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Pacific Northwest National Laboratory
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Consequences of Mixed Pixels on Temperature/Emissivity Separation

Patrick Heasler, Mike Foley, Sandy Thompson

Jan 2007

Prepared for the U.S. Department of Energy
under Contract DE-AC05-76RL01830

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Executive Summary

This report investigates the effect that a *mixed pixel* can have on temperature/emissivity separation (i.e. temperature/emissivity estimation using long-wave infra-red data). Almost all temperature/emissivity estimation methods are based on a model that assumes both temperature and emissivity within the imaged pixel are homogeneous. A mixed pixel has heterogeneous temperature/emissivity and therefore does not satisfy the assumption. Needless to say, this heterogeneity causes biases in the estimates that may cause problems in plume detection and certainly cause problems in temperature/emissivity estimation. This report quantifies the magnitude of these problems.

Acknowledgments

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Abbreviations and Acronyms

$\mathcal{B}(\nu, T)$	Planck Function at temperature T $\mathcal{B}(\nu, T) = \frac{2C_0\nu^2}{\exp(\frac{hC_0\nu}{KT})-1}$
$L_g(\nu)$	Radiance from the ground at wavenumber ν
$\varepsilon(\nu)$	Emissivity of ground
T	Temperature of ground in Kelvin
L_d	Downwelling Radiance
Radiance	Watts/(steridian cm)
ν	wavenumber cycles per cm

Contents

Executive Summary iii

Acknowledgments v

Abbreviations and Acronyms vii

1.0 The Mixed Pixel Problem 1.1

2.0 Temperature Emissivity Algorithms 2.1

2.0.1 Emissivity-Library (Eg-Library) Algorithm 2.1

2.1 Smoothed-Emissivity (Eg-Smooth) Algorithm 2.1

2.2 Mixed-Pixel Algorithm 2.2

3.0 Scenarios for Mixed Pixel Evaluation 3.1

4.0 Results 4.1

4.1 Expected Performance of the 3 Algorithms 4.1

4.2 Evaluation of Scenarios 4.1

5.0 Conclusions 5.1

6.0 References 6.1

Appendix A – Results for Each Test Pixel A.1

Figures

1.1 A typical average Planck function ($\bar{\mathcal{B}}$) versus the Planck function calculated at average temperature 1.2

A.1 Pixel 1: Dry Grass + Bare Soil, $sd(T) = 5C$ 6.2

A.2 Pixel 2: Auto + Asphalt, $sd(T) = 5C$ 6.3

A.3 Pixel 3: Bare Piping + Asphalt, $sd(T) = 5C$ 6.4

A.4 Pixel 4: Insulated Piping + Asphalt, $sd(T) = 5C$ 6.5

A.5 Pixel 5.1: Hot Stack + Asphalt Roof, $sd(T) = 5C$ 6.6

A.6 Pixel 5.2: Hot Stack + Asphalt Roof, $sd(T) = 10C$ 6.7

A.7 Pixel 5.3: Hot Stack + Asphalt Roof, $sd(T) = 20C$ 6.8

A.8 Pixel 6.1: Hot Stack + Tin Roof, $sd(T) = 5C$ 6.9

A.9 Pixel 6.2: Hot Stack + Tin Roof, $sd(T) = 10C$ 6.10

A.10 Pixel 6.3: Hot Stack + Tin Roof, $sd(T) = 20C$ 6.11

A.11 Pixel 7: Worst Case Pixel, $sd(T) = 20C$ 6.12

Tables

4.1 Summary of Mixed-Pixel Errors associated with a temperature variation of $sd(T) = 5C$ 4.2

4.2 Summary of Mixed-Pixel Errors associated with a temperature variation of $sd(T) = 5C, 10, and 20C$ 4.3

1.0 The Mixed Pixel Problem

The radiance emanating from the ground, as expressed by $L_g(\nu)$, is described by the radiation transmission model;

$$L_g(\nu) = \varepsilon(\nu)\mathcal{B}(\nu, T) + [1 - \varepsilon(\nu)]L_d(\nu) \tag{1.1}$$

where ε represents the emissivity of the ground, T the ground temperature, and L_d the downwelling atmospheric radiance. The term, $\mathcal{B}$, is, of course the Planck black-body function. The radiance observed at the instrument, $L_{obs}(\nu)$, is L_g modified by the atmospheric column, instrument error, (and possibly a plume). For example;

$$L_{obs}(\nu) = \tau_a(\nu)L_g(\nu) + L_u(\nu) + e \tag{1.2}$$

To simplify the formulas in this paper, the wavenumber argument, ν will be dropped from the terms. Also, we will eliminate Equation 1.2 from our evaluations because the atmospheric column does not contribute to the mixed-pixel effect. From this perspective, L_g represents the data available for calculating temperature/emissivity estimates.

Equation 1.1 is the heart of any temperature/emissivity (i.e. T, ε) estimation methodology. If this equation is wrong, or only approximately correct, then the approximation will limit the viability of any temperature/emissivity algorithm. This equation *is* correct for a homogeneous pixel; One that exhibits a spatially non-variable emissivity and temperature.

Here we want to investigate the consequences of observing a *mixed pixel*. In other words, the observed pixel is composed of several types of material, each having a different emissivity and temperature; Does this mixed pixel still obey the above equation, with ε and T representing some sort of average from the mixed pixel?

The answer is no in general, although the equation is correct for one type of mixed pixel (constant temperature). To derive the equation that is correct for a mixed pixel, suppose that the pixel is composed of n different material/temperature combinations, with combination i comprising W_i of the pixel area and having an emissivity of ε_i and temperature T_i. For each combination, the formula is correct, so we only need to sum up the the combinations to get the correct ground radiance;

$$L_g = \sum_{i=1}^{n} W_i[\varepsilon_i\mathcal{B}(T_i) + (1 - \varepsilon_i)L_d] \tag{1.3}$$

If we define average emissivity, $\bar{\varepsilon}$, and an average for the Planck functions, $\bar{\mathcal{B}}$ correctly, then L_g can be written as;

$$L_g = \bar{\varepsilon}\bar{\mathcal{B}} + (1 - \bar{\varepsilon})L_d \tag{1.4}$$

with the definitions for the averages being;

$$\bar{\varepsilon} = \sum_i W_i\varepsilon_i \tag{1.5}$$

and

$$\bar{\mathcal{B}} = \sum_i \frac{W_i \varepsilon_i \mathcal{B}(T_i)}{\bar{\varepsilon}} \tag{1.6}$$

