PREDICTING LONG-TERM INDOOR RADON CONCENTRATIONS FROM SHORT-TERM MEASUREMENTS: EVALUATION OF A METHOD INVOLVING TEMPERATURE CORRECTION

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ABSTRACT

Most studies which seek to determine uncertainty bounds in predicting long-term indoor radon concentration from short-term measurements, do so assuming radon variability to be a random quantity. The objective of this paper is to evaluate the potential of decreasing these uncertainty bounds if one assumes indoor radon variations to be in part influenced by certain time-varying known physical driving forces. From daily averaged data from three occupied unmitigated residences, for which continuous measurements were taken for about a year, the stack effect (as also the ambient temperature) has been identified as the predominant physical driving force. We find that the uncertainty bounds for predicting long-term radon concentrations, when explicit recognition is given to the year-long variation in stack effect, are reduced drastically in one house, less so in another, and marginally in the third. Probable physical causes behind these observations are also discussed. A general mathematical equation is derived for predicting these uncertainty bounds in terms of climatic variability, a factor dependent on house and surrounding soil characteristics, and the strength of the physical model. Though the mathematical equation is correct within the framework of the assumptions made, more associated studies and analysis involving a larger data base are required before the benefits and scope of this technique could be fully appreciated in terms of practical applicability and relevance.

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STATEMENT OF PROBLEM

The issue of defining bounds to the uncertainty associated with predicting

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the long-term (by which one generally implies, yearly) average[2] of indoor radon concentrations from single short-term (i.e., 1 to 15 day period) observations has generated great interest in the radon research community. This has arisen not only because of the practical implications in terms of health hazards to inhabitants, but also because of mandatory indoor radon testing laws required for realty transactions. The problem is especially complex given that indoor radon concentrations vary widely during the day, from day-to-day, and often show strong seasonal patterns which are house specific since they depend upon soil type, climate, house construction, house dynamics, and occupant behavior (1-5). Though the number of studies addressing the issue of predicting yearly indoor radon levels from short-term screening tests is relatively small, it would nevertheless be appropriate to start by taking stock of past research in this area.

There are basically two types of research thrusts: (a) one that involves analysis of survey data from a large number of houses, for example (6), and (b) one that involves detailed analysis of a few houses in which continuous measurements have been performed (3-5). The advantage of approach (a) is that it enables statistically rational and generalizable uncertainty bounds to be determined, while the disadvantage is that the uncertainty bounds are rather large. Ref. (6) finds an uncertainty range of 5 times the short-term screening value for 95% confidence level when no consideration is given to time of year, and of the order of 3 times when one explicitly considers the season during which the single measurement was performed. One way of decreasing these uncertainty bounds is to perform additional survey tests with stratified sampling which consists of partitioning the population into groups each of which is more homogeneous than the population itself. The stratified sampling could distinguish between season, geographic location, soil type, house construction and equipment type. Such an approach, which has been used in previous studies, for example, Ref. (7), could be investigated in the framework of certain current programs, for example, the Florida Radon Research Program (FRRP) (8).

The basic disadvantage of approach (b) is that practical and generalizable uncertainty bounds are difficult to establish given the wide differences from one house to another. However, what such an approach does provide is insight into the day-to-day variability of indoor radon concentrations and how and to what extent these are affected by the various climatic and house-specific parameters. Such information would also enable sound experimental design and proper identification of the sample strata in the framework of approach (a).

Indoor radon concentrations vary widely from day-to-day and also show strong seasonal patterns (4,5). A former study (9) had suggested that an average of screening measurements taken during two different seasons of the year would provide a more satisfactory estimate of the yearly average than a

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[2]Current scientific thinking seems to assume that the arithmetic mean concentration is more representative of the exposure risk than are other indices, such as median or geometric mean.

214

single measurement. A short-term measurement strategy which involved performing measurements during each of the four seasons of the year (although impractical in terms of actual implementation) was shown to provide long-term estimates within 25% accuracy (when the associated instrument error is overlooked).

Parameter sets affecting indoor radon concentrations can be divided into three groups. The first includes the intrinsic properties of the soil and the location and concentration of the radon source with respect to the house. The second set is made up of the characteristics of the building sub-structure and super-structure and of the equipment in the house. The third set consists of climatic parameters like ambient temperature, and wind magnitude and direction. The coupled influence of the second and third sets is generally acknowledged to be the primary cause of the day-to-day year-long variability of indoor radon concentrations, while the mean concentration level is largely influenced by the first set of parameters. Note that the primary concern in the present study is to capture the variability of radon and not to predict the magnitude of the mean concentration level as such.

Thus, predicting long-term indoor radon concentrations from short-term measurements is essentially an uncertain process since indoor radon concentrations vary during the year. Most studies, though implicitly acknowledging that this variation is the result of variation in certain physical driving forces, have limited themselves to treating (i.e., analyzing) indoor radon concentration data as made up of random observations. The specific objective of this study is to evaluate a technique whereby the indoor radon data are analyzed as being the response of a physical system subject to varying input physical forces. Since random effects are bound to be present in any physical system, the total observed radon variation over a year can be visualized as consisting of two components: a deterministic component resulting from certain physical forces, and an unexplained random component. The practical relevance of such an approach is that it would have the potential of decreasing the uncertainty bounds, at a prespecified confidence level, in predicting the long-term indoor radon concentration when a single short-term measurement is made.

