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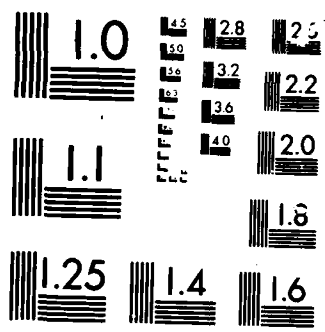

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Regression models for predicting building material distribution in four northeastern cities

Carolyn J. Merry and Perry J. LaPotin

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The Corps of Engineers conducted a field sampling program for inventorying building materials in the northeastern United States, and the data from the field program were compiled into a data base for statistical analysis. Correlation coefficients were derived between the independent variables and the surface area of the five building material types. The correlation coefficients were used in an optimal stepwise regression model developed for each material class for each city. A number of factors appear to be significantly associated with the distribution of building material exposure. However, the variables do not correlate at levels required for constructing adequate predictive models that would be applicable to other sampling locations.

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PREFACE

This report was prepared by Carolyn J. Merry, Research Physical Scientist, Earth Sciences Branch, Research Division, U.S. Army Cold Regions Research and Engineering Laboratory, and Perry J. LaPotin, Research and Computer Engineer, Department of Physics and Astronomy, Dartmouth College, Hanover, New Hampshire.

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DISTRIBUTION IN FOUR NORTHEASTERN CITIES

Carolyn J. Merry and Perry J. LaPotin

INTRODUCTION

The Corps of Engineers conducted a field sampling program for inventorying building materials in the northeastern United States during 1984 and early 1985. Data were collected from March through April 1984 in New Haven, Connecticut, from July through August 1984 in Portland, Maine, from December 1984 through February 1985 in Pittsburgh, Pennsylvania, and from January through February 1985 in Cincinnati, Ohio (Fig. 1). The field inventory program and the collected data for each of the cities are described in previous reports (Merry and LaPotin 1985a,b,c and d). The purpose of this report is to describe the correlation coefficients found between the variables collected during the field survey and the surface area of the five building material types. The Statistical Package for the Social

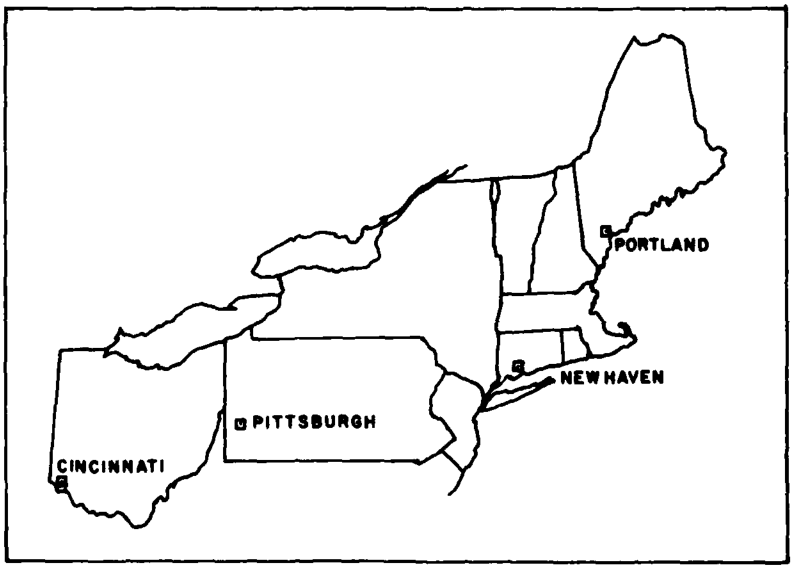

Figure 1. Site location map of the four cities.

Sciences (SPSS) software was used in our statistical analyses (Nie et al. 1975). The correlation coefficients between the variables were used in an optimal stepwise regression model developed for each material class for each city.

The building material types inventoried during the field sampling program are shown in Table 1. The 21 material classes were grouped into five building material classes based on the recommendation of Interagency Task Group G members* (Table 1; Rosenfield 1984). The five building material classes included painted (APAINT), mortar (AMORT), galvanized (AGALV), stone (ASTONE), and other (AOTHER) exposed materials (Table 1). The five

Table 1. The 21 material types grouped into five material classes.

APAINT
- Painted wood (excl. stained)
- Painted steel
- Painted aluminum
- Painted masonry
- Painted concrete
- Painted stucco
- Painted other material
- Painted other material (cannot identify)

AMORT
- Bare brick
- Bare block
- Bare field stone

AGALV
- Bare galvanized steel

ASTONE
- Bare marble
- Bare limestone
- Bare granite

AOTHER
- Bare wood (incl. stained)
- Bare concrete
- Bare glass
- Bare vinyl
- Bare other material
- Bare other material (cannot identify)

*F.W. Lipfert, Dept. of Energy and Environment, Brookhaven National Laboratory, pers. comm., 1984.

classes were chosen principally to correspond with available damage/cost functions.*

A number of classification variables were collected in addition to the building material types and exposures. The independent variables were chosen for the regression analysis because they were available for the four northeastern cities and at other large cities throughout the United States. The four major types of classifiers were the following: sampling frame, land use, building type, and census demographic data.

The sampling frames for each of the cities were developed using information from census variables and the U.S. Geological Survey digital land cover data base (Rosenfield 1984, Wray 1984). Each sampling frame consists of a number of census tracts that have a commonality on the basis of population density, number of single-unit dwellings and land use (Rosenfield 1984). Five to six sampling frames were defined for each city. Land use categories were obtained from the U.S. Geological Survey land use/land cover data at a 1:250,000 scale (Anderson et al. 1976, Mitchell et al. 1977).

Census variables were taken from the 1980 census data. (In the case of New Haven, Connecticut, only the 1970 census data were available for defining the sampling frames.) The census variables included tract population, number of residential dwelling units, number of one-unit structures, area of built residential land, area of built nonresidential land, area of open land with buildings, and the area of open land without buildings.

Building types were determined during the field inventory by Corps field personnel. Information about the building was recorded on a building worksheet form designed by a committee of the Corps, EPA and the Bureau of Standards (Merry 1985 in prep). The building type variable describes the usage of the building (e.g. education, hospital, one-unit housing, etc.). The building type variable may not be available at other cities in digital form like the land cover, census information and sampling frame definition (using the land use and census variables). However, building type had been found to be a good variable for use in predicting building surface area (Merry and LaPotin 1985). Therefore, the variable was included in our analysis.

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*F.W. Lipfert, Dept. of Energy and Environment, Brookhaven National Laboratory, pers. comm., 1984.

DESCRIPTION OF THE CLASSIFICATION VARIABLES

In the analysis, the classification variables of sampling frame, land use and building type were clustered and subdivided into a series of "dummy" or indicator variables. The clustering of the dummy variables was based on their associated regression weights (or coefficients). The variables with coefficients not significantly different (at the 10% level) were clustered together. All other variables remained as separate dummy variables to be entered into the final regression model. The data used in our analysis were from only the sample points that contained buildings (Table 2). The "empty footprints" were not considered in our analysis.

There were five sampling frame indicators used in our correlation analysis (variables SF1 to SF5, Table 3). Sample frame 6 (NRUR) was not used as an indicator variable, since data were only obtained for the NRUR sampling frame in Portland. Data were not obtained for NRUR in the other three cities. Pittsburgh and Cincinnati each contained four frames, and therefore show empty rows in the correlation matrices discussed below within sampling frame indicator SF5. (Sample points within the NSUB [SF5] and NRUR [SF6] were not inventoried in Pittsburgh and Cincinnati because of

Table 2. The number of footprints with buildings (and without) for the four sampled cities.

	Sampling frame*					
City	UCBD	ULIC	UMFR	USFR	NSUB	NRUR
Portland, Maine	42 (42)	59 (23)	44 (34)	35 (39)	24 (46)	16 (57)
New Haven, Connecticut	90 (17)	53 (65)	66 (45)	35 (78)	41 (86)	--
Pittsburgh, Pennsylvania	60 (22)	85 (14)	82 (23)	90 (12)	--	--
Cincinnati, Ohio	72 (27)	48 (45)	47 (51)	69 (28)	--	--

*UCBD - Urban Central Business District
ULIC - Urban Livelihood Industrial Commercial
UMFR - Urban Multi-Family Residential
USFR - Urban Single-Family Residential
NSUB - Nonurban Surburbanizing
NRUR - Nonurban Rural

Table 3. Description of the variables used in the correlation analysis.

Variable	Description of variable
SF1	Sampling frame 1, UCBD, Urban central business district
SF2	Sampling frame 2, ULIC, Urban livelihood industrial commercial
SF3	Sampling frame 3, UMFR, Urban multi-family residential
SF4	Sampling frame 4, USFR, Urban single-family residential
SF5	Sampling frame 5, NSUB, Nonurban suburbanizing
LU11	Land use type 11, Residential
LU12	Land use type 12, Commerial and services
LU13	Land use type 13, Industrial
LU14	Land use type 14, Transportation, communications and utilities
LU1617	Land use types 16 and 17, Mixed urban or built-up land and other urban or built-up land
LU2122	Land use types 21 and 22, Cropland and pasture and orchard, groves, vineyards, nurseries, and ornamental agricultural areas
T1	Building type: One housing unit, residential
TMULTI	Building type: Multi-unit residential housing (includes 2, 3 to 4, 5 to 9, 10 to 19, 20 to 49, and 50 or more housing units)
TOFFICE	Building type: Office buildings
TCOMMIND	Building type: Commercial and industrial buildings
TRELIGED	Building type: Religious and educational buildings
POP	Total population within a census tract
DU	Number of dwelling units within a census tract
U1	Number of one-unit structures within a census tract
ALAND	Total land area of a census tract
ABR	Area of built residential land
ABNR	Area of built non-residential land
AOB	Area of open land with buildings
AO	Area of open land without buildings

monetary and time constraints.) Five sample frames were used in New Haven. Portland contained six sampling frames; five are displayed in the correlation tables. (SF6 is contained within the constant term in a predictive model discussed later.)

Land use classes were clustered into six classes labeled LU11, LU12, LU13, LU14, LU1617, and LU2122. The numbers identify the U.S. Geological Survey land use class, with four digit numbers indicating combined categories (for example, LU1617 implies land use classes 16 and 17). The remaining land use classes were either observed with low frequency across the sampled cities, or were not significant within the clustering program.

Table 4. Correlation matrix for the Portland, Maine, data variables.

	APAINT	AMORT	AGALV	ASTONE	AOTHER
SF1	.2113**	.2010*	.0544	.1024	.1376
SF2	.0717	-.0026	-.0645	.0324	-.0718
SF3	-.0450	.0972	-.0533	-.0505	.0243
SF4	-.1685*	-.1216	-.0465	-.0446	-.1049
SF5	-.0620	-.1336	.1699*	-.0353	.0164
LU11	-.1703*	-.2722**	-.1032	-.0982	-.0750
LU12	.0845	.2770**	-.0697	.1470	.1418
LU13	-.0571	.1591*	.0493	-.0183	-.0015
LU14	.1878*	-.0154	.0916	-.0248	-.0551
LU1617	-.0120	-.0335	-.0267	-.0253	-.0345
LU2122	-.0423	-.0428	.5596**	-.0097	-.0071
T1	-.1706*	-.3394**	-.0933	-.0884	-.1815*
TMULTI	.0240	-.0535	-.0502	-.0472	-.0872
TOFFICE	.0680	.1356	-.0238	.2115**	.0287
TCOMMIND	.1460	.1426	-.0221	-.0431	.0851
TRELIGED	-.0819	.1269	-.0162	-.0154	.0189
POP	-.1742*	-.2119**	.0541	-.0780	-.1011
DU	-.1465	-.0857	.0299	-.0252	-.0107
U1	-.1624*	-.2446**	.1124	-.0753	-.0784
ALAND	-.0779	-.1791*	.1227	-.0469	-.0249
ABR	-.0903	-.1797*	.2460**	-.0479	-.0496
ABNR	-.0687	-.1704*	.0778	-.0402	-.0186
ADB	-.0624	-.1740*	.1009	-.0406	-.0174
AD	-.0699	-.1822*	.1111	-.0436	-.0210

* - Significance ≤ 0.01
** - Significance ≤ 0.001

between the combined land use class LU2122 (the cropland plus orchard category) and the amount of galvanized material exposed. However, this may be due to the galvanized material used to construct the barns and other sheds on farm property. One would expect that galvanized material would be positively correlated with urbanized classes, where it is often observed, and would be negative in rural cropland categories where it is less frequently sighted. This correlation suggests that either an anomalous amount of galvanized material was observed in the rural cropland/orchard category or an intervening variable (outside of our analysis and not being accounted for) is pulling the correlation sign opposite to that anticipated.