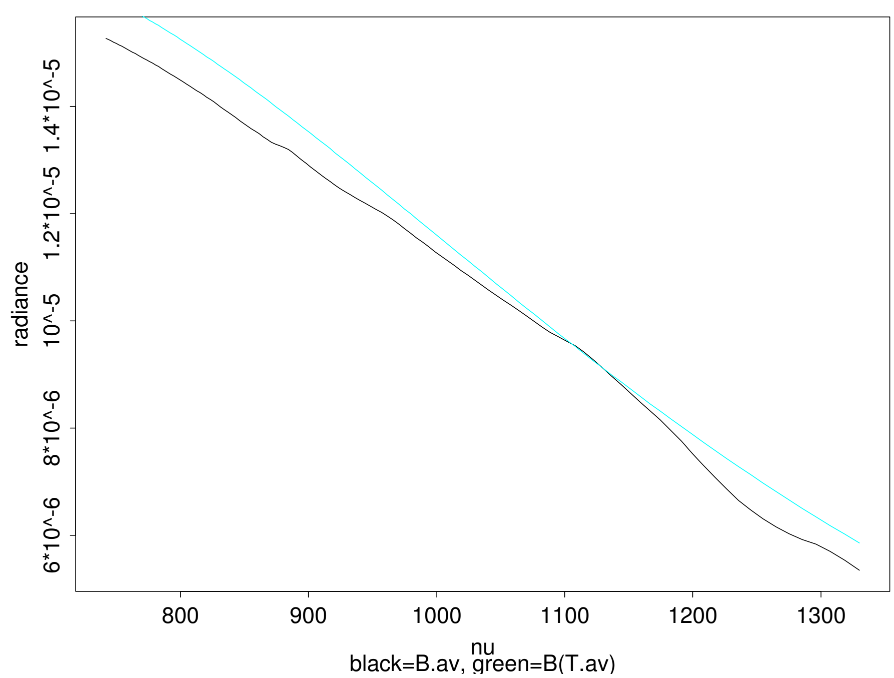
Equation 1.4 seems to suggest that mixed-pixel radiance can be expressed with an equation that is the same form as the homogeneous pixel Equation 1.1. The problem, however, resides with the average $\bar{\mathcal{B}}$ which can no longer be represented by a Planck function. That is, $\bar{\mathcal{B}} \neq \mathcal{B}(T)$ for any choice of T.

Using least squares, one can select a value for T that produces a Planck function that is as close as possible to $\bar{\mathcal{B}}$ (denote this value by $\hat{T}$), so that the mixed pixel radiance can be decomposed into a mixed-pixel error and a portion that *can be* fitted by the homogeneous-pixel model;

$$L_g = \bar{\varepsilon}[\bar{\mathcal{B}} - \mathcal{B}(\hat{T})] + \bar{\varepsilon}\mathcal{B}(\hat{T}) - (1-\bar{\varepsilon})L_d \tag{1.7}$$

with the term, $\bar{\varepsilon}[\bar{\mathcal{B}} - \mathcal{B}(\hat{T})]$ representing *the mixed-pixel error*. Figure 1.1 illustrates the differences that can occur between $\bar{\mathcal{B}}$ and $\mathcal{B}(\hat{T})$ for a typical mixed pixel. Note that the average $\bar{\mathcal{B}}$ is no longer smooth. $\bar{\mathcal{B}}$ can also be flatter than a Planck function.

Figure 1.1. A typical average Planck function ($\bar{\mathcal{B}}$) versus the Planck function calculated at average temperature



This report will calculate the mixed-pixel error for several mixed pixel configurations and use the results to determine:

- How does a mixed pixel affect temperature/emissivity separation?

- When are the mixed pixel effects insignificant?
- If there are significant effects, can they be rectified?

2.0 Temperature Emissivity Algorithms

To evaluate the severity of this mixed-pixel error for various background scenarios, we will fit 3 simplified temperature/emissivity algorithms to the scenarios. Two of the algorithms are simplified versions of the most popular methods for doing temperature/emissivity separation and are based upon the "homogeneous" pixel model presented in Equation 1.1. The last algorithm attempts to account for pixel heterogeneity in a simple manner, and is derived from the mixed-pixel radiance model presented in Equation 1.7. This algorithm is included to see how much of an improvement one might expect to see if mixed-pixels were treated more correctly in an estimation algorithm.

2.0.1 Emissivity-Library (Eg-Library) Algorithm

The first homogeneous pixel algorithm assumes that one knows a good deal about background emissivity. The information on background emissivity is available as an "emissivity library" that includes all the materials present in the background being imaged. Emissivities from this library are plugged into equation 1.1 and regression (least squares) is used to find the best emissivity/temperature fit to L_g.

The typical algorithm tries to find the best *single* material from the library to fit a pixel, but since we are examining mixed-pixels, we will use linear combinations of the library emissivities. We will also assume that one knows which materials are present in the mixed-pixel, so the algorithm does not have to search the library for the best combination of emissivities. This assumption simplifies the estimation problem considerably. If we assume that the mixed pixel consists of n library materials with emissivities, ε_i, then the specific regression formula for algorithm is;

$$L_g = (\sum_{i=1}^{n} \beta_i \varepsilon_i)\mathcal{B}(\beta_0) + [1 - \sum_{i=1}^{n} \beta_i \varepsilon_i] L_d + E \tag{2.1}$$

with β_i representing the unknown parameters to be determined by regression.

Use of an emissivity library in some fashion is the basis for several temp/emiss algorithms, see for example (Mitchel 2005) or (Li et al. 1999). The simplified "Emissivity Library" is meant to represent this class of algorithms in the test. Notice that it should perform better than the more general algorithms in this class because (1) the emissivity-library is highly restricted, and (2) the model allows for a mixture of emissivities.

2.1 Smoothed-Emissivity (Eg-Smooth) Algorithm

The second homogeneous pixel algorithm is constructed from the assumptions that Chris Borel ((Borel 1997), (Borel and Clodius 1999), and (Borel 2003)) has formulated for temperature/emissivity separation. This algorithm assumes that emissivity is "smooth" and uses this feature to estimate temperature and emissivity (using the rough down-welling radiance term L_d). Use of such a smoothness assumption is at the heart of most popular temp/emiss separation algorithms (see (Knutson et al. 2004) or (Turner et al. 2005) for other examples).

To get the correct pixel temperature, Equation 1.1 is solved for emissivity, which results in;

$$\varepsilon = \frac{L_g - L_d}{\mathcal{B}(T) - L_d} \tag{2.2}$$

The pixel temperature, T is then varied until the smoothest version of ε is found, with smoothness identified by a small standard deviation of $\varepsilon - \varepsilon(smooth)$.

We also considered a Bayesian regression model that we developed from Borel's assumption. For this regression model, the smoothness in ε is expressed in a Bayesian prior on emissivity, which is determined by estimating it from background calibration data (i.e. data containing no gas plumes). We do not present the performance of the Bayesian Regression model in this paper, because Chris Borel's algorithm is more widely used. Also, the performance of the Bayesian model and Borel's are roughly the same for mixed pixels.

2.2 Mixed-Pixel Algorithm

This algorithm is a modified version of the Eg-library algorithm that attempts to use a better expression for the $\bar{\mathcal{B}}$ term in Equation 1.7. For this regression model, the term $\bar{\mathcal{B}}$ is modeled by a cubic spline containing 10 terms, a mathematical form that gives us sufficient flexibility to adequately describe $\bar{\mathcal{B}}$. Figure 1.1 illustrates the type of curve the cubic spline must describe. This Figure displays $\bar{\mathcal{B}}$ for a mixed pixel verses the Planck function calculated from an average pixel temperature. The average $\bar{\mathcal{B}}$ can have a shallower slope than a Planck function and may also exhibit bumps such as those displayed in the example. Use of splines is intended to allow the regression model to account for these bumps.

