

ERDC/CERL TR-09-22

Construction Engineering  
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**US Army Corps  
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*DoD Corrosion Prevention and Control Program*

## **Development of a Predictive Corrosion Model Using Locality-Specific Corrosion Indices**

Final Report on Project FAR-15 for FY06

Sean Morefield, Susan A. Drozdz, Vincent F. Hock,  
William H. Abbott, David Paul, and Jana L. Jackson

August 2009



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Final report

Approved for public release; distribution is unlimited.

Prepared for Office of the Secretary of Defense (OUSD(AT&L))  
3090 Defense Pentagon  
Washington, DC 20301-3090

Under Military Interdepartmental Purchase Requests 6FCERB1023 and  
6H6AG3CPC1

**Abstract:** This Office of the Secretary of Defense Corrosion Prevention and Control Program project developed a statistical model of atmospheric corrosion of selected metals. This model relates measured corrosion rates at test sites (mainly military bases) worldwide to critical environmental variables. These variables are (1) a measure of atmospheric chlorides, (2) rainfall, and (3) relative humidity values at several levels. The measured corrosion rates obtained at test sites over the period of CY05 – CY07. Additionally this database includes much more data obtained from similar DoD monitoring activities over nearly the last decade. This serves to enhance the statistical relevance of the developed model. The model includes algorithms for several metals that have been routinely used in the monitoring work. These include copper, 6061 T6 aluminum, 7075 T6 aluminum, and a low carbon (1010) steel.

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## Preface

This demonstration was performed for the Office of the Secretary of Defense (OSD) under Department of Defense (DoD) Corrosion Control and Prevention Project FAR-15, “Development of Corrosion Indices and Life Cycle Prediction for Equipment and Facilities”; Military Interdepartmental Purchase Requests MIPR 6FCERB1023 and 6H6AG3CPC1, dated 2006. The proponent was the U.S. Army Office of the Assistant Chief of Staff for Installation Management (ACSIM), and the stakeholder was the U.S. Army Installation Management Command (IMCOM). The technical monitors were Daniel J. Dunmire (OUSD(AT&L)Corrosion), Paul M. Volkman (IMPW-E), and David N. Purcell (DAIM-FDF).

The work was performed by the Materials and Structures Branch (CEERD-CF-M), Facilities Division (CF), U. S. Army Engineer Research and Development Center – Construction Engineering Research Laboratory (ERDC-CERL), Champaign, IL. The ERDC-CERL project managers were Sean Morefield and Vincent F. Hock. Significant portions of this work were performed by under contract W9132-06-D-0001, Delivery Order Number 0017 to Mandaree Enterprise Corporation, subcontracted to William H. Abbott and Jana L. Jackson of Battelle, Columbus, OH. The contribution of Dr. David Paul, Battelle, is also acknowledged.

At the time this report was prepared, the Chief of the ERDC-CERL Materials and Structures Branch was Vicki L. Van Blaricum (CEERD-CF-M), the Chief of the Facilities Division was L. Michael Golish, (CEERD-CF), and the Technical Director for Installations was Martin J. Savoie (CEERD-CV-ZT). The Deputy Director of ERDC-CERL was Dr. Kirankumar Topurdurti and the Director was Dr. Ilker Adiguzel.

The Commander and Executive Director of the U.S. Army Engineer Research and Development Center was COL Richard B. Jenkins and the Director was Dr. James R. Houston.



## Executive Summary

This technology research and demonstration project, performed under the Office of the Secretary of Defense OSD Corrosion Prevention and Control program, developed an atmospheric corrosivity rate model based on geographic location. These rates are based on statistical models for the atmospheric corrosion rates of bare copper, 6061 T6 aluminum, 7075 T6 aluminum, and a low carbon (1010) steel. These materials are found in military vehicles, aircraft and facilities. These are regarded as empirical models that have a basis in the critical environmental variables that control the corrosion processes. These are regarded as various measures of atmospheric moisture and atmospheric chlorides. The modeling challenge was to determine for each metal the algorithm that gave the best fit to the available field data through use of these critical variables. A further constraint was the self-imposed requirement that the environmental data inputs should be readily available from public sources or relatively easy to obtain.

This work within these constraints was successful and resulted in linear models yielding correlation coefficients in the range of 0.8 . Such values far exceed any prior work which has given coefficients in the range of 0.5 or less. This may be due in part to the large database of field reaction rates that was available from prior studies by Battelle.

These models have been incorporated into a software package. The models can be run from a PC and allow the user to display corrosion rates/severity levels for locations in the database along with confidence intervals on the results. In addition, the user can calculate corrosion rates for new locations that have not been previously monitored provided that the appropriate weather data are available.

## Unit Conversion Factors

Multiply	By	To Obtain
degrees Fahrenheit	$(F-32)/1.8$	degrees Celsius
feet	0.3048	meters
gallons (U.S. liquid)	3.785412 E-03	cubic meters
inches	0.0254	meters
mils	0.0254	millimeters
square feet	0.09290304	square meters

# **1 Introduction**

## **1.1 Problem statement**

Throughout the world, corrosion maintenance is most often based on finding and fixing the damage prior to its becoming a structural or safety concern. The Department of Defense (DoD) has identified this approach as inadequate to meet mission criticality, e.g. equipment and facilities availability to support deployment, training, and readiness. There has been little emphasis on the development of engineering tools needed for the management of this corrosion and the associated maintenance and repair actions. The benefits and longevity of corrosion prevention and control measures have not been quantified so optimization of these actions has not been possible. As the DoD fleets and facilities have aged, the life limiting degradation mechanisms have shifted from those associated with usage to those associated with time. The costs of corrosion maintenance have risen drastically. Furthermore, the concerns for corrosion, which previously had centered around cost, have now begun to include structural integrity and safety. This shift has dictated a change to a prediction and management approach beyond just simply finding and fixing.

In order to address these issues, ERDC-CERL has developed and demonstrated a corrosion rate prediction model. This corrosivity model quantifies the severity of atmospheric corrosion, which takes into account different geographic locations, local weather conditions, and distance from a sea coast. The model allows for querying the corrosion index of a particular location included in the survey, and is also capable of predicting the corrosivity of other, new, locations not included in the surveyed locations.

The corrosion rate model is designed for use by three groups of people in mind. Facility engineers can use it to make decisions regarding material selection and other corrosion prevention measures. It is also designed to support decisions for allocation of installation maintenance funding. A third group includes groups responsible for maintaining equipment that is relocating to a different geographic area. Corrosion prevention measures may require adjustment in order to provide adequate protection of the equipment under their supervision due to changes in the corrosivity of the environment.

## 1.2 Objective

The objective of this project was to develop and validate a statistical model of atmospheric corrosion of selected metals, and implement the model into a software application.

## 1.3 Approach

The model was created from several different data sources. The raw atmospheric corrosion data came from a previously funded FY05 Project AR-F-311 "Measuring the Rates and Impact of Corrosion on DoD on Equipment and Installations." Additional atmospheric corrosion data came from other DoD projects which utilized the same sample form factor which made the data integration transparent. Local weather data were incorporated from open sources such as the Air Force Combat Climatology Center (AFCCC) and from reliable state and private-sector sources.

The statistical analysis methods were applied to the raw weather and location data collected as part of CPC AR-F-311. The atmospheric corrosion data collected from analyzed samples was empirically correlated against the weather severity aggregated data collected from the site.

A complete set of 12-month cumulative weather data for the 160 sites were subjected to a classification algorithm known as Partitioning Around Medoids (PAM). In this methodology, a number of desired data sub-groups is selected and the routine calculates how good a choice that number of partitions is. The weather data parameters examined included relative humidity, precipitation, and atmospheric deposition of chlorides. The analysis conducted on the available weather data examined the consequences of choosing 2, 3, and 4 groupings. It was found that the 12-month weather data was optimally clustered into 3 distinct groupings: dry, wet and severe.

The atmospheric corrosion model was developed by means of empirical regression. The measured corrosion rate for each metal type was correlated to the weather data from its location. The resulting empirical fit parameters constitute the model.

The clustered weather data and atmospheric corrosion data were entered into an Microsoft Excel spreadsheet. The software user interface is built around an Access database. It has been tested under a number of versions of Microsoft Windows, including Windows XP. Section 2.2 presents a de-

tailed description of how to install and use the software, and indicates what the various screens should look like to the user.

Appendix A contains the project management plan describing the proposed project scope and funding details. Appendix B describes the general framework and a more detailed model development, as well as a statistical analysis. Appendix C details how the atmospheric and weather data was clustered and processed. Appendix D gives a graphical representation of how the weather data was partitioned around medoids. Appendix E details the specific code used to create the model. Appendix F contains basic instructions on how to install the model application program on a desktop computer and acquaints the user with the program's various input screens. Appendix G presents select outputs of the model, comparing the predicted corrosion loss to the observed corrosion data for selected sites and metals with regression plot.

## **2 Technical Investigation**

### **2.1 Project overview**

In order to make an atmospheric corrosivity model that was capable of predicting the corrosivity of the sites not included in the exposure data project in FY05, datasets from several other variables were needed. Specifically, historic data from weather stations was collected from the weather agency closest to the sample exposure rack was collected. The distance from the weather station to the exposure rack was also noted. Variables including humidity, precipitation, temperature, humidity were all acquired for the period of rack exposure. Relevant weather data was obtained from open sources such as the Air Force Combat Climatology Center (AFCCC) and from reliable state, local and private-sector sources. These data were assembled into Microsoft Excel spreadsheets for statistical analyses.

The atmospheric corrosion rate database was assembled in order to begin the statistical analysis. The model and database are constructed to allow new data to be added as it becomes available. However, given the magnitude of data already incorporated, additional data should have little impact on the model.

The statistical analyses of the weather data consisted of partitioning along medoids. This is an analysis which aggregates the weather into groups that display coherency. For additional detail see Appendix D. The models were developed, implemented as a computer application, and tested in April 2007. Further work was conducted to enhance the algorithm accuracy.

### **2.2 Model development**

The corrosion indices and predictive algorithms were developed for application to metals exposed to the open atmosphere, not sheltered.

A complete set of 12-month cumulative weather data for the 160 sites were subjected to a classification algorithm known as Partitioning Around Medoids (PAM). In this methodology, a number of desired data sub-groups is selected and the routine calculates how good a choice that number of partitions is. The weather data parameters examined included relative humidity, precipitation, and atmospheric deposition of chlorides. The analysis

conducted on the available weather data examined the consequences of choosing 2, 3, and 4 groupings. It was found that the 12-month weather data was optimally clustered into 3 distinct groupings: dry, wet and severe. The categories are derived from a weighed average of humidity, rainfall and chlorides for a location. The quantitative definition for these categories is expanded in Appendix B.

Algorithms have been developed by means of empirical regression for each of these categories in order to give more precise predictions.\* The measured corrosion rate for each metal type was correlated to the weather data from its location. The resulting empirical fit parameters constitute the model. Correlation coefficients have been calculated for each metal and weather grouping and these appear to be in the range of 0.75. This is considered quite good for work of this type and represents a significant advance over prior published work, such as the PACER LIME model† and others, where coefficients of no better than 0.5 have been achieved.

The clustered weather data and atmospheric corrosion data are stored in a Microsoft Excel spreadsheet. The software user interface is built around a Microsoft Access database. It has been tested under a number of versions of Microsoft Windows, including Windows XP.

### 2.3 Model output examples

Figure 2.1 – Figure 2.4 show examples of graphical output for each of four metals at a single site. The model had to be run separately for each of the metals. In these cases the agreements between actual and predicted corrosion is relatively good. Generally, most data fall within the 95% confidence intervals.

It should be noted that cases will be found in which the agreement is not as good and where actual values lie above the upper limits. The reasons for this have often been resolved and in the most general case it is a matter of where available weather data were recorded (by other parties). There is a fundamental assumption/requirement in any work of this type that the weather and corrosion data are coincident in time (usually not a problem)

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\* This information is provided as background for the interested technical reader, but understanding it is not necessary for the end user to take advantage of the model.

† Summitt, R., and F.T. Fink. August 1980. *PACER LIME: An Environmental Corrosion Severity Classification System*. DTIC Final Technical Report TR-80-4102-PT-1.

and location. In the event that the locations are not identical/very close, it would be a judgment call whether the weather data should be applicable to the monitored location. This problem is most likely to occur in coastal regions where monitoring is occurring within the first ½ mile or so of the coast. Often, the weather station will be somewhat further inland and not near the corrosion samples. In these cases, the measured corrosion rates are likely to be much higher than predicted values, since it has been shown that corrosion rates may vary almost exponentially with distance from ocean within at least the first half-mile.

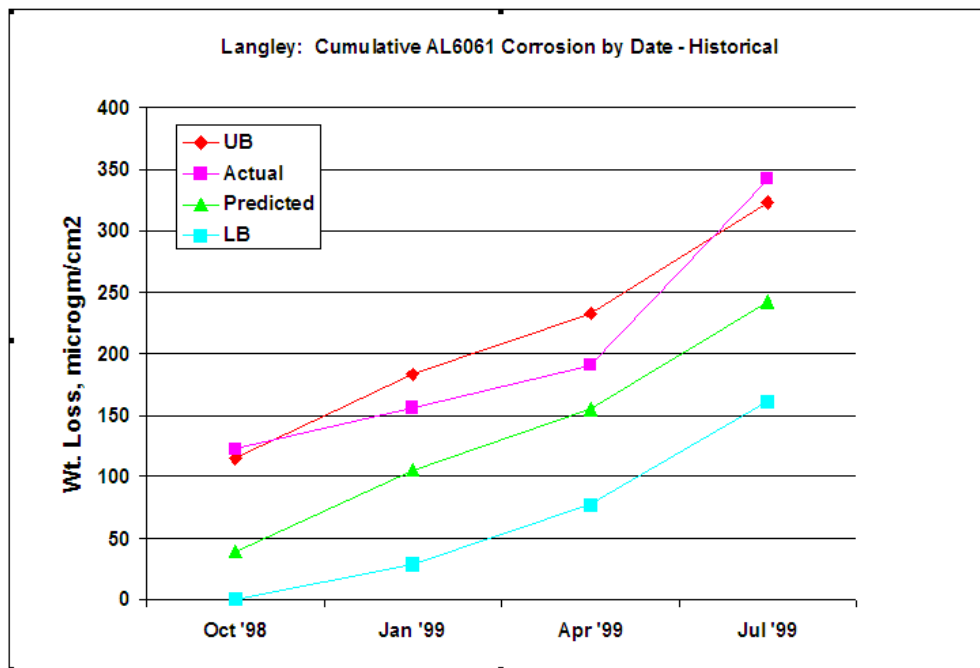


Figure 2.1. Screen output example for corrosion of 6061 Al at Langley



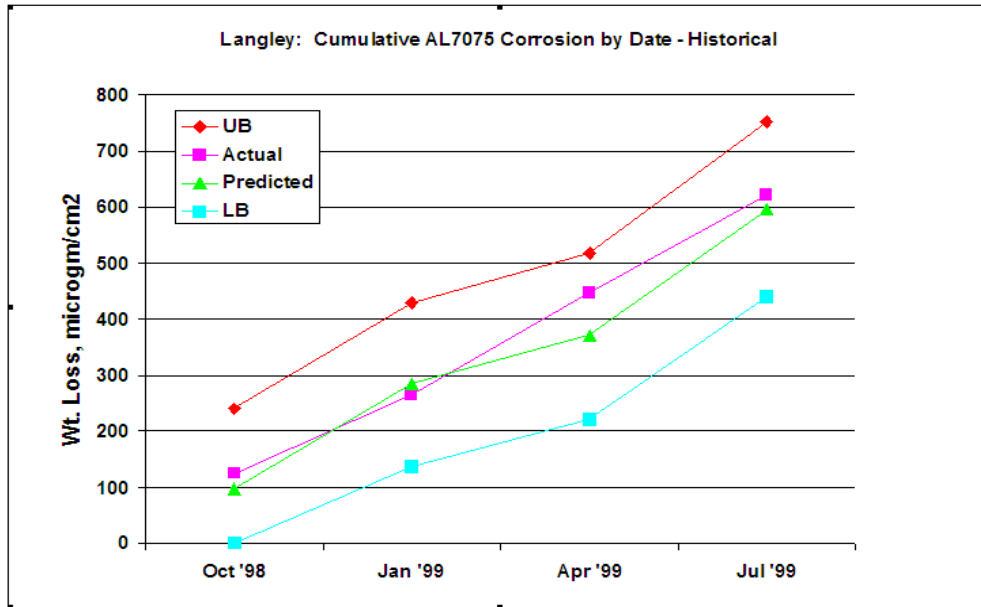


Figure 2.2. Screen output example for corrosion of 7075 Al at Langley.

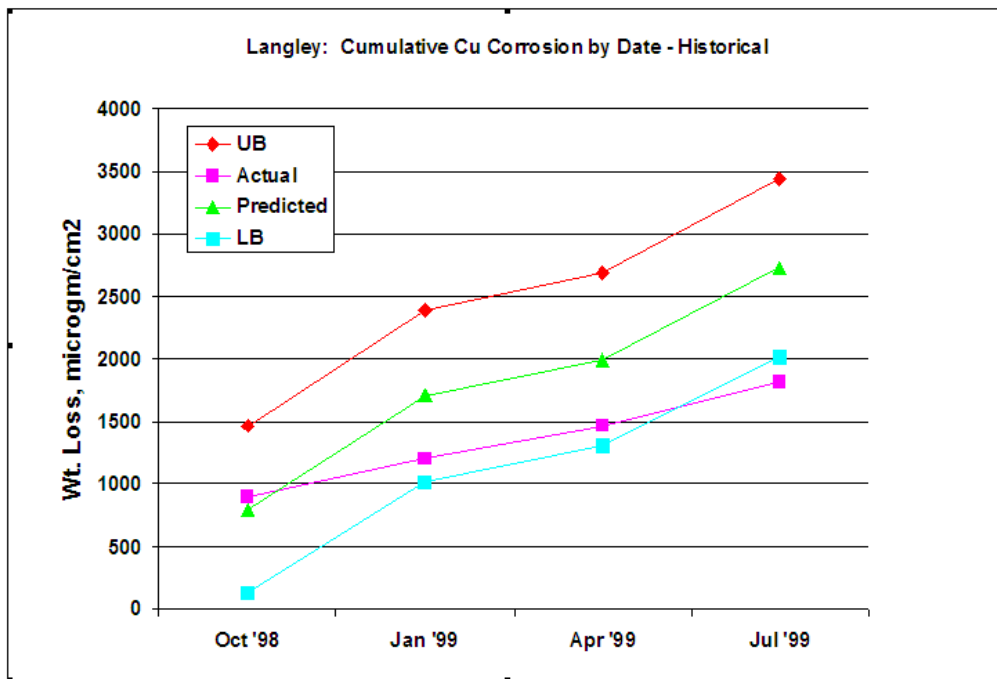


Figure 2.3. Screen output example for corrosion of copper at Langley.

