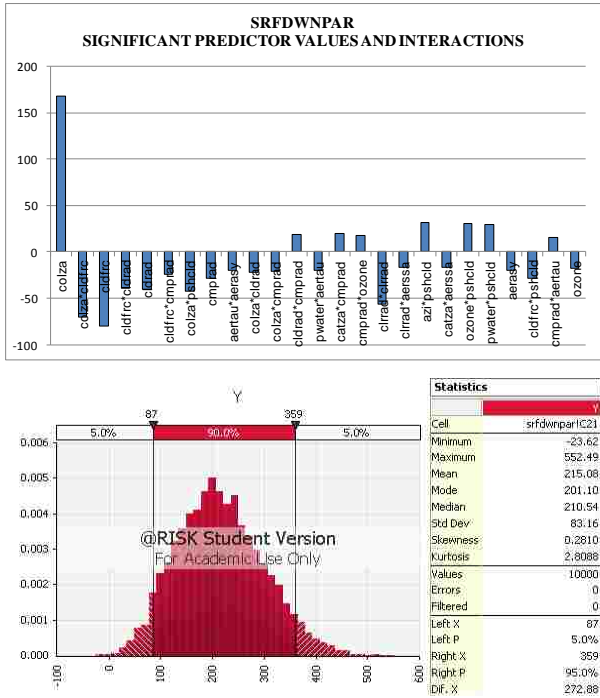


Figure 45. Mt Everest Uncertainty Analysis - SRFDWNP

Mt Everest Uncertainty Analysis – TOAUPCLRSKY

| TOAUPCLRSKY   |              |
|---------------|--------------|
| Factor        | Coeff        |
| cmprad        | 28.08594375  |
| colza*catza   | -12.48455411 |
| catza         | 8.542688042  |
| azi*azi       | -18.19181946 |
| colza         | -7.359728147 |
| colza*azi     | 4.181818923  |
| clrrad*cmprad | -3.579170005 |
| azi*cldfrc    | 3.237370537  |
| cldrad*aerasy | -2.991458407 |
| colza*aertau  | -2.834459597 |
| azi           | -3.717278773 |
| cldfrc*aerasy | -2.31513047  |
| catza*azi     | 2.194297311  |
| aerasy        | 2.790570979  |
| pwater*pwater | -7.23034489  |
| cldfrc*aerssa | -1.836246912 |
| colza*aerasy  | -1.967619323 |
| pwater*pschld | -3.426030704 |
| colza*colza   | 6.443851787  |
| colza*clrrad  | 1.846923003  |
| catza*aerssa  | 1.615533467  |
| colza*ozone   | 1.7015175    |

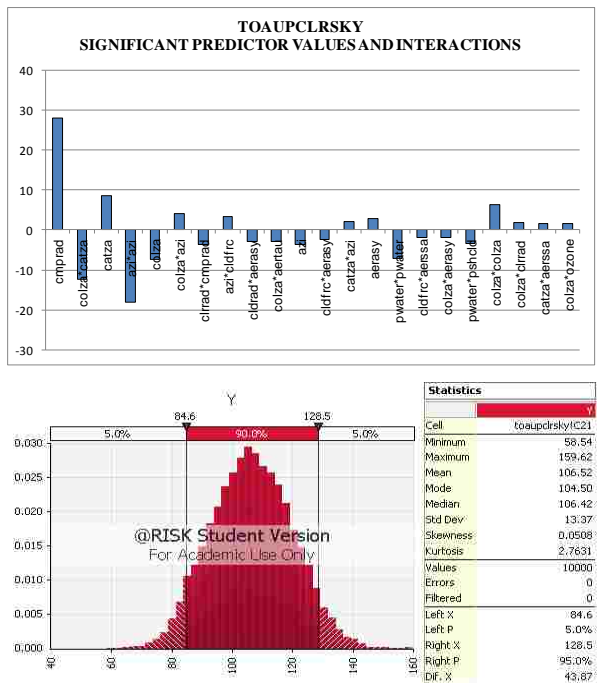


Figure 46. Mt Everest Uncertainty Analysis – TOAUPCLRSKY

Mt Everest Uncertainty Analysis – SRFDWNCLRSKY

| SRFDWNCLRSKY  |             |
|---------------|-------------|
| Factor        | Coeff       |
| colza         | 460.366976  |
| pwater        | -23.3020002 |
| colza*pwater  | -14.9595004 |
| colza*colza   | 8.62582081  |
| colza*cmprad  | 2.29443524  |
| ozone         | -3.10150979 |
| cldfrc*cldfrc | 6.19800771  |
| clrrad        | -2.35605445 |
| cldrad*aerssa | -1.60355184 |
| azi*aertau    | -1.50291742 |
| colza*aerasy  | -1.39950016 |
| cldrad*cmprad | -1.35897829 |
| pwater*aertau | 1.33302459  |
| catza*azi     | 1.17236344  |
| colza*aertau  | 1.1166829   |
| pwater*aerasy | -1.14421463 |
| ozone*aertau  | -1.11103815 |
| cldrad*ozone  | 0.9820843   |
| cmprad        | 1.43009056  |
| colza*ozone   | -1.11970294 |
| azi           | -1.45515446 |
| pwater*pschld | -1.95444577 |
| aerasy        | 1.29114401  |