The actual regression model utilized is of the form;

$$L_g = \varepsilon \mathcal{B}_g + (1 - \varepsilon) L_d \tag{2.3}$$

where the emissivity, ε has the same form as in the "emissivity-Library model", in other words;

$$\varepsilon = \sum_i \beta_i \varepsilon_i \tag{2.4}$$

and $\mathcal{B}_g$ is modeled with cubic B-splines;

$$\mathcal{B}_g(\nu) = \sum_i \alpha_i Bspl_i(\nu) \tag{2.5}$$

We had expected that the average Planck function would be fairly smooth and therefore could be adequately modeled by a spline function with just a few knot points (initially 4). We found that more flexibility was required and after some experimentation, selected 11 knot points (i.e. 10 parameters for the spline). Even this degree of flexibility does not always produce perfect fits, as one will see in the upcomming examples.

The mixed-pixel model, as defined above, does not produce an estimate for background temperature. To allow comparison of this model to the other two, we calculate an average brightness temperature from $\mathcal{B}_g$ and use it as the the estimate for background temperature, T.

3.0 Scenarios for Mixed Pixel Evaluation

To evaluate the mixed-pixel effect under "relevant" conditions, we have constructed pixels consisting of just two materials, with each material consisting of 50% of the pixel area. The emissivity spectra used were extracted from the NEFDS data base, and the material combinations are those that we would frequently expect to see in an actual image. When selecting emissivities for particular material pairs from the NEFDS data set, we did attempt to select two emissivities that differed the most.

The instrument used for the scenario is a push-broom instrument with 128 channels displaying a measurement error of approximately 0.2%. Descriptions, of the 10 "test pixels" constructed for this evaluation are as follow;

Tests with "small" Temperature Variation: $sd(T) = 5C$ or ($\Delta T = 10C$),

Pixel 1: Dry Grass + Bare Soil. This represents a pixel from open fields within an industrial site. The temperature difference, $\Delta T = 10C$ is a larger variation than one would expect to see for a field containing dead grass. If the grass were growing, such a large temperature difference could occur.

Pixel 2: Auto + Asphalt. This represents a pixel from a parking lot, partially filled with cars, a pixel that frequently occurs within images of industrial sites. The "auto" is actually painted metal and within the NEFDS data-base painted metal can exhibit very different emissivity spectra. For this test case, we have chosen a paint with a dramatic dip at wavenumber 1020.

Pixel 3: Bare Piping + Asphalt. This represents a type of mixed-pixel one might see in a refinery. For this case the $\Delta T = 10C$ value chosen might be small; The piping might contain a fluid at a temperature that differs substantially from ambient.

Pixel 4: Insulated Piping + Asphalt. This again represents a type of mixed-pixel one might see in a refinery. The insulation is assumed to be covered with reflective metal, which has a relatively low emissivity.

Tests with larger Temperature Variation:

Pixel 5.1-5.3: Hot Stack + Asphalt Roof, $sd(T) = 5, 10, 20C$. In this case the pixel contains a stack, emitting hot gas, so this scenario focuses on a background that would occur very frequently in plume detection problems. We assume that the instrument is looking directly into the stack (and that the stack has a relatively large diameter, as it comprises 50% of the pixel area). Because of this configuration the stack should produce classic black-body radiation, and we have assumed its emissivity is one.
Asphalt also has an emissivity very near to one, so these scenarios quantify the effect of temperature variation when emissivity is homogeneous. For these pixels we consider three ΔT values to quantify the effect of temperature variation.

Pixel 6.1-6.3: Hot Stack + Tin Roof, $sd(T) = 5, 10, 20C$. These pixels again represent a background one would frequently see behind a plume. In contrast to the 5.1-5.3 pixels, the emissivity of the roof is quite different from that of the hot stack, so this sequence of scenarios are meant to quantify the effect of temperature variation when emissivity also exhibits substantial variation.

Pixel 7: Worst Case Pixel: Bare Piping + Asphalt, $sd(T) = 20C$. This is Pixel 3 with an increased temperature difference. Pixel 3 seemed to be a difficult case for the temp/emiss models, so we increased the temperature variation to see how much errors would increase.

The plots of the emissivity curves used for each of these cases are presented in Appendix A, along with fitted terms from the three algorithms.

4.0 Results

4.1 Expected Performance of the 3 Algorithms

From the mixed-pixel decomposition presented in Section 1, one can deduce the magnitude of the mixed pixel error is related to the magnitude of the temperature variations in the mixed pixel. All temperature/emissivity algorithms considered in this report will fit L_g exactly when the temperature variations are zero. As one makes the temperature variation in a pixel larger, the mixed pixel error will become larger. Therefore, it should be possible to identify a bound on temperature that would cause the mixed pixel errors to be small.

The formulas presented in Section 1 also demonstrate that the converse is *not* true; If emissivity variations are zero, a mixed pixel effect can still exist! Since this condition can be expected to happen whenever a homogeneous material is differentially heated, we can expect to experience mixed pixel problems, even when imaging "homogeneous" backgrounds.

4.2 Evaluation of Scenarios

For the 10 test-pixels X 3 temp/emiss models evaluated, we calculate the estimation error associated with the four model terms,i.e. L_g, ε, $\mathcal{B}_g$, and T. Relative error is used to quantify the first three terms, while the difference, $\hat{T} - \bar{T}$, is used for the last. For example, the relative error of L_g is defined as;

$$RE(L_g) = \sqrt{\frac{1}{n}\sum_{i}^{n}\left[\frac{\hat{L}_g(\nu_i) - L_g(\nu_i)}{L_g(\nu_i)}\right]^2} \tag{4.1}$$

From a gas estimation view-point, the most important term to be estimated is the ground radiance, L_g. If this term can be accurately estimated (even when the temperature and emissivity estimates are distorted) then the mixed-pixel problem should have little consequence to plume estimation. For this problem, the instrument and atmospheric variability (which we will call measurement error), produce a relative error of approximately 0.2%. Hence, as a rough rule of thumb, we will consider L_g error to be significant if it is above 0.2% and acceptable if less than this number.

In Tables 4.1 and 4.2, the cases where L_g error is above 0.2% have been identified in the comment columns. One can see a significant difference in performance between the three algorithms. The Eg-Library model has problems meeting the threshold, particularly when the pixel temperature variation is large. The poor performance of this model is somewhat of a surprise; One can conclude from these results that *temperature variations can cause a poor fit even when one has good knowledge of background emissivity.* Mixed-pixel errors may be one of the reasons that models using emissivity libraries do so poorly.