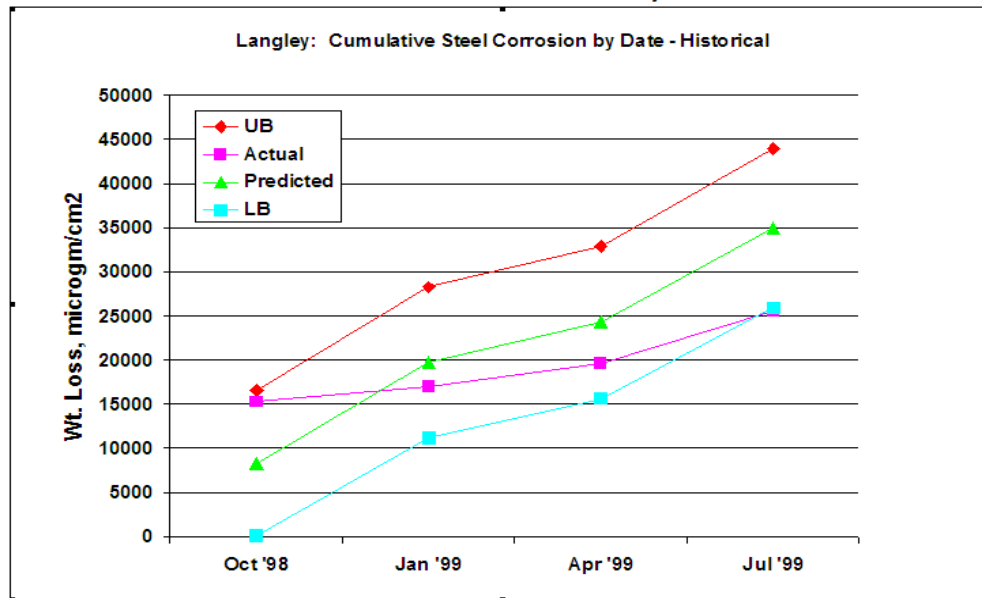


Figure 2.4. Screen output example for corrosion of steel at Langley.

Figure 2.5 – Figure 2.7 show the results of such plots for 7075 T6 aluminum according to the site data currently in the embedded Access database. A “perfect” correlation would be for all data to cluster around a 45 degree line for each condition. In reality the results are quite good particularly in consideration of the fact that these are real field data. A few outliers are shown for each case. The reasons for most of these situations are generally known; however, for information purposes we are investigating whether there is a simple way for the user to know what these sites are as one can do in Excel plots by simply pointing to the plotted points.

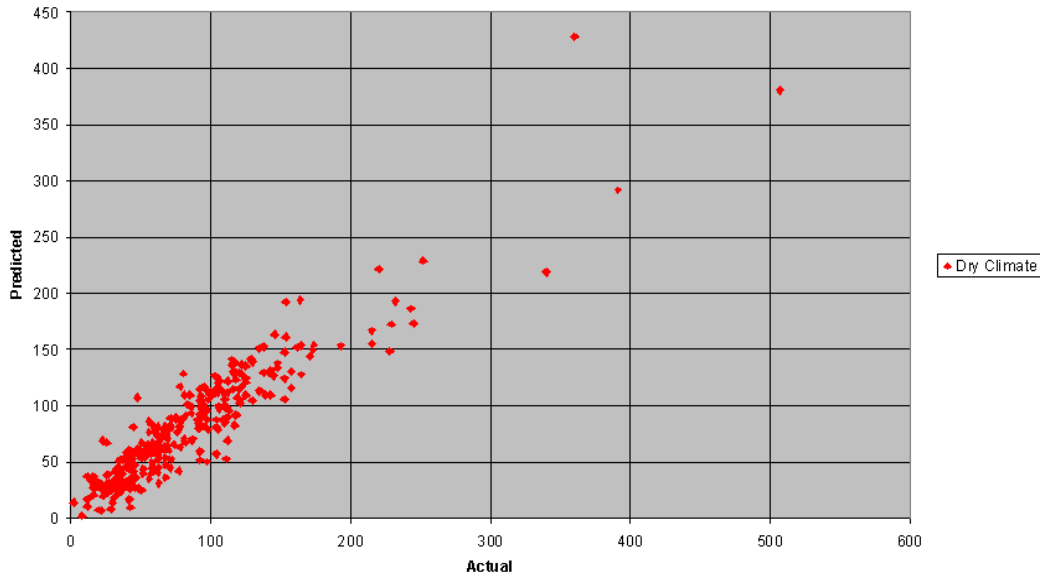


Figure 2.5. Predicted vs actual graphing screen showing summary of current results for all 7075 T6 data in "dry" locations.

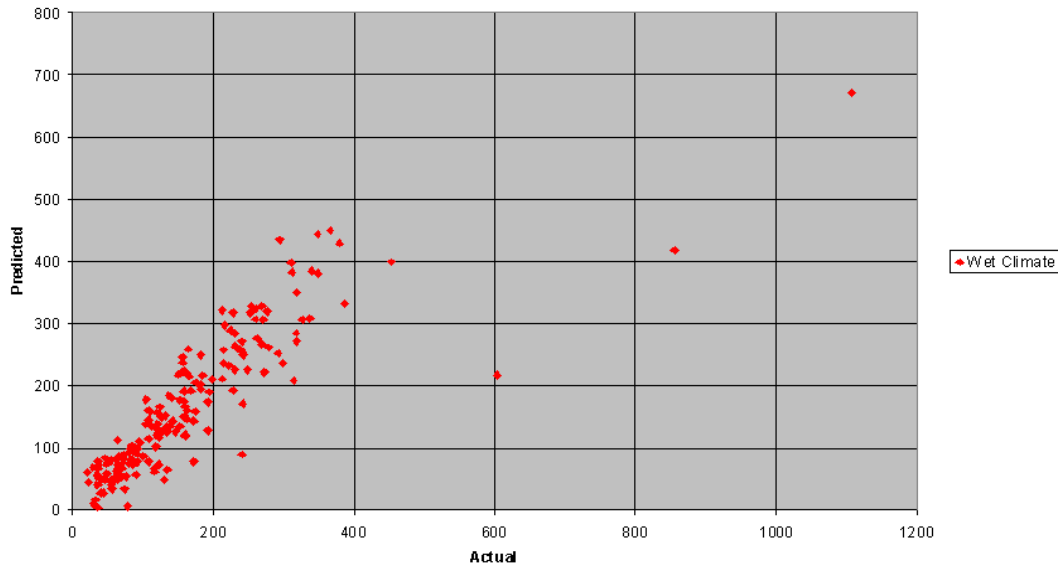


Figure 2.6. Predicted vs actual graphing screen showing summary of current results for all 7075 T6 data in "wet" locations.

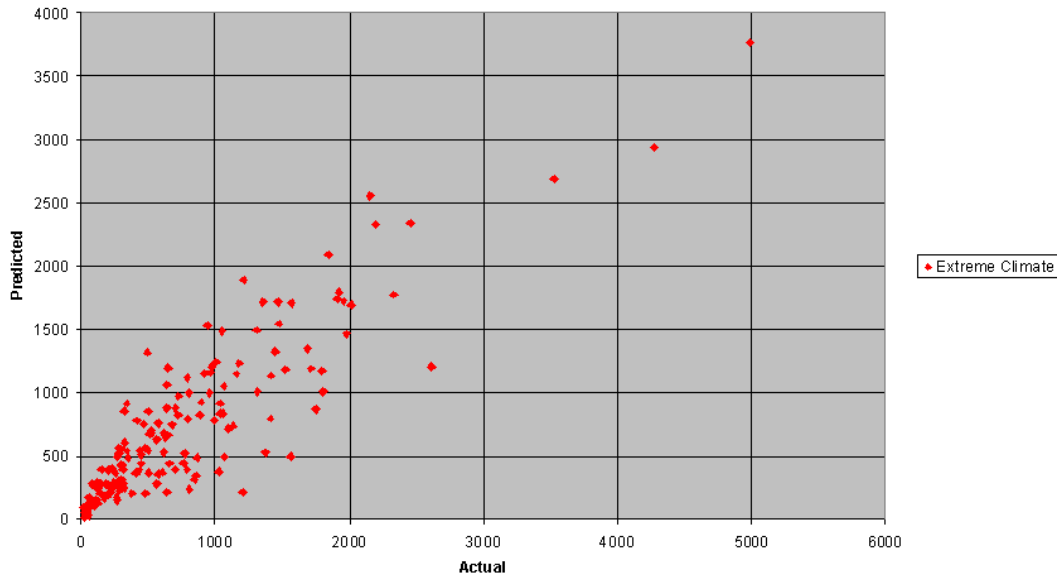


Figure 2.7. Predicted vs actual graphing screen showing summary of current results for all 7075 T6 data in “extreme” locations.

Figure 2.8 shows output of corrosion kinetics for four Coast Guard stations. Predicted cumulative corrosion is plotted at 3-month intervals. One 3-month interval equals one sequence for this plot. The slope of the line indicates the corrosion rate for that material and location. Steeper slopes indicate a greater corrosivity.

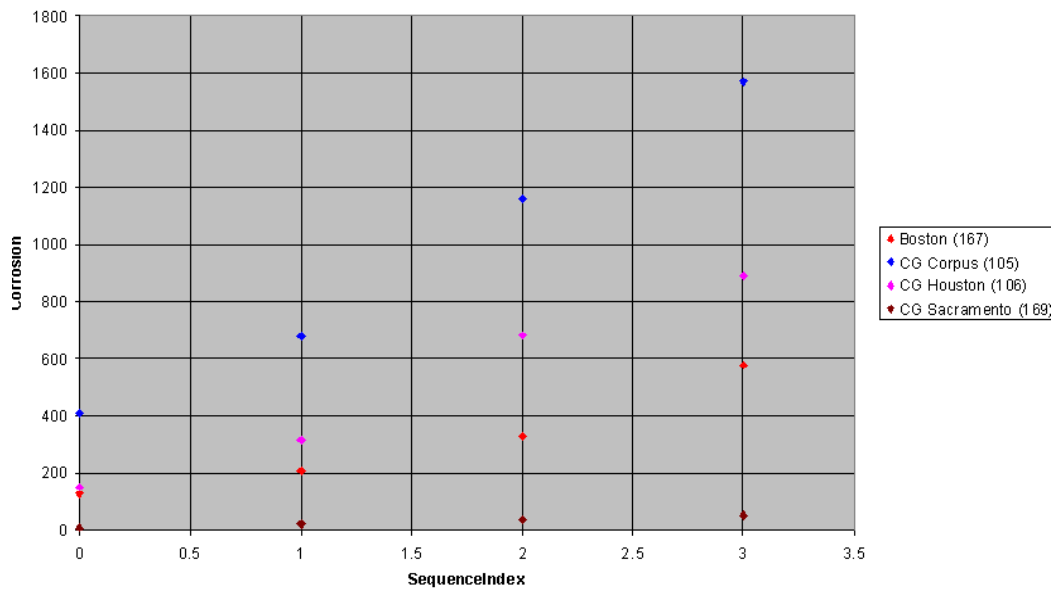


Figure 2.8. Plotting routine example for four coast guard stations and corrosion of 7075 T6 aluminum.

## **3 Discussion**

### **3.1 Metrics**

The basis for the corrosion severity model is quantitative data on environmental corrosivity collected through atmospheric exposure of standardized metallic corrosion specimen sets and statistically correlated with their corresponding climate and geospatial data. The reference metrics employed in this work were as follows:

- The standard Battelle corrosion test racks provided a consistent atmospheric test methodology to gather the data used in the model. The specific panel methodology is also described in the final report for the FY05 CPC project AR-F-315, “Development of Corrosion Indices and Life Cycle Prediction for Equipment and Facilities”
- Alloy composition standards for the sample metals are as published by ASTM International: ASTM B308/B308M-02, ASTM A108, and ASTM B152 for aluminum, steel, and copper samples, respectively. The specific alloys used were copper, 6061 T6 aluminum, 7075 T6 aluminum, and a low carbon (1010) steel.
- Weather data compiled from the Air Force Combat Climatology Center (AFCCC) and other repositories.

The primary metric used to validate the model was statistical analysis of its application to specific geospatial locations, comparing the severity index with the observed data. A comparison of the actual cumulative corrosion levels to the 95% prediction intervals associated with the models demonstrates that the actual cumulative corrosion levels are contained within them 83.7% of the time. Overall, this agreement describes both an improvement in accuracy over previous atmospheric models such as the PACER LIME methodology (Summitt and Fink 1980) while being more comprehensive in scope. This “internal challenge” method of model validation is more fully expanded in Appendix E.

### **3.2 Results**

The change in corrosion for a given metal at a given site from the end of the preceding observation period to the end of the current observation period was regressed on the concomitant variables given in Table B9, for

each metal and weather group. This yielded a total of 15 regression models, which are described in Appendix E. From this appendix, the regression coefficients, t-tests, adjusted R<sup>2</sup>, and other model details may be found. Table B10 describes the properties of these models. From this table, it is seen that 11 of the 15 models have excellent adjusted R<sup>2</sup> values (greater than 72.3% in all cases). The predominance of the good explanatory power of the variables in Table B9 suggests that the variable selection method (see section B3.2.2) worked.

### **3.3 Lessons learned**

Tests of the models have shown that a major limitation is that location for the predictions must be in proximity to the location where the weather data are collected. This is particularly true in coastal locations adjacent to saline bodies of water. At this time it is estimated that the point of weather data collection is optimum at 0.25 miles or less from the location of interest.

## 4 Economic Summary

### 4.1 Costs and assumptions

The OMB Circular A94, Appendix B is used for this return on investment calculation, assuming a 7% discount rate. This project is expected to facilitate more effective management of corrosion across the DoD. If widely used and supported, it will increase operational and planning awareness of how materials selection and microclimates contribute to degrade facilities and equipment, crystallizing corrosion knowledge in an institutional tool. The ROI calculation is a comparison between baseline operational costs and the operational costs with the tool in place.

For this project, the baseline is the present method of doing business, which does not have in place a formal, quantitative software tool to assist corrosion prevention in material selection and design of weapons and facilities. The new system will improve materials selection and design of facilities and weapons systems and will lead directly to savings in life cycle maintenance and replacement costs. Also, it is assumed that the benefit will take 2 years to grow as implementation expands.

The full benefit of this technology is not expected to be realized immediately, since improved designs have associated procurement lead times, and their financial benefits will pay dividends over a long period of time. The benefit of this project could be applied widely across the DoD to address the truly massive costs of corrosion. A 2003 report to Congress by the Government Accountability Office states that the estimated cost of corrosion to DoD is between \$10 billion – \$20 billion annually.”\* The Army facilities portion of this corrosion cost is estimated to be \$300M annually, or about 17% of the annual Army facilities O&M budget. Because of the difficulty to quantify the benefits of this project, we estimate very conservatively estimate that this cost can be decreased by 1% per year. Even this ultra-conservative estimate for the Army Facilities yields a significant ROI of 33.07.

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\* Report to Congress, Department of Defense Long-Term Strategy to Reduce Corrosion and the Effects of Corrosion on the Military Equipment and Infrastructure of the Department of Defense, and United States General Accounting Office, Opportunities to Reduce Corrosion Costs and Increase Readiness, GAO-03-753, July 2003, page 3.

## 4.2 Projected return on investment (ROI)

Table 1 shows the Return on Investment calculation. This return will most likely manifest through direct improvements in the quality and readiness of Army facilities. The ROI calculation is run for a 10-year period, and is likely to be much larger if applied to both weapons and facilities design, as well as across the Armed Services. The return could also increase if applied for a longer time. There will be a cost to deploy and maintain the software, on the order of \$2,000 per year.

Table 4.1. Return on investment calculation.

<b>Return on Investment Calculation</b>							
							500
							33.07
							Percent 3307%
							14 16,550 16,536
A	B	C	D	E	F	G	H
Future Year	Baseline Costs	Baseline Benefits/Savings	New System Costs	New System Benefits/Savings	Present Value of Costs	Present Value of Savings	Total Present Value
1			2	500	2	467	485
2			2	500	2	437	435
3			2	3,000	2	2,449	2,447
4			2	3,000	2	2,289	2,287
5			2	3,000	1	2,139	2,136
6			2	3,000	1	1,999	1,995
7			2	3,000	1	1,868	1,867
8			2	3,000	1	1,748	1,745
9			2	3,000	1	1,632	1,631
10			2	3,000	1	1,524	1,524
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## **5 Conclusions and Recommendations**

### **5.1 Conclusions**

This work has produced an operational corrosion-rate predictive model based on indices developed through statistical analysis of a large database of empirical corrosion and weather records. Software implementations of the model are available for the metals included for copper, 6061 T6 aluminum, 7075 T6 aluminum, and a low carbon (1010) steel. The large databases compiled for this project are available to researchers and other parties interested in developing refinements or further applications based on the corrosion indices and predictive model.

By running a plot of predicted corrosion rate estimates against the actual observed corrosion rate data collected, the model showed a strong linear trend. This strong positive correlation of over 0.75 is a strong quantitative measurement of the model accuracy. This is a significant improvement over previous models which have shown much lower correlation rates.

The corrosion indices and predictive models may be used to estimate corrosion rates for the subject metals at field sites worldwide. This has proved to be important for new bases where there has been no prior history of operations or corrosion monitoring. All that is required is a minimal amount of weather data, and either an estimate or measurement of atmospheric chlorides. These data are available wherever flight operations are conducted.

### **5.2 Recommendations**

#### **5.2.1 Applicability**

The purpose of the software is to increase awareness of how atmospheric environmental severity varies with site location. Engineers benefit from having good information in making appropriate material selection choices for corrosion prevention and control. Planners benefit from accurate severity factors to make economic decisions for maintenance.

### 5.2.2 Implementation

When the model is cleared for release, distribution will be recommended through the DoD Corrosion Defense (CorrDefense) website, [www.corrdefense.org](http://www.corrdefense.org). Presentations and papers will be given at national technical conferences in order to publicize the availability to prospective users interested in adopting the model and dataset.