As anticipated, one-unit housing structures (T1) show below-average exposures across each composite class because of their smaller size. The exposure is shown to be significantly smaller in the paint, mortar and other material classes. In addition, Portland structures tend to have a larger stone exposure in the office buildings (the 0.001 significance level between stone exposure [ASTONE] and TOFFICE shows a positive correlation of 0.21).

Painted and stone materials appear to decline in one-unit structures (U1) in a similar manner as in the one-unit housing type (T1). Mortar and other materials also decline in the U1 variable, but approximately 10% less than the corresponding T1 variable. Correlations between population and painted and mortar exposures suggest that more populated tracts tend to have below-average exposure of painted and mortar surfaces. A negative association exists between population with stone and the other classified materials above the 0.01 significance level. In addition, population appears positively correlated with galvanized material exposure, suggesting the reverse relationship between population and galvanized material exposure. The exposure of stone and other materials appears essentially independent of all the census variables for the Portland SMSA (all correlations above the 0.01 significance level). The area of built residential land is positively correlated with galvanized materials, and is as expected, since galvanized material is more commonly observed in the urbanized area. The remaining census variables are essentially uncorrelated with AGALV.

New Haven

The New Haven results (Table 5) indicate that sampling frame 1, the UCBD, is significantly correlated with the exposure of mortar, galvanized steel, and other classified materials. The positive correlation implies that sighted exposures for these materials increase significantly, given the building is located within the UCBD. The negative association between painted material exposure and the UCBD indicator SF1 implies that painted surface exposure tends to decline in the New Haven UCBD, rather than increase as was noted in the Portland UCBD. In addition, the exposure of galvanized materials, shown to be significant in the rural NSUB class in Portland, is significant in the urbanized UCBD class in New Haven.

New Haven land use indicators suggest that the transportation land use category (LU14) accounts for the significantly larger exposure of galvanized and other classified materials. The mixed urban and built-up land accounts for the increased exposure of mortar, stone, and other material facings. Painted surface exposure is independent of land use class. However, the mixed and other urban categories appear to exhibit below-average exposures.

Table 5. Correlation matrix for the New Haven, Connecticut, data variables.

	APAINT	AMORT	AGALV	ASTONE	AOTHER
SF1	-.1185	.1905**	.2570**	.0937	.2759**
SF2	-.0562	-.0066	-.0817	.1066	-.0177
SF3	.1271	-.0177	-.0957	-.0920	-.1294
SF4	.0336	-.1112	-.0669	-.0658	-.1242
SF5	.0354	-.1186	-.0721	-.0699	-.0735
LU11	.0873	-.1104	-.1231	-.1188	-.1677*
LU12	.0602	-.0367	-.0429	-.0422	-.0821
LU13	.0391	-.0465	-.0426	-.0422	.0009
LU14	.0246	-.0816	.2767**	-.0001	.1902**
LU1617	-.1307	.2676**	.0781	.1953**	.1808*
LU2122	-.0335	-.0566	-.0400	-.0393	-.0424
T1	.0888	-.2989**	-.1294	-.1261	-.2268**
TMULTI	.0501	.0010	-.0658	-.0627	-.0612
TOFFICE	-.0792	.0679	.0336	.2835**	.2686**
TCOMMIND	-.0573	.0997	.2327**	-.0905	.1150
TRELIGED	-.0358	.2116**	-.0545	.1229	.0650
POP	.0417	-.1489*	-.1980**	-.0573	-.2551**
DU	.0630	-.1274	-.1693*	-.1562*	-.2613**
U1	.0194	-.2149**	-.1468*	-.1378	-.2288**
ALAND	.0064	-.1543*	-.0830	-.0787	-.1260
ABR	.0132	-.1621*	-.1046	-.0994	-.1509*
ABNR	-.0483	-.1038	-.0551	-.0348	-.0844
AOB	.0067	-.1513*	-.0662	-.0635	-.1056
AO	-.0504	-.1350	-.0857	-.0846	-.1347

* - Significance ≤ 0.01

** - Significance ≤ 0.001

Single-unit residential housing in New Haven (T1) is negatively correlated with mortar and other materials at the 0.001 level and above. These structures tend to be below average in their material exposure in all categories, except the painted category in which the correlation is close to zero. This relationship was similar in Portland. New Haven office buildings are positively associated with the exposure of stone and other material facings. Also, commercial and industrial buildings exhibit above-average galvanized material exposures. Religious and educational buildings in New Haven (primarily associated with the Yale University campus) show above average exposures of mortar and stone. The mortar material class also showed minor correlation in Portland with religious and educational buildings.

Painted material exposure appears independent of the census variables in New Haven, with correlations below 0.08. However, the exposure of mortar, galvanized steel, and other materials is significantly associated with tract population, the number of dwelling units, and the number of one-unit structures. These relationships were not as apparent in Portland, except for the continued significant association between mortar exposure and the census variables.

<u>Pittsburgh</u>

In Table 6 the Pittsburgh correlations are provided. As with the findings in the Portland and New Haven samples, the UCBD appears to be the significant classification variable responsible for above-average material exposures. The UCBD tract in Pittsburgh is significantly correlated with each composite material type at the 0.001 level and above. Unlike New Haven, however, Pittsburgh has painted material that is significantly associated with the sampling frames of UCBD. The negative association between USFR and painted material for Pittsburgh is of the same order of magnitude as that for the Portland data. Negative associations appear between the less urban sampling frames (UMFR and USFR) at significance levels exceeding those found in New Haven (UMFR and USFR) and Portland (only UMFR).

The land use variables suggest that the Pittsburgh residential class accounts for significantly smaller exposures of each composite material type, whereas buildings classified in commercial services account for significantly above-average material exposures. These patterns agree well

Table 6. Correlation matrix for the Pittsburgh, Pennsylvania, data variables.

	APAINT	AMORT	AGALV	ASTONE	AOTHER
SF1	.2610**	.2783**	.2100**	.3224**	.3703**
SF2	.0773	.0769	-.0485	.0464	-.0742
SF3	-.1423*	-.1073	-.0662	-.1436*	-.1169
SF4	-.1645*	-.2132**	-.0706	-.1861**	-.1353*
SF5	.	.	.	.	.
LU11	-.2397**	-.2495**	-.1124	-.2520**	-.2043**
LU12	.1853**	.2665**	.1225	.3557**	.3068**
LU13	.1765**	.0865	-.0088	.0061	-.0441
LU14	-.0139	-.0336	.0853	-.0493	-.0293
LU1617	.0110	.0439	-.0180	-.0515	-.0186
LU2122	-.0695	-.0915	-.0291	-.0756	-.0550
T1	-.2502**	-.3098**	-.1069	-.2638**	-.2064**
TMULTI	.0664	.1632*	.0119	.1250	.1239
TOFFICE	.3147**	.1199	.0056	.1565*	-.0122
TRELIGED	-.0092	.0309	.0847	.0254	.0940
POP	-.1596*	-.2300**	-.0899	-.2147**	-.1832**
DU	-.1121	-.2111**	-.0948	-.2152**	-.1870**
U1	-.1839**	-.2446**	-.0977	-.2377**	-.1887**
ABR	-.0246	-.0118	-.0097	.0020	-.0188
ABNR	.1040	.0895	.0766	.1616*	.0990
AOB	-.1000	-.1273	-.0401	-.1109	-.0777
AO	-.1151	-.1555*	-.0511	-.1353	-.0969

* - Significance ≤ 0.01
** - Significance ≤ 0.001

with findings in Portland. The New Haven data show a negative rather than positive association between mean material exposure and buildings categorized in commercial services. Painted material exposure in Pittsburgh is significantly lower in residential sections of the city (LU11), and significantly higher in commercial (LU12) and industrial (LU13) areas. A similar pattern was not observed in New Haven, where painted material exposure was roughly independent of land use category.

As previously indicated, single-unit housing buildings tend to exhibit below-average material exposures. This association is shown to be significant in Pittsburgh for all materials, except galvanized steel, at the 0.001 level and above. Correlations also indicate that Pittsburgh office buildings tend to display painted, mortar and stone facings at above-average levels. In addition, multi-unit residential structures are shown to be roughly independent of each composite material class except mortar. The religious and educational buildings are shown to be independent of material exposure with correlations of 0.1 and below.

The exposure of painted, mortar, stone and other materials in Pittsburgh is significantly correlated with tract population, the number of dwelling units, and the number of one-unit structures. For the remaining census variables, the correlations are close to zero and independent, if not negatively correlated. The galvanized steel exposure is independent of all census variables.

<u>Cincinnati</u>

The Cincinnati correlations (Table 7) suggest that the UCBD accounts for the majority of material exposure in all classes, except bare galvanized steel, which is essentially uncorrelated. The level of correlation is particularly strong between the other categorized materials (AOTHER) and the UCBD sampling frame. The AOTHER category is also negatively correlated with the USFR sampling frame. The remaining sampling frames are shown to be either independent or negatively associated with the composite material exposures. Therefore, below average exposures of materials in the more rural Cincinnati sampling frames and above average exposures for structures in the urban central business district would be expected.

Buildings classified in the residential land use category (LU11) are shown to be negatively associated with material exposure, as with findings in the three previous cities. In Pittsburgh and Cincinnati, the level of

Table 7. Correlation matrix for the Cincinnati, Ohio, data variables.

	APAINT	AMORT	AGALV	ASTONE	AOTHER
SF1	.3047**	.3008**	.0060	.3013**	.4839**
SF2	-.0658	-.0534	-.0511	-.1024	-.1427
SF3	-.1333	-.1025	-.0315	-.0886	-.1629*
SF4	-.1335	-.1673*	.0663	-.1367	-.2208**
SF5	.	.	.	.	.
LU11	-.2959**	-.2701**	-.1055	-.2049**	-.3670**
LU12	.1929*	.0689	.1109	.1935*	.1857*
LU13	.0648	.1981*	.0602	-.0468	.0508
LU14	.1575*	.1644*	-.0340	.1462	.3383**
LU1617	-.0486	-.0205	-.0093	-.0203	-.0409
LU2122	-.0622	-.0360	-.0115	-.0250	-.0440
T1	-.3277**	-.3052**	-.0929	-.1965*	-.3627**
TMULTI	-.0771	-.0283	-.0273	-.0565	-.0606
TOFFICE	.0188	.2375**	-.0093	-.0203	-.0131
TCOMMIND	-.1057	.1950*	-.0201	.1272	.0404
TRELIGED	-.0409	-.0254	-.0066	-.0144	-.0305
POP	-.2690**	-.2205*	-.0155	-.2192*	-.3512**
DU	-.2767**	-.2023*	-.0105	-.2104*	-.3354**
U1	-.2628**	-.2256*	.0067	-.2131*	-.3466**
ABR	-.2288*	-.2084*	.0405	-.1910*	-.3072**
ABNR	.2756**	.1041	-.0065	.0128	.1281
AOB	-.0989	-.0843	.1005	-.1000	-.1273
AO	-.1061	-.1105	.0823	-.0806	-.1248

* - Significance $\leq$ 0.01
** - Significance $\leq$ 0.001

correlation is significant at the 0.001 level and above for each composite material category, except for bare galvanized steel. Buildings observed in the transportation land use class are shown to exhibit above-average paint, mortar, and particularly other classified materials, at significance levels above 0.01 (0.001 for the other materials category). This correlation is reversed, however, in Pittsburgh where similar categorization produced below-average exposures in the paint, mortar, stone and other material categories. In Portland, the transportation land use class was roughly independent of all materials other than the painted category. In New Haven, the class was shown to be significantly correlated with galvanized steel and other material categories.