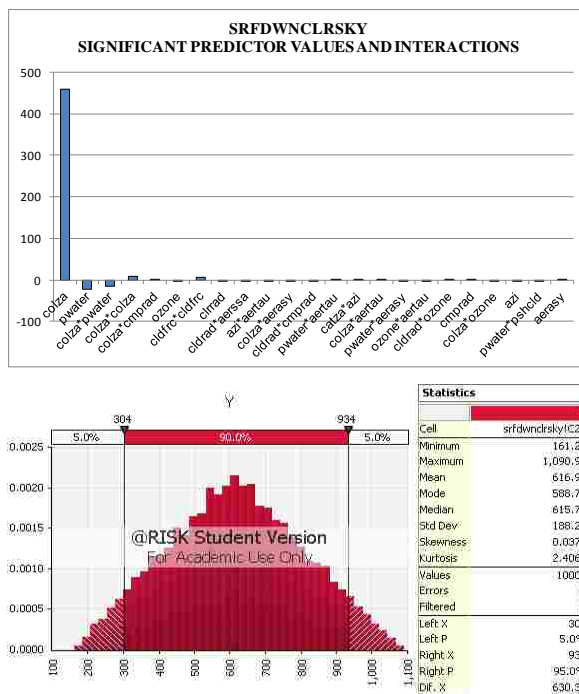


Figure 47. Mt Everest Uncertainty Analysis – SRFDWNCLRSKY

Mt Everest Uncertainty Analysis - SRFUPCLRFLX

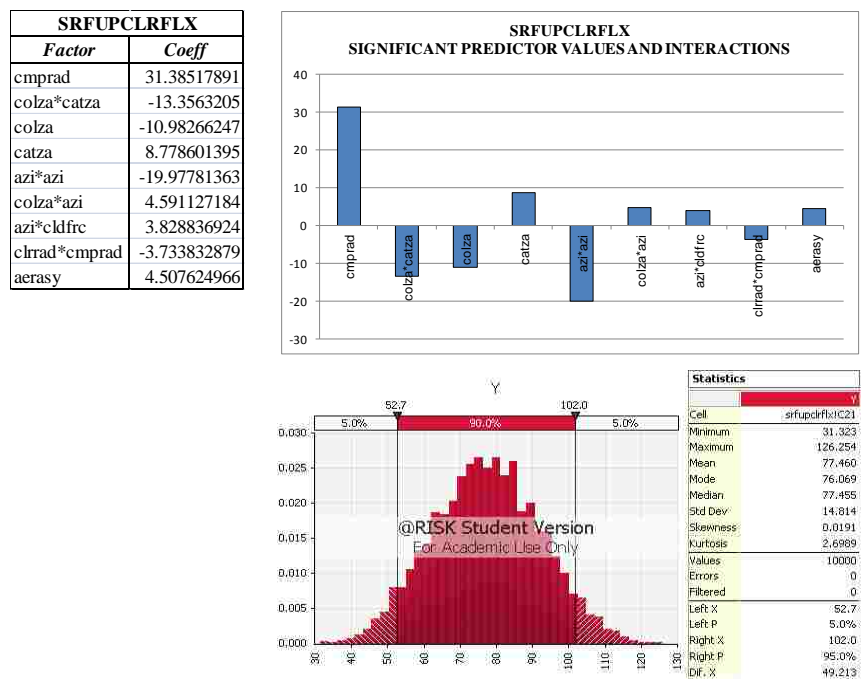


Figure 48. Mt Everest Uncertainty Analysis - SRFUPCLRFLX

Mt Everest Region Uncertainty Analysis – OAOB

| OAOB          |            |
|---------------|------------|
| Factor        | Coeff      |
| colza         | -0.0223361 |
| colza*cmprad  | -0.0169499 |
| clrad         | 0.01719964 |
| cldrad*aerssa | 0.01103449 |
| ozone*aertau  | 0.00951393 |
| cldfrc*cldfrc | -0.0343328 |
| pwater*aerasy | 0.00953877 |
| pwater*pwater | 0.0308236  |
| azi*aertau    | 0.00939853 |
| colza*aerasy  | 0.00854435 |
| pwater        | -0.0112192 |
| colza*aertau  | -0.0080458 |
| aerasy        | -0.0105223 |
| cldrad*cmprad | 0.00810724 |
| pwater*aertau | -0.0086045 |
| catza*cmprad  | 0.00791291 |
| pwater*pschld | 0.01395011 |
| aerasy*aerasy | 0.0231104  |

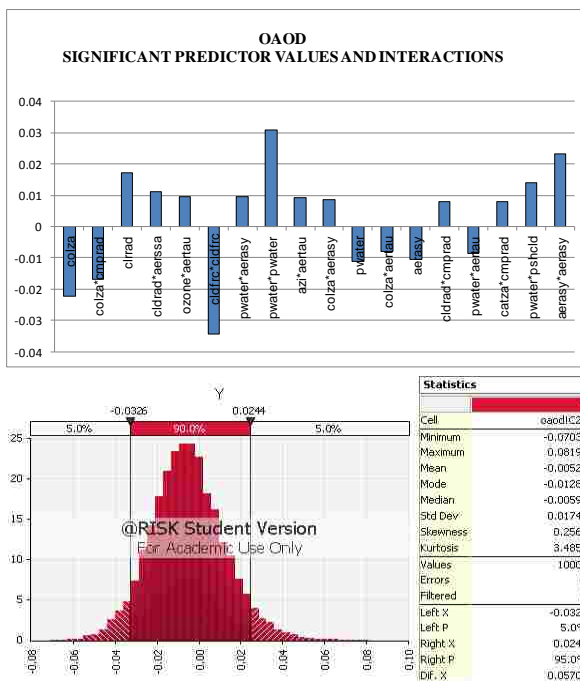


Figure 49. Mt Everest Region Uncertainty Analysis – OAOB

Mt Everest Region Uncertainty Analysis – OCOD

| OCOD          |             |
|---------------|-------------|
| Factor        | Coeff       |
| catza*cldrad  | 40.83936264 |
| colza         | -52.3517345 |
| colza*cmprad  | 40.26863886 |
| aerasy*aerasy | -104.59517  |
| aertau        | -37.4995004 |
| colza*catza   | 26.17542681 |
| clrrad*cldrad | 70.70473175 |
| aerasy        | -26.5136479 |

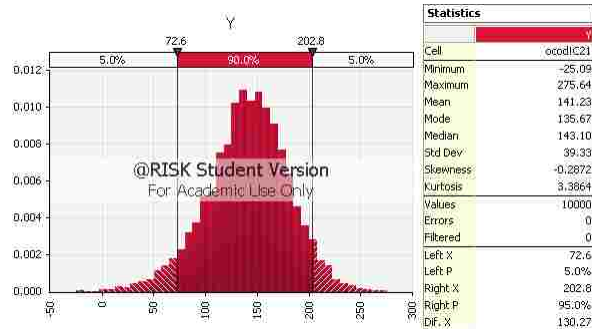
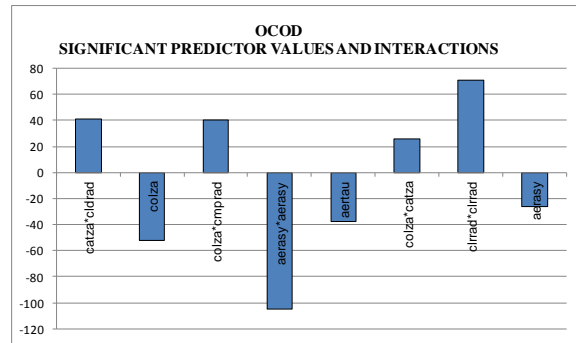