DESCRIPTION OF DATA

This study is based on year-long continuous data collected by Princeton University in three occupied residences, designated H2, H21, and H22, in the Princeton area of New Jersey. H2 is a two-story structure with a full basement made up of hollow cinder-block walls, and an attached garage that was built in 1980. It has very little tree cover and sits in the middle of several acres of open land. Heating is provided by a gas fired forced air heating system while cooling is supplied by a central air-conditioner. The house has a gravel bed under the slab, while the soil underneath is relatively impermeable.

H21 is a single-story ranch-style house with a partial basement, the remainder of the house being of slab-on-grade construction. This house, which is about 30 years old, is surrounded with trees. The basement walls are of hollow cinder block. This house also has a gravel bed under the slab. The heating system is a gas furnace while a central air-conditioner supplies cooling.

H22 is a 60 year old balloon-construction three-story house with a partial basement and floor drains. There is tree coverage on two sides while the other two sides are exposed. Unlike the other two houses, the subslab material is soil. The house is heated by radiators, while cooling is provided by a central air-conditioner. Because of this, the air handler is used only for cooling. Detailed descriptions of the houses and of the continuous data taken during the period the houses were unmitigated can be found in Ref. (4).

We have screened and reduced the data stored as 1/2 hour averages into daily averages since this is more appropriate for this study. Periods during which data were available for all three houses are given in Table 1, while the parameters selected for analysis are described in Table 2. Variations in temperature differences are often more appropriate than those of temperature to explain indoor radon variations (4). For example, differences between TB and TA have been designated as TBA in this study. Table 3 assembles the mean and standard deviation of the various parameters over the entire period during which data were available. One notes that the standard deviations are generally large compared to the mean values for most parameters.

IDENTIFICATION OF PHYSICAL MODEL

The first step is to describe the system in terms of a model. One approach is to construct a physical model based on mass balances akin to that of, say, Ref. (10). This approach is not only involved mathematically but is also house specific in that the physical geometry of the house dictates the inclusion, or exclusion, of certain air and radon flow paths, which themselves may be uncertain. An alternative approach, and the one adopted in this study, is to formulate a statistical model; for example, a simple linear regression model. We shall have to identify the model parameters (i.e., the important driving forces) and the regression coefficients from the data at hand.

Table 4 presents the correlation coefficients [see any statistics book, say (11), for definition] of the radon quantities (RNB and RNL) with the other parameters which are described in Table 2. TLA is strongly collinear with TBA and has not been included in Table 4. We note that the correlation coefficients of H21 are strongest while those of H2 and H22 are lower [which is consistent with Ref. (4)]. What is most surprising is that RNL variability is much better explained (i.e., has stronger correlation coefficients) than that of RNB. One would have expected the reverse since the conventional understanding is that soil gas first enters the house via the basement from where it finds its way to the living area by a combination of several house-specific pathways. The stack effect, represented by TBA (and TLA), seems to be the most important [again, consistent with Ref. (4)]. The effect of HAC on indoor radon values is smaller (correlation coefficients about 0.25). Moreover, since TLA and HAC are collinear, there does not seem to be much

216

incentive in using regression models for radon with HAC as a second variable (4)[3]. Though TSB seems collinear with RNL for H21, the interpretation of the TSB measurement as a physical parameter may be spurious, given that the temperature probe is close enough to the basement to be affected by both basement and soil temperatures (4).

Table 5 assembles the values of the adjusted coefficients of determination (11), i.e., the adjusted R^2 values obtained by a linear regression of indoor radon parameters (RNB and RNL) with four different models. We note that there is much greater variation in quality of fit (i.e., in R^2 values) of the regression models across houses than between models. Whatever variability the models fail to account for is dominated by certain house-level factors that are not greatly influenced by the model parameter sets chosen. Radon models for H21 are generally satisfactory ($R^2 \sim 0.6 - 0.8$) despite the fact that the basement window was open during a large portion of the time. On the other hand, models for RNB in H2 are extremely poor, an occurrence which could be attributed to the fact that the subsoil is relatively fine-grained and compacted thereby offering large resistance to radon migration in the soil. Consequently, for the same magnitude of the forcing functions, the resulting variation in indoor radon levels would be less important than in other houses. Models for RNB in H22 are also poor. Probable causes are that the house has distinct zones and prior experiments indicate the presence of short-circuit air flow paths from the subslab to the attic via the walls.

We find that models with TA (Model 1) or TBA (Model 2) are equally good while there does not seem to be any advantage in including HAC as an additional parameter. A previous study (12) had indicated that at half-hour time intervals the physical mechanism affecting radon entry into the basement is akin to a one-way valve dictated by temperature differences between soil, basement, and ambient. Consequently, we have also investigated a model explicitly separating the positive and negative values of TBA. This pertains to Model 3 of Table 5. We note that, though Model 3 has higher R^2 values, the improvement is generally only a few percentage points and does not justify the added complexity in the model structure when daily time scales of averaging are used.