On the other hand, the Eg-smooth model seems to fit L_g well in all but the most extreme cases. Failure for this model only occurs in Pixel 7, the "worst case" example. Of course, the Eg-smooth model cannot accomplish this without incurring substantial error in other terms. For

Table 4.1. Summary of Mixed-Pixel Errors associated with a temperature variation of $sd(T) = 5C$

Temp/Emiss Model	Errors $RE(L_g)$	$RE(E_g)$	$RE(\bar{B})$	$\hat{T} - \bar{T}$	Comments on L_g
	Pixel 1: Dry Grass + Bare Soil				
Eg-Lib	0.05	0.17	0.18	0.11	
Eg-Smooth	0.09	0.22	0.20	0.24	
Mix-Pix	0.01	0.13	0.13	0.13	
	Pixel 2: Auto + Asphalt				
Eg-Lib	0.06	0.17	0.17	0.10	
Eg-Smooth	0.07	0.19	0.16	0.13	
Mix-Pix	0.01	0.15	0.15	0.11	
	Pixel 3: Bare Piping+Asphalt				
Eg-Lib	0.38	1.02	1.41	-0.25	Lg Error Large
Eg-Smooth	0.17	0.57	0.67	-1.22	
Mix-Pix	0.03	0.13	0.16	-0.96	
	Pixel 4: Ins. Piping+Asphalt				
Eg-Lib	0.24	0.51	0.88	-2.77	Lg Error Large
Eg-Smooth	0.08	0.22	0.35	-3.38	
Mix-Pix	0.01	0.04	0.06	-3.26	

RE=Relative Error, in percent, Instrument RE=0.2%.

example, both Emissivity and the Planck term exhibit a 2.5% error for the worst case, Pixel 7. Another important characteristic of the fit to mixed pixels is that this model cannot smooth out all of L_d from the estimate of L_g, so there is always the possibility that atmospheric features will be mistaken for plume gases. See the plots in Appendix A for examples of this.

The estimate for emissivity, $\hat{\varepsilon}_g$, would most frequently be used to identify the background material, by comparing the estimate to spectra in a library. An error of 1 to 2% would probably be acceptable for such a task, so one might be able to conclude that the emissivity estimates produced by an Eg-smooth model would be acceptable for background identification also.

From Table 4.2, one can determine the effect of pixel temperature variation on the Eg-smooth model. The table shows that temperature variation (at least for $sd(T) < 20C$) has little impact on the error in L_g, but does effect the error in the estimates for ε, $\mathcal{B}_g$, and T in a roughly linear fashion. We would conclude that the an Eg-smooth model produces acceptable results when the temperature variation is in the 5C range, but might produce unacceptable results (in emissivity estimates) if the temperature variation is larger than this.

A temperature standard deviation of 5C would be expected to be a good upper bound on most pixel's temperature variability; at least on pixels that have no artificially heated or cooled equipment. For example, the standard deviation between adjacent pixels at a large chemical plant was 2.5C. Hence the results in Table 4.1 illustrate the mixed pixel error we might expect to see in the

Table 4.2. Summary of Mixed-Pixel Errors associated with a temperature variation of $sd(T) = 5C, 10, and 20C$

Temp/Emiss Model	Errors $RE(L_g)$	$RE(E_g)$	$RE(\bar{B})$	$\hat{T} - \bar{T}$	Comments on L_g
	Low ε Var. Stack+Asphalt				
	Pixel 5.1: $sd(T) = 5C$				
Eg-Lib	0.09	0.26	0.30	0.07	
Eg-Smooth	0.04	0.15	0.13	0.22	
Mix-Pix	0.01	0.16	0.15	0.13	
	Pixel 5.2: $sd(T) = 10C$				
Eg-Lib	0.27	0.60	0.73	0.29	Lg Error Large
Eg-Smooth	0.04	0.36	0.33	0.67	
Mix-Pix	0.01	0.31	0.30	0.48	
	Pixel 5.3: $sd(T) = 20C$				
Eg-Lib	0.79	1.50	1.90	1.06	Lg Error Large
Eg-Smooth	0.05	0.96	0.90	2.10	
Mix-Pix	0.01	0.57	0.57	1.69	
	High ε Var. Stack+Metal Roof				
	Pixel 6.1: $sd(T) = 5C$				
Eg-Lib	0.20	0.32	0.57	3.14	Lg Error Large
Eg-Smooth	0.02	0.18	0.26	3.56	
Mix-Pix	0.01	0.04	0.06	3.44	
	Pixel 6.2: $sd(T) = 10C$				
Eg-Lib	0.38	0.53	0.98	6.47	Lg Error Large
Eg-Smooth	0.02	0.30	0.45	7.21	
Mix-Pix	0.01	0.04	0.06	7.03	
	Pixel 6.3: $sd(T) = 20C$				
Eg-Lib	0.68	0.66	1.36	13.63	Lg Error Large
Eg-Smooth	0.02	0.48	0.74	14.71	
Mix-Pix	0.02	0.04	0.07	14.44	
	Pixel 7: Worst Case, $sd(T) = 20C$				
Eg-Lib	0.97	4.70	6.31	1.06	Lg Error Large
Eg-Smooth	0.22	2.23	2.58	-3.74	Lg Error Large
Mix-Pix	0.11	0.61	0.75	-2.60	

most scene pixels and indicate that the mixed pixel effect is not significant for such temperature differences.

The results show that the Eg-library algorithms have a more difficult time fitting mixed-pixels than Eg-smooth models. It has been frequently noted that emissivity spectra from libraries frequently do not fit materials imaged in the field and the difficulty has been ascribed to inadequacies in the library. These results show that part of this problem could be due to the mixed-pixel effect. If one is using the temperature/emissivity algorithm to identify materials on the ground, it is important to account for the mixed pixel effect.

The final model presented in the tables, the "mixed-pixel" model, is our attempt to incorporate the mixed pixel effect into a Eg-library model, and would be expected to perform better than the other two. The results presented in the tables show that this is indeed the case, with the most dramatic improvement shown in the high temperature variation cases. Use of a model similar to this would be necessary when an emissivity library is being used. However, the mixed-pixel model doesn't seem to offer significant advantages over an Eg-smoothing model, if plume detection is the principal objective. In other words, an attempt to adapt an Eg-smoothing model to account for mixed-pixel error probably would not result in a model that performs better.

5.0 Conclusions

The major conclusions we have arrived at are;

- Mixed Pixel variations do affect temperature/emissivity estimates.

- The severity of mixed pixel effects is related to the temperature variations present in the pixel; A temperature variation of $sd(T) = 5C$ causes few problems, while larger variations can be a cause for concern.

- An algorithm that uses an “Emissivity-Library” are more sensitive to mixed-pixel errors than Emissivity-Smoothing algorithms.

- Emissivity-Smoothing algorithms do well at estimating L_g, even when mixed-pixel errors are present. These algorithms do less well at estimating emissivity or temperature.

- An improved temperature/emissivity model can be produced that accounts for the mixed pixel problem. However, the model doesn’t seem to offer significant improvements over an emissivity-smoothing model, at least for plume detection.

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Appendix A

Results for Each Test Pixel

Appendix A – Results for Each Test Pixel

This appendix presents a sequence of four plots for each test pixel evaluated in this study. The first plot in the sequence shows the emissivity and temperatures of the two materials present in the pixel. (In all pixels, each material comprises half of the pixel.)

The second plot presents the error for the L_g estimate (in terms of relative standard deviation, RSD). Since three algorithms have been evaluated, three error curves are plotted with black representing the Eg-Lib algorithm, green the Eg-smooth algorithm, and finally red, the mixed-pixel algorithm. Also plotted is a typical measurement error (approximately 0.2% RSD). In general, the measurement error is about 0.2%, but due to atmospheric variability, some bands exhibit a higher error.