Figure 50. Mt Everest Region Uncertainty Analysis – OCOD



### Mt Everest Region Uncertainty Analysis – SRFDWNPRS

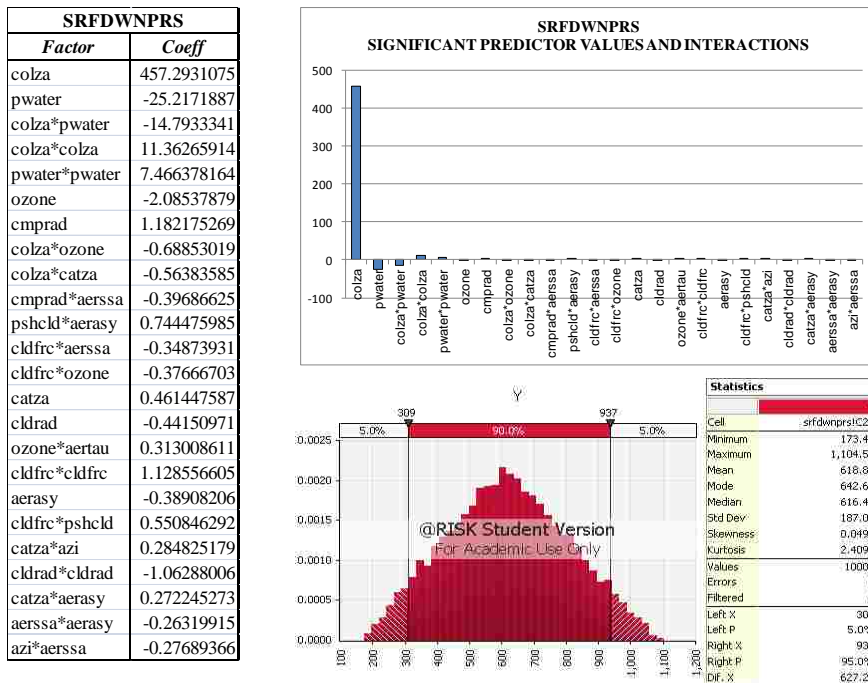


Figure 51. Mt Everest Region Uncertainty Analysis – SRFDWNPRS

### Mt Everest Region Uncertainty Analysis – TOAUPPRS

| TOAUPPRS      |              |
|---------------|--------------|
| Factor        | Coeff        |
| cmprad        | 32.97138338  |
| colza*catza   | -14.24964078 |
| colza         | -11.64593458 |
| catza         | 10.96398607  |
| azi*azi       | -17.58611668 |
| colza*azi     | 5.225927946  |
| colza*cmprad  | -4.063167432 |
| catza*azi     | 3.660590008  |
| cmprad*cmpra  | 12.20594659  |
| azi           | -4.577703504 |
| colza*colza   | 11.33746548  |
| azi*cldfrc    | 2.966800119  |
| cldrad*aerasy | -2.723635533 |
| colza*aertau  | -2.715823582 |
| cldfrc*aerssa | -2.224218589 |
| pshcld*aertau | -4.552308406 |
| catza*aerssa  | 2.214148146  |
| colza*aerasy  | -2.128742642 |
| aerasy        | 2.652347719  |
| pwater*aerssa | -2.077787043 |
| catza*pwater  | -2.129633011 |
| cldfrc*clrrad | 2.027819308  |
| cldfrc*aerasy | -1.926544966 |
| cldfrc*aertau | -1.921405425 |
| clrrad*cmprad | -1.770605799 |

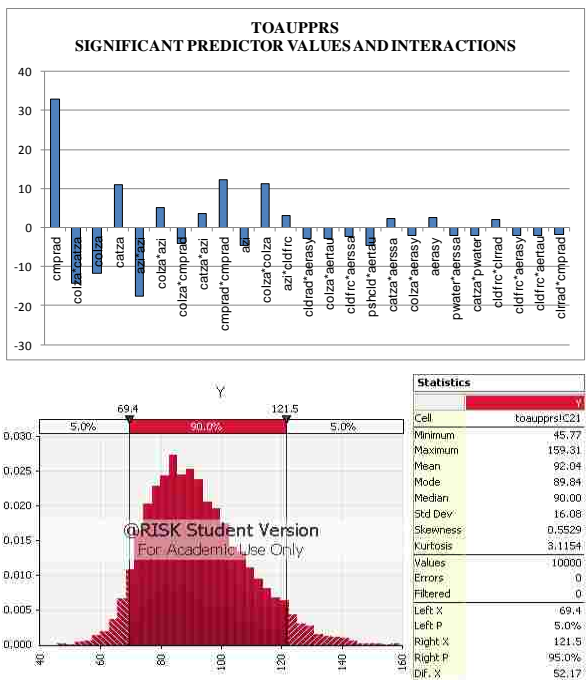


Figure 52. Mt Everest Region Uncertainty Analysis – TOAUPPRS

### Sahara Region Uncertainty Analysis – TOAUP

| TOAP          |              |
|---------------|--------------|
| Factor        | coeff        |
| colza*cldrad  | 68.39062124  |
| cldrad        | 77.92255889  |
| colza         | 76.23575322  |
| cldfrc*cldrad | 59.5209662   |
| cldfrc        | 58.19977046  |
| azi*azi       | -81.98043011 |
| azi*pwater    | -23.79097109 |
| clrrad        | 29.45267493  |
| colza*colza   | -75.21213035 |
| cldfrc*clrrad | -19.0421274  |
| cmprad        | 24.32985347  |
| colza*ozone   | 17.89145481  |
| clrrad*clrrad | 53.72519768  |
| ozone*aerssa  | 14.05165743  |
| cldfrc*cmprad | -14.09628605 |
| catza*aertau  | -12.82158492 |
| aertau*aerssa | 13.23852622  |
| catza*ozone   | -12.32247855 |
| pwater        | 16.95760771  |
| aertau*aerasy | -11.87402141 |
| cldrad*cmprad | -12.03113421 |
| colza*cldfrc  | 11.65230212  |
| pwater*pshld  | -22.05942324 |
| azi*aerasy    | 11.90322809  |
| azi*pshld     | -20.40872883 |
| clrrad*pwater | -10.97462113 |
| cmprad*aerasy | -9.906158987 |
| pshld*aerasy  | -19.18440678 |