We have also investigated model structures of the form RNB, RNL = f (TBA - c)$^+$ where c is a coefficient to be determined by regression and the + sign indicates that only positive values are retained in the regression analysis. This model structure, it will be noted, is akin to that used in building energy studies where comfort energy requirements are often regressed against degree-days (13). The improvement in R^2 values of such a model over those of Models

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[3]One of the findings of Ref. (4) was that there was limited, if no, incentive in formulating a model for indoor radon levels over the <u>entire</u> year which included HAC as a second variable. However for models on a <u>seasonal</u> basis, the inclusion of HAC does improve the models. These conclusions are however specific to the scope of Ref. (4) which was limited to three residences in central New Jersey.

217

1 and 2 was at most a few percentage points, while R^2 values were lower than those of Model 3.

ALTERNATIVE APPROACH TO ANALYZING INDOOR RADON DATA

In this section we shall seek to determine whether, and by how much, the two following approches of analyzing data narrow down the confidence bounds, or alternatively, the percentiles (11):

(a) entire variation of indoor radon concentration over the year is random. As noted earlier, this is the approach followed by most studies to date. In this case we shall merely inspect the data series of the normalized variable ($RN/\overline{RN}$) where RN could be either RNB or RNL, and $\overline{RN}$ is the long-term (i.e., the annual) average of RN;

(b) variation of indoor radon concentration is partly the result of variation in certain known physical forces which drive indoor radon. Only the residual variation, or the variation in indoor radon not explained by the model, is random.

The statistical analysis in the previous section suggested [as also did several studies, say (4)] that the most influential parameter which explains indoor radon levels is the stack effect, characterized by TBA or by TA. The following model structure is used to describe the output of the system:

$$\widehat{RN}_i = a' + b' \cdot TBA_i \qquad (1)$$

where RN could be either RNB or RNL,
a' and b' are the intercept and slope of the linear regression line,
subscript i represents individual observations, and
$\widehat{RN}$ is quantity deduced from the model rather than from measured data.

If $\overline{TBA}$ and $\overline{RN}$ are the long-term (i.e., the annual) averages of TBA and RN, respectively, then

$$(\widehat{RN}_i/\widehat{\overline{RN}}_i) = (a' + b' \cdot TBA_i)/(a' + b' \cdot \overline{TBA}) \qquad (2)$$

Subsequently, replacing $\widehat{RN}_i$ by RN_i, we have

$$\widehat{\overline{RN}}_i = RN_i \cdot (a'+b' \cdot \overline{TBA}) \; / \; (a'+b' \cdot TBA_i) \qquad (3)$$

Note that $\widehat{\overline{RN}}_i$ would be the value of the long-term indoor radon concentrations predicted from an individual or short-term observation RN_i by applying the temperature correction approach. Finally, this value has been normalized by dividing it by $\overline{RN}$, where $\overline{RN}$ is the long-term average of RN deduced from data (and assembled in Table 3). The data available for all three houses have been processed both as explained above and also by assuming them to be random; i.e., by merely dividing the RN_i values by $\overline{RN}$.

218

The percentiles of the associated distribution of daily values without [i.e., of ($RN_i/\overline{RN}$) data series] and with [i.e., of ($\widehat{RN}_i/\overline{RN}$) data series] temperature correction are given in Fig. 1. We note that there is a marked decrease in the uncertainty bounds for the indoor radon levels of H21, a smaller improvement in H22, and negligible improvement for H2. These are consistent with the R^2 values of the associated regression model, i.e., higher the R^2 value, more the improvement. The interpretation of the numbers in Fig. 1 is straightforward. For example, the results of RNL for H21 seem to indicate that we could hope to narrow the 90% uncertainty bounds in predicting the annual radon levels from a factor of 2.4 with no temperature correction down to 1.4 when the temperature correction is applied.

STATISTICAL METHODOLOGY TO DETERMINE BOUNDS ON PREDICTION ACCURACY

The scope of the evaluation in the previous section was limited since actual data from only three houses in the Princeton area were available. Though we were unable to demonstrate a significant advantage in our approach, reappraisal in the framework of future studies seems justified. In this section, we shall derive a mathematical equation to predict the theoretical uncertainty bounds resulting from our physical approach. This would permit our approach to be generalized to any climate and to different types of houses and soil conditions.

We shall assume a simple linear model structure between indoor radon concentration and a single driving force (say, ambient temperature since it is a variable easier to obtain than TBA, and has been found to be as good a predictor of RN as is TBA) such as:

$$RN = a + b \cdot TA \qquad (4)$$

Given inherent "noise" in the data and also that the effects of other driving forces are overlooked, the model will not be a perfect fit. This can be represented statistically as (11):

$$RN_i = a + b \cdot TA_i + \varepsilon_i \qquad (5)$$

where ε_i is the error term in the individual observations.