The second and third plots display the estimation errors in ε and $\mathcal{B}_g$ respectively. As a rough rule of thumb one would consider errors smaller than measurement error to be acceptable, while those significantly larger than this error to be unacceptable.

Figure A.1. Pixel 1: Dry Grass + Bare Soil, $sd(T) = 5C$

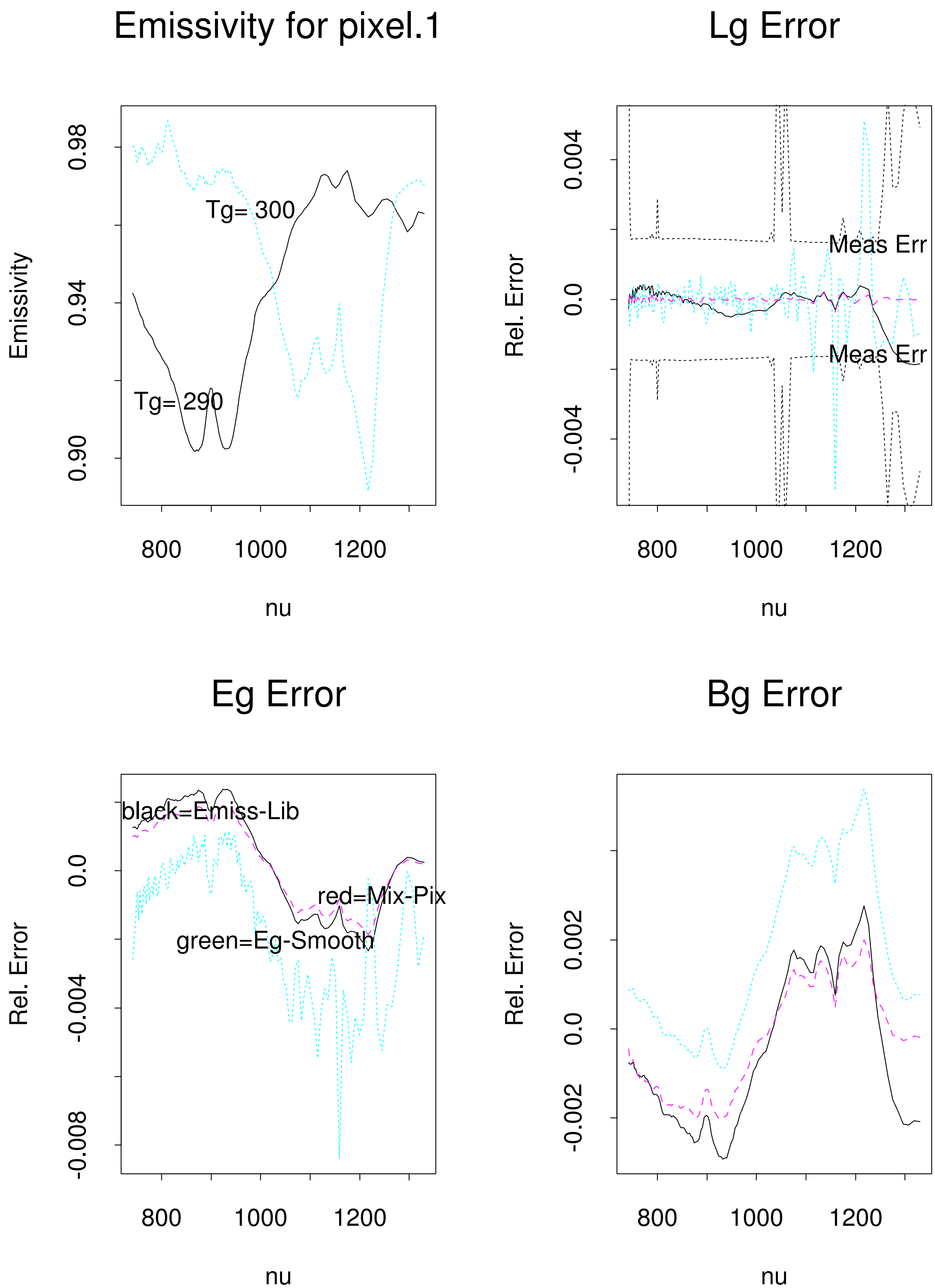


Figure A.2. Pixel 2: Auto + Asphalt, $sd(T) = 5C$

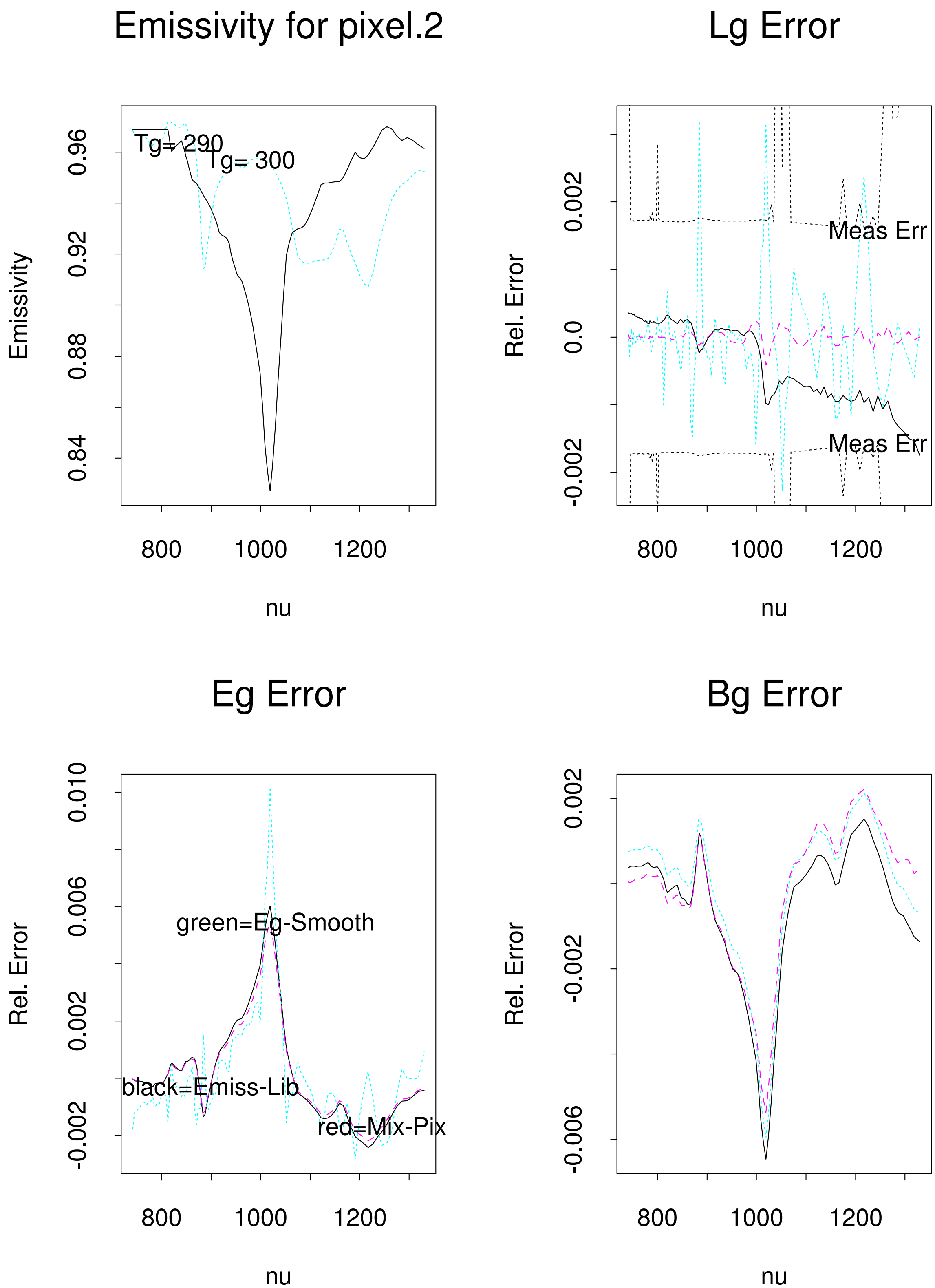


Figure A.3. Pixel 3: Bare Piping + Asphalt, $sd(T) = 5C$