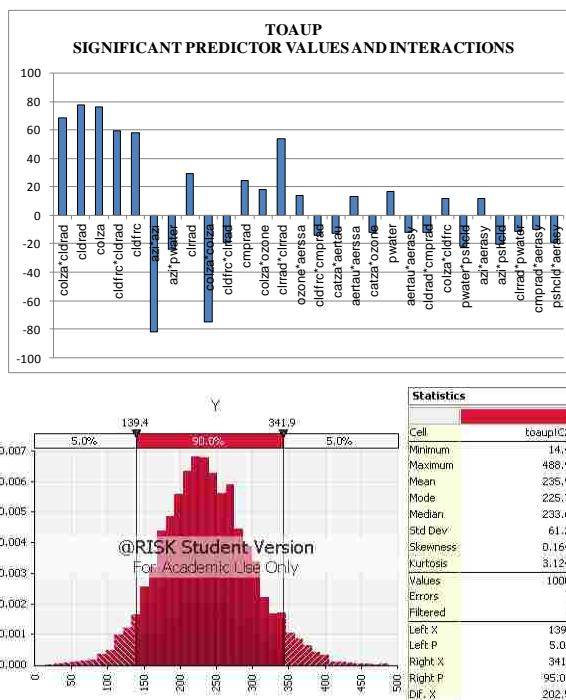


Figure 53. Sahara Region Uncertainty Analysis – TOAUP

Sahara Region Uncertainty Analysis - SRFDWNFLX

| SRFDWNFLX     |            |
|---------------|------------|
| Factor        | Coeff      |
| colza         | 262.934418 |
| colza*cldfrc  | -169.05225 |
| cldfrc        | -134.14734 |
| colza*cldrad  | 83.2386138 |
| clrrad        | 91.9743138 |
| cldrad        | 70.9238804 |
| cldfrc*cldrad | 47.661131  |
| cldfrc*aerssa | -39.725888 |
| clrrad*cmprad | 35.8124693 |
| aerasy        | 43.804609  |
| catza*cmprad  | -35.680645 |
| cldfrc*clrrad | -34.263547 |
| azi*cldfrc    | 32.5972216 |
| cldfrc*cmprad | 33.2111438 |
| cldfrc*pschld | -59.040097 |
| catza*pschld  | 60.1106455 |
| clrrad*pschld | -60.256494 |
| colza*azi     | 31.4107726 |
| pschld*aerasy | -52.594103 |
| cldrad*ozone  | 25.6195362 |
| aerssa*aerssa | 87.576564  |

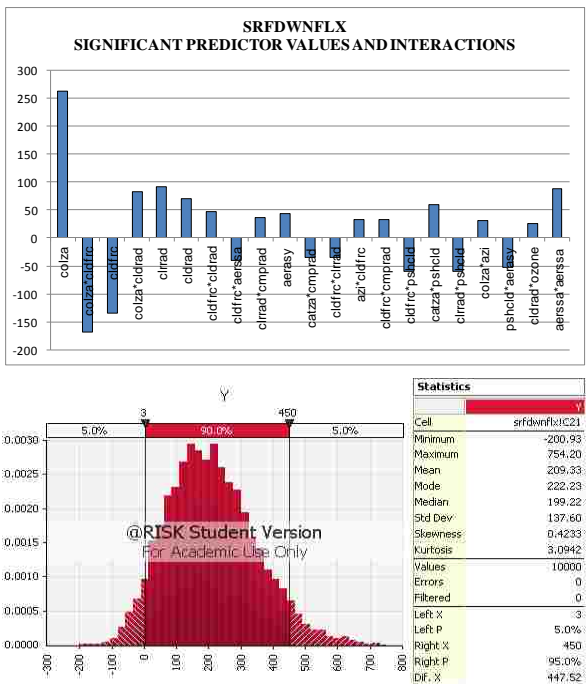


Figure 54. Sahara Region Uncertainty Analysis - SRFDWNFLX

Sahara Region Uncertainty Analysis – SRFDWNDIFF

| SRFDWNDIFF    |            |
|---------------|------------|
| Factor        | Coeff      |
| colza         | 158.995813 |
| cldfrc*cldrad | 73.4002988 |
| cldrad        | 87.4961675 |
| colza*cldrad  | 65.8438235 |
| aerasy        | 57.2552866 |
| cldfrc*clrrad | 45.9843309 |
| pwater*aerssa | 41.9663957 |
| clrrad*aerasy | -39.347206 |
| catza*cldrad  | -37.126781 |
| pshcld*aerasy | -67.08284  |
| cmprrad       | 48.2678926 |
| catza*clrrad  | 34.4947859 |
| cldfrc*pshcld | -57.310566 |