# **Appendix A: Project Management Plan for CPC Project AR-F-315**

## **TRI SERVICE PROGRAM DOD EQUIPMENT / FACILITIES**

**Development of Corrosion Indices and Life Cycle Prediction for  
Equipment and Facilities Based on the Corrosion Rates Determined  
From AR-F-311**

**TRI SERVICE PROGRAM  
EQUIPMENT/FACILITIES  
CORROSION PREVENTION AND CONTROL PROJECT PLAN  
Development of Corrosion Indices and Life Cycle Prediction for  
Equipment and Facilities Based on the Corrosion Rates Determined  
from AR-F-311**

15 June 2005

Submitted By:

Vincent F. Hock and

Richard Kinzie

U. S. Army Engineer Research & Development Center (ERDC)

Construction Engineering Research Laboratory (CERL)

Comm: 217-373-6753

(Project Number to be *assigned by OSD when approved*)

## 1. STATEMENT OF NEED

**PROBLEM STATEMENT:** Throughout the world, corrosion maintenance is most often based on finding and fixing the damage prior to its becoming a structural or safety concern. DoD has identified this approach as inadequate to meet mission criticality, e.g. equipment and facilities availability to support deployment, training, and readiness. There has been little emphasis on the development of engineering tools needed for the management of this corrosion and the associated maintenance and repair actions. The benefits and longevity of corrosion prevention and control measures have not been quantified so optimization of these actions has not been possible. As the DoD fleets and facilities have aged, the life limiting degradation mechanisms have shifted from those associated with usage to those associated with time. The costs of corrosion maintenance have risen drastically. Furthermore, the concerns for corrosion, which previously had centered around cost, have now begun to include structural integrity and safety. This shift has dictated a change to a prediction and management approach beyond just simply finding and fixing.

**IMPACT STATEMENT:** If this project is not funded, DoD fleet and installations managers will continue to manage corrosion primarily on a “find and fix” basis. New construction will continue to use materials selected based upon universal guidance and not take into account site-specific corrosion environments. Critical systems, such as heating, cooling and potable water systems and equipment, such as aircraft and weapons, will continue to fail prematurely and demand unscheduled repair or replacement.

## 2. PROPOSED SOLUTION

**TECHNICAL DESCRIPTION:** The prediction and management of corrosion damage requires first that the initial condition of the specific structure with respect to corrosion be defined. Subsequently the severity of the environment to which the structure is exposed must be measured and the time that the structure is exposed to that environment projected. The corrosion growth can then be projected with the use of appropriate models. The mechanical impacts of this damage can then be ascertained using structural models. This approach requires the development of multiple technologies and extensive amounts of data. Not only is extensive corrosion and structural modeling required, but also part specific damage definitions must be developed with the associated NDI techniques. This com-

plex effort will determine microclimate environmental severity factors and the associated corrosion growth rates.

This project will build a software based model of corrosion indices and use the data gathered under the FY05 Project AR-F-311 "Measuring the Rates and Impact of Corrosion on DoD on Equipment and Installations" and other related projects. This model of corrosion damage will be driven by microclimate atmospheric characteristics as well as materials and the geometry of construction details.

Previous corrosion index models have been only modestly successful in relating observed corrosion rates with microclimate data. The number of variables involved in atmospheric corrosion increases the complexity of the model, and empirical methods are frequently employed. We propose to also incorporate social behavioral data, including maintenance and equipment washdown cycle data. The model will build on previous corrosion studies at Army, Navy, Air Force and NASA sites which have measured site-specific corrosion data to predict how various materials are affected by the local environment.

Prior to this project, the accurate measurement of corrosion growth rates has also been elusive because accelerated laboratory methods seldom can be equated to time in the real environment. Likewise, well-developed and standardized outdoor exposure testing has been cumbersome and time consuming. There is a substantial body of corrosion rate data available from the previous project, ARF-311, which utilized a small exposure rack with coupons of bare copper, silver, two aluminum alloys, and mild steel as shown in Figure 1.

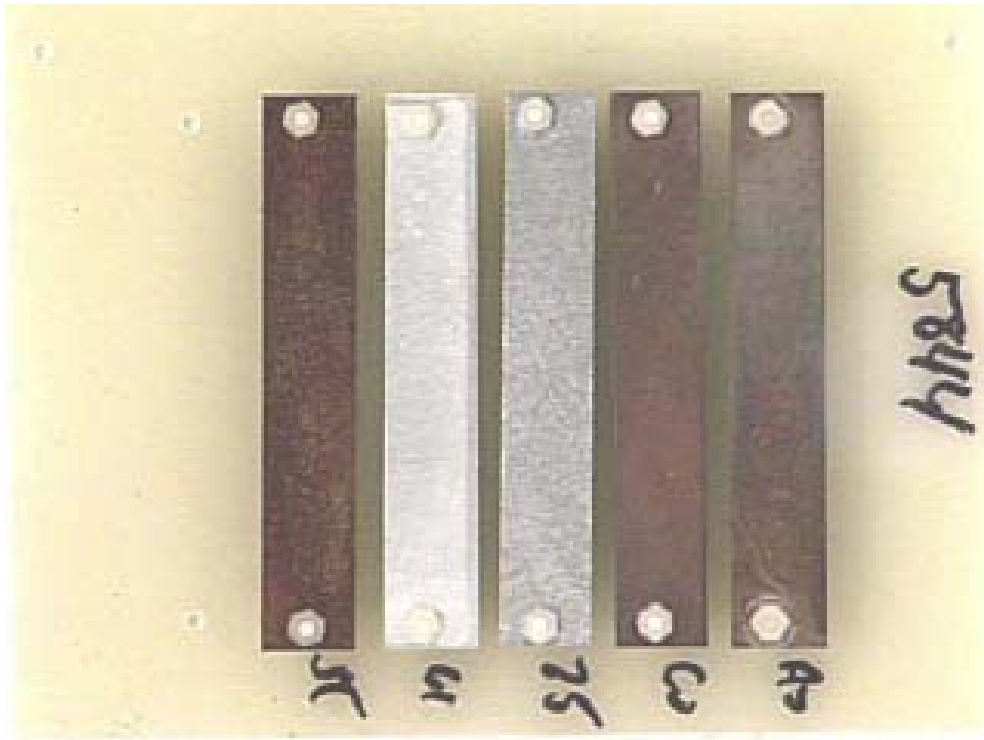


Figure 1. Metallic Exposure coupons on Plastic Standoffs

The silver and copper were analyzed for specific environmental components such as chlorides and other materials that drive the corrosion process. The steel and aluminum alloys were measured for weight loss. Analysis of the surface of these coupons also gave an indication of the type of damage, such as pitting or uniform material loss, which occurred. Additional weather data will be factored into the model by region, including humidity and rainfall data. Effective corrosion modeling requires extensive knowledge of structural corrosion beyond just the boldly exposed surfaces. Exfoliation corrosion typically occurs around fasteners on wing skins where the fastener and skin materials are galvanically dissimilar, i.e. steel fasteners in aluminum skin. Corrosion rates and damage inside occluded regions, such as those in crevices and lap joints, may be quite different than for the boldly exposed areas.

**TECHNOLOGY MATURITY:** The data required to build the corrosion modeling tool is available from various DoD, Academic, and Industrial sources. There is a high likelihood of building a successful model with a high correlation between microclimate data and observed corrosion rates. Project AR-F-311 and previous work were successful in establishing corrosion rates and impact for DoD installations representing a wide range of

environments and material exposures. This work extends the results of this effort for the development of a software based corrosion model for various environments.

**RISK ANALYSIS:** This is a **low risk** project, as the procedures for establishing corrosion rates and impact have been developed and implemented for DoD environments. This project will develop corrosion indices and life cycle prediction based upon the data.

**EXPECTED DELIVERABLES AND RESULTS/OUTCOMES:** The proposed FY06 work will develop a life cycle predictive tool to optimize preventive maintenance cycles based on region and material, for weapons and facilities. The predictive tool will be a location based corrosivity software model that will draw on the data acquired in the FY05 project. The downloadable software package which will assign a corrosion index to a site based on environmental data. The corrosion index will allow the user to develop select appropriate corrosion resistant materials, coatings, cathodic protection and water treatment for use in project specifications and maintenance practices. Material and process selection can then be tailored for both equipment and facilities DoD-wide based on the corrosion index. The efficacy of the corrosion index will also be determined for various environments.

**PROGRAM MANAGEMENT:** The Project Managers will be: Mr. Vincent Hock (ERDCCERL Project Manager and Metallurgist) and Mr. Richard Kinzie (USAF Corrosion Prevention and Control Office) The Associate Project Managers will be: Mr. Sean Morefield and Ms. Susan Drozd (ERDC-CERL). The stakeholders will be Mr. Steve Spadafora, NAVAIR, Mr. Steve Carr, USA, Mr. Tom Tehada (USN), Ms. Nancy Coleal (USAF), and Mr. David Purcell (ACSIM). Coordination with the Army Corrosion Programs Office is with Mr. Hilton Mills (AMC).

**This is a TriService Project.** Funds have been requested for Air Force, Army, and Navy representatives to participate in the evaluation of technology implementation.

### 3. COST/BENEFITS ANALYSIS

#### a. Funding (\$K):

Funding Source	OSD	IMA Matching
Labor	40	170
Materials	15	15
Navy / Air Force support	30	--
Travel	25	25
Report	90	90
Total	200	300

#### Development of Project Budget

The \$500K budget is realistic and adequate for the project scope. This budget includes \$300K in matching funds from HQ-IMA.

#### b. Return-On-Investment Computation:

1) Projected Useful Life Savings (ULS) is equal to the "Net Present Value (NPV) of Benefits and Savings" calculated from the Spreadsheet shown in Appendix 1 that is based on Appendix B of OMB Circular A94 using a 7% discount rate. ULS= \$16,500k (from OMB Spreadsheet in Appendix 1. Assumptions for this calculation are also given in Appendix 1).

2) Project Cost (PC) is shown as "Investment Required" in OMB Spreadsheet in Appendix 1; PC= \$500K.

ULS    \$16,500K

Potential ROI = ----- = ----- = 33.07

PC \$500K

The calculated ROI for this project, which is based on current best practices, projected maintenance and rehab cost, has the potential to increase over the multiple year implementation due to reduction in down time, which will result in increased indirect savings.

**c. Mission Criticality:** The operational benefits of implementation of the corrosion index for mission critical systems are: 1) enhanced performance,



safety and reliability, 2) life extension and reduced maintenance and repair for DoD facilities and equipment.

#### 4. SCHEDULE

##### MILESTONE CHART

EVENT	MONTHS AFTER RECEIPT OF FUNDS
Award Contract	2
Kickoff Meeting with Contractor	3
Initiate validation of indices	12
Complete Documentation	18

a. Note: If project is approved, ***bi-monthly status reports will be submitted*** (i.e. starting the first week of the second month after contract award and every two months thereafter until final report is completed). This report will be submitted to the DoD CPC Policy & Oversight office. Report will include project number, progress summary (and/or any issues), performance goals and metrics and upcoming events.

b. Examples of performance goals and metrics: include achieving specific milestones, reaching specific performance quality levels, meeting test and evaluation parameters, and/or successfully demonstrating a new system prototype.

#### Development Project Schedule

This project to establish rates of corrosion and impact of corrosion damage in specific environments will be completed, including final report, within 18 months. The goals of the project are: providing a basis for planning corrosion prevention and control for specific environments at DoD installations. Detailed milestones are given in the schedule section. Implementation of the chemical treatment system will be accomplished by Contractors. ERDC-CERL will provide overall management, contract monitoring and provide bi-monthly reports. Existing contract mechanisms, such as IDIQ and BAA will be used. ERDC-CERL will be able to award the contracts within 60 days of receipt of funds. Potential contractors have been identified.

## 5. IMPLEMENTATION

**a. Transportability / Transition approach:** Preventive maintenance actions dictated in General Series Equipment Corrosion Technical Manuals/Orders will be modified to reflect environmental severity impacts. Specific corrosion inspections and preventive maintenance frequencies will be optimized as determined by the weapon systems managers. Unified Facilities Guide Specifications (UFGS), Engineering Instructions (EI), Technical Instructions (TI), and Technical Manuals (TM), including updates, along with a final report describing the details of the project, will be developed and posted on the OSD Corrosion Exchange website. It is the intent of the Project Management Plan (PMP) to distribute the software tool at all DoD installations worldwide.

**b. Final Report:** A final report will be written 60 days after the project is completed. The report will reflect the project plan format as implemented and will include lessons learned.

### **Projected Benefits:**

Based on the results of the initial implementation of this approach for the USAF aircraft fleets, this project will be used to optimize materials selection and corrosion management approaches at the local level for DoD installations.

### **Operational Readiness**

An understanding of the local corrosion environment, corrosion rates for various materials, and the impact of corrosion damage will allow system developers and construction managers to select materials and plan corrosion prevention and control practices that will enhance the performance, reliability and safety of DoD equipment and facilities.

### **Management Support**

This project enjoys the support of the USAF Corrosion Prevention and Control Office, with specific support and funding from the USAF Aging Aircraft Office, Lt Col P. J. Clark. HQ-IMA and HQ-ACSIM are supporting this project. Moreover, the Army (HQIMA) plans to provide matching funds

(\$300K) for FY06. See attached Memorandum from ACSIM Director for Facilities and Housing in Appendix 1.

## 6. APPENDICES

### APPENDIX 1

#### **Return on Investment Assumptions and Calculation:**

The OMB Circular A94, Appendix B is used for this return on investment calculation, assuming a 7% discount rate. This project is expected to facilitate more effective management of corrosion across the DoD. If widely used and supported, it will increase operational and planning awareness of how materials selection and microclimates contribute to degrade facilities and equipment, crystallizing corrosion knowledge in an institutional tool. The ROI calculation is a comparison between baseline operational costs and the operational costs with the tool in place. For this project, the baseline is the present method of doing business, which does not have in place a formal, quantitative software tool to assist corrosion prevention in material selection and design of weapons and facilities. The new system will improve materials selection and design of facilities and weapons systems and will lead directly to savings in life cycle maintenance and replacement costs. Also, it is assumed that the benefit will take 2 years to grow as implementation expands. Also, the full benefit is not expected to manifest immediately, since improved designs have associated procurement lead times, and their financial benefits will pay dividends over a long period of time. The benefit of this project could be applied widely across the DoD to address the truly massive costs of corrosion. "The cost of corrosion to the DoD is estimated to be roughly between \$10 billion and \$20 billion annually.<sup>1</sup>" The Army facilities portion of this corrosion cost is estimated to be \$300M annually, or about 17% of the annual Army facilities O&M budget. Because of the difficulty to quantify the benefits of this project, we estimate very conservatively estimate that this cost can be decreased by 1% per year. Even this ultra-conservative estimate for the Army Facilities yields a significant ROI of 33.07. Table 1 shows the Return on Investment calculation. This return will most likely manifest through direct improvements in the quality and readiness of Army facilities. The ROI calculation is run for a ten year period, and is likely to be much larger if applied to both weapons and facilities design, as well as across the Armed Services. The return could also increase if applied for a longer time. There

will be a cost to deploy and maintain the software, on the order of \$2k per year.

<sup>1</sup> *REPORT TO CONGRESS, Department of Defense Long-Term Strategy to Reduce Corrosion and the Effects of Corrosion on the Military Equipment and Infrastructure of the Department of Defense, and United States General Accounting Office, Opportunities to Reduce Corrosion Costs and Increase Readiness, GAO-03-753, July 2003, page 3*

Table 1. Return on investment calculation.

Return on Investment Calculation							
Investment Required							500
Return on Investment Ratio						33.07	Percent 3307%
Net Present Value of Costs and Benefits/Savings						14	16,550 16,536
A	B	C	D	E	F	G	H
Future Year	Baseline Costs	Baseline Benefits/Savings	New System Costs	New System Benefits/Savings	Present Value of Costs	Present Value of Savings	Total Present Value
1			2	500	2	467	485
2			2	500	2	437	435
3			2	3,000	2	2,449	2,447
4			2	3,000	2	2,269	2,267
5			2	3,000	1	2,130	2,130
6			2	3,000	1	1,989	1,990
7			2	3,000	1	1,868	1,867
8			2	3,000	1	1,748	1,745
9			2	3,000	1	1,632	1,631
10			2	3,000	1	1,525	1,524
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**TRI SERVICE PROGRAM  
DOD EQUIPMENT / FACILITIES  
Development of Corrosion Indices and Life Cycle Prediction for Equipment and  
Facilities Based on the Corrosion Rates Determined From AR-F-311**

**Appendix 2**

**Signature Pages**

**6. COORDINATION SHEET**

<u>ORGANIZATION</u>	<u>SIGNATURE</u>	<u>DATE</u>
Associate Project Manager	<i>[Signature]</i>	27 SEP 2005
Project Manager	<i>Vincent J. Pol</i>	27 September 2005
ERDC/CERL Branch Chief	<i>Metzger</i>	28 SEP 05
AFRL/MLS-OLR	_____	_____
HQ ACSIM	_____	_____
HQ IMA	_____	_____
Tri Service Facilities WIPT Chair	_____	_____
HQ AMC	_____	_____

This is a Tri-Service Project. Funds have been requested for Air Force, Army and Navy representatives to participate in the evaluation of technology implementation.