As in the three previous cities, single-unit building types (T1) were shown to produce below average exposures in Cincinnati. In contrast, the office, commercial and industrial buildings show above-average exposures of mortar.

Several census variables are significantly correlated with the material types in the Cincinnati sample. All materials, except galvanized steel, are shown to be negatively correlated (at a significant level) with tract population, number of dwelling units, number of one-unit structures, and the area of built residential land. As anticipated, given the negative association with area of built residential land, the painted material is positively associated with the area of built non-residential land (ABNR is essentially the complement of ABR). In general, the association between all the material types and the census variables appears consistent across all the cities sampled (correlations are negative, usually significant at the 0.01 level, or simply close to zero and independent, if not negatively correlated).

REGRESSION ANALYSIS

The correlation coefficients shown in Tables 4-7 indicate that the composite material classes from each city are, at best, moderately associated with the classification/predictive variables. The degree of association is low, with paired correlation values below 0.3. Values of this magnitude in the simple correlation matrix suggest that simple univariate regression analysis of the exposure of the composite material types will yield low multiple correlations and corresponding small values for R^2. Therefore, an optimal stepwise regression approach was used to increase the level of explanation derived from sampling frame, land use, building type, and census variables. The independent variables shown along the left side of the correlation matrices (Tables 4-7) were entered into the regression model by use of an F-test (based on the partial correlations between variables in the model and the variables ready to enter into the model). The significance level for variables to enter into the model was set at the 0.05 level, which is a level customary in stepwise models of this type. The footprint size (FOOT) was entered into each model as a covariate variable and appears as the last independent variable next to the constant term. With this technique, the size of the footprint adjusts the magnitude of the material exposed within the footprint area used for each sampling frame (Table 8). This factor was necessary because the exposed walls in footprint variable (EWIF) were used in calculating the surface areas of the five composite material classes. The number of cases for each city shown for the regression models does not always equal the number of sample points with buildings (Table 2) because census variables were missing for several observations.

Table 8. Footprint sizes (in ft) of the sampling frame for each sampled city.

City	UCBD	ULIC	UMFR	USFR	NSUB	NRUR
Portland, Maine	139	144	90	87	364	364
New Haven, Connecticut	139	144	90	87	364	-
Pittsburgh, Pennsylvania	310	264	207	481	1164	2139
Cincinnati, Ohio	435	223	201	321	790	1608

The results of the optimal stepwise regression model runs are shown in Tables 9-13. Models for each of the five composite classes are presented along with corresponding standard error terms, t and F statistics, and significance levels. Independent variables are presented in the order in which they entered into the stepwise model. For example, variables with the highest partial correlation are entered in ranked order, adjusting for the components currently in the model. As an illustration, the painted material model for Portland was constructed by first entering the variable SF1, since SF1 had the highest correlation (0.21) with the variable APAINT (see the Portland correlation matrix, Table 4). The next variable entered, SF2, had the largest partial correlation of the remaining sampling frame variables given the variable SF1 (current entered into the model). In this step, groups of two are examined to see if any other pairs explain larger portions of the variability in the data. This is continued until no more variation is explained by the addition of variable pairs.

When examining the R^2 values and the regression standard error terms, additional indicators other than sampling frame, land use class, building type, and census variables are required to adequately explain the majority of the variability in building material exposure. Most of the models do display an F-statistic significant at the 0.01 level and above. The models for paint in New Haven and for galvanized steel in Cincinnati, however, show much less than adequate operating characteristics and have been listed only for completeness. Each t-statistic is shown to be signi-

Table 9. Regression models for painted materials.

PORTLAND: n = 205

Paint = 3618.92 SF1 + 1846.44 SF2 + 0.95 FOOT + 1893.31

(1028.30)	(915.84)	(4.75)	(908.04)
t = 3.52	t = 2.02	t = 0.20	t = 2.08
{0.00}	{0.05}	{0.84}	{0.04}

R^2 = 0.06 std err of regr = 5614.06 F = 4.41 [0.01]

NEW HAVEN: n = 276

Paint = -1202.02 LU1617 - 0.38 FOOT + 2949.65

(539.69)	(3.16)	(599.39)
t = -2.23	t = 1.12	t = 4.92
{0.03}	{0.90}	{0.00}

R^2 = 0.02 std err of regr = 4382.79 F = 2.48 [0.09]

PITTSBURGH: n = 291

Paint = 22552.13 TOFFICE + 11705.87 SF1 - 5.20 FOOT + 3651.97

(3889.48)	(2415.24)	(9.27)	(3315.95)
t = 5.80	t = 4.85	t = -0.56	t = 1.10
{0.00}	{0.00}	{0.58}	{0.27}

R^2 = 0.17 std err of regr = 16589.70 F = 19.24 [0.00]

CINCINNATI: n = 179

Paint = 3546.83 SF1 + 517.56 ABNR - 1.98 FOOT + 1732.67

(1855.84)	(221.71)	(9.32)	(2586.26)
t = 1.91	t = 2.33	t = -0.21	t = 0.67
{0.05}	{0.02}	{0.83}	{0.50}

R^2 = 0.14 std err of regr = 5340.90 F = 9.70 [0.01]

( ) = standard error of regression coefficient
{ } = significance of the t ordinate
[ ] = significance of the F ordinate

Table 10. Regression models for mortar materials.

PORTLAND: n = 205

Mortar =	-5585.83 T1	- 4007.93 TMULTI	- 3076.42 LU14	- 6.21 FOOT	+ 7034.17
	(867.39)	(1078.96)	(1222.11)	(4.53)	(919.67)
	t = -6.44	t = -3.72	t = -2.52	t = -1.37	t = 7.65
	{0.00}	{0.00}	{0.01}	{0.17}	{0.00}

R^2 = 0.19 std err of regr = 5330.33 F = 11.53 [0.01]

NEW HAVEN: n = 276

Mortar =	-1888.76 T1	+ 2129.94 TRELIGED	+ 1357.61 LU1617	+ 0.54 FOOT	+ 2016.03
	(663.70)	(908.20)	(608.48)	(3.24)	(635.74)
	t = -2.84	t = 2.35	t = 2.23	t = 0.17	t = 3.17
	{0.01}	{0.02}	{0.03}	{0.87}	{0.00}

R^2 = 0.12 std err of regr = 4340.06 F = 9.51 [0.01]

PITTSBURGH: n = 291

Mortar =	-5625.54 T1	+ 5487.10 SF1	- 1.29 FOOT	+ 7612.31
	(2079.28)	(2059.3)	(8.6)	(2481.83)
	t = -2.71	t = 2.67	t = -0.15	t = 3.07
	{0.01}	{0.01}	{0.88}	{0.00}

R^2 = 0.11 std err of regr = 12285.41 F = 12.08 [0.01]

CINCINNATI: n = 179

Mortar =	44237.49 TOFFICE	+ 5508.86 SF1	+ 9720.07 TCOMMIND	-2.68 FOOT	+ 2473.23
	(7435.4)	(2441.01)	(3076.31)	(12.76)	(3470.12)
	t = 5.95	t = 2.26	t = 3.16	t = -0.21	t = 0.71
	{0.00}	{0.03}	{0.00}	{0.83}	{0.48}

R^2 = 0.26 std err of regr = 7379.62 F = 15.43 [0.01]

() = standard error of regression coefficient
{} = significance of the t ordinate
[] = significance of the F ordinate

Table 11. Regression models for galvanized materials.

PORTLAND: n = 205

Galvanized =	6434.50 LU2122 +	277.77 ABR −	0.14 POP +	0.15 FOOT +	160.45
	(730.63)	(80.32)	(0.05)	(1.04)	(149.60)
	t = 8.81	t = 3.46	t = −2.87	t = 0.14	t = 1.07
	{0.00}	{0.00}	{0.00}	{0.89}	{0.28}

R^2 = 0.35 std err of regr = 982.79 F = 27.50 [0.01]

NEW HAVEN: n = 276

Galvanized =	4369.88 LU14 +	1451.70 TCOMMIND +	1267.78 SF1 +	0.74 FOOT −	357.27
	(1209.32)	(617.45)	(612.61)	(3.04)	(576.02)
	t = 3.61	t = 2.35	t = 2.07	t = 0.24	t = −0.62
	{0.00}	{0.02}	{0.04}	{0.81}	{0.54}

R^2 = 0.13 std err of regr = 4207.15 F = 9.83 [0.01]

PITTSBURGH: n = 291

Galvanized =	5854.13 SF1 −	0.62 FOOT +	333.58
	(1635.72)	(6.22)	(2191.74)
	t = 3.58	t = −0.10	t = 0.15
	{0.00}	{0.92}	{0.88}

R^2 = 0.04 std err of regr = 11249.67 F = 6.48 [0.01]

CINCINNATI: n = 179
Galvanized =

No variables entered in the model; no variables significant at the 0.05 level

() = standard error of regression coefficient
{} = significance of the t ordinate
[] = significance of the F ordinate

Table 12. Regression models for stone materials.

PORTLAND: n = 205

Stone = 1534.16 TOFFICE - 0.01 FOOT + 90.91

Stone =	1534.16 TOFFICE	- 0.01 FOOT	+ 90.91
	(502.29)	(1.48)	(252.47)
	t = 3.05	t = -0.01	t = 0.36
	{0.00}	{0.99}	{0.72}

R^2 = 0.04 std err of regr = 1751.69 F = 4.67 [0.01]

NEW HAVEN: n = 276

Stone = 2682.05 TOFFICE + 1090.94 SF2 + 768.03 LU1617 + 0.33 FOOT - 310.22

Stone =	2682.05 TOFFICE	+ 1090.94 SF2	+ 768.03 LU1617	+ 0.33 FOOT	- 310.22
	(580.38)	(402.81)	(324.95)	(1.85)	(364.34)
	t = 4.62	t = 2.71	t = 2.36	t = 0.18	t = -0.85
	{0.00}	{0.01}	{0.02}	{0.86}	{0.40}

R^2 = 0.12 std err of regr = 2568.14 F = 9.32 [0.01]

PITTSBURGH: n = 291

Stone = 946.30 LU12 + 1125.22 TOFFICE + 702.63 SF1 - 0.23 FOOT + 125.62

Stone =	946.30 LU12	+ 1125.22 TOFFICE	+ 702.63 SF1	- 0.23 FOOT	+ 125.62
	(247.57)	(360.57)	(273.59)	(0.87)	(322.37)
	t = 3.82	t = 3.12	t = 2.56	t = -0.27	t = 0.39
	{0.00}	{0.00}	{0.01}	{0.79}	{0.70}

R^2 = 0.17 std err of regr = 1533.79 F = 14.82 [0.01]

CINCINNATI: n = 179

Stone = 1650.97 SF1 - 1050.12 LU13 + 1854.41 TCOMMIND - 0.73 FOOT + 227.12

Stone =	1650.97 SF1	- 1050.12 LU13	+ 1854.41 TCOMMIND	- 0.73 FOOT	+ 227.12
	(695.78)	(444.55)	(851.68)	(3.53)	(960.96)
	t = 2.37	t = -2.36	t = 2.18	t = -0.21	t = 0.23
	{0.02}	{0.02}	{0.03}	{0.84}	{0.81}

R^2 = 0.13 std err of regr = 2035.98 F = 6.77 [0.00]

() = standard error of regression coefficient
{} = significance of the t ordinate
[] = significance of the F ordinate

Table 13. Regression models for other building materials.