The model implies that the observed RN variability could be due to a large variability in the driving force (i.e., TA) along with a small coupling coefficient (i.e., b) or vice versa. Thus we have separated the problem of long-term indoor radon variability into a location-dependent climatic effect and a climate-independent, location-, and house-characteristics-dependent effect.

219

If the variables RN and TA are assumed to be normally distributed variables[4] with no serial correlation, ε will be normally distributed, have zero mean, and a constant variance of $\sigma^2(\varepsilon)$; i.e., homoscedasticity is assumed in the basic physical process. Let n be the number of observations and R^2 the goodness-of-fit of the model given by eq. (4). Then, from the definition of R^2 (11):

$$R^2 = \frac{\sum_{i=1}^{n} (\widehat{RN}_i - \overline{RN})^2}{\sum_{i=1}^{n} (RN_i - \overline{RN})^2} \tag{6}$$

where $\widehat{RN}_i$ is the model predicted value [from eq.(4)], $\underline{RN}_i$ is the observed value, and $\overline{RN}$ the long-term average of RN.

Also

$$\sum_{i=1}^{n} (\widehat{RN}_i - \overline{RN})^2 = \sum_{i=1}^{n} b^2 \cdot (TA_i - \overline{TA})^2$$

$$= b^2 \cdot \overline{TA}^2 \cdot (n-1) \cdot \sigma^2 \left(\frac{TA_i}{\overline{TA}}\right) \tag{7}$$

Introducing this in eq. (6) we have

$$\overline{RN}^2 \cdot \sigma^2 \left(\frac{RN_i}{\overline{RN}}\right) = \frac{b^2}{R^2} \cdot \overline{TA}^2 \cdot \sigma^2 \left(\frac{TA_i}{\overline{TA}}\right) \tag{8}$$

From the above and from the definition of R^2, we find

$$\sigma^2(\varepsilon_i) = \frac{1 - R^2}{R^2} \cdot b^2 \cdot \overline{TA}^2 \cdot \sigma^2 \left(\frac{TA_i}{\overline{TA}}\right) \tag{9}$$

The standard deviation of the standardized quantity $(\varepsilon_i/\overline{RN})$, which is analogous to the Coefficient of Variation (11), is finally obtained

$$\sigma\left(\frac{\varepsilon_i}{\overline{RN}}\right) = \left(\frac{1 - R^2}{R^2}\right)^{1/2} \cdot \sigma\left(\frac{TA_i}{\overline{TA}}\right) \cdot \left(\frac{a}{b \cdot \overline{TA}} + 1\right)^{-1} \tag{10}$$

Eq. (10) is simply an equation which correlates the variation (quantified

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[4]Several studies [for example Ref. (4)] have found that the variable TA (and TBA) exhibits a normal distribution over an entire year, while indoor radon variables have no consistent agreement with either a normal or a log-normal distribution, though the latter is usually better.

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by the standard deviation) of RN not explained by the model in terms of three sets of parameters describing:

(a) location specific variation in the ambient temperature; i.e., $\sigma\ (TA_i/\overline{TA})$;

(b) house and surrounding soil dependent quantity specified by the factor (a/b), which has units of °C; and

(c) strength of the regression model between RN and TA designated by the R^2 value. Recall that the physical interpretation of the R^2 value is that it represents the percentage of the total variation in the response variable explained by (i.e., directly the result of variation in) the exogenous variable.

Since the variables RN_i and TA_i are assumed to be normally distributed, the critical values at different significance levels would correspond to the uncertainty ratios at different probability levels. For example, a 95% probability level would correspond to $(2 \cdot \sigma)$ [see Ref. (11)].

The above derivation could be easily extended to linear model structures with more than one driving force. One could adopt a similar methodology for the more-often-encountered case when the variable RN is not normally distributed while the variable TA is.

APPLICATION TO ACTUAL DATA

We shall illustrate how eq. (10) could be applied to specific locations. From 1 year's data of daily TA values provided by NOAA (14), we find for the Princeton area, $\sigma\ (TA) \simeq 8.5°C$ while $\overline{TA} = 12.8°C$. Values of the parameters a and b of eq. (4) are assembled in Table 6 for the three houses. From Table 6, we find (a/b) factors for RNB to be 78 for H2, 21.8 for H21, and 145 for H22. Interestingly, H21 is a one-story residence; H2, two-story, and H22, three-story. Thus one notes that (a/b) factors seem to increase with the height of the building. This observation is perhaps premature and needs to be evaluated further.

How the theoretical standard deviation of the variable $(\varepsilon_i/\overline{RN})$ would vary with R^2 for a wide range of (a/b) values for the Princeton area is shown in Fig. 2 generated from eq. (10). From the limited number of houses studied (other than H21 where basement window opening may be an abnormal occurrence), values of (a/b) are in the 80-150 range. Even for low values of R^2 (=0.2), one notes that the temperature correction approach could result in prediction intervals at the 95% confidence level (i.e., 2 standard deviations) not exceeding 1.4. This is a significant observation since it implies that uncertainty bounds of prediction can be drastically reduced by our physical approach even in a house where the indoor radon variability is weakly influenced by variation in the stack effect.