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6. COORDINATION SHEET

<u>ORGANIZATION</u>	<u>SIGNATURE</u>	<u>DATE</u>
Associate Project Manager	_____	_____
Project Manager	_____	_____
ERDC/CERL Branch Chief	_____	_____
AFRL/MLS-OLR	<i>R. C. Kingie</i>	<i>28 Sep 05</i>
HQ ACSIM	_____	_____
HQ IMA	_____	_____
Tri Service Facilities WPT Chair	_____	_____
HQ AMC	_____	_____

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DOD EQUIPMENT / FACILITIES  
Development of Corrosion Indices and Life Cycle Prediction for Equipment  
and Facilities Based on the Corrosion Rates Determined From AR-F-311**

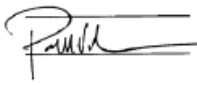
**6. COORDINATION SHEET**

<u>ORGANIZATION</u>	<u>SIGNATURE</u>	<u>DATE</u>
Associate Project Manager	_____	_____
Project Manager	_____	_____
ERDC/CERL Branch Chief	_____	_____
AFRL/MLS-OLR		<u>22 Sept 05</u>
HQ ACSIM		
HQ IMA	_____	_____
Tri Service Facilities WIPT Chair	_____	_____
HQ AMC	_____	_____

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<u>ORGANIZATION</u>	<u>SIGNATURE</u>	<u>DATE</u>
Associate Project Manager	_____	_____
Project Manager	_____	_____
ERDC/CERL Branch Chief	_____	_____
AFRL/MLS-OLR	_____	_____
HQ ACSIM	_____	_____
HQ IMA		29 Sep 05
Tri Service Facilities WIPT Chair	_____	_____
HQ AMC	_____	_____

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<u>ORGANIZATION</u>	<u>SIGNATURE</u>	<u>DATE</u>
Associate Project Manager	_____	_____
Project Manager	_____	_____
ERDC/CERL Branch Chief	_____	_____
AFRL/MLS-OLR	_____	_____
HQ ACSIM	_____	_____
HQ IMA	_____	_____
Tri Service Facilities WIPT Chair	<i>Thomas Leude</i>	9/29/05
HQ AMC	_____	_____

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**6. COORDINATION SHEET**

<u>ORGANIZATION</u>	<u>SIGNATURE</u>	<u>DATE</u>
Associate Project Manager	<u>isl</u>	<u>27 Sep 05</u>
Project Manager	<u>isl</u>	<u>27 Sep 05</u>
ERDC/CERL Branch Chief	<u>isl</u>	<u>28 Sep 05</u>
AFRL/MLS-OLR	<u>isl</u>	<u>28 Sep 05</u>
HQ ACSIM	<u>isl</u>	<u>15 June 05</u>
HQ IMA	<u>isl</u>	<u>29 Sep 05</u>
Tri Service Facilities WIPT Chair	<u>isl</u>	<u>15 June 05</u>
HQ AMC	<u>Will Entel</u>	<u>29 Sept 05</u>

This is a Tri-Service Project. Funds have been requested for Air Force, Army and Navy representatives to participate in the evaluation of technology implementation.

# Appendix B: Detailed Model Development and Statistical Analysis

## B.1 Introduction

Bare metal coupons - Aluminum 2024, Aluminum 6061, Aluminum 7075, Steel, and Copper – have been placed in widely varied locations around the globe. At regular intervals the cumulative corrosion in these metals has been measured, along with time of measurement. In addition, data have been obtained from public sources for other concomitant variables. These include percent time that relative humidity exceeded 70%, 80%, and 90% between the end of the previous time interval and the end of the current time interval; and cumulative precipitation through the end of current time interval. A measure of cumulative atmospheric chloride exposure through the end of the current time interval was also obtained from exposure of silver sensors. These data have been stored in a previously developed MSAccess database application and are available for querying.

The goal of this study is to develop a regression analysis of the corrosion levels of the various metals as a function of the critical environmental variables as defined in earlier analyses. As a first step, natural clusterings of overall weather type will be determined in order that the regression models for corrosion change be optimized to take fundamental weather “types” into account. A linear discriminant analysis will be used to build classification rules for these weather types so that as new locations are added to the database they may be appropriately classified according to the weather that predominates at those locations. The latter will be predominantly military bases worldwide.

The regression strategy is to build a model for the change in corrosion, of a given metal at a site having a known weather type, from the end of one time interval to the end of the subsequent time interval. The form of this model is linear and its structure is motivated by the previous work that was conducted in 2003. This metal- and weather-specific model may then be used to iteratively compute predictions for the cumulative corrosion in the given metal, over time, for a given site and specific concomitant variable values. The associated prediction intervals may also be built. It is de-

sirable to obtain a tractable set of regression models, ideally having the same structure.

## B.2. Data handling

### B.2.1. Data transfer

Data were extracted, by employees of Battelle Memorial Institute, from a MSAccess database application via table queries. The data were transferred via unsecured email by Bill Abbott (abbott@battelle.org) to David Paul, Ph.D. (david\_alan\_paul@yahoo.com), according to the following table:

Table B1. Data files and brief descriptions.

File Name	Description	Date of Transfer
All_AL2024_Data_1207.xls	AL2024 corrosion data only	26-Feb-07
qry_BaseResponsealldata_rev307.xls	Contains corrosion data, except for AL2024	5-Mar-07
qry_BaseExplanatory_alldata.xls	Concomitant variables	10-Mar-07

### B.2.2. Data processing and variable definitions

All data processing and statistical analyses were performed on a computer running WinXP Professional, SP2. The data were converted to comma-delimited format (.txt) and imported into an electronic database suitable for manipulation and statistical analysis. A substantial amount of data processing was required in order to build a database suitable for the statistical analysis. The details of these efforts are included in Appendix C. The following variables are included in the final database and are vital to the statistical analysis that is described in the next section:

Table B2. Description of key variables.

Variable Name	Definition
AFBASE	Name of geographic location/military base
ID	The ID value of the Air Force base. Valid values are from 1 to 243 by the software at time of data import
METAL	The type of metal being considered – AL2024, AL6061, AL7075, Steel, and Cu are the valid values for this variable.
TIMECHG	Denotes the length of time, in months, between the end of the preceding observation period and the end of the <i>current</i> observation period. TIMECHG is typically 3.0 months.
TIME	The cumulative elapsed time, in months, between TIME = 0 and the end of the <i>current</i> observation period.
RH70CHG / RH80CHG / RH90CHG	RHxCHG is defined to be the percentage of time the relative humidity exceeded x% from the end of the preceding observation period to the end of the <i>current</i> observation period.
RH70 / RH80 / RH90	RHx is the percentage of time the relative humidity exceeded x% from TIME = 0 to the end of the <i>current</i> observation period.
PRECIPCHG	The precipitation, in inches, from the end of the preceding observation period to the end of the <i>current</i> observation period.
PRECIP	The cumulative precipitation, in inches, from TIME = 0 to the end of the <i>current</i> observation period.
CHLORIDECHG	The atmospheric chloride exposure, measured in Å of silver chloride accumulated on silver sensors, from the end of the preceding observation period to the end of the <i>current</i> observation period.
CHLORIDE	The cumulative chloride exposure, measured in Å of silver chloride accumulated on silver sensors, from TIME = 0 to the end of the <i>current</i> observation period.
CORROSION_LAG	The cumulative corrosion for a given metal at a given site from TIME = 0 to the end of the <i>preceding</i> observation period.
CORROSION	The cumulative corrosion for a given metal at a given site from TIME = 0 to the end of the <i>current</i> observation period.
CORRCHG	The change in corrosion for a given metal at a given site from the end of the preceding observation period to the end of the <i>current</i> observation period.
DATYPE1	Indicates if the data came from the older method of observation (prior to 2004) or the newer method †

† Older method refers to practice of starting exposures of 4 sample sets at the same time in a test rack with planned removals at 3 month intervals over a 1 year period. Newer method refers to practice of exposing only one sample set at a time and exchanging every 3 months. These procedures may result in subtle differences in corrosion rates. Sample sets with ID<150 represent the Older Method.

## B.3. Statistical analysis

### B.3.1. Weather clusters and linear discriminant analysis

The humidity, precipitation, and chloride exposure at a particular location may be summarized using the 12-month cumulative humidity, precipitation, and chloride exposure at the site. This eliminates seasonal effects in the weather data.

Of the 177 total locations in the database, 12-month cumulative weather data are available in some form for 160 of these sites. This implies that 17 sites will remain unclassified according to weather type, and will not contribute to the subsequent regression modeling. Of the 160 sites having 12-month weather data, AL6061 records are predominant (not all metals were observed at equal time intervals):

Table B3. Amount of 12-month weather data available, by metal.

Metal	Proportion of Sites Having 12-Month Cumulative Weather Data
AL2024	62 / 160
AL6061	156 / 160
AL7075	137 / 160
Steel	139 / 160
Cu	99 / 160

The four sites not represented by AL6061 12-month cumulative weather measurements were “New Orleans 03 (208)”, “Amberley02 (103)”, “Stirling 02 (130)”, and “Williamtown02 (132)”. These weather data are available for these sites for the following metals:

Table B4. Metal-records providing 12-month cumulative weather data for those sites not represented by AL6061

Site Name	Metals for Which 12-month Cumulative Weather Data are Available
New Orleans 03 (208)	AL2024
Amberley02 (103)	AL7075, Steel
Stirling 02 (130)	AL7075, Steel
Williamtown02 (132)	AL7075, Steel

Therefore, 12-month cumulative weather data from AL6061 records were augmented with records from AL2024 and AL7075 to form a complete set of available 12-month cumulative weather data for the 160 sites actually contributing such data. These data were subjected to a classification algorithm known as Partitioning Around Medoids (PAM). In this methodology, the user specifies the number of desired groupings, and the method then derives the optimal allocation of these groupings to the various Air Force bases. The analysis conducted on the available weather data examined the consequences of choosing 2, 3, and 4 groupings. The variables used in this classification analysis are given in the following table:

Table B5. Variables used to classify sites according to 12-month weather data.

Variable Name	Definition
ID	The ID value of the location.
METAL	Data restricted to AL6061, AL2024, and AL7075 records.
TIME	Data restricted to TIME = 12 records.
RH70	RH70 is the percentage of time the relative humidity exceeded 70% from TIME = 0 to TIME = 12.
PRECIP	The cumulative precipitation, in inches, from TIME = 0 to TIME = 12.
CHLORIDE	The cumulative chloride exposure, measured in Å of silver chloride accumulated on silver sensors, from TIME = 0 to TIME = 12.

It was found that the 12-month weather data was optimally clustered into 3 distinct groupings. Graphical analyses and text supporting this claim may be found in Appendix D. The table on the following page shows the distributions of key variables within these three groupings. Weather group 1 may be considered “extreme” with respect to chloride exposure; weather group 2 may be considered “wet” because it exhibits the highest RH70 and PRECIP median values; and weather group 3 may be considered “dry” since it has the lowest RH70 and second lowest PRECIP median values.

It is of interest to note that the distribution of the DATTYPE1 variable is not uniform across the three groupings of weather data. A DATTYPE1 value of one (1) indicates that the data were collected using the newer method of sampling, while a value of zero (0) indicates that the data were collected using an older method. This detail is presented for information purposes, but in the final software available to users this distinction will be transparent.

Table B6. Summary statistics for key weather variables in the different weather groupings.

Grouping	N =	RH70 Median †	RH80 Median †	RH90 Median †	PRECIP Median ‡	CHLORIDE Median *	DATTYPE1 Mean **
None (all data)	160 (100%)	59.07	42.250	20.853	39.840	5,501	0.4063 (65 sites using new collection method)
1 ("extreme")	22 (14%)	62.78	38.000	11.5000	31.495	24,147	0.5455 (12 sites using new collection method)
2 ("wet")	47 (29%)	62.94	45.75	22.25	48.25	10,876	0.4043 (19 sites using new collection method)
3 ("dry")	91 (57%)	54.75	41.50	21.75	37.47	2,859	0.3736 (34 sites using new collection method)

† The RHx values represent the median percentage of time that the relative humidity exceeded x% from TIME = 0 through the end of the 12th month (TIME = 12).

‡ Precipitation is measured in inches of rainfall.

\* Chloride ion exposure is measured in Å of silver chloride accumulated on silver sensors.

\*\* DATTYPE takes the value zero (0) for those sites whose measurements were collected using an older method. DATTYPE takes the value one (1) for sites whose measurements were collected using a newer method.

Once the 160 sites having 12-month cumulative weather measurements were classified into one of three weather groupings, a linear discriminant rule was constructed, assuming proportional priors. The rule is summarized in the following table and may be used to classify new sites into one of the three weather groupings:

Table B7. Linear discriminant functions developed from the three weather groupings.

Grouping	Intercept	RH70 Coefficient	PRECIP Coefficient	CHLORIDE Coefficient
1 ("extreme")	-27.53927	0.24527	0.01993	0.00125
2 ("wet")	-11.60465	0.20943	0.03930	0.00056
3 ("dry")	-6.02955	0.17848	0.02111	0.00022



Given the relevant 12-month cumulative weather data (i.e., RH70, PRECIP, and CHLORIDE), a new site is classified into Group  $j$ , if the linear discriminant function for Group  $j$  is larger than either of the other two discriminant functions. For example, if the 12-month cumulative weather values for a new site are:

$$\{RH70 = 55.0, PRECIP = 41.5, CHLORIDE = 12,000\}$$

then the three discriminant functions are:

$$\text{Group 1: } -27.53927 + 0.24527(55.0) + 0.01993(41.5) + 0.00125(12000) = 1.03329$$

$$\text{Group 2: } -11.60465 + 0.20943(55.0) + 0.03930(41.5) + 0.00056(12000) = 8.26495$$

$$\text{Group 3: } -6.02955 + 0.17848(55.0) + 0.02111(41.5) + 0.00022(12000) = 7.30292$$

which implies that the new site would be classified into Group 2 since this discriminant function yields the largest value.

Again, these distinctions will be transparent to the user of the software. The effect will be for the software to utilize the best algorithm to predict the response of the metal-weather combination.

### B.3.2. Regression models for change in corrosion

The following table illustrates the amount of corrosion change data available for each type of metal, broken down by weather type and method of data collection (i.e., whether or not the data was collected using the older or newer methods described at the bottom of Table 2):

Table B8. Number of records corresponding to corrosion change for a given metal, by weather grouping and method of data collection.

Metal	Weather Group 1 ("extreme")			Weather Group 2 ("wet")			Weather Group 3 ("dry")		
	All Data	Older Data (ID < 150)	Newer Data (ID ≥ 150)	All Data	Older Data (ID < 150)	Newer Data (ID ≥ 150)	All Data	Older Data (ID < 150)	Newer Data (ID ≥ 150)
AL2024	58	0 †	58	93	0 †	93	172	0 †	172
AL6061 ‡	113	50	63	223	130	93	448	271 **	177
AL7075	93	30	63	198	105	93	409	235	174

	Weather Group 1 ("extreme")			Weather Group 2 ("wet")			Weather Group 3 ("dry")		
Steel	88	30	58	207	114	93	414	245	169
Copper	63	35	28 *	124	70	54	324	195	129

† Indicates that the method of data collection cannot be used as a regression covariate for AL2024.

‡ More data is available for AL6061, both overall and in each subcategory, than for any other metal.

\* Fewest number of records in any cell in the table, among those subcategory cells having nonzero counts.

\*\* Most number of records in any cell in the table, among those subcategory cells having nonzero counts.

Following the regression modeling strategy described in Harrell , it is desirable that the linear models that are developed not exhibit over-fitting or regression to the mean. From the guidelines in this text, it was determined that each regression model should consume no more than approximately 10 degrees of freedom. Ideally each model should also have the same structure so that differences between metals and weather groupings with respect to corrosion can be more easily determined.

#### *B.3.2.1. Assessment of data collection method*

The first step in the model-building process was to determine the statistical significance of DATTYPE1. If this concomitant variable is statistically significant, it implies that the method of data collection significantly impacts the measured corrosion levels, an undesirable result. Weather groups 2 and 3 had the most sites where the data collection was performed using the newer method (19 and 34, respectively) and AL6061 data is the most abundant of any metal. Any significant impact from DATTYPE1 with respect to R2 is most likely to be seen with these AL6061 data.

Therefore, an initial set of models for corrosion change in AL6061 for weather groups 2 and 3 was built. One set of models included RH70CHG, PRECIPCHG, CHLORIDECHG, CORROSION\_LAG, and all possible two-way interactions between RH70CHG, PRECIPCHG, CHLORIDECHG, and CORROSION\_LAG, for a total of 10 degrees of freedom each. Another set of models included the same predictor variables, with the addition of DATTYPE1, for a total of 11 degrees of freedom each.

The adjusted R2 for the AL6061 models excluding DATTYPE1, and associated with weather groups 2 and 3, were 72.9% and 72.4%, respectively.

The adjusted R<sup>2</sup> for the AL6061 models including DATTYPE1, and associated with weather groups 2 and 3, were 75.1% and 74.1%, respectively. The increase in R<sup>2</sup> due to the inclusion of DATTYPE1 is marginal; therefore, DATTYPE1 was dropped from further consideration in all model building for all metals.

#### *B.3.2.2. Variable selection*

The base model used in Section 3.2.1 to evaluate the influence of the method of data collection may include variables that do not contribute important information to the understanding of corrosion change, and may exclude important predictors. Therefore, the following variable selection method was adopted:

1. Approximately 10 total degrees of freedom will be allocated to each model, and the structure of the models will be the same.
2. Initial models for all metals except AL2024, and only for weather groups 2 and 3, will include the variables RH70CHG, PRECIPCHG, CHLORIDECHG, CORROSION\_LAG, and all possible two-, three-, and four-way interactions between them. These models will be used to determine which interaction terms should be kept in the final set of models used for all metals and all weather groups. There are a total of eight (8) initial models.
3. When a choice exists, preference is given to interaction terms of lesser order.
4. Two-, three- and four-way interaction terms will only be kept if they are statistically significant at  $\alpha = 0.10$  across at least 3 of the 8 models being considered
5. All main effects involving RH70CHG, PRECIPCHG, CHLORIDECHG, CORROSION\_LAG will be kept no matter what.

Application of this methodology yielded the following eight concomitant variables to be used in all the models for corrosion change:

**Table B9. Concomitant variables (including interaction terms) selected for use in all regression models.**

Variable Name
CHLORIDECHG
CORROSION_LAG
PRECIPCHG
RH70CHG
RH70CHG : CHLORIDECHG
RH70CHG : CORROSION_LAG
RH70CHG : CHLORIDECHG : PRECIPCHG
RH70CHG : CHLORIDECHG : CORROSION_LAG : PRECIPCHG

### *B.3.2.3. Modeling results*

The response variable CORRCHG (for a definition, see Table B2) was regressed on the concomitant variables given in Table B9, for each metal and weather group. This yielded a total of 15 regression models, which are described in Appendix E. From this appendix, the regression coefficients, t-tests, adjusted R<sup>2</sup>, and other model details may be found. Table B10 describes the properties of these models. From this table, it is seen that 11 of the 15 models have excellent adjusted R<sup>2</sup> values (greater than 72.3% in all cases). The predominance of the good explanatory power of the variables in Table 9 suggests that the variable selection method described in Section 3.2.2 worked.

Appendix F contains several pages of graphs showing the ability of these models to forecast total corrosion for a selected group of sites and metals. In the process of forecasting the total corrosion at the end of time k, the forecasted total corrosion at the end of time k-1 is treated as fixed and substituted for CORROSION\_LAG in the regression models. This has the effect of producing prediction intervals that are narrower than nominal.

Table B10. Summary of regression model characteristics.