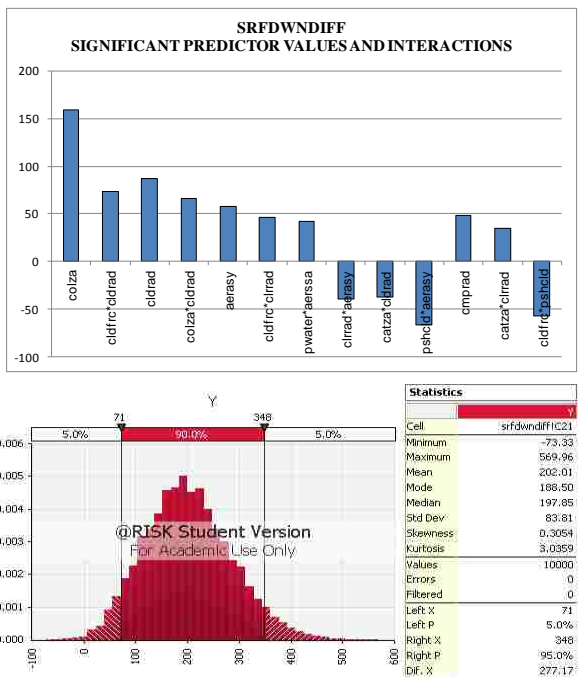


Figure 55. Sahara Region Uncertainty Analysis – SRFDWNDIFF

### Sahara Region Uncertainty Analysis – SRFUPFLX

| SRFUPFLX      |            |
|---------------|------------|
| Factor        | Coeff      |
| colza*cldfrc  | -39.109631 |
| colza*cmprad  | 37.6194556 |
| cmprad        | 42.3674919 |
| clrrad        | 40.4612058 |
| colza         | 36.271801  |
| cldfrc        | -38.127272 |
| colza*cldrad  | 28.6975464 |
| clrrad*cmprad | 16.5567837 |
| cmprad*ozone  | 17.0680577 |
| catza*cmprad  | -17.596431 |
| azi*aerasy    | 16.927317  |
| cldfrc*clrrad | -16.891187 |
| colza*pwater  | 16.461125  |
| aertau*aerasy | -15.278109 |
| catza*azi     | -15.171536 |
| cldrad        | 20.09292   |
| aerasy        | 18.557046  |
| catza*pschld  | 27.446019  |
| colza*catza   | -14.275139 |
| cldrad*pwater | -13.650386 |
| cldfrc*pschld | -22.869758 |
| cldrad*cldrad | 45.8384275 |
| cldfrc*aerssa | -10.926154 |
| ozone*aertau  | -11.339642 |
| pschld*aerasy | -21.541378 |

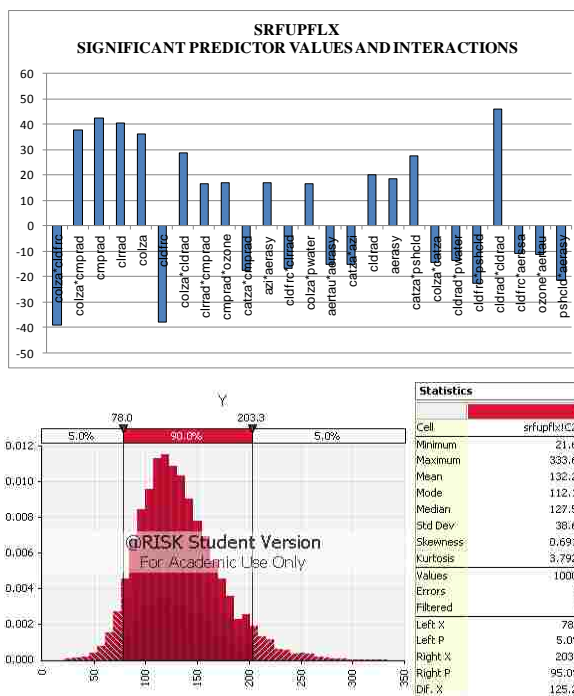


Figure 56. Sahara Region Uncertainty Analysis – SRFUPFLX

### Sahara Region Uncertainty Analysis – SRFDWNDIFPAR

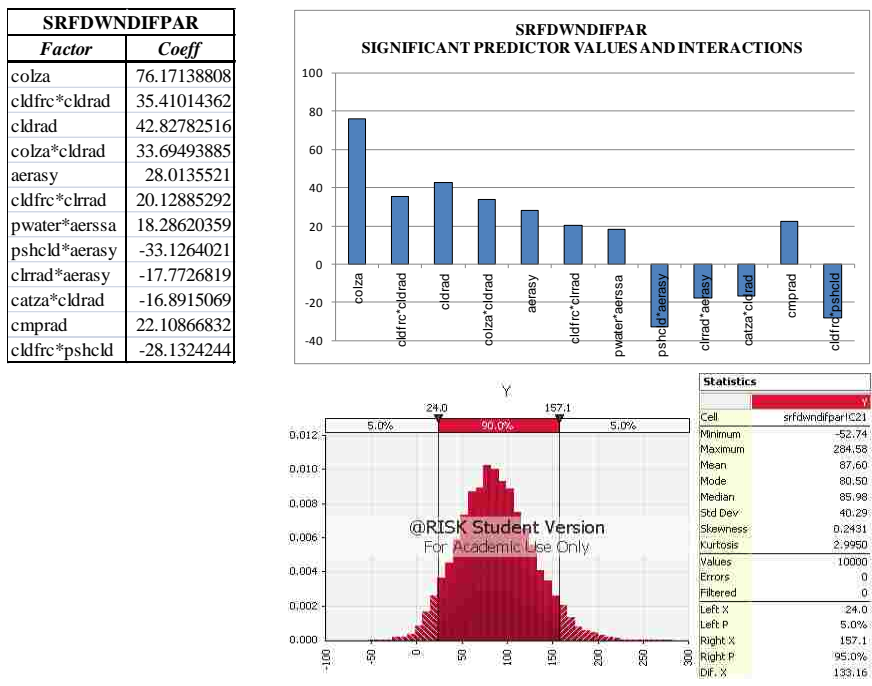


Figure 57. Sahara Region Uncertainty Analysis – SRFDWNDIFPAR

### Sahara Region Uncertainty Analysis – SRFDWNP

| SRFDWNP        |           |
|----------------|-----------|
| Factor         | Coeff     |
| colza          | 123.94878 |
| colza*cldfric  | -74.61908 |
| cldfric        | -58.44368 |
| colza*cldrad   | 41.532625 |
| clrrad         | 42.926397 |
| cldrad         | 34.58565  |
| cldfric*cldrad | 23.568943 |
| cldfric*aerasy | -18.22793 |
| aerasy         | 22.790737 |
| clrrad*cmprad  | 17.326195 |
| catza*cmprad   | -17.09944 |
| catza*pschld   | 29.671894 |
| cldfric*pschld | -28.43139 |
| azi*cldfric    | 15.225023 |
| cldfric*cmprad | 15.060658 |
| pschld*aerasy  | -27.02957 |
| cldfric*clrrad | -15.13978 |
| clrrad*pschld  | -27.75018 |
| colza*pwater   | 14.138402 |
| colza*azi      | 13.703002 |