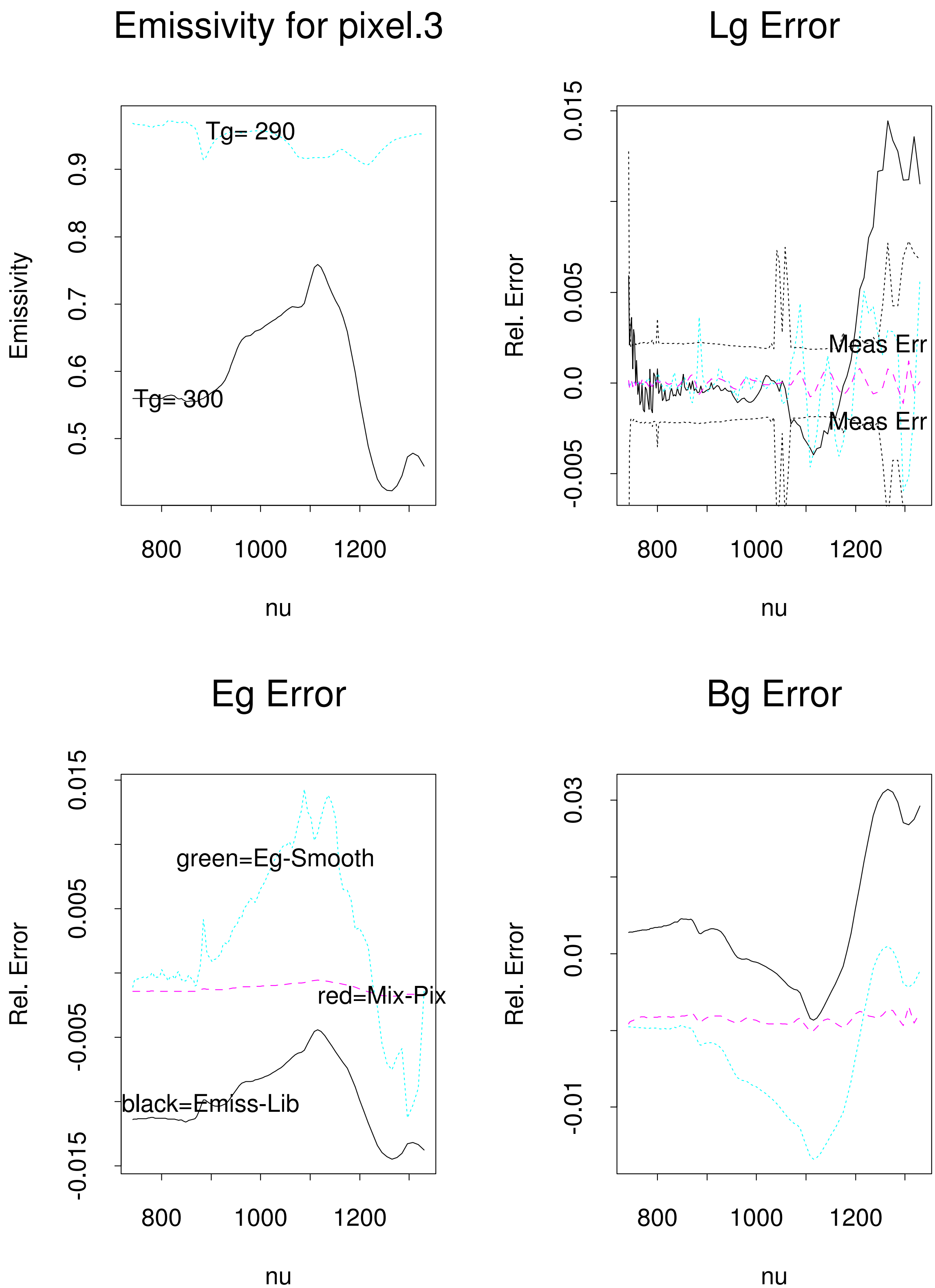


Figure A.4. Pixel 4: Insulated Piping + Asphalt, $sd(T) = 5C$

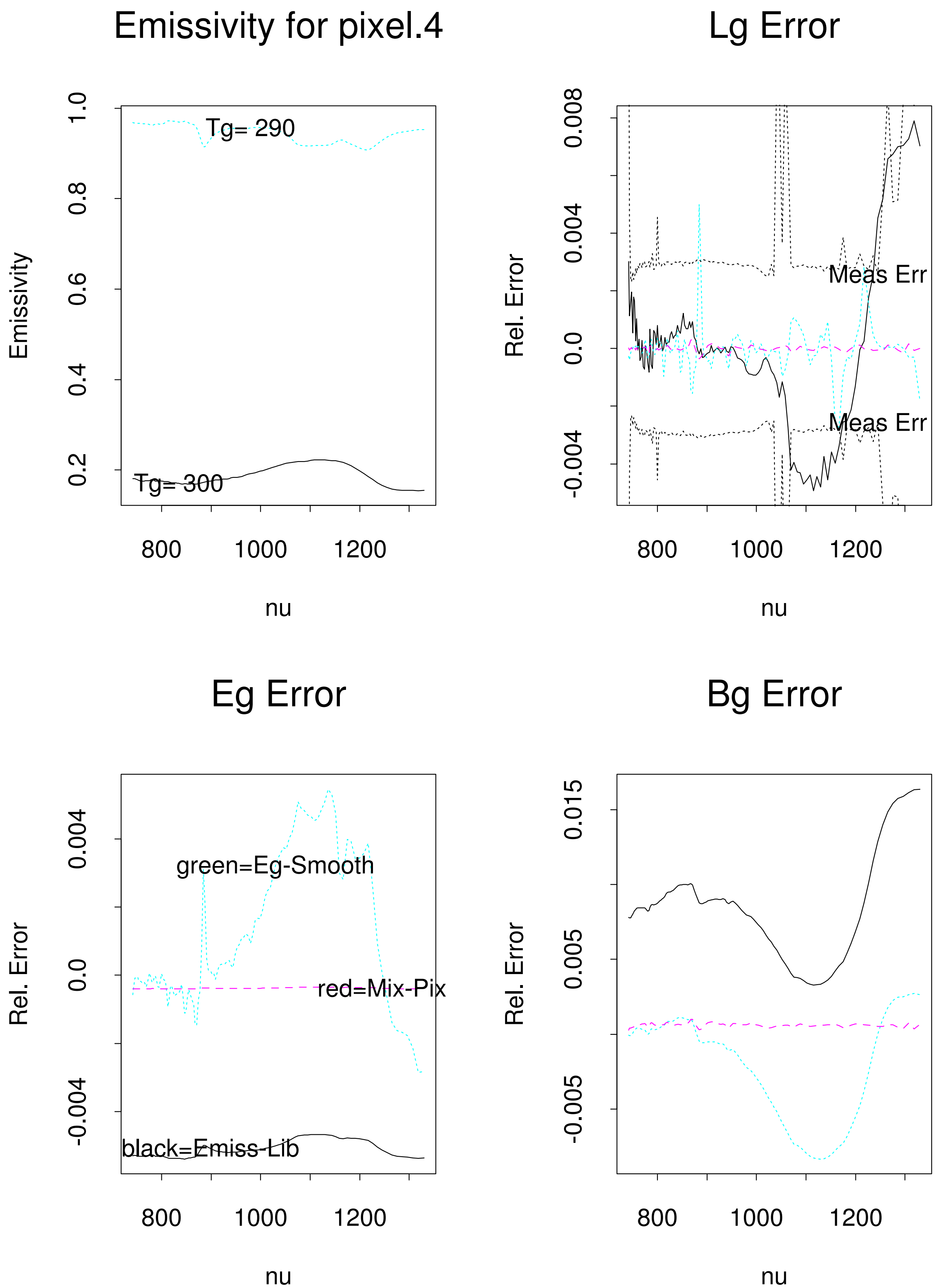


Figure A.5. Pixel 5.1: Hot Stack + Asphalt Roof, $sd(T) = 5C$

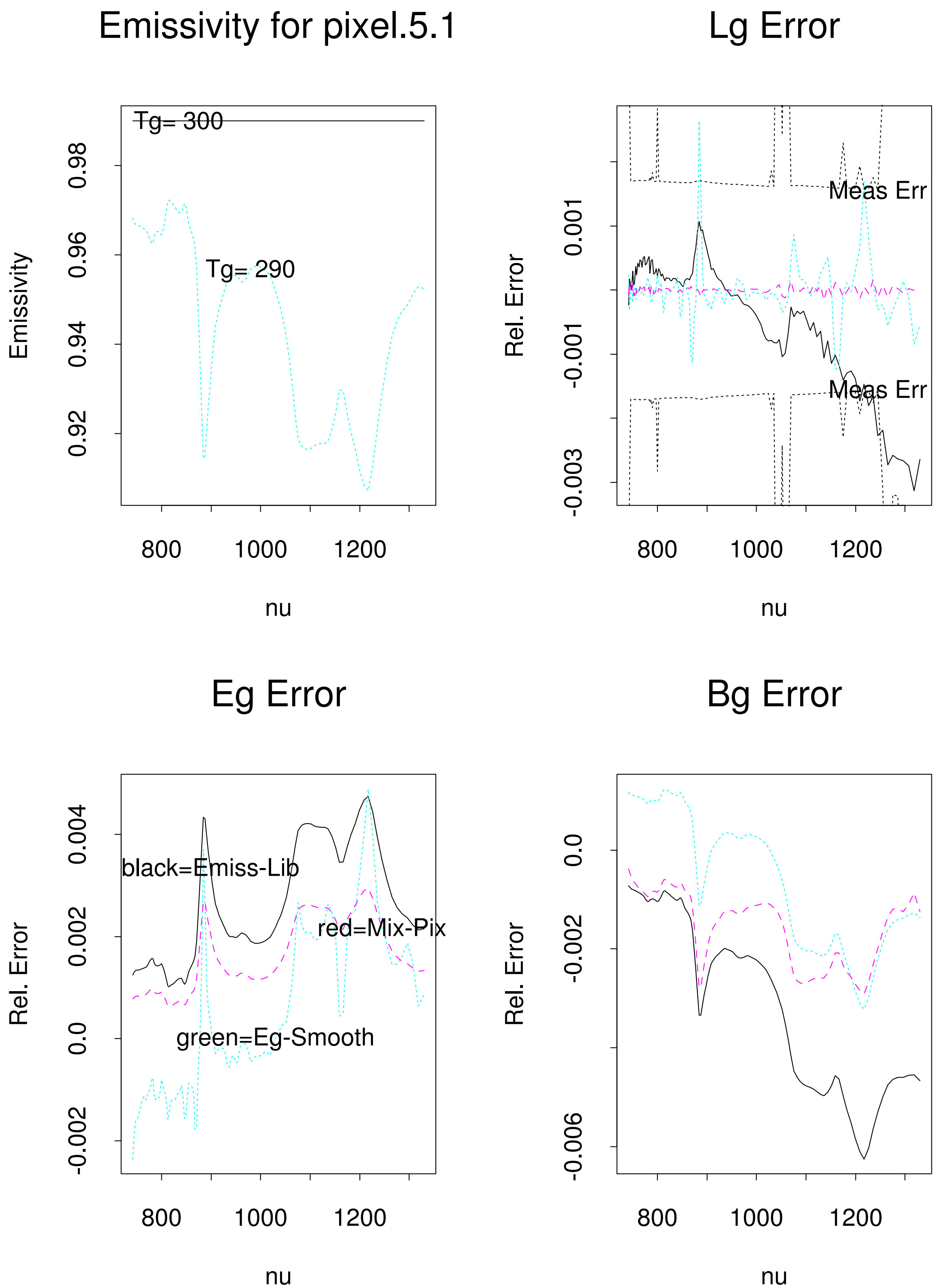