As a preliminary illustration, Table 7 assembles values of σ (TA) and $\overline{TA}$

for a few locations in the U.S for different averaging times. To within one decimal accuracy, the arithmetic mean is essentially independent of averaging time interval while the standard deviation decreases with length of averaging interval. If the standard deviation values for each location are normalized with respect to the 1-day value, we note that the decrease with averaging time is fairly linear and location independent (Fig. 3). Thus, we note that an averaging interval of 15 days will lead to a 35% decrease in the standard deviation of the ambient temperature variability over the year as compared to a 1-day time scale of averaging, while an averaging interval of 1 week would result in a 20% decrease. Though an exponential fit to these data points would be more accurate, we find that a linear fit to the normalized standard deviation versus averaging time (in days) yields an R^2 of 0.93 with a slope of -0.023 (SEM = 0.002).

The possible range of variation of the factor (a/b), representative of the soil conditions and house construction practices prevalent in widely different geographic locations in the U.S., is unknown at present. Either analyzing existing radon survey data or gathering data explicitly for this purpose may be tasks worth evaluating in the framework of future radon projects. An alternate, and perhaps more promising, approach is to infer the parameters a and b from the house response when certain simple "stressed" experiments on the house are performed. Such experimental protocols have yet to be satisfactorily formulated and validated, but initial attempts are underway in the Research House Study of the FRRP (8). Efforts such as the above would, hopefully, permit numerical values of a and b to be specified dependent on generic building construction type and soil conditions.

CONCLUSIONS

The physical approach advocated in this study, whereby one visualizes indoor radon variations as the response of a physical system acted upon by certain varying and known forces, has been shown to have the potential of decreasing the uncertainty bounds associated with the problem of having to predict long-term indoor radon levels from short-term screening tests. The physical system can be described by a regression model with the stack effect as the single most influential driving force. How such a model approach fares with respect to the conventional procedure, of assuming indoor radon variability to be random, has been evaluated with daily averaged data for over a year in three occupied houses. It has been found to be distinctly advantageous in one house, moderately advantageous in another, and marginally so in the third.

The theoretical uncertainty bounds of prediction resulting from the physical approach can be predicted from a mathematically derived equation expressing the normalized standard deviation of the variation of indoor radon not explained by the model (i.e. the random component), in terms of three sets of parameters: location-dependent statistics of ambient temperature, a factor describing the coupling between the soil and the house, and the strength of the regression model. How the equation could be applied to individual geographic locations has been illustrated by generating a figure of the theoretical uncertainty bounds for the Princeton area. An important observation is that the strength of the regression model is not a significant parameter provided the corresponding R^2 values of the regression model are greater than about 0.2, thereby suggesting that the approach could be potentially useful over a variety of housing stock and soil conditions. However, more associated studies and analysis involving a larger data base are required before the benefits and scope of the present technique could be fully appreciated in terms of practical applicability and relevance.

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224

TABLE 1. PERIODS DURING WHICH DATA WERE AVAILABLE.

House	Period	No. of Months
H2	10/15/1986 - 6/24/1987	8
H21	1/15/1988 - 10/31/1988	10
H22	3/11/1988 - 9/28/1989	18

TABLE 2. DESCRIPTION OF VARIOUS PARAMETERS CHOSEN FOR THIS STUDY.

TA	-	Ambient dry-bulb temperature, (°C)
TB	-	Basement temperature, (°C)
TL	-	Living area temperature, (°C)
TBA	-	Difference between basement and ambient air temperatures, (°C)
TLA	-	Difference between living area and ambient air temperatures, (°C)
HAC	-	Fraction of the time during which the heating and air-conditioning equipment was on,
RNB	-	Radon level in the basement, (pCi/L)
RNL	-	Radon level in the living area, (pCi/L)

TABLE 3. MEAN AND STANDARD DEVIATION OF CERTAIN IMPORTANT PARAMETERS FOR ALL THREE HOUSES OVER THE ENTIRE PERIOD OF DATA AVAILABILITY.

		H2			H21			H22		
		Arith-metic Mean	St. Dev.	Geo-metric Mean	Arith-metic Mean	St. Dev.	Geo-metric Mean	Arith-metic Mean	St. Dev.	Geo-metric Mean
TA	(°C)	7.4	8.52	-	12.5	8.64	-	13.8	8.80	-
TB	(°C)	16.1	2.16	16.0	19.4	2.06	19.3	23.2	3.75	-
TL	(°C)	19.8	2.73	19.3	21.1	2.81	20.9	21.4	2.44	21.3
TBA	(°C)	8.6	6.72	-	6.8	7.92	-	9.4	9.48	-
TLA	(°C)	12.1	7.99	-	8.2	6.61	-	7.2	6.82	-
HAC	(-)	0.20	0.151	-	0.18	0.214	-	0.16	0.273	-
RNB	(pCi/L)	22.8	10.21	21.4	93.0	106.25	42.4	63.6	46.44	49.9
RNL	(pCi/L)	15.3	5.44	13.6	36.8	39.82	19.8	13.6	11.03	8.2

TABLE 4. CORRELATION COEFFICIENTS OF RADON WITH PHYSICAL PARAMETERS USING THE ENTIRE DATA SET. THE VARIABLE TLA HAS NOT BEEN INCLUDED SINCE IT IS STRONGLY COLLINEAR WITH TBA, AND THE STRENGTH OF THE CORRELATION COEFFICIENTS OF THIS VARIABLE WITH RADON LEVELS IS ESSENTIALLY SIMILAR TO THAT OF TBA.