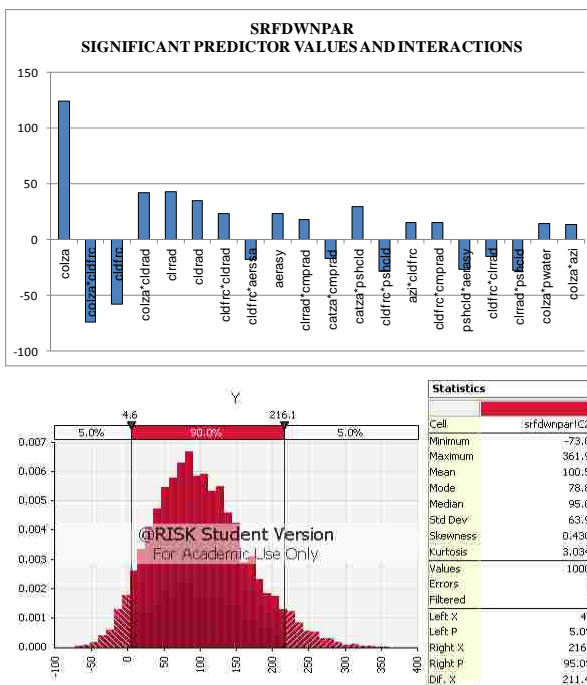


Figure 58. Sahara Region Uncertainty Analysis – SRFDWNP



### Sahara Region Uncertainty Analysis – TOAUPCLRSKY

| TOAUPCLRSKY   |             |
|---------------|-------------|
| Factor        | Coeff       |
| colza         | 52.0662509  |
| colza*cmprad  | 31.6031883  |
| emprad        | 41.82472616 |
| clrad         | 37.87289069 |
| clrad*cmprad  | 17.02927593 |
| colza*colza   | -54.0331051 |
| colza*catza   | -12.8580388 |
| catza*azi     | -7.15745649 |
| pwater*pschld | -12.2930922 |
| catza*cmprad  | -6.52282036 |
| colza*pwater  | 6.222012799 |
| cldrad*ozone  | 5.542442481 |
| cldfrc*aertau | -6.08537905 |
| ozone*ozone   | -18.9576108 |

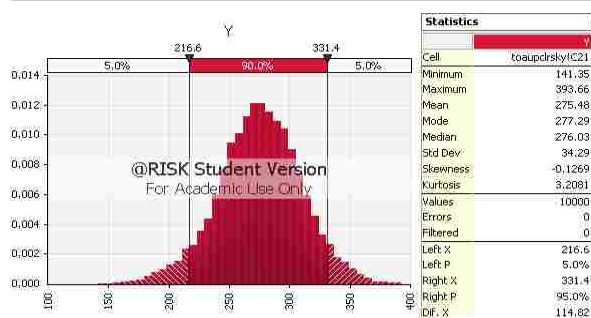
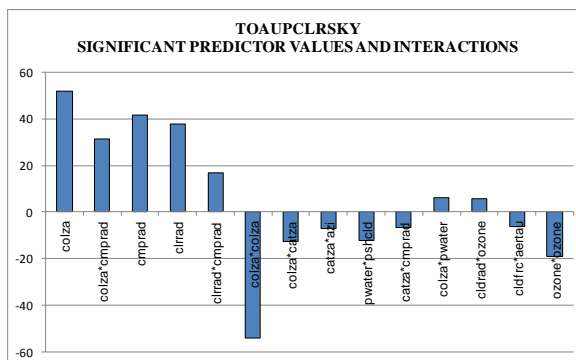


Figure 59. Sahara Region Uncertainty Analysis – TOAUPCLRSKY

Sahara Region Uncertainty Analysis – SRFDWNCLRSKY

| SRFDWNCLRSKY  |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza         | 411.541155   |
| clrad         | 106.3595251  |
| catza*clrad   | -36.30101584 |
| clrad*cmprad  | 23.91685801  |
| clrad*aerasy  | 23.79899311  |
| pwater*aerssa | -23.06573262 |
| pwater        | -28.76275957 |
| cldfrc*aerssa | -18.73160873 |
| catza*ozone   | -17.93359175 |
| colza*clrad   | 19.05508947  |
| catza*cldrad  | 17.34402443  |
| aerssa*aerssa | 59.98843646  |
| pshcld*aertau | 34.45971052  |
| pwater*pwater | 55.14423974  |

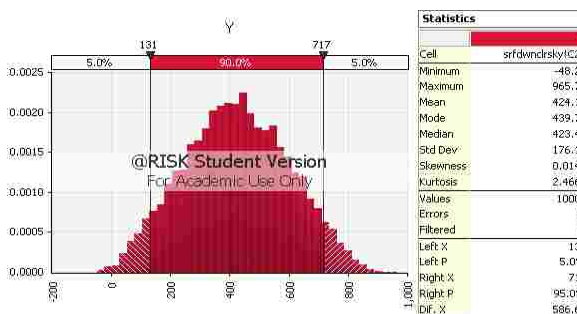
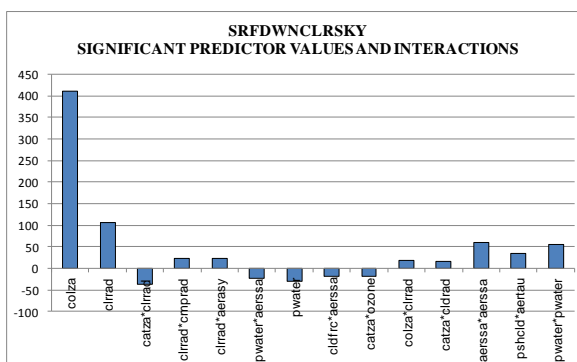


Figure 60. Sahara Region Uncertainty Analysis – SRFDWNCLRSKY

### Sahara Region Uncertainty Analysis – SRFUPCLRFLX

| SRFUPCLRFLX    |            |
|----------------|------------|
| Factor         | Coeff      |
| colza          | 62.1431711 |
| colza*cmprad   | 46.8815612 |
| cmprad         | 60.0330833 |
| clrrad         | 48.8075758 |
| colza*colza    | -58.927408 |
| colza*catza    | -16.253341 |
| clrrad*cmpra   | 13.819982  |
| colza*pwater   | 11.0304883 |
| colza*clrrad   | -11.179131 |
| catza*azi      | -9.333395  |
| cldrad*ozone   | 7.04082853 |
| cldfric*aertau | -7.6872693 |