PORTLAND: n = 205

Other = -2594.41 T1 - 2345.51 TMULTI - 1879.04 LU14 + 2.18 FOOT + 3037.03

(607.34)	(755.48)	(855.71)	(3.17)	(643.94)
t = -4.27	t = -3.10	t = -2.20	t = 0.69	t = 4.72
{0.00}	{0.00}	{0.02}	{0.49}	{0.00}

R^2 = 0.10 std err of regr = 3732.24 F = 5.28 [0.01]

NEW HAVEN: n = 276

Other = 1963.25 SF1 + 3150.15 TOFFICE + 2.00 FOOT + 1040.51

(648.08)	(1095.94)	(3.26)	(603.41)
t = 3.03	t = 2.87	t = 0.61	t = 1.72
{0.00}	{0.00}	{0.54}	{0.09}

R^2 = 0.10 std err of regr = 4534.90 F = 10.24 [0.01]

PITTSBURGH: n = 291

Other = 29767.56 SF1 + 12646.30 LU12 - 0.26 FOOT + 91.15

(6992.91)	(6310.74)	(22.07)	(8009.63)
t = 4.26	t = 2.00	t = -0.01	t = 0.01
{0.00}	{0.05}	{0.99}	{0.99}

R^2 = 0.15 std err of regr = 39203.51 F = 16.37 [0.01]

CINCINNATI: n = 179

Other = 7671.51 SF1 - 2908.40 LU13 - 5.02 FOOT + 2664.83

(2021.28)	(1290.74)	(10.24)	(2779.70)
t = 3.80	t = -2.25	t = -0.49	t = 0.96
{0.00}	{0.03}	{0.63}	{0.34}

R^2 = 0.22 std err of regr = 5933.30 F = 16.64 [0.01]

() = standard error of regression coefficient
{} = significance of the t ordinate
[] = significance of the F ordinate

ficant to the 0.05 level and above for the stepwise entered variables in all the models. The footprint variable (FOOT) is a covariate in the models and often yields t-values above the 0.05 level.

Painted materials

For the painted material regression models, the indicator for the UCBD sampling frame (SF1) appears with a significant t-statistic in three of the four sampled cities. In each instance, the positive weight for the coefficient suggests that painted material rises significantly as one samples structures in the UCBD sampling frame. In New Haven, where the sampling frame did not enter into the model, land use category LU1617 (the mixed and other urban category) explains the largest proportion of the variability in painted material exposure. However, the negative association between urban land use and painted exposure (between APAINT and LU1617) appears counter-intuitive, with respect to the positive association usually displayed in the other indicators of urbanization, such as SF1. The negative association holds for all the cities, except Pittsburgh (Tables 4-7). The R^2 value and the significance of the F-statistic for the New Haven regression model suggest that the variables available for the regression were inadequate to formulate a cohesive model of painted material exposure.

The models for Pittsburgh and Cincinnati explain 17% and 14%, respectively, of the variability in painted material exposure. In Pittsburgh the standard error of the regression is large (16,590 ft^2); however, the corresponding F-statistic is shown to be significant at the 0.001 level and above.

A census variable (area of built residential land) is contained within the Cincinnati model and shows a postive correlation with painted materials. The Portland model also shows that SF2, the ULIC, is positively correlated with painted materials with a coefficient about one-half the value associated with SF1. The Cincinnati and Portland models display similar standard errors and corresponding significance levels for the F-statistic.

Mortar materials

The exposure of mortar materials is shown to be significantly associated with the presence of single-unit housing (T1). The T1 indicator appears in the predictive models for Portland, New Haven and Pittsburgh as the first entered variate that corresponds to the highest correlated component. In each case, the variable T1 is significant to the 0.01 level and above (strongly significant in the Portland model to the 0.001 level and above). The signs appear reasonable in each of the models for mortar exposure. In Portland, the presence of single-unit and multi-unit housing, and the transportation land use (variables T1, TMULTI, LU14) were strongly associated with below-average mortar exposure. In New Haven, the mortar exposure rose substantially within the religious/educational category (TRELIGED) and the mixed and other urban category (LU1617), only to decline within the single-unit housing variable. Mortar exposure in Pittsburgh is strongly associated with the UCBD, where it is most often sighted, and is shown to be significantly lower within the single-unit housing that surrounds the city. Similarly, Cincinnati displays positive association for mortar exposure in the UCBD, but also indicates that office and commercial buildings in that city exhibit above-average exposures of mortar materials.

The R^2 values for the mortar predictive models are, generally speaking, more substantial than those found for the painted material exposure. In addition, each model displays an F-value significant at the 0.01 level and above.

Galvanized materials

The predictive models for galvanized material exposure indicate that a wide range of factors affect the level of exposure for this material. In Portland, the cropland/orchard land use category is shown to be the most important single variable in explaining galvanized metal exposure. Conversely, the cropland/orchard land use category does not enter into the models for the other three cities in any significant manner. For New Haven, buildings located within the transportation land use and structures used for commercial and industrial purposes are shown to be the two most important factors affecting galvanized exposure. In New Haven and Pittsburgh, the indicator for buildings within the UCBD (SF1) entered positively into the models. This variable loading suggests that significantly above-average galvanized exposure was sighted within the UCBD in both cities. The fact that no other variable enters into the Pittsburgh model (other than the footprint covariate) indicates that the variable SF1 is the only factor, at the 0.005 significance level, associated with the exposure of galvanized steel. Also, no variables were found to significantly affect galvanized material exposure in Cincinnati.

Census variables are shown to be significantly associated with the galvanized steel exposure in Portland, and are shown to be insignificant for the other three cities (the variables did not step into the model at the 0.005 level). The coefficients in the Portland model indicate that average galvanized steel exposure rises with the area built residential (ABR) category and declines with rising population (POP). The respective units of these coefficients are average square feet of exposed galvanized steel per square foot of residential land area and average square feet exposed galvanized steel per capita.

The regression summary statistics indicate that each developed model is significant at the 0.01 level and above. The R^2 values indicate that in Portland, 35% of the variability in galvanized exposure is explained within the model. The cropland/orchard land use category is the single factor producing this higher R^2 value (the correlation between AGALV and LU2122 is 0.56, see Table 4). As stated previously, this relationship may be spurious or non-representative of the normal galvanized steel exposure.

Stone materials

The exposure of bare stone materials is shown to be strongly associated with the presence of office buildings (TOFFICE). In three of the four surveyed cities, this factor enters positively into the predictive models with a high t-statistic and corresponding low significance values (0.001 and above in Portland, New Haven and Pittsburgh). In Portland and New Haven, the office building indicator is shown to be the single most important predictive variable (it is the only non-covariate variable to enter into the Portland model). In New Haven, mixed and other urban structures (LU1617) and buildings contained within the UMFR (SF2) are positively associated with above-average stone exposures. For Pittsburgh, this positive relationship is primarily due to buildings in the commercial services land use class (LU12) and the UCBD (SF1). Cincinnati structures found within the UCBD associate with above-average stone exposure; however, buildings categorized by the industrial land use class show declining stone exposure (the negative coefficient with LU13, Table 7). As with the SF1 variable, the variable for commercial and industrial buildings in Cincinnati is also positively associated with stone exposure.

The R^2 values for each of the stone models explain between 4 and 17% of the variability. Each model for predicting stone exposure is shown to be significant at the 0.01 level and above (0.001 for Cincinnati).

Other materials

The distribution of other categorized materials is closely linked to the indicator for the UCBD in New Haven, Pittsburgh and Cincinnati. In each case, this variable entered first into the corresponding model, yielding a strongly significant value for the t-statistic (significant at the 0.001 level and above). The Portland model suggests that single- and multi-unit housing tend to have below-average exposure in the other material class. In addition, buildings found within the transportation land use category are negatively associated with the average size of other materials exposure. One additional problem with this model is in the operating range with which it is usable. As an extreme example, buildings located within the transportation land use category (LU14 = 1) of the USFR sampling frame (FOOT = 87) that are single-unit structures (T1 = 1) yield an average exposure for the category of other materials that is below zero. Therefore, the model's capacity to predict other material exposure should only be accepted in light of the standard error associated with the model.

The presence of office buildings in New Haven suggests that an average of 3150 ft^2 of other material exposure should be added onto the estimate. Buildings located within the UCBD of New Haven tend to have 5113 ft^2 more of other material types (3150 + 1963) exposed than corresponding non-UCBD office buildings. Similarly, structures in Pittsburgh tend to be larger in the UCBD and prevalently exposed with other material types. The commercial services indicator enters into the Pittsburgh model with a fairly strong t significance (0.05). Together, buildings found within the UCBD under the commercial land use category tend to be greater than 42,000 ft^2 (29768 + 12646) more exposed with other materials than corresponding non-commercial UCBD structures. The Cincinnati model suggests that buildings found within the industrial land use category (LU13) are less exposed in the other materials category.

Summary statistics indicate that each model has a corresponding F-statistic significant to the 0.01 level. In Cincinnati, the R^2 value suggests that 22% of the other exposed materials is explained in the regression model; the remaining models for other building materials explain a somewhat lower percentage.

Distribution of residuals

In linear statistical models of the type presented, the residuals are known to have an expected value of zero with some positive variance σ^2. These residuals are contained within Appendix A. For each model, a standardized histogram is presented to check for symmetry in the residual's distribution and to identify the frequency of outliers. Superimposed on the standardized residual histogram is an expected residual distribution, given that the residuals come from a normal distribution with a mean of zero, and variance σ^2 (estimated from the sampling distribution). For each residual diagram, the frequency of occurrence (labeled N), the corresponding exponential value of the occurrence (labeled EXP N), and the standardized value of the residuals (along the histogram axis) are provided. Also shown for each model is a normal probability (or P-P) plot for the standardized residuals. These plots show the behavior of the predictive models at different operating levels. Along the vertical axis of the P-P plot is the observed value for the standardized residual from the model. The horizontal axis represents the expected residual magnitude from the normal distribution. Residual values below the 45° line suggest that the expected residuals are greater than those actually observed. Under these conditions, the model tends to underpredict the actual value of the dependent variable ($Y-\hat{Y}$ = residual). Conversely, the model overpredicts values whose residuals are above the 45° line. Using the P-P plots, one may therefore examine the adequacy of the model at varying magnitude levels.

The residual distributions for the painted material models indicate that the residuals are somewhat non-symmetrical. The means appear centered about the expected value of zero with a frequency far in excess (particularly for Pittsburgh) of that expected by the theoretical normal distribution. Also, the diagrams indicate that two observations in Portland and Cincinnati, three in Pittsburgh, and five in New Haven have standardized residuals above 3.0 (these are labeled within the OUT category). The normal P-P plot suggests that the painted material models tend to underpredict the size of exposed paint surfaces with smaller paint magnitudes, but tends to overpredict these values for larger buildings. In general, the behavior of these residuals appear quite good considering the less than adequate R^2 values corresponding to the painted material models.

The residuals for the mortar material models lie along the 45° line more closely than for the painted material models. This is not surprising since the R^2 values are about 10% higher. However, more outlier values are observed above the 3.0 or -3.0 standardized residual values. The P-P plots show essentially the same relationship as the painted material models for underpredicting exposed mortar surfaces with smaller mortar magnitudes, but overpredicting mortar surfaces for larger buildings.

The galvanized steel models are shown to strongly underpredict low magnitude exposures and strongly overpredict high magnitude exposures. Also, small deviations from the expected produce wide deviations in the observed values around the 0.5 expected probability. This implies that the models are relatively unstable in their predictive capabilities. In Portland the galvanized steel exposure was strongly associated with the cropland/orchard land use category. Two observations for galvanized exposure are below the standardized residual level of -3.0 and one observation is above the standardized residual level of 3.0 on the residual diagram. The normal P-P plot suggests that although this model has a comparatively high R^2 value, its usefulness for predicting galvanized steel exposure is limited. There is only one indicator variable (SF1) in the Pittsburgh model (Table 11) affecting the residual distribution. The R^2 value for the Pittsburgh model was close to zero.