Metal Model	Weather Group 1 ("extreme")			Weather Group 2 ("wet")			Weather Group 3 ("dry")		
	R <sup>2</sup>	Adjusted R <sup>2</sup>	p-value	R <sup>2</sup>	Adjusted R <sup>2</sup>	p-value	R <sup>2</sup>	Adjusted R <sup>2</sup>	p-value
AL2024	59.3%	50.9%	< 0.0001	78.5%	75.9%	< 0.0001	52.1%	49.2%	< 0.0001
AL6061	78.8%	76.8%	< 0.0001	74.5%	73.3%	< 0.0001	72.9%	72.3%	< 0.0001
AL7075	79.6%	77.1%	< 0.0001	54.1%	51.6%	< 0.0001	52.5%	51.3%	< 0.0001
Steel	83.5%	81.4%	< 0.0001	75.4%	74.2%	< 0.0001	73.5%	72.8%	< 0.0001
Copper	83.4%	80.4%	< 0.0001	75.6%	73.4%	< 0.0001	75.6%	74.8%	< 0.0001

## B.4 Conclusions

The regression models for corrosion change were successfully used to build forecasts for total corrosion, over time, for five types of bare metal coupons over three distinct types of cumulative weather. There were a total of 15 different regression models, each using the same set of predictor variables.

This methodology is inherently an approximation to a true repeated-measures statistical model. Furthermore, the regression methodology adopted in this analysis (and the previous analysis from 2003) explicitly assumed that the amount of corrosion change was linearly related not only to the weather exposure in a particular time interval, but also to the previous time interval's cumulative corrosion levels.

Table 11 summarizes the %relative error in predicted cumulative corrosion levels versus actual cumulative corrosion levels. The formula used to compute %relative error is as follows:

$$\frac{\text{Actual Cumulative Corrosion} - \text{Predicted Cumulative Corrosion}}{\text{Actual Cumulative Corrosion}} * 100 \quad (1.1)$$

Therefore, negative values in Table 11 imply that the predicted cumulative corrosion levels generally exceed the actual cumulative corrosion levels. Positive values in Table 11 have the opposite interpretation.

Upon inspection of Table 11, it is clear that there is generally a systematic bias such that predicted values at early time points (3 or 6 months) are generally less than the measured cumulative corrosion values. It is also clear that at later time points (9 or 12 months) there is a systematic bias such that predicted cumulative corrosion values are generally larger than the measured cumulative corrosion values. Those models having higher adjusted R<sup>2</sup> values tended to perform better than those having smaller adjusted R<sup>2</sup> values; nevertheless, with the exception of AL7075 in the “extreme” weather environment, the described systematic bias is apparent.

The appearance of a systematic bias calls into question the optimality of the assumption that corrosion change is linearly related to the predictor variables that are available. This suggests that future corrosion modeling efforts be undertaken to determine what, if any, nonlinear relationships exist between corrosion change and the available predictor variables (i.e., CORROSION\_LAG, RH70CHG, etc.). Exponential models may be indicated as a first step in any such effort.

Despite the appearance of biases in the predicted cumulative corrosion levels, the models developed in this report should continue to be useful. A comparison of the actual cumulative corrosion levels to the 95% prediction intervals associated with the models demonstrates that the actual cumulative corrosion levels are contained within them 83.7% of the time. This is very similar to the results obtained in 2003, and therefore represents a moderate and historically tolerable departure from the nominal 95%. Furthermore, the models developed in this report are better capable of handling a wider variety of weather patterns and types of metal – no models had previously been developed for AL2024.

Table B11. Median % relative error of predictions from the regression models

	Weather Group 1 ("extreme")	Weather Group 2 ("wet")	Weather Group 3 ("dry")
Metal Model	%Relative Error (TIME = 3, 6, 9, 12)	%Relative Error (TIME = 3, 6, 9, 12)	%Relative Error (TIME = 3, 6, 9, 12)
AL2024	(-49%, -29%, -19%, -13%) †	(17%, -3%, -6%, -38%)	(22%, -1%, -10%, -14%) †
AL6061	(20%, 10%, 1%, -1%)	(20%, 7%, -8%, -14%)	(18%, -2%, -9%, -9%)
AL7075	(-7%, 8%, 4%, 12%)	(14%, -19%, -42%, - 42%) †	(23%, 7%, -6%, -26%) †
Steel	(9%, -1%, -1%, -13%)	(33%, 16%, 3%, -20%)	(17%, 8%, -2%, -11%)
Copper	(11%, 4%, -1%, -8%)	(20%, -3%, -10%, -19%)	(45%, 14%, -35%, -45%)

† The regression models for these metal x weather group combinations have adjusted R2 values that are significantly lower than the rest of the models. See Table B10.





## Appendix C: Data Processing

### C.1. Modifications prior to data merging

The file “qry\_BaseResponsealldata\_rev307.txt” was modified according to the following list of changes and saved as “Response.txt”:

1. Deleted all records corresponding to AL2024 or missing corrosion levels.
2. Set the predicted, upper bound, and lower bound corrosion values to 0 at time = 0
3. Dropped HISTORYID, STARTDATE
4. Renamed several variables:
5. BASENAME = AFBASE
6. RECORDDATEMONTH = MONTH
7. RECORDDATEYEAR = YEAR
8. QUARTERINSEQUENCE = TIME

The file “qry\_BaseExplanatory\_allldata.txt” was modified according to the following list of changes and saved as “Explanatory.txt”:

1. Dropped HISTORYID
2. Renamed several variables:
3. ASSIGNEDID = ID
4. RECORDDATEYEAR = YEAR
5. CHLORINE = CHLORIDE
6. BASENAME = AFBASE
7. RECORDDATEMONTH = MONTH

The file “All\_AL2024\_Data\_1207.txt” was modified according to the following list of changes and saved as “AL2024.txt”:

1. Dropped BASE, START, RECORDDATEMONTH, RECORDDATEYEAR, MONTH, YEAR, STARTDATE
2. Renamed several variables:
3. BASENAME = AFBASE
4. QUARTERINSEQUENCE = TIME
5. ASSIGNEDID = ID

6. Converted the inputted Base ID numbers from the default character format to a numeric format

## **C.2 Merging the data, and modifications after data merging**

Firstly, the Response.txt and Explanatory.txt datasets were merged according to unique combinations of AFBASE, YEAR, MONTH. The resultant dataset was then modified according to the following list of changes and saved as "Corrosion.txt":

1. Dropped observations where the METAL variable was missing
2. Fixed a variety of METAL labeling mistakes:
  - a. "AL6062" changed to "AL6061"
  - b. "Copper" changed to "Cu"
  - c. "AL7076" changed to "AL7075"
3. Added the AL2024.txt records to the Corrosion.txt data – this is the first point at which the variables in the AL2024.txt data match up with the variables in Corrosion.txt.
4. For those records where MONTH, YEAR are available (ie, for non-AL2024 records), created a unifying DATE variable
5. Modified the data to make sure that at time = 0, all of the weather variables (RH70, RH80, RH90, PRECIP, CHLORIDE) are also 0.
6. Ensured that the Base ID variable was well-defined across all records for a given Base, when the ID existed. This consistency was not necessarily found in the raw data.
7. Some of the Bases did not have an ID. The following were fixed:
  - a. "Wheeler (229)" → ID = 229
  - b. "Whidbey (230)" → ID = 230
  - c. "Williamtown02 (132)" → ID = 132
  - d. "Winnipeg (231)" → ID = 231
  - e. "Amberley02 (103)" → ID = 103
  - f. "Knoxville (198)" → ID = 198
8. Created an indicator variable to denote observations that were collected using a "new" method vs the older method in the original database:
  - a. Base ID > 150 → "New Method", otherwise → "Old Method"
9. There were a handful of sites that had only one record for a given metal. These records were dropped since they are not helpful in model building.

The Corrosion.txt data was saved as "Corrosion.xls" and sent to Bill Abbot for examination. Two problems surfaced: some of the TIME variables did not match up with the DATE-variable ordering, and some sites had missing weather data for one or more types of metal. This initiated a back-and-forth process taking several weeks. The final result of this iterative data-cleaning was the new MSEXcel file "Corrosion3.xls". This file was then subjected to the following modifications and saved as "Corrosion3.txt":

1. There were a few sites that had duplicate records for the same METAL and DATE (but possibly different corrosion values). These duplicates were eliminated by creating a single record whose corrosion value corresponded to the mean of the corrosion values in the duplicate records.
2. A few of the corrosion values were not strictly non-decreasing, meaning that the measured corrosion levels in successive time periods would actually decrease. As this is nonsensical, these records were fixed using the following logic:
  - a. If AFBASE = "Daytona 75 (180)" and METAL = "AL2024" and TIME = 12 → CORROSION = 6159
  - b. If AFBASE = "KSC 1/4 (199)" and METAL = "AL7075" and TIME = 6 → CORROSION = 1475
  - c. If AFBASE = "KSC 1/4 (199)" and METAL = "AL7075" and TIME = 9 → CORROSION = 1657
  - d. If AFBASE = "West Jefferson (227)" and METAL = "AL7075" and TIME = 3 → CORROSION = 52
  - e. If AFBASE = "MSP 02 (124)" and METAL = "Steel" and TIME = 9 → CORROSION = 7969
3. Renamed several variables to indicate the fact that they correspond strictly to the weather exposure of the metals in a particular time interval (ie, do NOT represent cumulative weather exposure levels):
  - a. RH70 = RH70CHG
  - b. RH80 = RH80CHG
  - c. RH90 = RH90CHG
  - d. PRECIP = PRECIPCHG
4. Created several variables:
  - a. CORROSION\_LAG --- This is the cumulative corrosion in the previous time period
  - b. CORRCHG --- The change in corrosion from previous time period to the end of the current time period
  - c. TIME\_LAG --- The cumulative time of exposure up through the the previous time period

- d. TIMECHG --- The change in cumulative time from the previous period to the end of the current period, i.e. how long the current period is.
- e. CHLORIDE\_LAG --- The cumulative chloride exposure through the end of the previous time period
- f. CHLORIDECHG --- The chloride exposure only in the current time period
- g. RH70,RH80,RH90 --- These are the CUMULATIVE percentages of time where the relative humidity has exceeded 70%,80%, and 90%. These values take into account the length of time from time = 0 to the end of the current period.
- h. PRECIP --- Cumulative precipitation to the end of the current period

## Appendix D: Plots of Partitioning Around Medoids Clustering

Based on the graphical representations of the 2, 3, and 4 cluster solutions (Figure D1, Figure D2, and Figure D3), the  $k = 3$  cluster solution is clearly better. The  $k = 2$  cluster solution shows that Group 1 has a great many sites that are poorly classified (the negative silhouette width values on the left side of the graph). These sites do not classify easily into either Group 1 or 2. The  $k = 4$  solution shows that one of the groups only has two sites – Group 4. It is difficult to imagine defining a weather cluster on the basis of only two observed sites, and this solution is therefore not recommended.

The  $k = 3$  solution demonstrates excellent properties. There are a reasonable number of sites classed into each weather grouping – Groups 1, 2, and 3 have 22, 47, and 91 sites, respectively. The average silhouette width is 0.65, implying that there are sharp distinctions between the weather groups with respect to 12-month weather averages. Finally, there is little to suggest that sites are being improperly classified as evidenced by the virtual lack of negative silhouette values. Table B6 summarizes the cumulative weather variables for these three groupings.

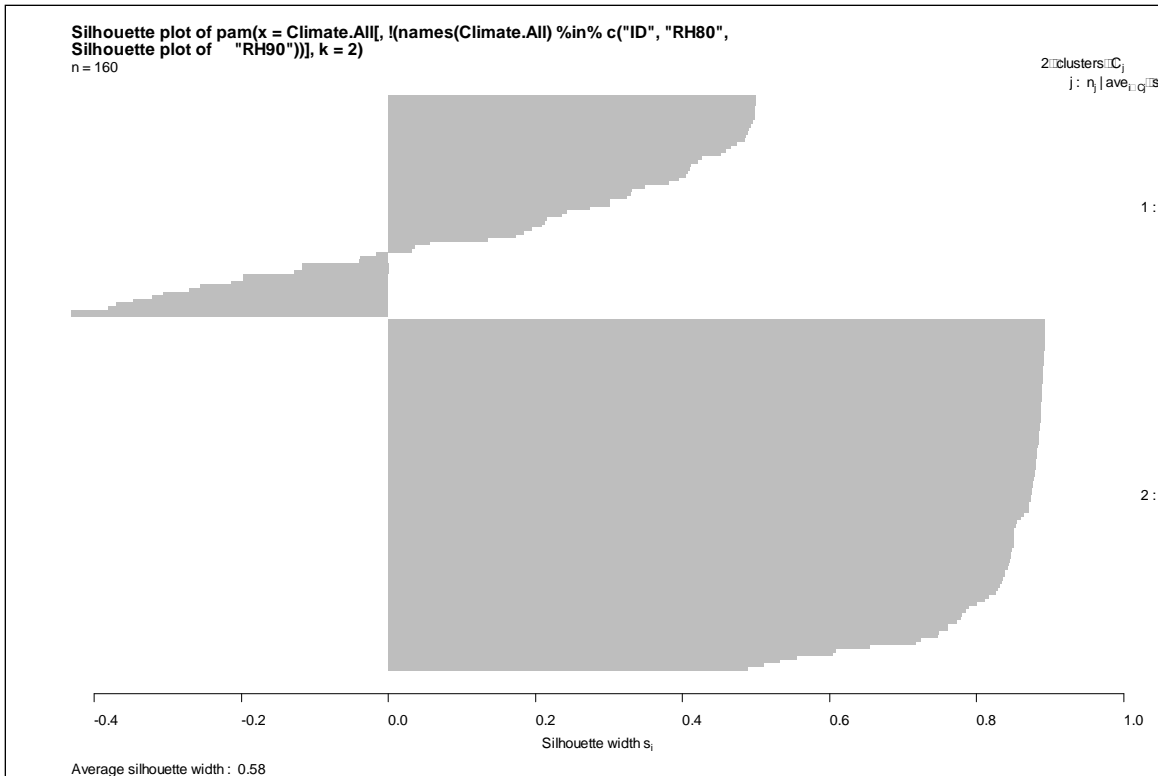


Figure D1. Average silhouette width and sample sizes for k = 2 clusters

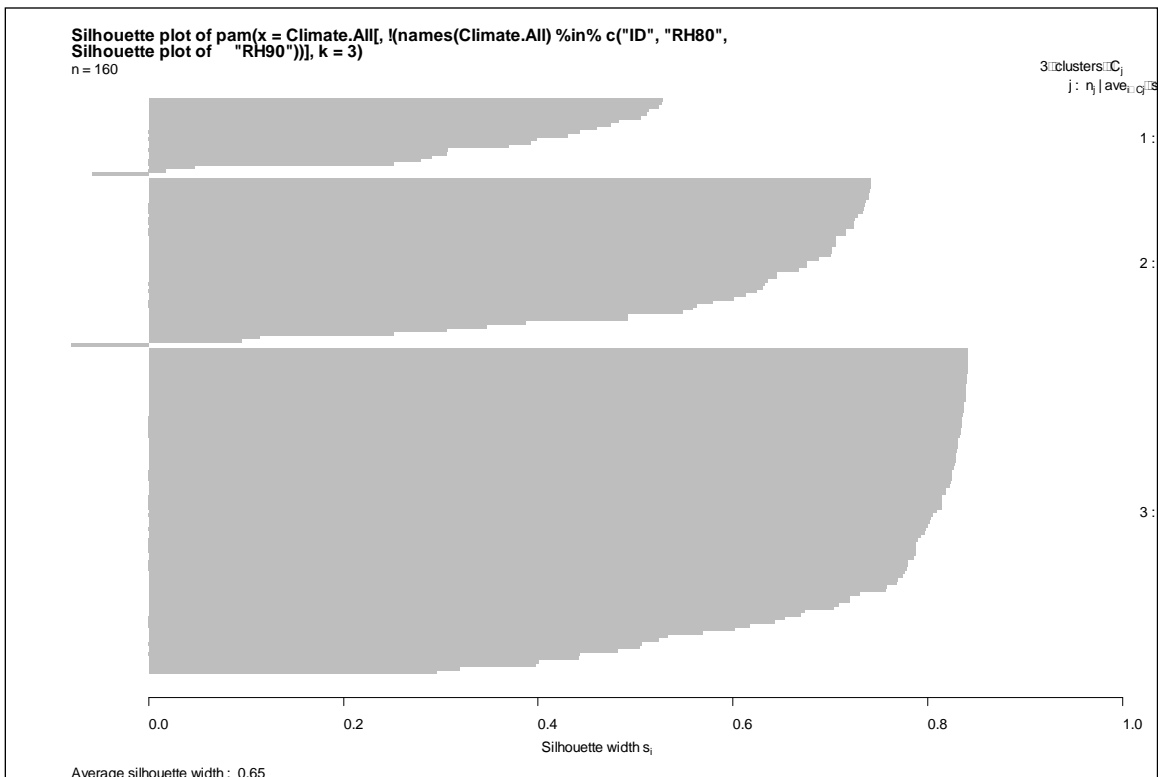


Figure D2. Average silhouette width and sample sizes for k = 3 clusters.

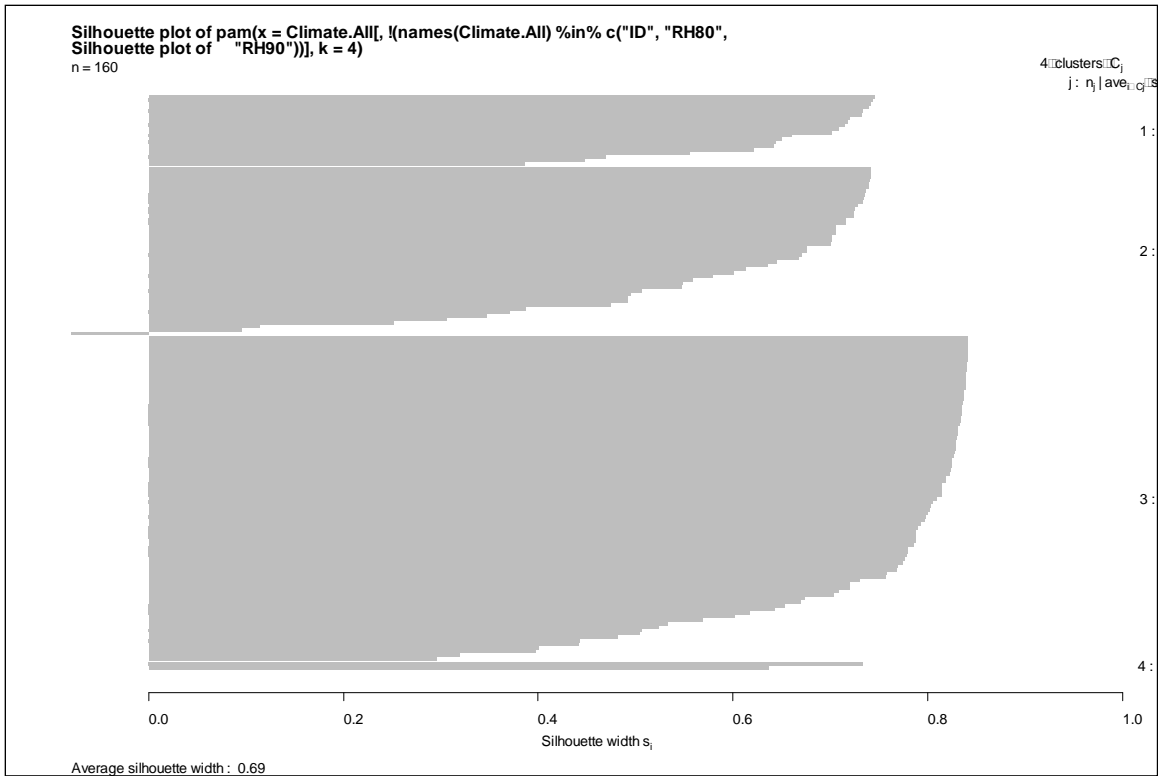


Figure D3. Average silhouette width and sample sizes for k = 4 clusters.