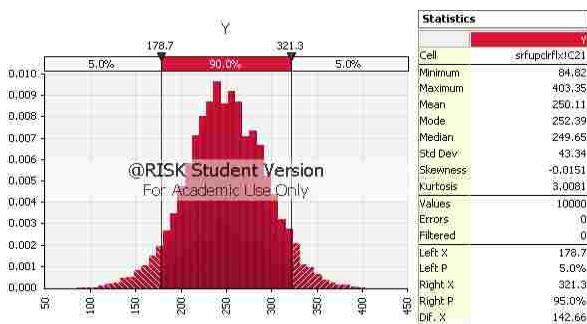
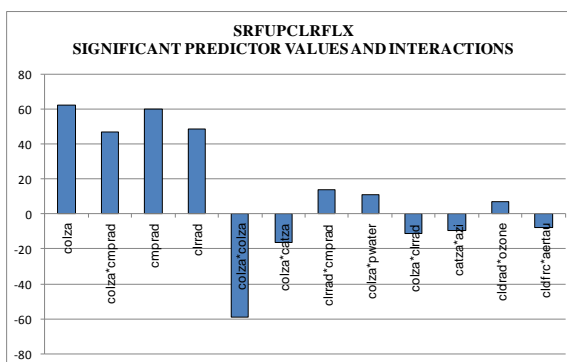


Figure 61. Sahara Region Uncertainty Analysis – SRFUPCLRFLX

### Sahara Region Uncertainty Analysis – OAOB

| OAOB          |            |
|---------------|------------|
| Factor        | Coeff      |
| clrad         | -0.698158  |
| catza*clrad   | 0.15598779 |
| colza*clrad   | 0.13353706 |
| clrad*aerasy  | -0.1230666 |
| clrad*cmprad  | -0.1048407 |
| pwater*aerssa | 0.10221233 |
| catza*ozone   | 0.08961933 |
| cldfrc*aerssa | 0.08102086 |
| catza*cldrad  | -0.0772305 |
| aerssa*aerssa | -0.2499258 |
| cldfrc*aertau | 0.07363462 |

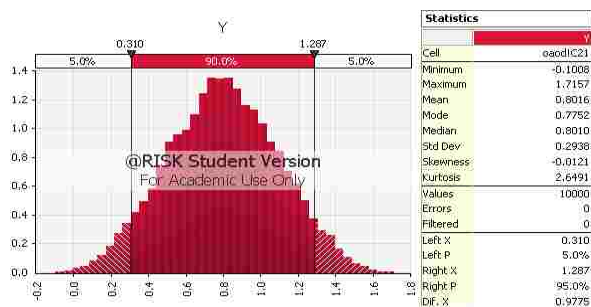
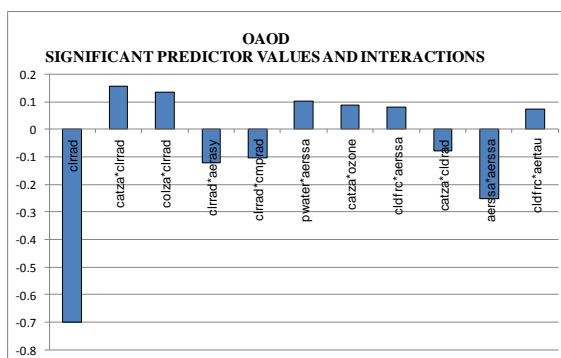


Figure 62. Sahara Region Uncertainty Analysis – OAOB

### Sahara Region Uncertainty Analysis – OCOD

| OCOD          |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza*cldrad  | -78.75440927 |
| colza*pwater  | 45.06836112  |
| catza*cldrad  | 33.2074559   |
| azi*cldfrc    | 31.81527529  |
| colza         | -41.8621949  |
| colza*colza   | 102.3657803  |
| cldrad*cmprad | 26.7863888   |
| colza*cldrad  | -27.03889742 |
| aerssa        | -39.66527272 |
| aerasy        | -31.43605328 |
| cmprad*aerssa | 23.66797602  |
| pwater        | -29.58478322 |
| cldfrc*ozone  | 20.98220286  |
| aerssa*aerssa | -68.43263971 |
| cldfrc*cmprad | 20.17258347  |
| pwater*aertau | -20.74541053 |
| colza*catza   | 19.41752766  |
| pwater*pschld | -35.61526734 |
| cldrad*ozone  | 16.22640896  |
| azi*cldrad    | -18.05678151 |
| colza*pschld  | -31.08132355 |