In the stone material regression models, the Portland residuals strongly overpredict high magnitude exposures and underpredict low magnitude exposures, similar to what was found in the galvanized material residuals. There is only one indicator variable (TOFFICE) in the Portland model (Table 12) that is affecting the residual distribution. The R^2 value for the Portland model was close to zero. On the other hand, the R^2 value for the remaining three cities was slightly higher. As a result, the residuals for New Haven, Pittsburgh and Cincinnati are more stable and similar to the residual distributions found for the painted and mortar models.

The residuals for the other materials regression models are again similar to what was found for the painted and mortar materials residual distributions. In general, the residuals appear encouraging considering the low R^2 values observed for the regression models. The residuals should be compared with the regression model statistics to fully determine the predictive behavior of each model.

SUMMARY AND CONCLUSIONS

Four cities have been surveyed to examine the distribution of exposed materials on buildings. In each city, information on the sampling frame containing the observation, the corresponding land use class, the building type or usage identifier, and the census variables indexed by the census tract have been collected and organized within a composite data base. Simple correlational analysis between the primary predictive variables and the exposed composite material per structure was examined. The results indicate that a low level of association exists between the independent variables and the actual building material exposed (usually with absolute magnitude below 0.3).

An attempt to adequately explain the variability of exposed material was tried using an optimal stepwise regression for each material type. As a function of the stepwise methodology, the models displayed the importance of each independent variable within the overall composite model. Summaries for these models suggest that the census variables (population, number of dwelling units, number of one-unit structures, total land area, area built residential, area built non-residential, area open with buildings, and area open) contribute little to the prediction of material exposure. In 17 of the 19 presented models, census variables did not enter into the regression equation at the 0.05 level. In the two developed models containing census variables, one for the prediction of exposed paint in Cincinnati and the other for the prediction of galvanized metal in Portland, the respective census variables (area built non-residential, area built residential and tract population) were found to be significant at the 0.02 level and above.

Of the sampling frame variables examined, the indicator for the UCBD (variable SF1) was shown to most often affect the degree of material exposure. As anticipated, the loading for this variable is always positive, reflecting the larger than average building size and, therefore, larger than average exposure for selected materials. For example, in both Portland and Cincinnati, the contribution of the variable SF1 to painted exposure is close to 3500 ft^2; the contribution in Pittsburgh is approximately six times larger.

A number of land use factors were shown to significantly affect the mean material exposure. For stone and other materials in Pittsburgh, the commercial services land use class positively affected the degree of exposure. Conversely, the industrial land use category in Cincinnati negatively associates with stone and other exposed materials. Buildings found within the transportation land use category were shown to contain below-average mortar and other materials exposure in Portland and above-average galvanized material exposure in New Haven.

The mixed and other urban land use class significantly affects the degree of exposure in New Haven. For painted buildings the association is negative, whereas a positive contribution exists for the mortar and stone materials. The final land use indicator, the cropland/orchard category, was strongly associated with increased galvanized steel exposure in Portland, but was found to be an insignificant factor in all other cities.

The single most important series of variables for predicting material exposure in the four sampled locations are the building type indicators. The office building indicator (TOFFICE) is shown to be strongly significant (with positive contribution) at the 0.001 level and above for painted exposure in Pittsburgh, mortar exposure in Cincinnati, stone exposure in Portland, New Haven and Pittsburgh, and other materials exposure in New Haven. In addition, the indicator for single-unit housing (T1) appears to be the single most important negative factor in Portland, New Haven and Pittsburgh mortar exposure, as well as the single most important negative factor in other exposed materials in Portland. For each model where T1 enters as an independent variable, it is significant to the 0.01 level and above (0.001 in Portland).

In summary, the basic set of independent variables that have been collected for the four cities appear to inadequately explain the variability in composite exposed materials at the building level. The analysis presented suggests that a number of factors appear to be significantly associated with the distribution of material exposure. However, they do not strongly correlate at levels required to construct adequate predictive models that would be applicable to other sampling locations. The behavior of these models implies that a series of critical variables (for example, the UCBD, the office buildings, and single-unit housing indicator) show promising levels of association with material exposure in multiple locations. However, the actual degree of correlation and subsequent low degree of explanation limits the practical usefulness for these factors. In conclusion, we find little indication for accepting the basic premise that census/demographic variables are significant in explaining the nature of building material exposure. We believe that additional factors should be examined to adequately explain the exposed material distribution in other locations.

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APPENDIX A. RESIDUAL DISTRIBUTION HISTOGRAMS AND PLOTS FOR THE REGRESSION MODELS FOR THE FOUR CITIES.

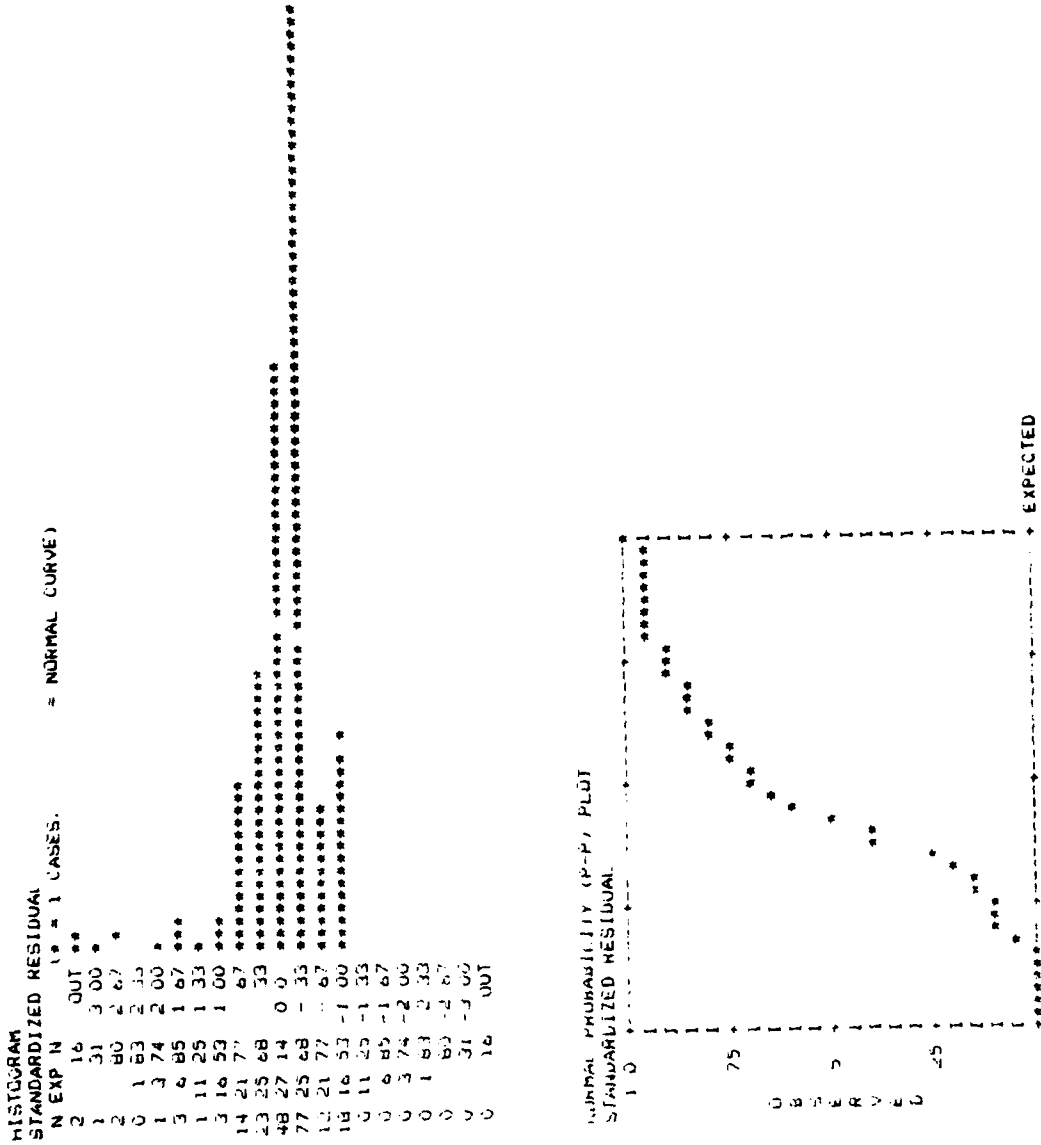


Table A1. Residual distribution for painted material, Portland, Maine.

```
HISTOGRAM
STANDARDIZED RESIDUAL
 N EXP N        (* = 1 CASES,      . = NORMAL CURVE)
 5     16    OUT *****
 0     31   3 00
 3     80   2 67  **
 3   1 83   2 33 * *
 1   3 74   2 00 *
 1   6 85   1 67 *
 5  11 25   1 33 *****
 3  16 53   1 00 ***
 7  21 77     67 *******
13  25 68     33 *************
60  27 14   0 0  ************************* ********************************
55  25 68   - 33 ************************* ******************************
19  21 77   - 67 *******************
25  16 53  -1 00 **************** ********
 4  11 25  -1 33 ****
 0   6 85  -1 67
 0   3 74  -2 00
 0   1 63  -2 33
 0     80  -2 67
 0     31  -3 00
 0     16    OUT
```

```
NORMAL PROBABILITY (P-P) PLOT
STANDARDIZED RESIDUAL
  1 0 +---------+---------+---------+---------*
      I                                    ***I
      I                              ******   I
      I                        ******         I
      I                     **                I
   75 +                                       +
      I                  ***                  I
O     I                                       I
B     I                 *                     I
S     I                *                      I
E   5 +                                       +
R     I                                       I
V     I                                       I
E     I             ***                       I
D     I            *                          I
  .25 +          **                           +
      I                                       I
      I       ****                            I
      I    ***                                I
      I                                       I
      +****-----+---------+---------+---------+ EXPECTED
               .25        .5       .75       1.0
```

Table A2. Residual distribution for mortar material, Portland, Maine.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N  EXP N       (* = 2 CASES.      . = NORMAL CURVE)
  2     16   OUT *
  0     31  3.00
  0     80  2.67
  1   1 83  2.33
  0   3 74  2.00
  0   6 85  1.67
  0  11 25  1.33
  0  16 53  1.00
  0  21 77   .67
 22  25 68   .33 ***********
136  27 14   0 0 *************.*******************************************************
 39  25 68  -.33 ************.*******
  0  21 77  -.67
  4  16 53 -1.00 **
  0  11 25 -1.33
  0   6 85 -1.67
  0   3 74 -2.00
  0   1 83 -2.33
  0     80 -2.67
  0     31 -3.00
  1     16   OUT *
```

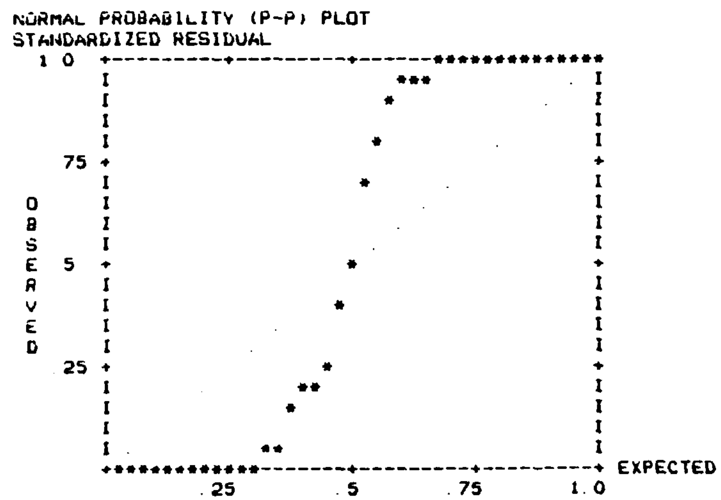


Table A3. Residual distribution for galvanized material, Portland, Maine.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N  EXP N       (* = 2 CASES,         . = NORMAL CURVE)
  2      16   OUT *
  0      31  3.00
  0      80  2.67
  0    1.83  2.33
  0    3.74  2.00
  0    6.85  1.67
  0   11.25  1.33
  0   16.53  1.00
  0   21.77   .67
  2   25.68   .33 *
189   27.14  0.0  ******************************************************************************************************
  0   25.68  -.33
  2   21.77  -.67 *
 10   16.53 -1.00 *****
  0   11.25 -1.33
  0    6.85 -1.67
  0    3.74 -2.00
  0    1.83 -2.33
  0     .80 -2.67
  0     .31 -3.00
  0     .16   OUT

                                   * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
```