	H2				H21				H22			
	TA	TBA	HAC	TSB	TA	TBA	HAC	TSB	TA	TBA	HAC	TSB
RNB	0.12	-0.09	-0.24	-	-0.81	0.78	-0.20	0.04	0.05	-0.12	-0.23	0.04
RNL	-0.52	0.49	0.29	-	-0.84	0.87	-0.02	0.51	-0.56	0.54	-0.29	-0.09

TABLE 5. ADJUSTED R^2 VALUES OF DIFFERENT INDOOR RADON MODELS USING DAILY AVERAGE DATA.

	Model 1	Model 2	Model 3	Model 4
<u>RNB</u>				
H2	0.02	0.01	0.02	0.04
H21	0.66	0.62	0.64	0.67
H22	0.02	0.01	0.04	-
<u>RNL</u>				
H2	0.26	0.23	0.26	0.26
H21	0.71	0.76	0.81	0.81
H22	0.31	0.29	0.30	-

Model 1: RNB, RNL = f (TA)
Model 2: RNB, RNL = f (TBA)
Model 3: RNB, RNL = f [$(TBA)^+$, $(TBA)^-$]
Model 4: RNB, RNL = f (TA, HAC)

TABLE 6. VALUES OF THE REGRESSION COEFFICIENTS OF DAILY AVERAGE INDOOR RADON USING THE LINEAR MODEL IN TA (Eq. 4).

	RNB				RNL			
	Intercept (pCi/L)	SEM	Slope (pCi/L/°C)	SEM	Intercept (pCi/L)	SEM	Slope (pCi/L/°C)	SEM
H2	21.72	0.94	0.28	0.16	17.71	0.43	-0.33	0.04
H21	218.30	6.70	-9.99	0.44	85.41	2.33	-3.87	0.15
H22	50.62	4.70	0.35	0.29	23.35	0.93	-0.71	0.06

TABLE 7. YEARLY MEAN AND STANDARD DEVIATIONS OF DAILY AVERAGE AMBIENT TEMPERATURE FOR A FEW LOCATIONS [FROM DATA SUPPLIED BY REF. (14) FOR 1978]. THE ARITHMETIC MEAN VALUE FOR ALL LOCATIONS IS ESSENTIALLY NOT AFFECTED BY THE TIME SCALE OF AVERAGING.

City	State	Mean (°C)	Standard Deviation (°C) 1-day	3-day	7-day	15-day
1. Atlantic City	NJ	12.8	9.8	9.0	8.2	6.2
2. Houston	TX	19.3	7.9	7.2	6.5	5.2
3. Miami	FL	24.3	4.4	3.8	3.5	2.7
4. Newark	NJ	12.6	9.6	8.7	7.6	5.1
5. Portland	OR	12.9	6.0	5.5	5.0	4.0
6. Tallahassee	FL	19.1	7.4	6.8	6.3	4.9