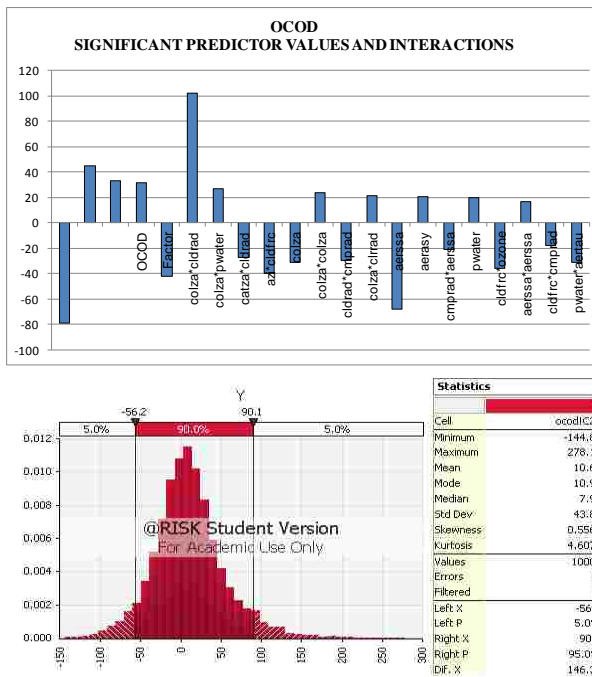


Figure 63. Sahara Region Uncertainty Analysis – OCOD

### Sahara Region Uncertainty Analysis – SRFDWNPRS

| SRFDWNPRS     |              |
|---------------|--------------|
| Factor        | Coeff        |
| colza         | 476.4209807  |
| pwater        | -40.28675512 |
| colza*pwater  | -22.98679254 |
| pwater*pwater | 17.52213564  |
| colza*colza   | 7.636701048  |
| cmprad        | 1.980448098  |
| ozone         | -1.751331696 |
| pschld*aerasy | 1.82644355   |
| aerasy        | -1.150494451 |
| cmprad*aerssa | -0.859999452 |
| colza*cmprad  | 0.910177921  |
| colza*catza   | -0.888353295 |
| cldfrc*ozone  | -0.896823924 |
| aertau        | 1.152680343  |
| cldfrc*cldfrc | 2.500101323  |
| colza*ozone   | -0.751566679 |
| aerssa*aerasy | -0.661628654 |
| cldfrc*aerssa | -0.612597382 |
| cldfrc*pschld | 1.219399108  |
| cldfrc*clrrad | -0.663068517 |
| ozone*aertau  | 0.607323397  |
| clrrad        | -0.803732392 |
| clrrad*aerssa | -0.58682963  |
| pwater*aerssa | 0.581852338  |
| cldrad*cldrad | -2.184902192 |
| cldfrc*aertau | -0.601238959 |
| catza         | 0.76435898   |
| catza*cldrad  | -0.547098387 |

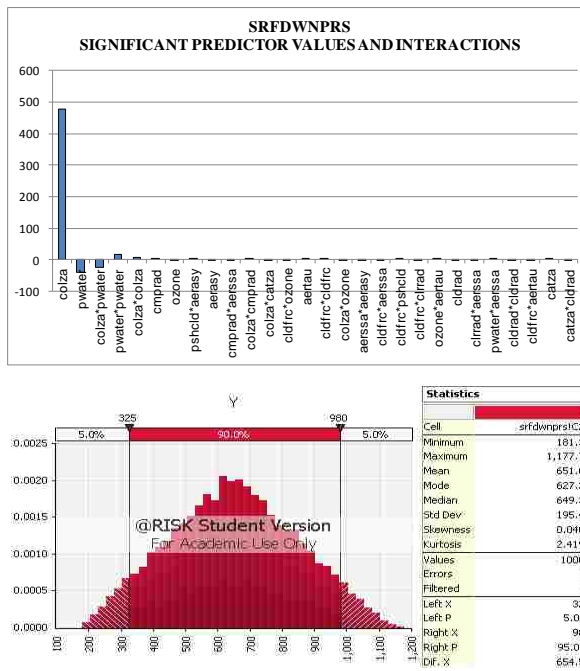


Figure 64. Sahara Region Uncertainty Analysis – SRFDWNPRS

Sahara Region Uncertainty Analysis – TOAUPPRS

| TOAUPPRS      |             |
|---------------|-------------|
| Factor        | Coeff       |
| cmprad        | 69.83403216 |
| colza*cmprad  | 52.07710442 |
| colza         | 58.43191222 |
| colza*colza   | -80.773844  |
| colza*catza   | -20.213591  |
| pwater*aerssa | 10.78433038 |
| colza*pwater  | 9.366714724 |
| catza*azi     | -8.90294332 |
| cldrad*ozone  | 8.119839882 |
| colza*aertau  | 8.066928245 |
| aertau        | 10.40494033 |
| catza*pwater  | -7.48995828 |
| azi*azi       | -22.5316049 |
| cmprad*aertau | 7.336534485 |
| catza*aertau  | -7.1247751  |

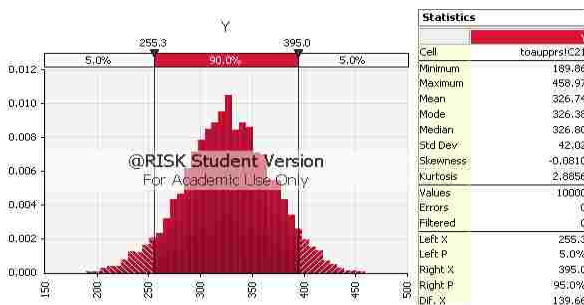
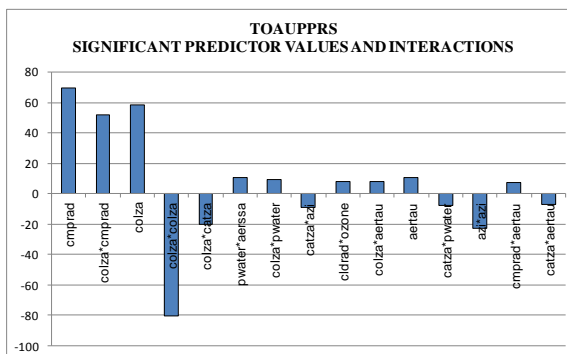


Figure 65. Sahara Region Uncertainty Analysis - TOAUPPRS

## VITA

PATRICIA A. QUIGLEY  
613 Carlton Drive  
Hampton, VA 23666  
(757) 864-7418

EDUCATION:

Old Dominion University – Department of Engineering Management, 5115 Hampton Boulevard,  
Norfolk, VA 23529

Old Dominion University – M.S Engineering Management (12/12)

Strayer University – B.S. Computer Information Systems (3/07)

Community College Air Force - A.A.S. Aerospace Control & Warning Systems (5/85)

Thomas Nelson Community College - A.A.S. Mechanical Engineering (5/92)

Community College of the Air Force - A.A.S. Avionics Systems (7/11)

EMPLOYMENT HISTORY:

Company: NASA/CSC/SAIC/SSAI - FEB 1998 to present

Position: Functional Test Engineer/Senior Software Engineer/Analyst/System Administrator

Company: NASA/Analytical Services and Materials - SEP 1995 to FEB 1998

Position: Assistant Research Scientist

Company: Lockheed Engineering and Science Corporation - OCT 1992 to SEP 1995

Position: Engineer Aide

MILITARY EXPERIENCE:

Active duty Air Force – 1979 – 1987 – Aerospace Control and Warning Systems

Army National Guard – JAN 87 – JAN 90 – Artillery Unit

Air National Guard – 19 FEB 08 – PRESENT (F22 Avionics)