NORMAL PROBABILITY (P-P) PLOT
STANDARDIZED RESIDUAL

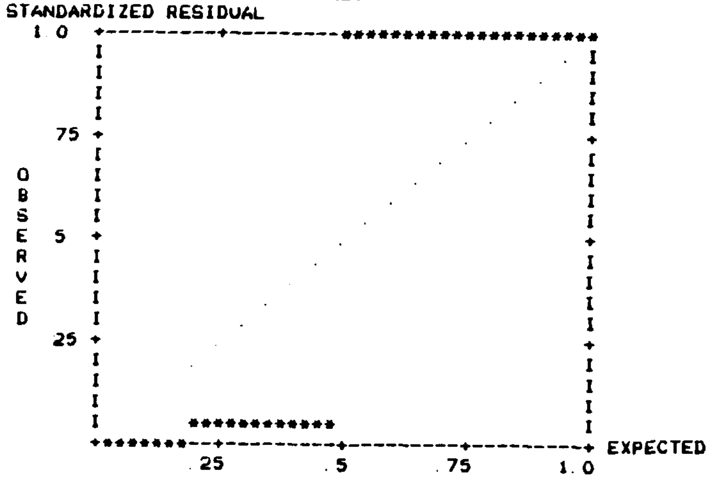


Table A4. Residual distribution for stone material, Portland, Maine.

```
HISTOGRAM
STANDARDIZED RESIDUAL
 N EXP N       (* = 1 CASES,         . NORMAL CURVE)
 2     16    OUT **
 2     31  3 00 **
 2     80  2 67  .
 0   1 83  2 33
 1   3 74  2 00 *
 2   6 85  1 67 **
 4  11 25  1 33 ****
 1  16 53  1 00 *
 6  21 77    67 ******
18  25 68    33 ******************
68  27 14  0 0  **************************.******************************************
45  25 68  -  33 ************************** ******************
19  21 77  -  67 *******************
15  16 53 -1 00 ***************
 0  11 25 -1 33
 0   6 85 -1 67
 0   3 74 -2 00
 0   1 83 -2 33
 0     80 -2 67
 0     31 -3 00
 0     16   OUT
```

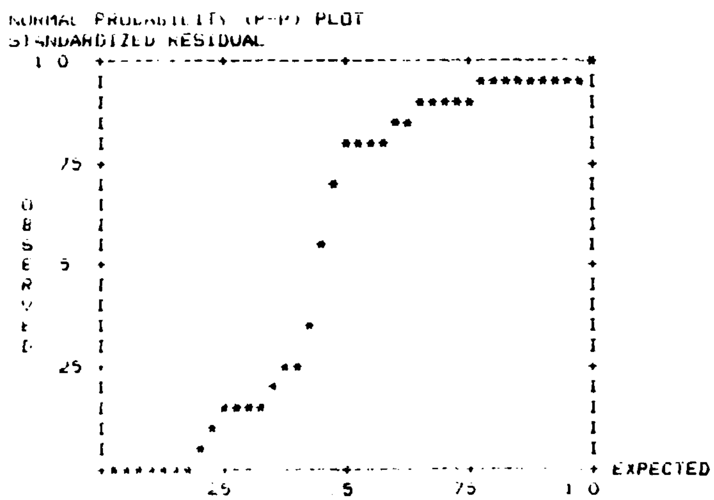


Table A5. Residual distribution for other material, Portland, Maine.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N  EXP N      (* = 2 CASES.        = NORMAL CURVE)
  5     22   OUT ***
  0     44  3 00
  1   1 11  2 67
  1   2 54  2 33
  0   5 20  2 00
  5   9 53  1 67 ***
  6  15 64  1 33 ***
 11  22 99  1 00 ******
 15  30 27    67 ********
 18  35 70    33 *********
 47  37 72  0 0  ****************** *****
124  35 70  - 33 ***************** *********************************************
 52  30 27  - 67 ************** ***********
  0  22 99 -1 00
  0  15 64 -1 33
  0   9 53 -1 67
  0   5 20 -2 00
  0   2 54 -2 33
  0   1 11 -2 67
  0     44 -3 00
  0     22   OUT
```

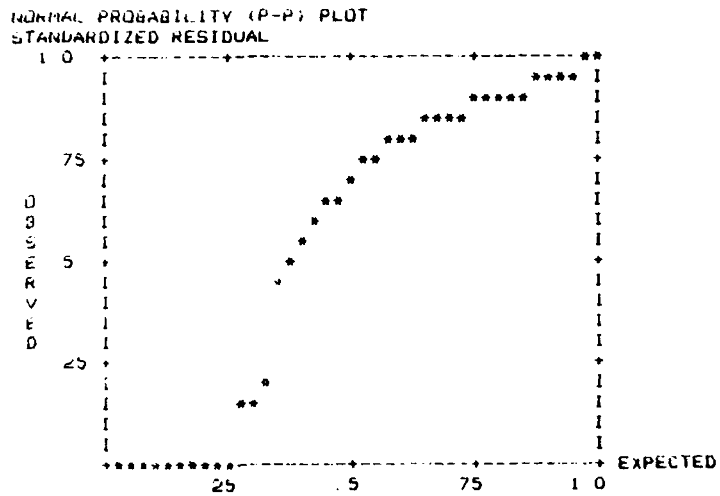


Table A6. Residual distribution for painted material, New Haven, Connecticut.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N  EXP N       (* = 1 CASES,        = NORMAL CURVE)
  7      22   OUT *******
  1      44   3 00 *
  1    1 11   2 67
  0    2 54   2 33
  0    5 20   2 00
  6    9 53   1 67 ******
  5   15 64   1 33 *****
  6   22 99   1 00 ******
 14   30 27     67 **************
 21   35 70     33 *********************
102   37 72   0 0  ****************************************************************************************************
 65   35 70   - 33 *****************************************************************
 44   30 27    -67 ********************************************
  5   22 99  -1 00 *****
  8   15 64  -1 33 ********
  0    9 53  -1 67
  0    5 20  -2 00
  0    2 54  -2 33
  0    1 11  -2 67
  0      44  -3 00
  0      22    OUT

                                  * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
```

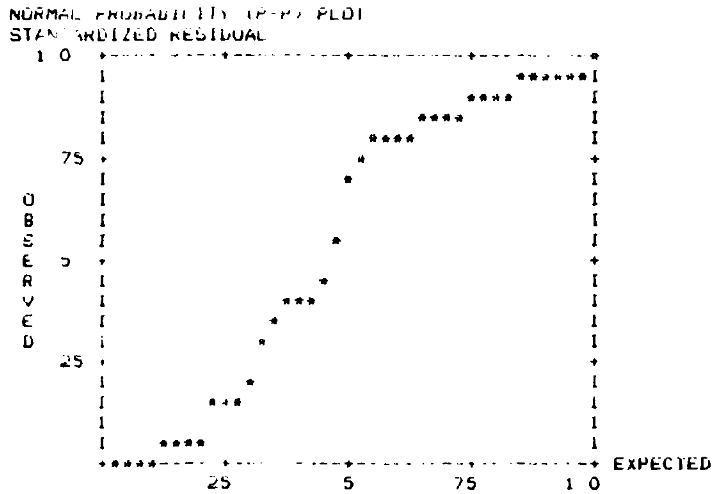


Table A7. Residual distribution for mortar material, New Haven, Connecticut.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N  EXP N         (* = 2 CASES,        = NORMAL CURVE)
  6      22   OUT ***
  0      44  3 00
  0   1  11  2 67
  0   2  54  2 33
  2   5  20  2 00 *
  0   9  53  1 67
  1  15  64  1 33 *
  1  22  99  1 00 *
  0  30  27    67
  2  35  70    33 *
165  37  72  0 0  ***********************************************************************************
 61  35  70  -  33 *******************************
 36  30  27  -  67 ******************
  2  22  99 -1 00 *
  5  15  64 -1 33 ***
  4   9  53 -1 67 **
  0   5  20 -2 00
  0   2  54 -2 33
  0   1  11 -2 67
  0      44 -3 00
  0      22   OUT

                               * * * * * * * * * * * * * * * * * * * * * * * * * * * * *

NORMAL PROBABILITY (P-P) PLOT
STANDARDIZED RESIDUAL
  1 0 +---------+---------+---------+--------**
      I                   ***************** I
      I                                     I
      I                                     I
      I                                     I
  75  +                                     +
      I                                     I
O     I                   *                 I
B     I                                     I
S     I                                     I
E  5  +                                     +
R     I                                     I
V     I                ****                 I
E     I                                     I
D     I                                     I
  25  +             *                       +
      I                                     I
      I          ****                       I
      I                                     I
      I    *******                          I
      ****------+---------+---------+-------+ EXPECTED
               25         5        75     1 0
```

Table A8. Residual distribution for galvanized material, New Haven, Connecticut.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N   EXP N        (* = 2 CASES,        . = NORMAL CURVE)
  5      22    OUT ***
  1      44   3 00 *
  0    1 11   2 67
  1    2 54   2 33
  0    5 20   2 00
  1    9 53   1 67 *
  0   15 64   1 33
  1   22 99   1 00 *
  2   30 27     67 *
  3   35 70     33 **
132   37 72   0 0  ***************** **************************************************
111   35 70   -  33 **************** ***********************************
 10   30 27   -  67 *****
  4   22 99  -1 00 **
 14   15 64  -1 33 *******
  0    9 53  -1 67
  0    5 20  -2 00
  0    2 54  -2 33
  0    1 11  -2 67
  0      44  -3 00
  0      22    OUT
```