227

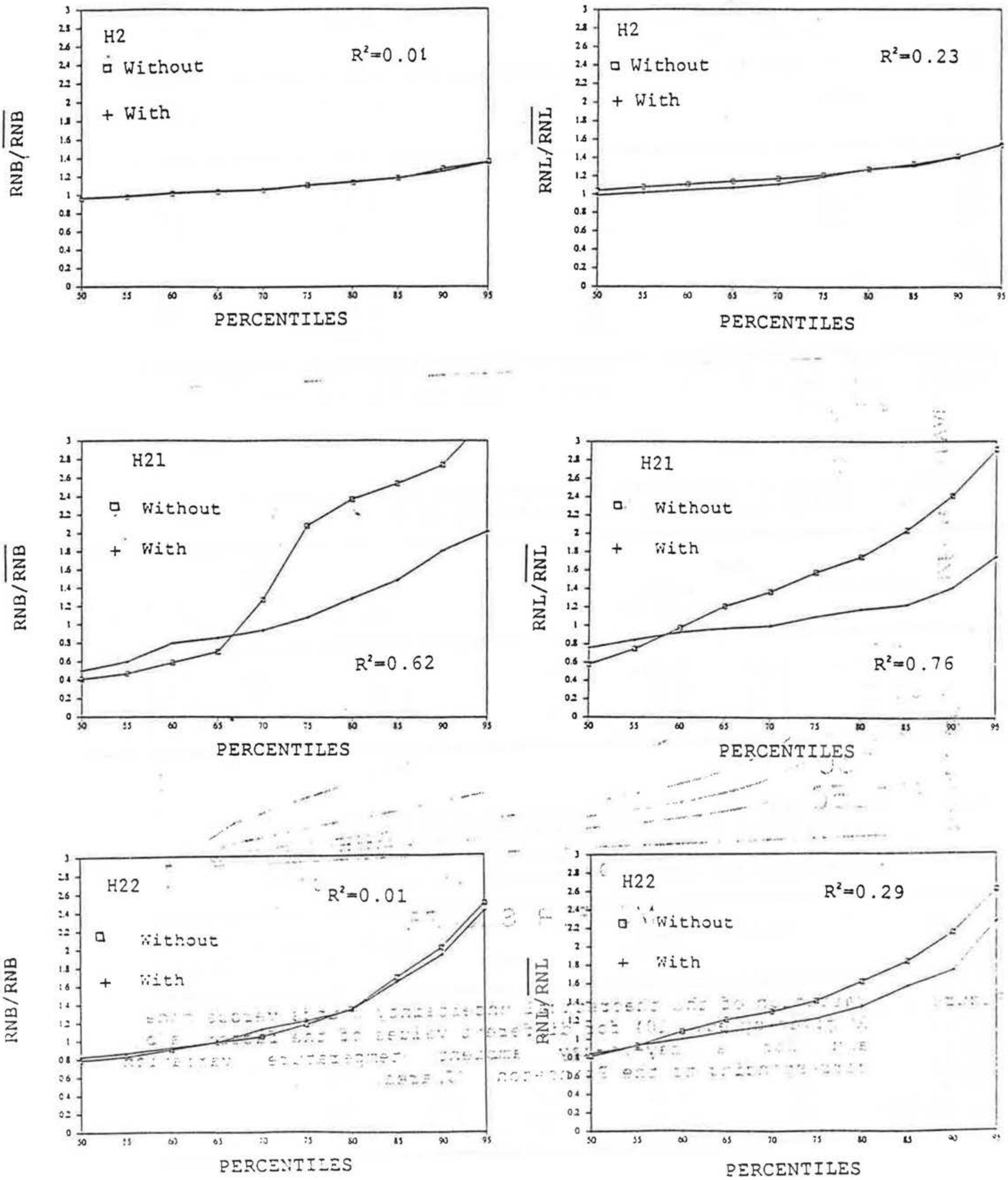

Figure 1. Percentiles of 1-day ratios of normalized basement and living area radon concentrations with and without temperature correction for all three houses. The associated R^2 values of the regression model given by eq. (1) are also shown.