## Appendix E: Regression Models

This section details the code used in the creation of the model.

### E.1. Linear models for CORRCHG in AL2024

#### E.1.1 “Extreme” weather model (Group 1)

```
> summary(AL2024.gp1.lml)
```

Call:

```
lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
  CHLORIDECHG + CORROSION_LAG:RH70CHG + H70CHG:CHLORIDECHG +
  RH70CHG:PRECIPCHG:CHLORIDECHG +
  CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
  sion.Data2[Corrosion.Data2$Metal == "AL2024" & Corro-
  sion.Data2$Group == 1, ])
```

Residuals:

```
   Min 1Q  Median 3Q  Max
-1261.9 -183.4 -38.1  72.3 3046.9
```

Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG -5.36e-01  4.25e-01 -1.26  0.215
RH70CHG 8.24e+00  4.51e+00  1.83  0.075 .
PRECIPCHG -1.53e+01  3.80e+01 -0.40  0.690
CHLORIDECHG 4.54e-03  2.23e-02  0.20  0.840
CORROSION_LAG:RH70CHG 9.81e-03  6.44e-03  1.52  0.136
RH70CHG:CHLORIDECHG 7.34e-05  7.26e-04  0.10  0.920
RH70CHG:PRECIPCHG:CHLORIDECHG 4.53e-05  8.23e-05  0.55  0.585
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG -2.85e-08  1.96e-08 -
1.46  0.153
```

---

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 593 on 39 degrees of freedom

Multiple R-Squared: 0.593, Adjusted R-squared: 0.509

F-statistic: 7.1 on 8 and 39 DF, p-value: 9.35e-06

### E.1.2 “Wet” weather model (Group 2)

```
> summary(AL2024.gp2.lml)
```

Call:

```
lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
  CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
  RH70CHG:PRECIPCHG:CHLORIDECHG +
  CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
  sion.Data2[Corrosion.Data2$Metal == "AL2024" & Corro-
  sion.Data2$Group == 2, ])
```

Residuals:

```
Min 1Q Median 3Q Max
-565.9 -129.2 -34.4 31.9 991.2
```

Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG -7.21e-02 1.94e-01 -0.37 0.7109
RH70CHG 4.63e+00 1.74e+00 2.66 0.0098 **
PRECIPCHG -9.58e+00 1.12e+01 -0.86 0.3946
CHLORIDECHG 2.09e-02 2.85e-02 0.74 0.4649
CORROSION_LAG:RH70CHG 7.77e-03 2.48e-03 3.14 0.0025 **
RH70CHG:CHLORIDECHG -1.60e-03 8.58e-04 -1.86 0.0674 .
RH70CHG:PRECIPCHG:CHLORIDECHG 1.09e-04 5.69e-05 1.91 0.0600 .
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG -5.08e-08 2.74e-08 -
1.85 0.0684 .
```

---

```
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 254 on 67 degrees of freedom

Multiple R-Squared: 0.785, Adjusted R-squared: 0.759

F-statistic: 30.5 on 8 and 67 DF, p-value: <2e-16

### E.1.3 “Dry” weather model (Group 3)

```
> summary(AL2024.gp3.lml)
```

Call:

```
lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
  CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
  RH70CHG:PRECIPCHG:CHLORIDECHG +
  CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
  sion.Data2[Corrosion.Data2$Metal == "AL2024" & Corro-
  sion.Data2$Group == 3, ])
```

Residuals:

```
Min 1Q Median 3Q Max
-324.10 -31.48 -4.71 13.88 628.17
```

Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG 2.60e-01 1.72e-01 1.51 0.133
RH70CHG 5.03e-01 4.12e-01 1.22 0.224
PRECIPCHG -1.60e+00 2.85e+00 -0.56 0.575
CHLORIDECHG 6.73e-03 1.75e-02 0.38 0.702
CORROSION_LAG:RH70CHG -2.98e-03 2.69e-03 -1.11 0.270
RH70CHG:CHLORIDECHG 9.52e-04 5.14e-04 1.85 0.066 .
RH70CHG:PRECIPCHG:CHLORIDECHG -3.18e-05 3.82e-05 -0.83 0.407
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG 1.90e-07 7.69e-08
2.47 0.015 *
```

---

```
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 91.1 on 131 degrees of freedom

Multiple R-Squared: 0.521, Adjusted R-squared: 0.492

F-statistic: 17.8 on 8 and 131 DF, p-value: <2e-16

## E.2. Linear models for CORRCHG in AL6061

### E.2.1 “Extreme” weather model (Group 1)

```
> summary(AL6061.gp1.lm2)
```

Call:

```
lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
  CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
  RH70CHG:PRECIPCHG:CHLORIDECHG +
  CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
  sion.Data2[Corrosion.Data2$Metal == "AL6061" & Corro-
  sion.Data2$Group == 1, ])
```

Residuals:

```
   Min 1Q  Median 3Q  Max
-128.87 -42.50  -5.69  31.29 169.29
```

Coefficients:

```
   Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG 7.49e-02 1.73e-01 0.43 0.667
RH70CHG 8.52e-01 3.14e-01 2.72 0.008 **
PRECIPCHG 2.15e+00 1.53e+00 1.41 0.163
CHLORIDECHG -2.29e-04 2.38e-03 -0.10 0.924
CORROSION_LAG:RH70CHG 4.39e-04 2.93e-03 0.15 0.881
RH70CHG:CHLORIDECHG 1.37e-04 5.74e-05 2.39 0.019 *
RH70CHG:PRECIPCHG:CHLORIDECHG -9.37e-06 4.66e-06 -2.01 0.048 *
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG 2.76e-09 1.41e-08
0.20 0.845
```

---

```
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 60.9 on 83 degrees of freedom

Multiple R-Squared: 0.788, Adjusted R-squared: 0.768

F-statistic: 38.6 on 8 and 83 DF, p-value: <2e-16

## E.2.2 “Wet” weather model (Group 2)

```
> summary(AL6061.gp2.lm2)
```

Call:

```
lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
  CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
  RH70CHG:PRECIPCHG:CHLORIDECHG +
  CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
  sion.Data2[Corrosion.Data2$Metal == "AL6061" & Corro-
  sion.Data2$Group == 2, ])
```

Residuals:

```
   Min 1Q  Median 3Q  Max
-106.65 -31.66  -6.09  20.93  236.70
```

Coefficients:

```
   Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG -6.02e-02  1.14e-01  -0.53  0.599
RH70CHG 8.82e-01  2.21e-01  3.99  9.8e-05 ***
PRECIPCHG -6.28e-01  8.53e-01  -0.74  0.462
CHLORIDECHG 1.02e-02  4.98e-03  2.05  0.042 *
CORROSION_LAG:RH70CHG 3.13e-03  1.63e-03  1.93  0.056 .
RH70CHG:CHLORIDECHG -6.18e-05  1.11e-04  -0.56  0.579
RH70CHG:PRECIPCHG:CHLORIDECHG 1.68e-06  3.45e-06  0.49  0.627
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG -1.41e-08  1.32e-08  -
1.07  0.286
```

---

```
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 52 on 171 degrees of freedom

Multiple R-Squared: 0.745, Adjusted R-squared: 0.733

F-statistic: 62.5 on 8 and 171 DF, p-value: <2e-16

## E.2.3 “Dry” weather model (Group 3)

```
> summary(AL6061.gp3.lm2)
```

Call:

```
lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
  CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
  RH70CHG:PRECIPCHG:CHLORIDECHG +
  CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
  sion.Data2[Corrosion.Data2$Metal == "AL6061" & Corro-
  sion.Data2$Group == 3, ])
```

Residuals:

```
Min 1Q Median 3Q Max
-45.75 -14.31 -0.63 12.57 95.47
```

Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG 2.66e-01 5.19e-02 5.12 5.0e-07 ***
RH70CHG 3.78e-01 5.41e-02 7.00 1.3e-11 ***
PRECIPCHG 1.31e-01 2.74e-01 0.48 0.632
CHLORIDECHG 3.63e-03 3.11e-03 1.17 0.244
CORROSION_LAG:RH70CHG -4.33e-03 9.78e-04 -4.42 1.3e-05 ***
RH70CHG:CHLORIDECHG 1.86e-04 8.15e-05 2.28 0.023 *
RH70CHG:PRECIPCHG:CHLORIDECHG -6.22e-06 5.81e-06 -1.07 0.285
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG 2.98e-08 3.95e-08
0.76 0.450
```

---

```
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 20.4 on 350 degrees of freedom
```

```
Multiple R-Squared: 0.729, Adjusted R-squared: 0.723
```

```
F-statistic: 118 on 8 and 350 DF, p-value: <2e-16
```

### E.3. Linear models for CORRCHG in AL7075

#### E.3.1 "Extreme" weather model (Group 1)

```
> summary(AL7075.gp1.lm1)
```

Call:

```
lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
  CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
  RH70CHG:PRECIPCHG:CHLORIDECHG +
  CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
  sion.Data2[Corrosion.Data2$Metal == "AL7075" & Corro-
  sion.Data2$Group == 1, ])
```

Residuals:

```
Min 1Q Median 3Q Max
-409.6 -133.2 -46.3 42.7 758.2
```

Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG -4.38e-01 1.77e-01 -2.48 0.01581 *
RH70CHG 4.59e+00 1.44e+00 3.19 0.00214 **
PRECIPCHG -4.80e+00 7.83e+00 -0.61 0.54177
CHLORIDECHG 4.53e-03 8.40e-03 0.54 0.59102
CORROSION_LAG:RH70CHG 1.01e-02 2.49e-03 4.06 0.00013 ***
RH70CHG:CHLORIDECHG 4.00e-05 2.41e-04 0.17 0.86887
RH70CHG:PRECIPCHG:CHLORIDECHG 6.11e-07 1.84e-05 0.03 0.97370
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG -2.00e-08 6.67e-09 -
3.00 0.00381 **
```

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 239 on 67 degrees of freedom

Multiple R-Squared: 0.796, Adjusted R-squared: 0.771

F-statistic: 32.6 on 8 and 67 DF, p-value: <2e-16

### E.3.2 “Wet” weather model (Group 2)

```
> summary(AL7075.gp2.lm1)
```

Call:

```
lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
  CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
  RH70CHG:PRECIPCHG:CHLORIDECHG +
```

```
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
sion.Data2[Corrosion.Data2$Metal == "AL7075" & Corro-
sion.Data2$Group == 2, ])
```

Residuals:

```
Min 1Q Median 3Q Max
-504.3 -117.1 -50.0 16.5 1558.5
```

Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG 2.67e-01 1.72e-01 1.56 0.122
RH70CHG 2.45e+00 1.27e+00 1.94 0.054 .
PRECIPCHG 3.43e-01 6.09e+00 0.06 0.955
CHLORIDECHG 4.43e-03 2.38e-02 0.19 0.853
CORROSION_LAG:RH70CHG -1.58e-03 2.27e-03 -0.70 0.488
RH70CHG:CHLORIDECHG -3.96e-05 6.29e-04 -0.06 0.950
RH70CHG:PRECIPCHG:CHLORIDECHG 2.65e-07 2.98e-05 0.01 0.993
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG 2.37e-08 1.71e-08
1.39 0.167
```

---

```
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 259 on 151 degrees of freedom

Multiple R-Squared: 0.541, Adjusted R-squared: 0.516

F-statistic: 22.2 on 8 and 151 DF, p-value: <2e-16

### E.3.3 "Dry" weather model (Group 3)

```
> summary(AL7075.gp3.lm1)
```

Call:

```
lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
RH70CHG:PRECIPCHG:CHLORIDECHG +
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
sion.Data2[Corrosion.Data2$Metal == "AL7075" & Corro-
sion.Data2$Group == 3, ])
```



Residuals:

```

  Min 1Q  Median 3Q  Max
-284.80 -26.53 -5.91 13.06 840.36

```

Coefficients:

```

  Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG 2.04e-01 7.24e-02 2.81 0.0052 **
RH70CHG 3.93e-01 2.19e-01 1.79 0.0745 .
PRECIPCHG -4.71e-01 1.21e+00 -0.39 0.6971
CHLORIDECHG 5.11e-03 1.21e-02 0.42 0.6727
CORROSION_LAG:RH70CHG -2.10e-03 1.23e-03 -1.70 0.0903 .
RH70CHG:CHLORIDECHG 1.10e-03 3.33e-04 3.31 0.0010 **
RH70CHG:PRECIPCHG:CHLORIDECHG -6.36e-05 2.09e-05 -3.05 0.0025 **
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG 2.28e-07 4.96e-08
4.60 6.2e-06 ***

```

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 79.5 on 321 degrees of freedom

Multiple R-Squared: 0.525, Adjusted R-squared: 0.513

F-statistic: 44.3 on 8 and 321 DF, p-value: <2e-16

## E.4. Linear models for CORRCHG in Steel

### E.4.1 "Extreme" weather model (Group 1)

```
> summary(Steel.gp1.lm1)
```

Call:

```

lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
  CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
  RH70CHG:PRECIPCHG:CHLORIDECHG +
  CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
  sion.Data2[Corrosion.Data2$Metal == "Steel" & Corro-
  sion.Data2$Group == 1, ])

```

Residuals:

```

Min 1Q Median 3Q Max
-23361 -4699 162 3545 34705

Coefficients:

Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG -6.56e-02 1.74e-01 -0.38 0.71
RH70CHG 8.87e+01 6.55e+01 1.35 0.18
PRECIPCHG 4.16e+02 3.94e+02 1.06 0.30
CHLORIDECHG 3.15e-01 4.14e-01 0.76 0.45
CORROSION_LAG:RH70CHG 3.54e-03 2.93e-03 1.21 0.23
RH70CHG:CHLORIDECHG 1.86e-02 1.12e-02 1.66 0.10
RH70CHG:PRECIPCHG:CHLORIDECHG -3.33e-04 1.01e-03 -0.33 0.74
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG -7.78e-09 1.03e-08 -
0.76 0.45

Residual standard error: 10700 on 63 degrees of freedom

Multiple R-Squared: 0.835, Adjusted R-squared: 0.814

F-statistic: 39.9 on 8 and 63 DF, p-value: <2e-16

```

#### E.4.2 “Wet” weather model (Group 2)

```

> summary(Steel.gp2.lml)

Call:
lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
RH70CHG:PRECIPCHG:CHLORIDECHG +
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
sion.Data2[Corrosion.Data2$Metal == "Steel" & Corro-
sion.Data2$Group == 2, ])

Residuals:

Min 1Q Median 3Q Max
-22332 -4648 -694 3833 56121

Coefficients:

Estimate Std. Error t value Pr(>|t|)

```

```

CORROSION_LAG -1.89e-01 1.27e-01 -1.49 0.137
RH70CHG 6.43e+01 4.08e+01 1.57 0.117
PRECIPCHG 2.19e+01 2.00e+02 0.11 0.913
CHLORIDECHG 1.43e+00 8.03e-01 1.78 0.076 .
CORROSION_LAG:RH70CHG 7.56e-03 1.69e-03 4.47 1.5e-05 ***
RH70CHG:CHLORIDECHG -1.10e-02 2.02e-02 -0.55 0.586
RH70CHG:PRECIPCHG:CHLORIDECHG 1.13e-03 1.03e-03 1.10 0.272
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG -4.05e-08 1.59e-08 -
2.54 0.012 *

```

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8720 on 158 degrees of freedom

Multiple R-Squared: 0.754, Adjusted R-squared: 0.742

F-statistic: 60.7 on 8 and 158 DF, p-value: <2e-16

#### E.4.3 “Dry” weather model (Group 3)

```
> summary(Steel.gp3.lml)
```

Call:

```

lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
RH70CHG:PRECIPCHG:CHLORIDECHG +
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG -1, data = Corro-
sion.Data2[Corrosion.Data2$Metal == "Steel" & Corro-
sion.Data2$Group == 3, ])

```

Residuals:

```

Min 1Q Median 3Q Max
-9677 -2374 -556 2027 15976

```

Coefficients:

```

Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG 2.45e-01 5.85e-02 4.18 3.7e-05 ***
RH70CHG 4.77e+01 1.08e+01 4.44 1.2e-05 ***

```

```

PRECIPCHG 1.49e+02 6.03e+01 2.47 0.01394 *
CHLORIDECHG 8.50e-01 5.68e-01 1.50 0.13565
CORROSION_LAG:RH70CHG -3.99e-03 1.13e-03 -3.54 0.00046 ***
RH70CHG:CHLORIDECHG 4.99e-02 1.62e-02 3.07 0.00228 **
RH70CHG:PRECIPCHG:CHLORIDECHG -4.82e-03 1.17e-03 -4.13 4.6e-05
***
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG 1.73e-07 2.77e-08
6.24 1.3e-09 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 3750 on 325 degrees of freedom
Multiple R-Squared: 0.735, Adjusted R-squared: 0.728
F-statistic: 112 on 8 and 325 DF, p-value: <2e-16

```

## E.5. Linear models for CORRCHG in Copper

### E.5.1 “Extreme” weather model (Group 1)

```

> summary(Cu.gp1.lm1)

Call:
lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
  CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
  RH70CHG:PRECIPCHG:CHLORIDECHG +
  CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
  sion.Data2[Corrosion.Data2$Metal == "Cu" & Corrosion.Data2$Group
  == 1, ])