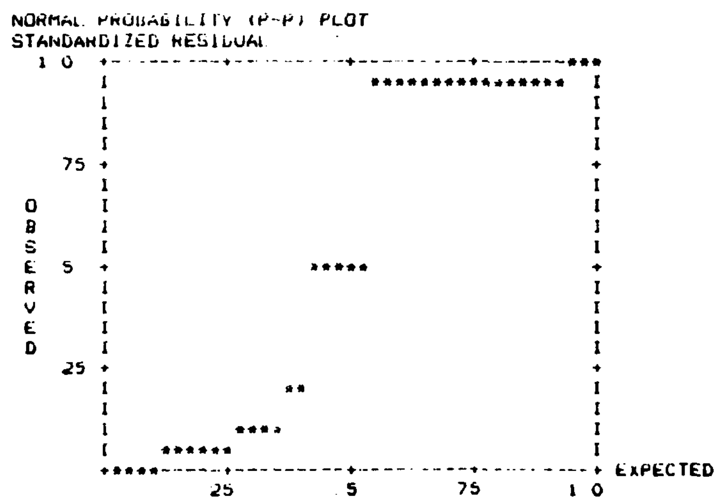


Table A9. Residual distribution for stone material, New Haven, Connecticut.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N  EXP N        (* = 1 CASES         . = NORMAL CURVE)
  5     22    OUT *****
  0     44   3 00
  1   1 11   2 67
  2   2 54   2 33 **
  2   5 20   2 00 **
  3   9 53   1 67 ***
  3  15 64   1 33 ***
  7  22 99   1 00 *******
  8  30 27     67 ********
 21  35 70     33 *********************
 81  37 72   0 0  **************************************.*******************************************
113  35 70   - 33 ************************************.****************************************************************************
 28  30 27   - 67 ****************************
  4  22 99  -1 00 ****
  7  15 64  -1 33 *******
  0   9 53  -1 67
  0   5 20  -2 00
  0   2 54  -2 33
  0   1 11  -2 67
  0     44  -3 00
  0     22    OUT
```

NORMAL PROBABILITY (P-P) PLOT
STANDARDIZED RESIDUAL

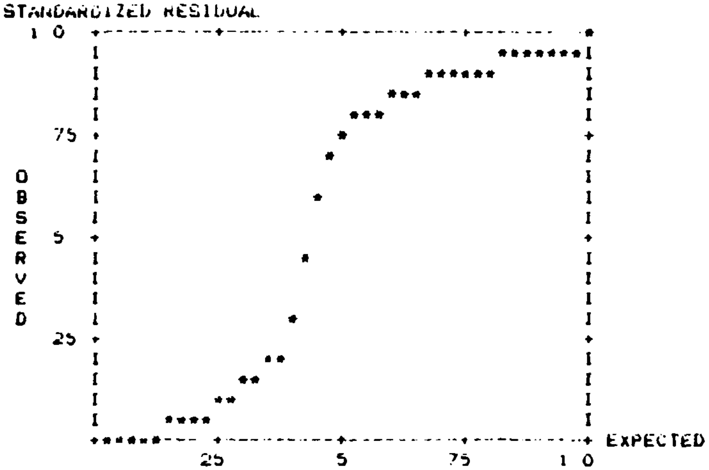
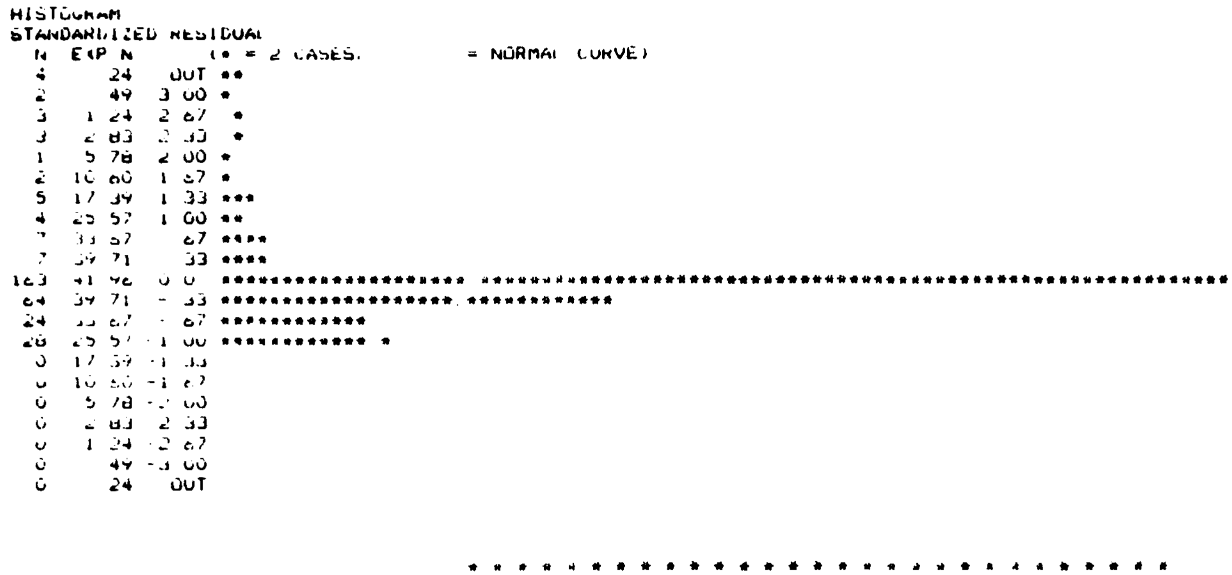


Table A10. Residual distribution for other material, New Haven, Connecticut.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N  EXP N      (* = 2 CASES.        = NORMAL CURVE)
  3     24   OUT **
  2     49  3 00 *
  1   1 24  2 67
  3   2 83  2 33  *
  0   5 78  2 00
  1  10 60  1 67 *
  0  17 39  1 33
  7  25 57  1 00 ****
  0  33 67    67
 19  39 71    33 **********
228  41 96  0 0  ******************** ******************************************************************************************
 11  39 71  -  33 ******
 33  33 67  -  67 ****************
  1  25 57 -1 00 *
  6  17 39 -1 33 ***
  1  10 60 -1 67 *
  1   5 78 -2 00 *
  0   2 83 -2 33
  0   1 24 -2 67
  0     49 -3 00
  0     24   OUT
```

```
    NORMAL PROBABILITY (P-P) PLOT
    STANDARDIZED RESIDUAL
      1 0 +----------+----------+----------+---------+
          I                         *************I
          I                      ***             I
          I                    **                I
          I                                      I
       75 +                   *                  +
          I                                      I
    O     I                                      I
    B     I                                      I
    S     I                                      I
    E   5 +                  *                   +
    R     I                                      I
    V     I                                      I
    E     I                                      I
    D     I                 *                    I
       25 +                                      +
          I                                      I
          I         ********                     I
          I        *                             I
          I  *****                               I
          +***-------+----------+----------+-----+ EXPECTED
                    25          5         75    1 0
```

Table All. Residual distribution for painted material, Pittsburgh, Pennsylvania.



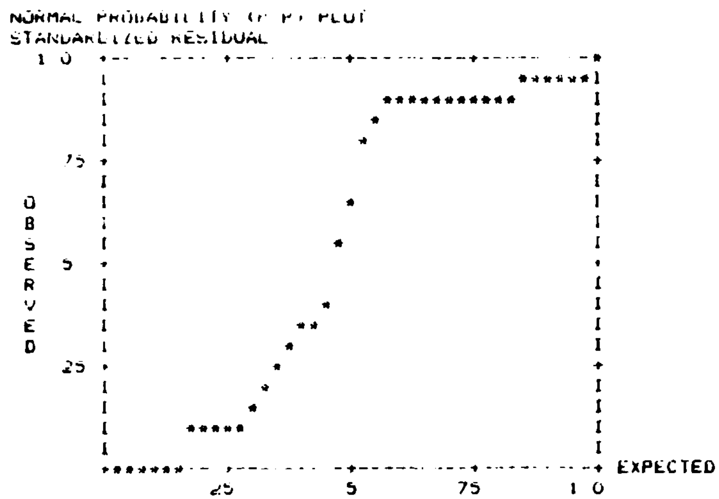


Table A12. Residual distribution for mortar material, Pittsburgh, Pennsylvania.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N  EXP N       (* = 3 CASES,        * NORMAL CURVE)
  3      24    OUT *
  0      49   3 00
  0    1 24   2 67
  0    2 83   2 33
  1    5 78   2 00
  0   10 60   1 67
  0   17 39   1 33
  0   25 57   1 00
  0   33 67     67
  7   39 71     33 **
252   41 96   0 0  ************* ******************************************************************************
  9   39 71   - 33 ***
 45   33 67   - 67 ********** ****
  0   25 57  -1 00
  0   17 39  -1 33
  0   10 60  -1 67
  0    5 78  -2 00
  0    2 83  -2 33
  0    1 24  -2 67
  0      49  -3 00
  0      24    OUT

                                   * * * * * * * * * * * * * * * * * * * * * * * * * * * * *

NORMAL PROBABILITY (P-P) PLOT
STANDARDIZED RESIDUAL
  1 0  +---------+---------+-----**************
       I                  ******              I
       I                                      I
       I                                      I
       I                                      I
   75  +                                      +
       I                                      I
 O     I                                      I
 B     I                                      I
 S     I                                      I
 E   5 +                                      +
 R     I                                      I
 V     I                                      I
 E     I                                      I
 D     I                                      I
   25  +                                      +
       I                                      I
       I           ********                   I
       I                                      I
       I                                      I
       ***********-----  --+---------+---------+ EXPECTED
                 25        5        75        1 0
```

Table A13. Residual distribution for galvanized material, Pittsburgh, Pennsylvania.

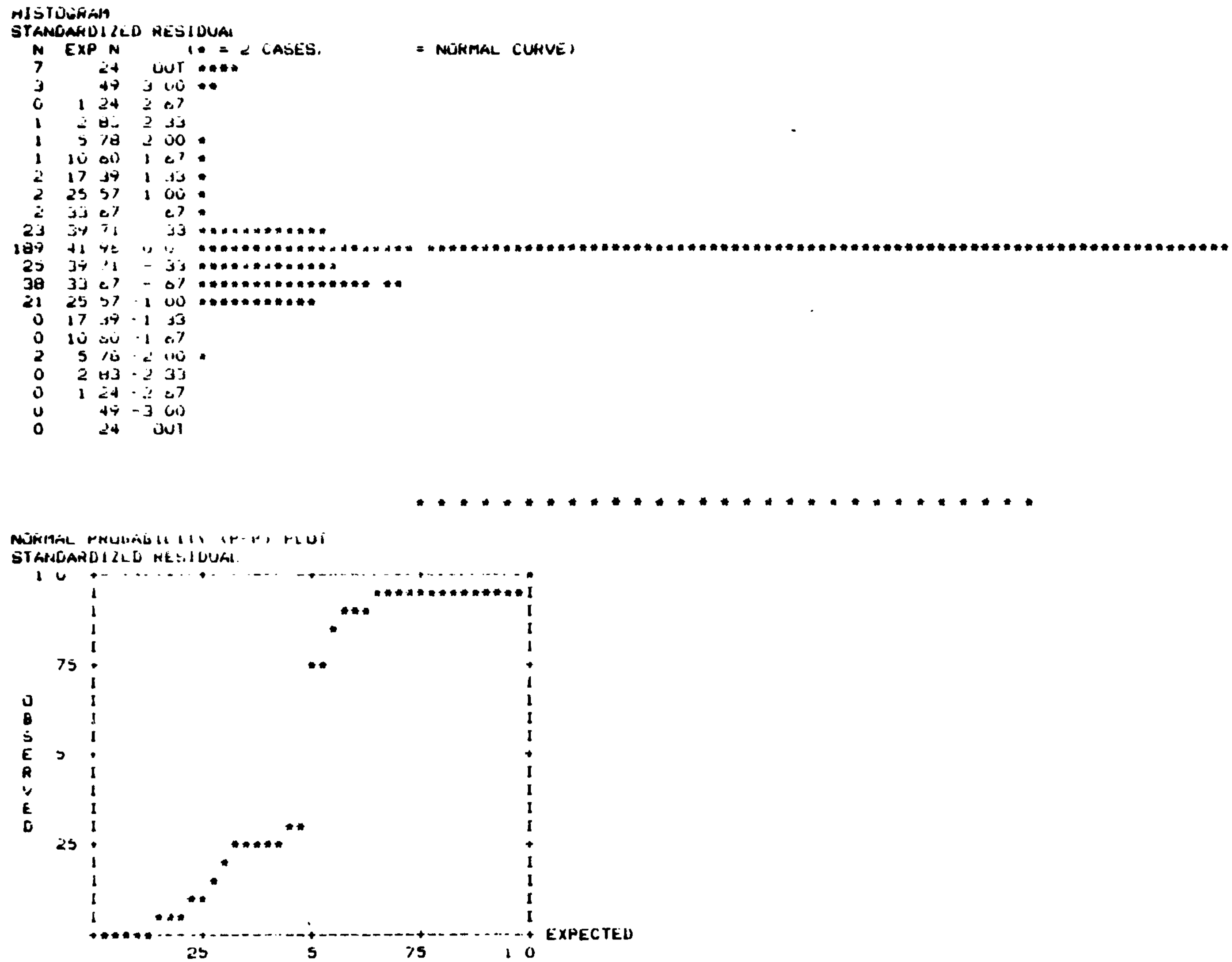


Table A14. Residual distribution for stone material, Pittsburgh, Pennsylvania.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N  EXP N        (* = 4 CASES.        = NORMAL CURVE)
  4     24    OUT **
  0     49   3 00
  0   1 24   2 67
  1   2 83   2 33
  1   5 78   2 00 *
  4  10 60   1 67 **
  1  17 39   1 33 *
  2  25 57   1 00 *
  1  33 67     67 *
 13  39 71     33 *******
212  41 76    0 0 ********************* **************************************************************************
 36  39 71   - 33 *******************
 16  33 67   - 67 ********
 26  25 57  -1 00 ************
  0  17 39  -1 33
  0  10 60  -1 67
  0   5 78  -2 00
  0   2 83  -2 33
  0   1 24  -2 67
  0     49  -3 00
  0     24    OUT

                                   * * * * * * * * * * * * * * * * * * * * * * * * * * * * *

NORMAL PROBABILITY (P-P) PLOT
STANDARDIZED RESIDUAL
  1 0  +-------+----------+---------+-------**
       I                  ***************  I
       I                **                 I
       I               *                   I
       I                                   I
   75  +                                   +
       I                                   I
 O     I                                   I
 B     I                                   I
 S     I                                   I
 E  5  +                                   +
 R     I                                   I
 V     I                                   I
 E     I                                   I
 D     I                                   I
   25  +             *****                 +
       I                                   I
       I      *****                        I
       I   ***                             I
       I **                                I
       ******--+---------+---------+-------+ EXPECTED
              25         5        75      1 0
```