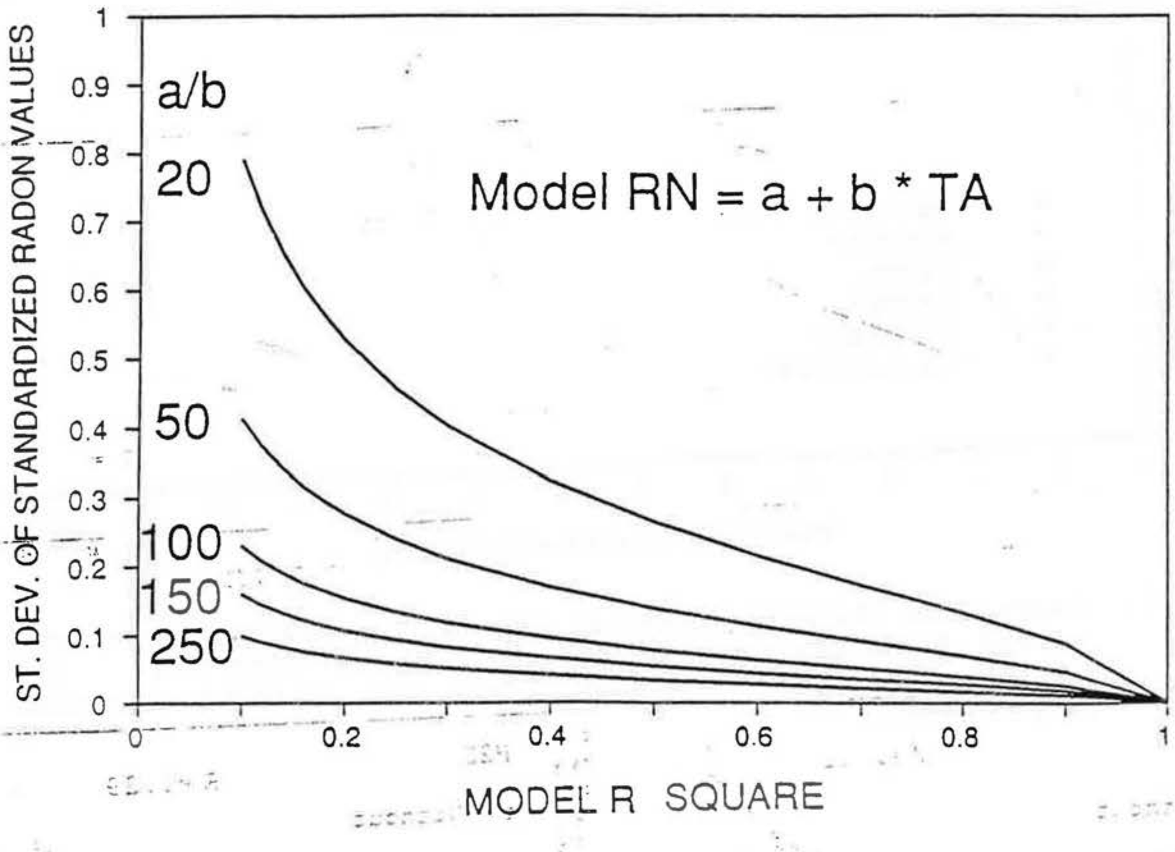

Figure 2. Variation of the theoretical uncertainty bounds versus model R^2 given by eq. (10) for different values of the factor (a/b) and for a day-to-day ambient temperature variation corresponding to the Princeton, NJ, area.

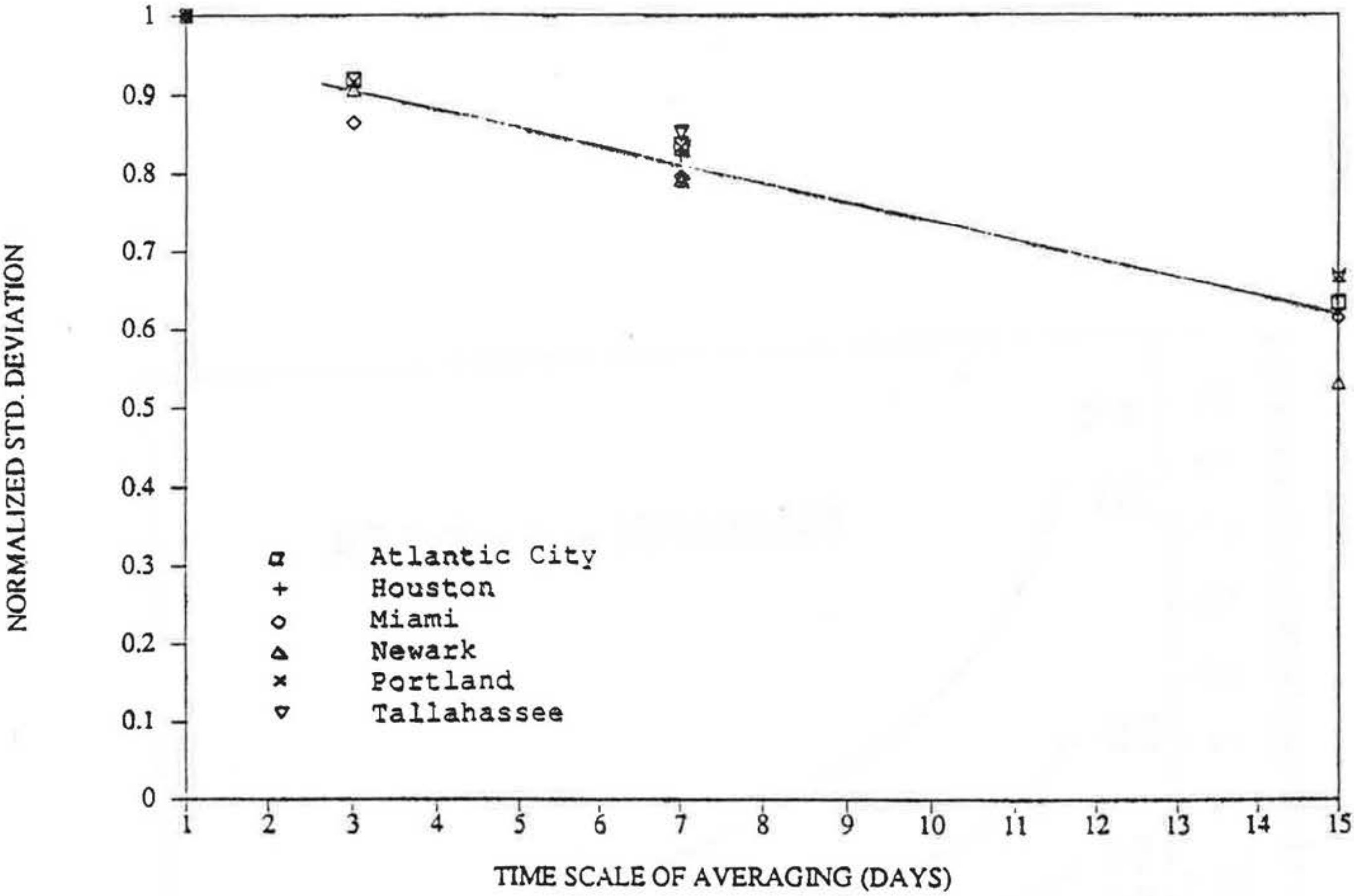

Figure 3. Normalized standard deviation values of ambient temperature versus time scale of averaging for six locations. The variation is close to being linear and is fairly location independent.