Residuals:

    Min     1Q   Median     3Q    Max
-2564.1 -969.7  -47.7   849.6 3159.6

Coefficients:

    Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG 1.50e-01 2.57e-01 0.58 0.562
RH70CHG 3.32e+01 1.31e+01 2.54 0.015 *

```

```

PRECIPCHG 2.35e+01 6.85e+01 0.34 0.733
CHLORIDECHG 3.57e-01 3.77e-01 0.95 0.349
CORROSION_LAG:RH70CHG 4.89e-05 4.50e-03 0.01 0.991
RH70CHG:CHLORIDECHG -4.89e-03 6.43e-03 -0.76 0.451
RH70CHG:PRECIPCHG:CHLORIDECHG -1.95e-04 2.06e-04 -0.95 0.347
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG 2.04e-08 1.66e-08
1.23 0.227

```

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1490 on 43 degrees of freedom

Multiple R-Squared: 0.834, Adjusted R-squared: 0.804

F-statistic: 27.1 on 8 and 43 DF, p-value: 2.09e-14

## E.5.2 “Wet” weather model (Group 2)

```
> summary(Cu.gp2.lm1)
```

Call:

```

lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
RH70CHG:PRECIPCHG:CHLORIDECHG +
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
sion.Data2[Corrosion.Data2$Metal == "Cu" & Corrosion.Data2$Group
== 2, ])

```

Residuals:

```

Min 1Q Median 3Q Max
-2600 -852 -128 539 4588

```

Coefficients:

```

Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG 2.68e-01 1.11e-01 2.42 0.018 *
RH70CHG 5.55e+00 7.88e+00 0.70 0.483
PRECIPCHG 2.99e+01 4.33e+01 0.69 0.491
CHLORIDECHG -1.22e-02 2.09e-01 -0.06 0.954

```

```

CORROSION_LAG:RH70CHG -8.87e-04 1.77e-03 -0.50 0.617
RH70CHG:CHLORIDECHG 7.22e-03 4.55e-03 1.59 0.116
RH70CHG:PRECIPCHG:CHLORIDECHG -3.16e-04 2.08e-04 -1.52 0.132
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG -1.48e-09 1.04e-08 -
0.14 0.887
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1290 on 92 degrees of freedom
Multiple R-Squared: 0.756, Adjusted R-squared: 0.734
F-statistic: 35.6 on 8 and 92 DF, p-value: <2e-16

```

### E.5.3 “Dry” weather model (Group 3)

```
> summary(Cu.gp3.lml)
```

Call:

```
lm(formula = CORRCHG ~ CORROSION_LAG + RH70CHG + PRECIPCHG +
CHLORIDECHG + CORROSION_LAG:RH70CHG + RH70CHG:CHLORIDECHG +
RH70CHG:PRECIPCHG:CHLORIDECHG +
CORROSION_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG - 1, data = Corro-
sion.Data2[Corrosion.Data2$Metal == "Cu" & Corrosion.Data2$Group
== 3, ])

```

Residuals:

```

Min 1Q Median 3Q Max
-1397 -486 -135 347 3026

```

Coefficients:

```

Estimate Std. Error t value Pr(>|t|)
CORROSION_LAG 5.31e-01 5.62e-02 9.45 < 2e-16 ***
RH70CHG 9.11e+00 2.30e+00 3.97 9.5e-05 ***
PRECIPCHG -1.80e+01 1.29e+01 -1.39 0.165
CHLORIDECHG 2.90e-01 1.15e-01 2.52 0.012 *
CORROSION_LAG:RH70CHG -2.59e-03 1.11e-03 -2.34 0.020 *
RH70CHG:CHLORIDECHG -5.57e-03 3.57e-03 -1.56 0.121

```

RH70CHG:PRECIPCHG:CHLORIDECHG 7.83e-05 2.53e-04 0.31 0.757

CORROSION\_LAG:RH70CHG:PRECIPCHG:CHLORIDECHG 7.92e-08 8.29e-08  
0.96 0.340

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 711 on 253 degrees of freedom

Multiple R-Squared: 0.756, Adjusted R-squared: 0.748

F-statistic: 98 on 8 and 253 DF, p-value: <2e-16





## Appendix F: Instructions for Installing Application Program

In order for the software to run correctly, the executable version of the model must reside in the same folder with 2 other files. These files are Excel spreadsheets with the precise names of Base Explanatory Import and Base Response Import. Example files are provided on the same disc with the model. This requirement exists even if the files are empty of data. However, it is worth noting that these same files provide the means from which new data can be imported into the model. A review of the file headings will immediately indicate which type of data should go into which file. See Appendix B for more detail.

Figure F1 shows the Main Menu which should appear after clicking on the Model icon. At this point, the only button that should be relevant is the one called Build Scenario. Clicking on this button should lead to Figure F2 which is the Main Screen for the model.

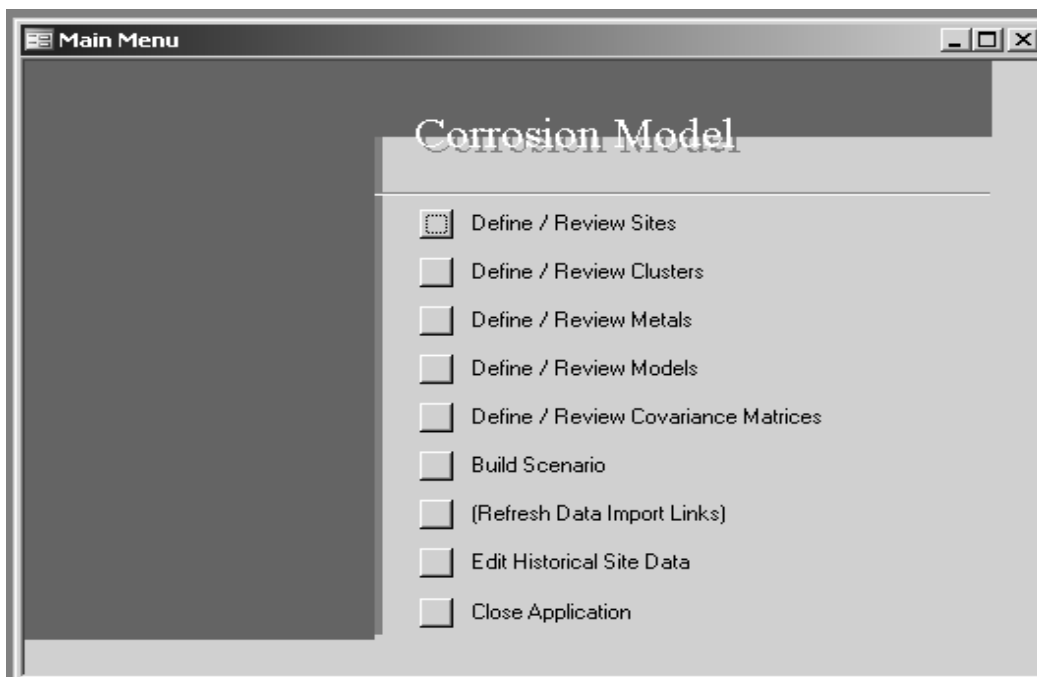


Figure F1. Startup screen/main menu.

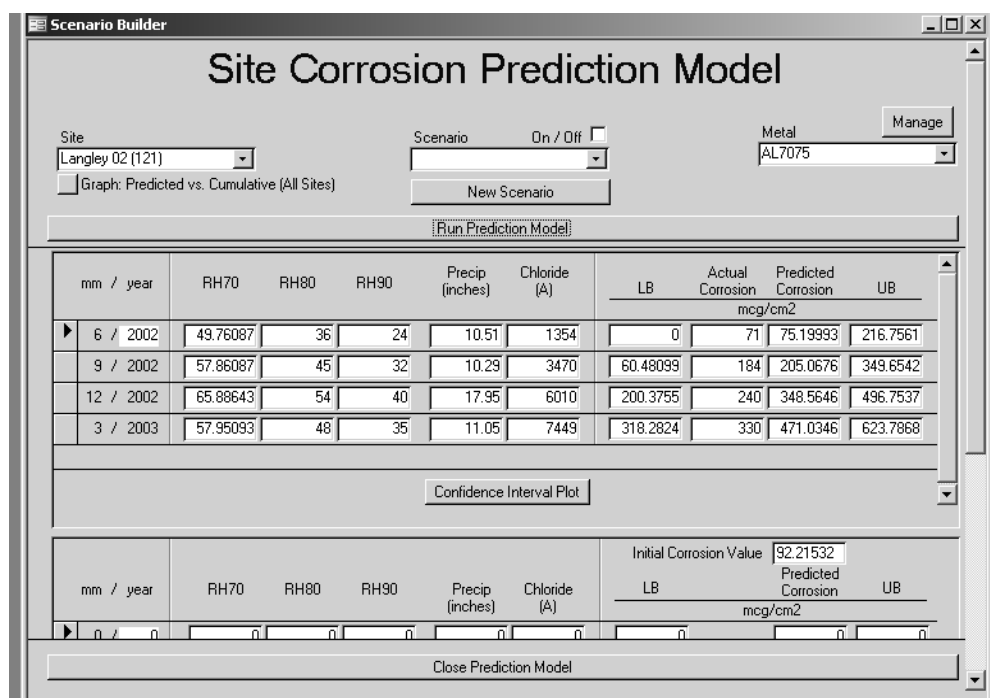


Figure F2. Main screen showing output and raw data for a particular site and metal.

Attention should be drawn to the Manage button at the upper right of the screen. This provides the entry to a password protection feature that still exists and which allows one to select a particular metal of interest. At present the password is set to 1234. In the example shown the metal for which data are displayed is 7075.

There is a dropdown box at the left with the name Site. This allows for selection of one of many sites for which data already exist in the Access database. This database actually resides within the model and in one sense serves as a repository of field and associated weather data collected by Battelle studies over the last decade.

When a site is selected, the associated data for that particular site appears in the boxes in the center of the screen as shown in Figure F2. It is noted that the various RH values shown are those representing the percentage of time during the interval in question that the humidity exceeded 70, 80, and 90% relative humidity. The precipitation value is total rainfall in inches over the same period. The chloride value is given as an equivalent film thickness of silver chloride obtained on Battelle silver sensors exposed for the same period.

The four right-most boxes show values related to corrosion. The only data actually as inputs to the model are the values called Actual Corrosion. These are the corrosion data collected by Battelle and expressed as cumulative weight loss in micrograms per square centimeter through the end of each monitoring period. The remaining values in the other three boxes are values calculated from the statistical models. These include the upper and lower 95% confidence boundaries.

If we return briefly to Figure F1 attention may be drawn to the button, Edit Historical Site Data. This may take one to the screen of Figure F3. This allows one to make any manual corrections to any of the raw data. It is also possible using this screen to add new data. However, in this event and if the data are more than a few lines, it is probably more efficient to Import data from any new data residing in the Excel spreadsheets mentioned earlier. The Import feature can be accessed from the Define/Review Site button. The resulting screens should be self explanatory.

**Metals Reference**

	Metals Reference	MetalID	Metal	Description	Comments
▶ +		1	AL6061	AL6061 Aluminu	
+		3	Cu	Copper	
+		4	Steel	Steel	
+		5	AL7075	AL7075 Aluminu	

Record: 1 of 5

Select New Site Here: Atlanta (159)

Current Site Name: Atlanta (159) ID: 159

**Climatology Data**

	Year	Month	RH70	RH80	RH90	Precip
▶	2003	11	60.430646835	43	23	
	2004	3	47.5480912285	37	15	
	2004	6	40.7369510543333	26	5	
	2004	9	55.9260179056667	39	7	
*	0	0	0	0	0	

Select New Site Here: [ ]

Current Site Name: [ ] ID: [ ]

Close

Figure F3. Data editing feature.

It might be noted in Figure F2 and Figure F3 that each site name has a unique ID. In these cases the sites Langley02 and Atlanta have IDs associated with them of 121 and 159, respectively. These are not user determined but are assigned by the software on data import. The user should not attempt to alter these.

There is a box in the center of Figure F2 labeled Run Prediction Model. This should routinely be activated to produce any updates to the data in the boxes below. Once this is done, the user can run the graphical output features in the model that can be activated from the box Confidence Interval Plot.

Recent updates have been made to the software. Operations are little changed from what was just described. However, some new features have been added. These features are shown in Figure F4 and Figure F5. The main change in the Main Menu screen is the routine for Generalized Plotting.

Figure 9 shows changes in the Site Corrosion screen that was accessed from the Build Scenario button. There are 2 changes. One is to add a result to describe an ESI level (Environmental Severity Index). This is largely a term derived from USAF definitions. The second change is to a graphing routine that was designed to show Actual vs Predicted corrosion rates by metal and for each of three possible categories of environment (Dry, Wet, or Extreme) as defined by statistical criteria. These can be run for one metal and condition combination at a time. However, we are examining the possible option of making this inclusive of all three conditions and by metal.

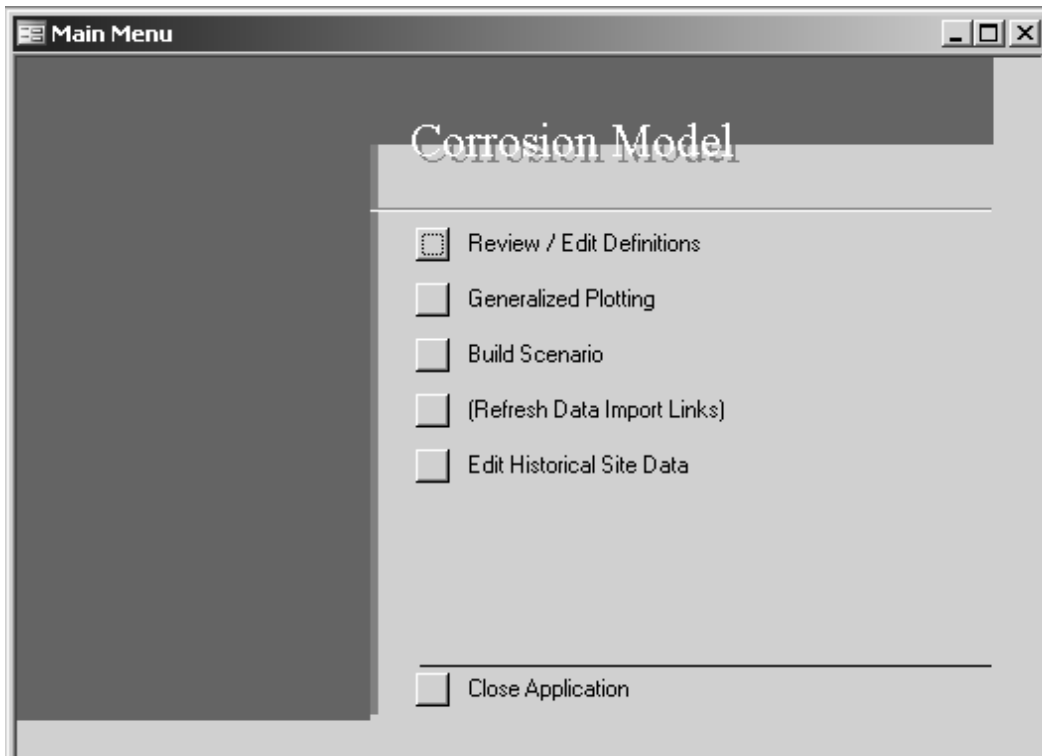


Figure F4. Main screen with new addition for plotting routine.

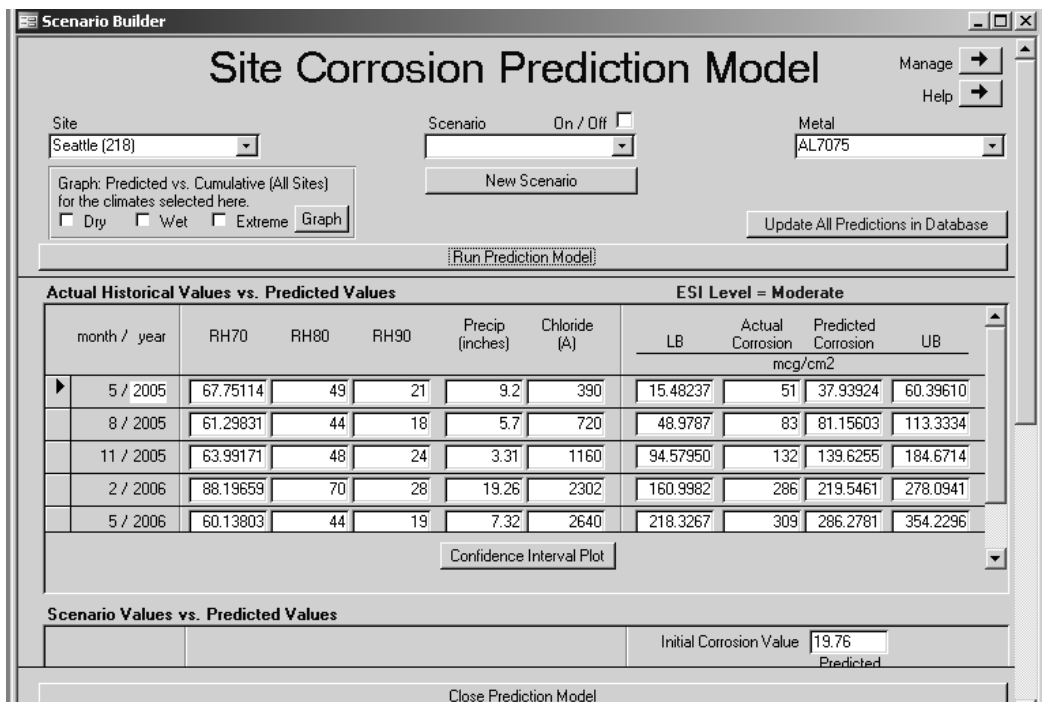


Figure F5. Scenario screen with additions of graph options for cumulative vs predicted values by metal and ESI.

Figure F6 shows the new screen accessible from the Main Menu for various graphing options. The main intent originally was to allow the user to

graph kinetics by metal and compare various sites. However, this was quickly expanded to allow graphing of other critical variables.

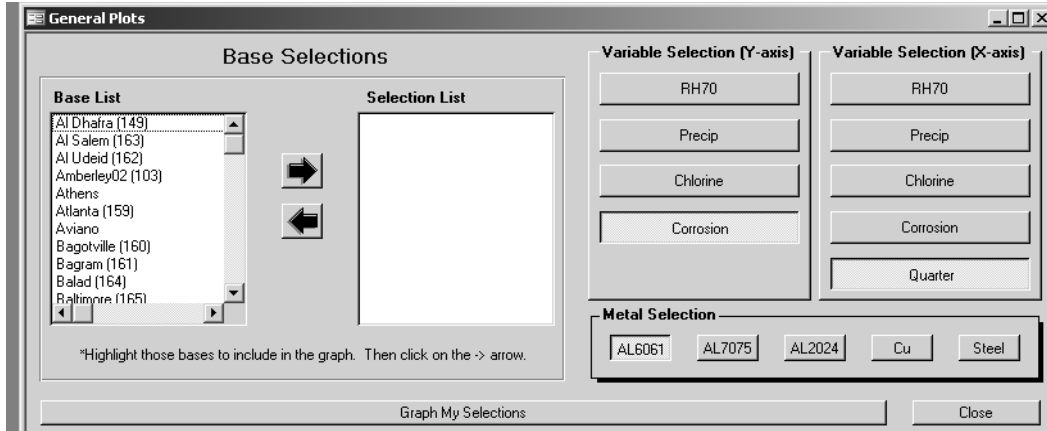


Figure F6. Plotting routine options.

# Appendix G: Plots of Regression Models for Selected Sites and Metals

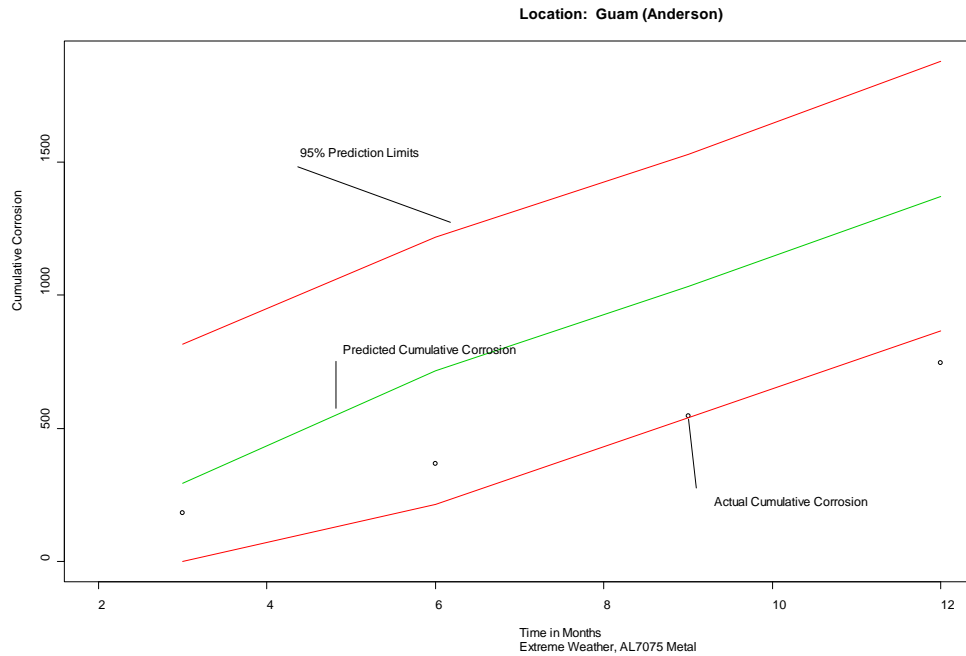


Figure G1. Depiction of modeled results vs actual results for Guam (Anderson), AL7075.

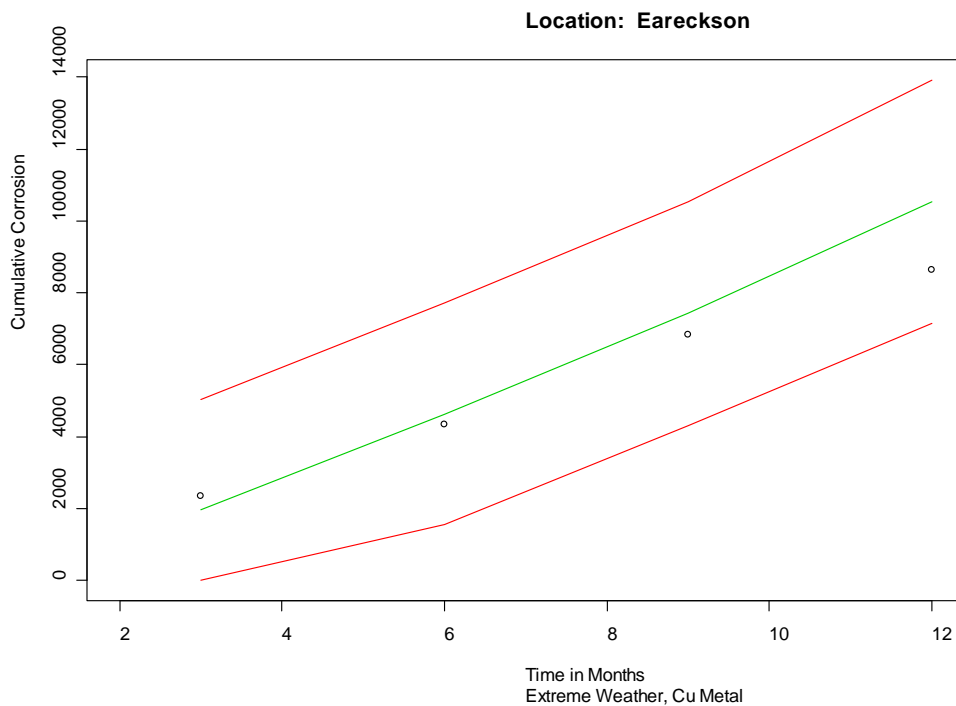


Figure G2. Depiction of modeled results vs actual results for Eareckson, Cu.

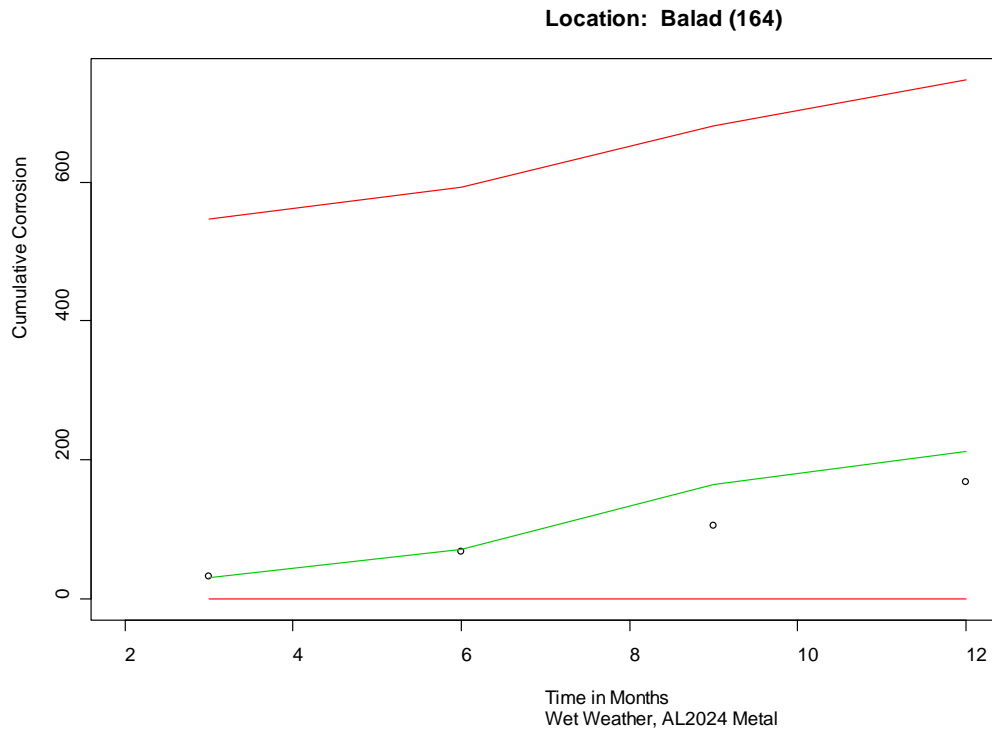


Figure G3. Depiction of modeled results vs actual results for Balad (164), AL2024.

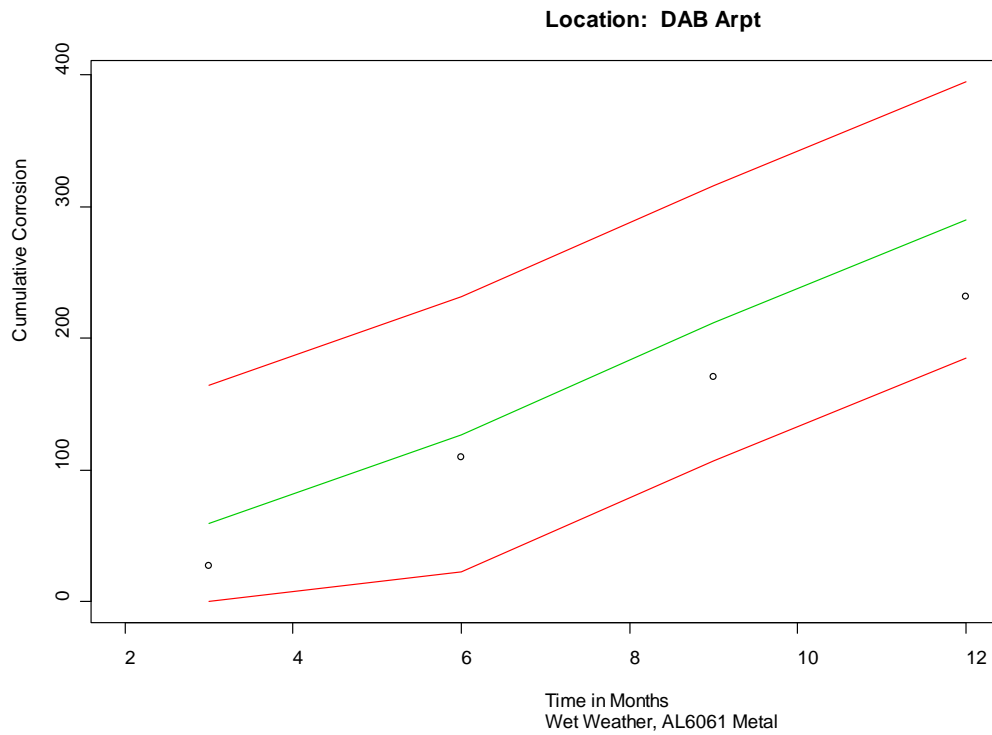


Figure G4. Depiction of modeled results vs actual results for DAB Arprt, AL6061.



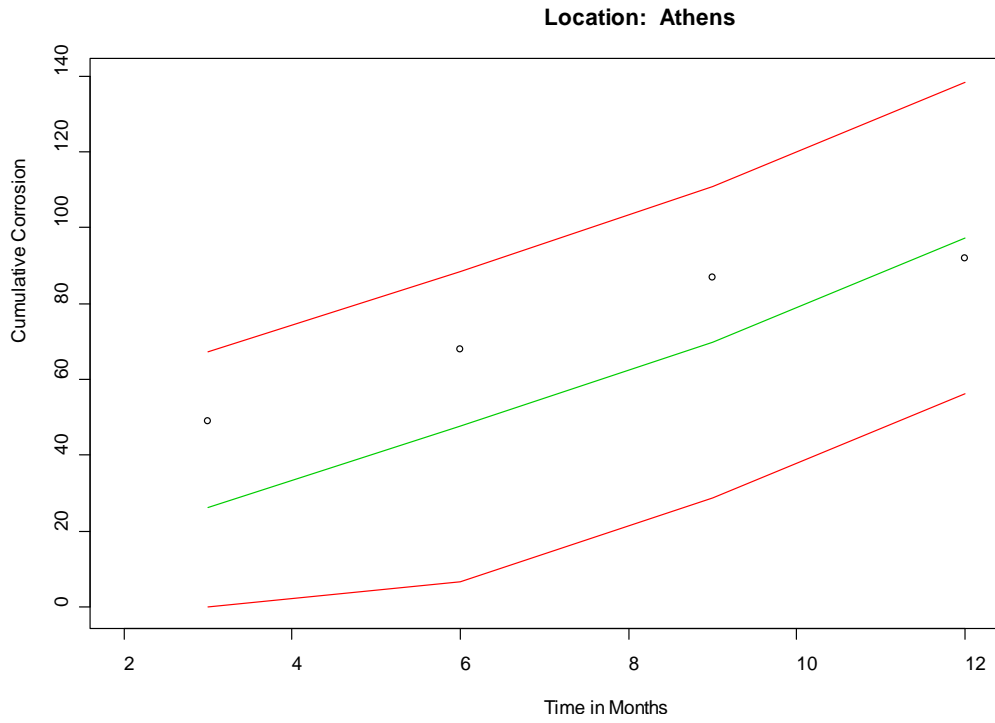


Figure G5. Depiction of modeled results vs actual results for Athens, AL6061.

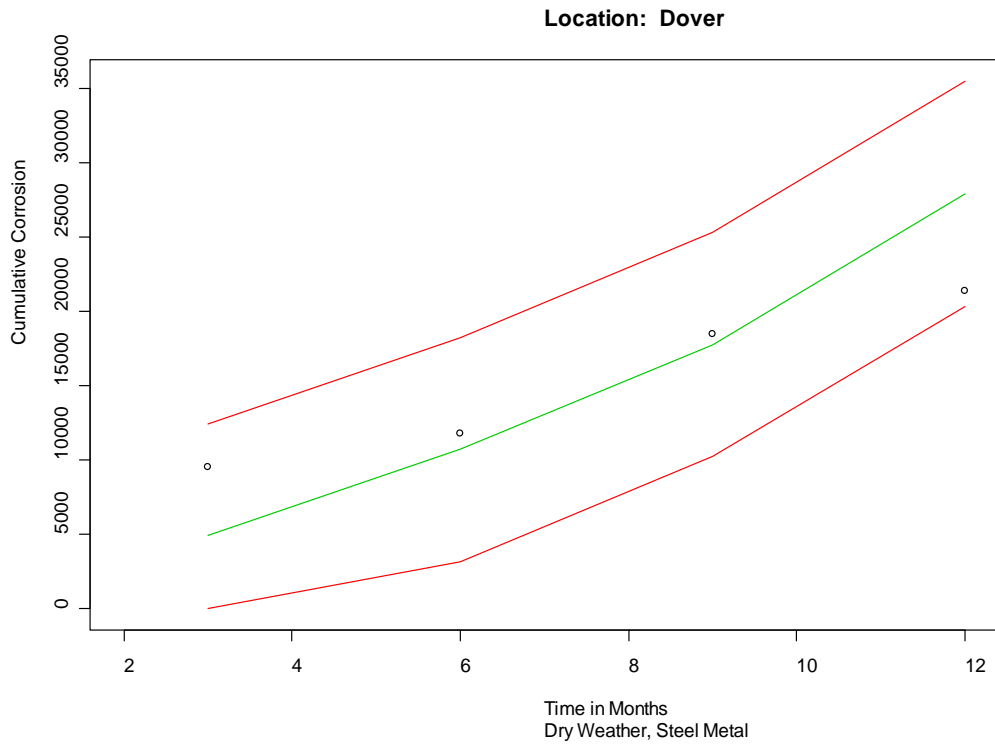


Figure G6. Depiction of modeled results vs actual results for Dover, Steel.

# REPORT DOCUMENTATION PAGE

*Form Approved*  
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<b>1. REPORT DATE (DD-MM-YYYY)</b> August 2009		<b>2. REPORT TYPE</b> Final		<b>3. DATES COVERED (From - To)</b>	
<b>4. TITLE AND SUBTITLE</b> Development of a Predictive Corrosion Model Using Locality-Specific Corrosion Indices				<b>5a. CONTRACT NUMBER</b>	
				<b>5b. GRANT NUMBER</b>	
				<b>5c. PROGRAM ELEMENT NUMBER</b> Corrosion Prevention and Control	
<b>6. AUTHOR(S)</b> Sean Morefield, Susan A. Drozd, Vincent F. Hock, William H. Abbott, David Paul, and Jana L. Jackson				<b>5d. PROJECT NUMBER</b> CPC FAR-15	
				<b>5e. TASK NUMBER</b> MIPR 6FCERB1023	
				<b>5f. WORK UNIT NUMBER</b>	
<b>7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)</b>  U.S. Army Engineer Research and Development Center Construction Engineering Research Laboratory P.O. Box 9005 Champaign, IL 61826-9005				<b>8. PERFORMING ORGANIZATION REPORT NUMBER</b>  ERDC/CERL TR-09-22	
<b>9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)</b>  U.S. Army Installation Management Command Engineering Office, Directorate of Public Works (IMPW-E) 2511 Jefferson Davis Hwy. Arlington, VA 22202				<b>10. SPONSOR/MONITOR'S ACRONYM(S)</b>  IMCOM	
				<b>11. SPONSOR/MONITOR'S REPORT NUMBER(S)</b>	
<b>12. DISTRIBUTION / AVAILABILITY STATEMENT</b>  Approved for public release; distribution is unlimited.					
<b>13. SUPPLEMENTARY NOTES</b>					
<b>14. ABSTRACT</b>  This Office of the Secretary of Defense Corrosion Prevention and Control Program project developed a statistical model of atmospheric corrosion of selected metals. This model relates measured corrosion rates at test sites (mainly military bases) worldwide to critical environmental variables. These variables are (1) a measure of atmospheric chlorides, (2) rainfall, and (3) relative humidity values at several levels. The measured corrosion rates obtained at test sites over the period of CY05 – CY07. Additionally this database includes much more data obtained from similar DoD monitoring activities over nearly the last decade. This serves to enhance the statistical relevance of the developed model. The model includes algorithms for several metals that have been routinely used in the monitoring work. These include copper, 6061 T6 aluminum, 7075 T6 aluminum, and a low carbon (1010) steel.					
<b>15. SUBJECT TERMS</b>  corrosion prevention, modeling, Corrosion Prevention and Control Program (CPC), corrosion rates					
<b>16. SECURITY CLASSIFICATION OF:</b>			<b>17. LIMITATION OF ABSTRACT</b>	<b>18. NUMBER OF PAGES</b>	<b>19a. NAME OF RESPONSIBLE PERSON</b>
<b>a. REPORT</b>  Unclassified	<b>b. ABSTRACT</b>  Unclassified	<b>c. THIS PAGE</b>  Unclassified			85