Table A15. Residual distribution for other material, Pittsburgh, Pennsylvania.

```
HISTOGRAM
STANDARDIZED RESIDUAL
 N EXP N       (* = 1 CASES,        = NORMAL CURVE)
 2     14   OUT **
 1     27  3 00 *
 1     70  2 67
 0   1 60  2 33
 4   3 27  2 00 ** *
 1   5 98  1 67 *
 3   9 82  1 33 ***
 4  14 44  1 00 ****
15  19 01    67 ***************
15  22 42    33 ***************
47  23 69  0 0  *********************** ***********************
46  22 42  - 33 ********************** ***********************
15  19 01  - 67 ***************
19  14 44 -1 00 ************** *****
 6   9 82 -1 33 ******
 0   5 98 -1 67
 0   3 27 -2 00
 0   1 60 -2 33
 0     70 -2 67
 0     27 -3 00
 0     14   OUT
```

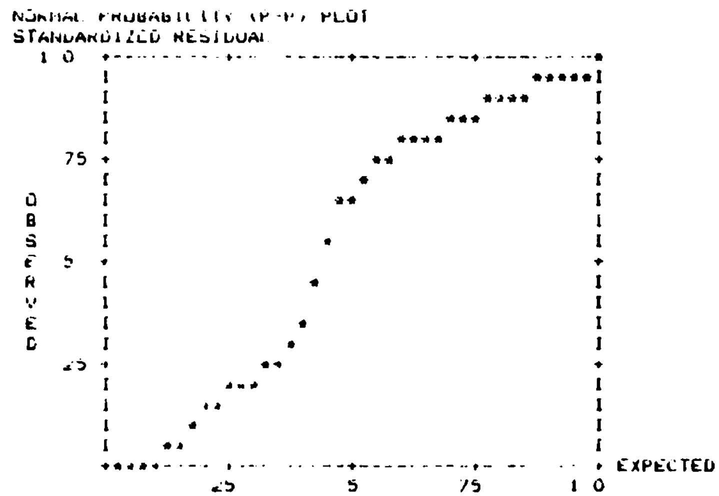


Table A16. Residual distribution for painted material, Cincinnati, Ohio.

```
HISTOGRAM
STANDARDIZED RESIDUAL
 N EXP N         (* = 1 CASES.        = NORMAL CURVE)
 5     18   OUT *****
 1     36  3 00 *
 0     92  2 67
 1   2 11  2 33 *
 2   4 31  2 00 **
 2   7 89  1 67 **
 0  12 95  1 33
 2  19 03  1 00 **
 5  25 07    67 *****
23  29 57    33 ***********************
68  31 24   0 0 ******************************* ***************************************************
62  29 57  - 33 ****************************** *******************************
14  25 07  - 67 **************
28  19 03 -1 00 ****************** *********
 1  12 95 -1 33 *
 1   7 89 -1 67 *
 0   4 31 -2 00
 0   2 11 -2 33
 0     92 -2 67
 0     36 -3 00
 1     18   OUT *
```

NORMAL PROBABILITY (P-P) PLOT
STANDARDIZED RESIDUAL

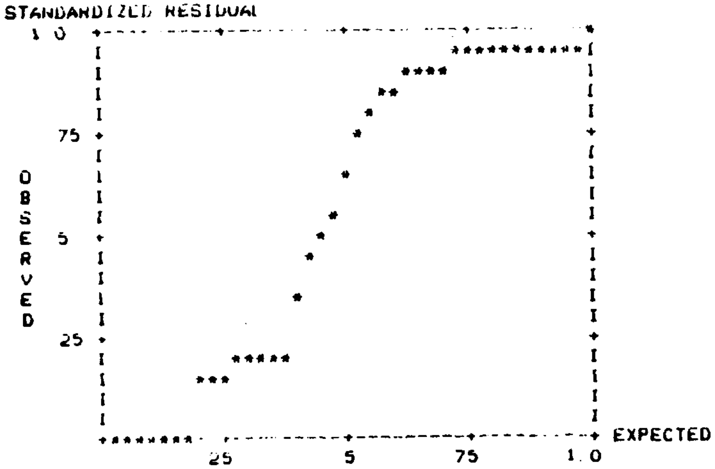


Table A17. Residual distribution for mortar material, Cincinnati, Ohio.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N  EXP N        (* = 3 CASES.        = NORMAL CURVE)
  2      18   OUT *
  0      36  3 00
  0      92  2 67
  0    2 11  2 33
  0    4 31  2 00
  0    7 89  1 67
  1   12 95  1 33
  0   19 03  1 00
  0   25 07    67
  2   29 57    33 *
231   31 24  0 0  ********* **************************************************************
  0   29 57  - 33
  0   25 07  - 67
  0   19 03 -1 00
  0   12 95 -1 33
  0    7 89 -1 67
  0    4 31 -2 00
  0    2 11 -2 33
  0      92 -2 67
  0      36 -3 00
  0      16   OUT
```

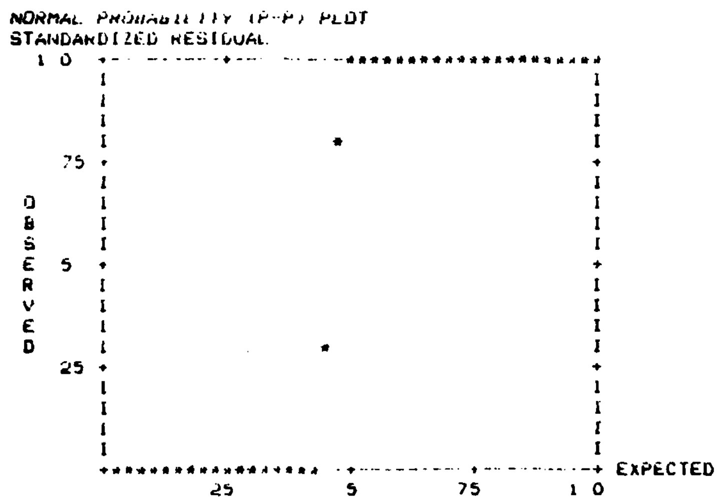


Table A18. Residual distribution for galvanized material, Cincinnati, Ohio.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N  EXP N        (* = 2 CASES.         = NORMAL CURVE)
  6     18   OUT ***
  0     36  3 00
  0     92  2 67
  0   2 11  2 33
  0   4 31  2 00
  2   7 89  1 67 *
  0  12 95  1 33
  1  19 03  1 00 *
  3  25 07    67 **
 13  29 57    33 *******
146  31 24   0 0 ***************.**********************************************************
 21  29 57  -  33 ***********
 38  25 07  -  67 ************.******
  6  19 03 -1 00 ***
  0  12 95 -1 33
  0   7 89 -1 67
  0   4 31 -2 00
  0   2 11 -2 33
  0     92 -2 67
  0     36 -3 00
  0     16   OUT
```

NORMAL PROBABILITY (P-P) PLOT
STANDARDIZED RESIDUAL

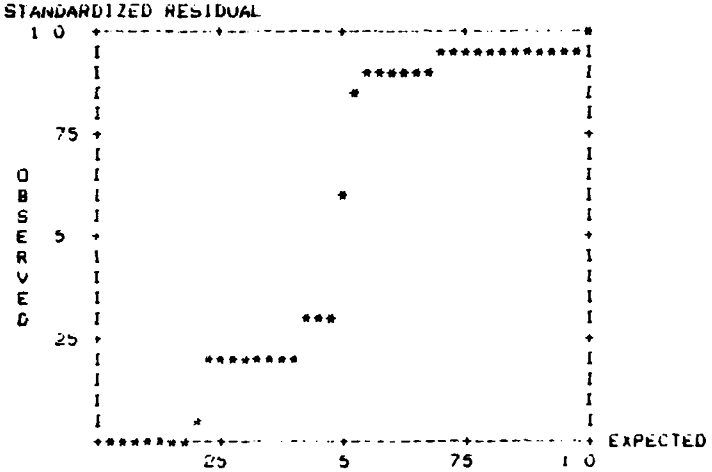


Table A19. Residual distribution for stone material, Cincinnati, Ohio.

```
HISTOGRAM
STANDARDIZED RESIDUAL
  N   EXP N      (* = 1 CASES.        = NORMAL CURVE)
  4      18   OUT ****
  2      36  3 00 **
  0      92  2 67
  0    2 11  2 33
  1    4 31  2 00 *
  3    7 89  1 67 ***
  2   12 95  1 33 **
  9   19 03  1 00 *********
  3   25 07    67 ***
 15   29 57    33 ***************
109   31 24  0 0  ******************************* *****************************************************************************
 51   29 57  - 33 ***************************** *********************
 11   25 07  - 67 ***********
 17   19 03 -1 00 *****************
  9   12 95 -1 33 *********
  0    7 89 -1 67
  0    4 31 -2 00
  0    2 11 -2 33
  0      92 -2 67
  0      36 -3 00
  0      18   OUT
```

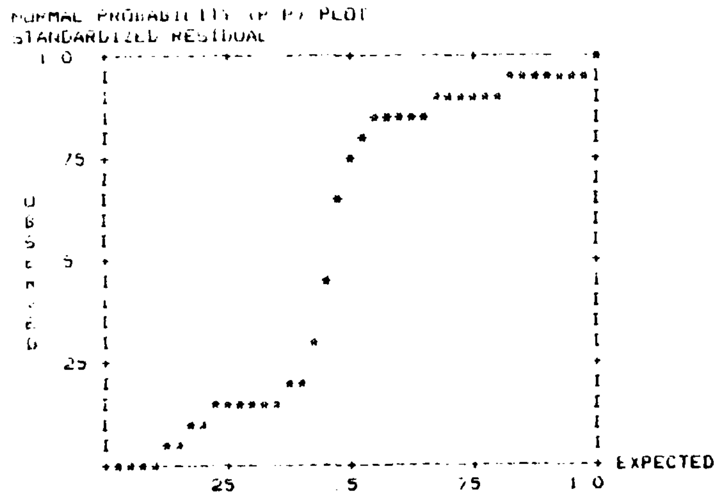


Table A20. Residual distribution for other material, Cincinnati, Ohio.

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