Figure A.6. Pixel 5.2: Hot Stack + Asphalt Roof, $sd(T) = 10C$

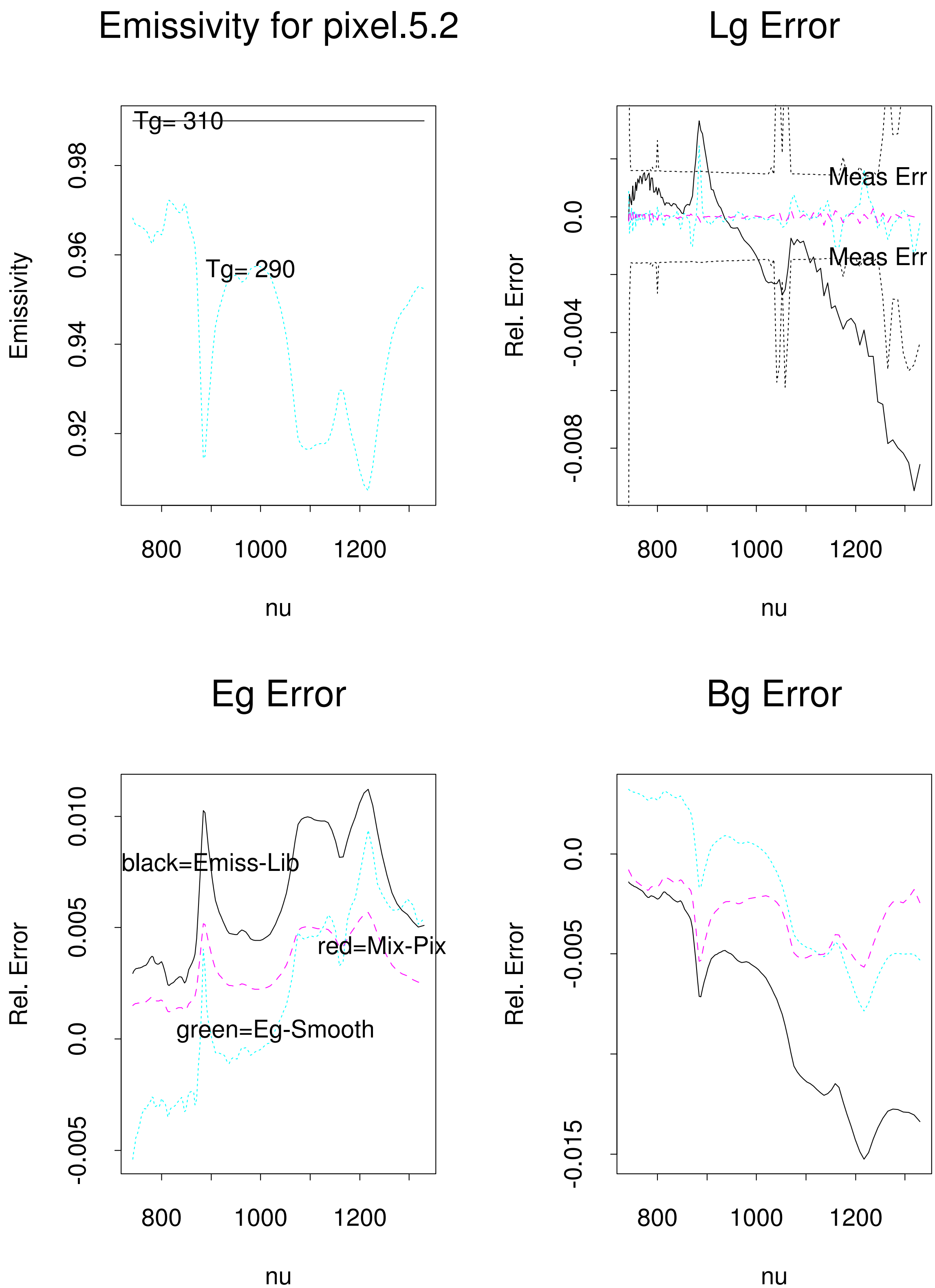


Figure A.7. Pixel 5.3: Hot Stack + Asphalt Roof, $sd(T) = 20C$

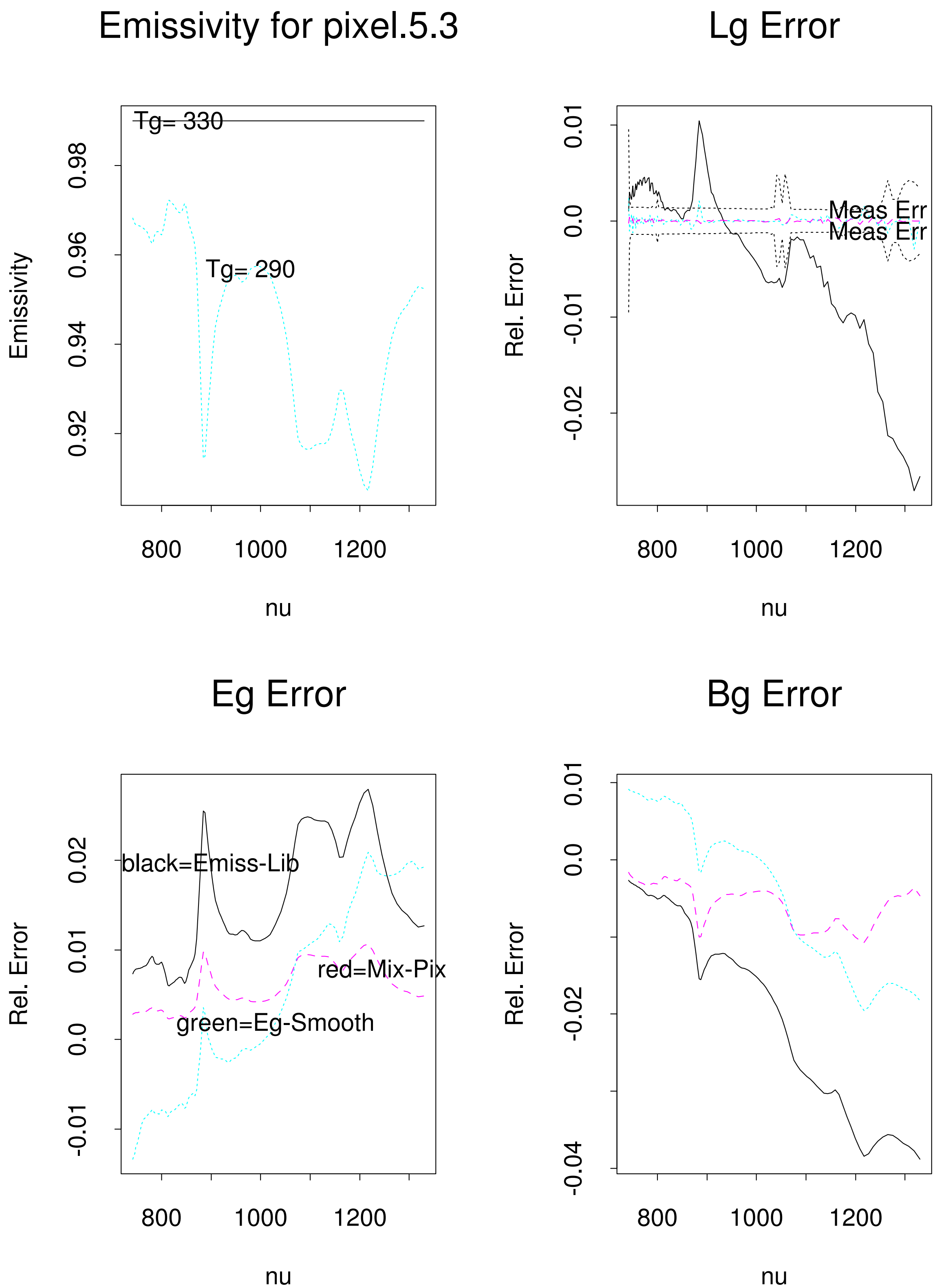


Figure A.8. Pixel 6.1: Hot Stack + Tin Roof, $sd(T) = 5C$

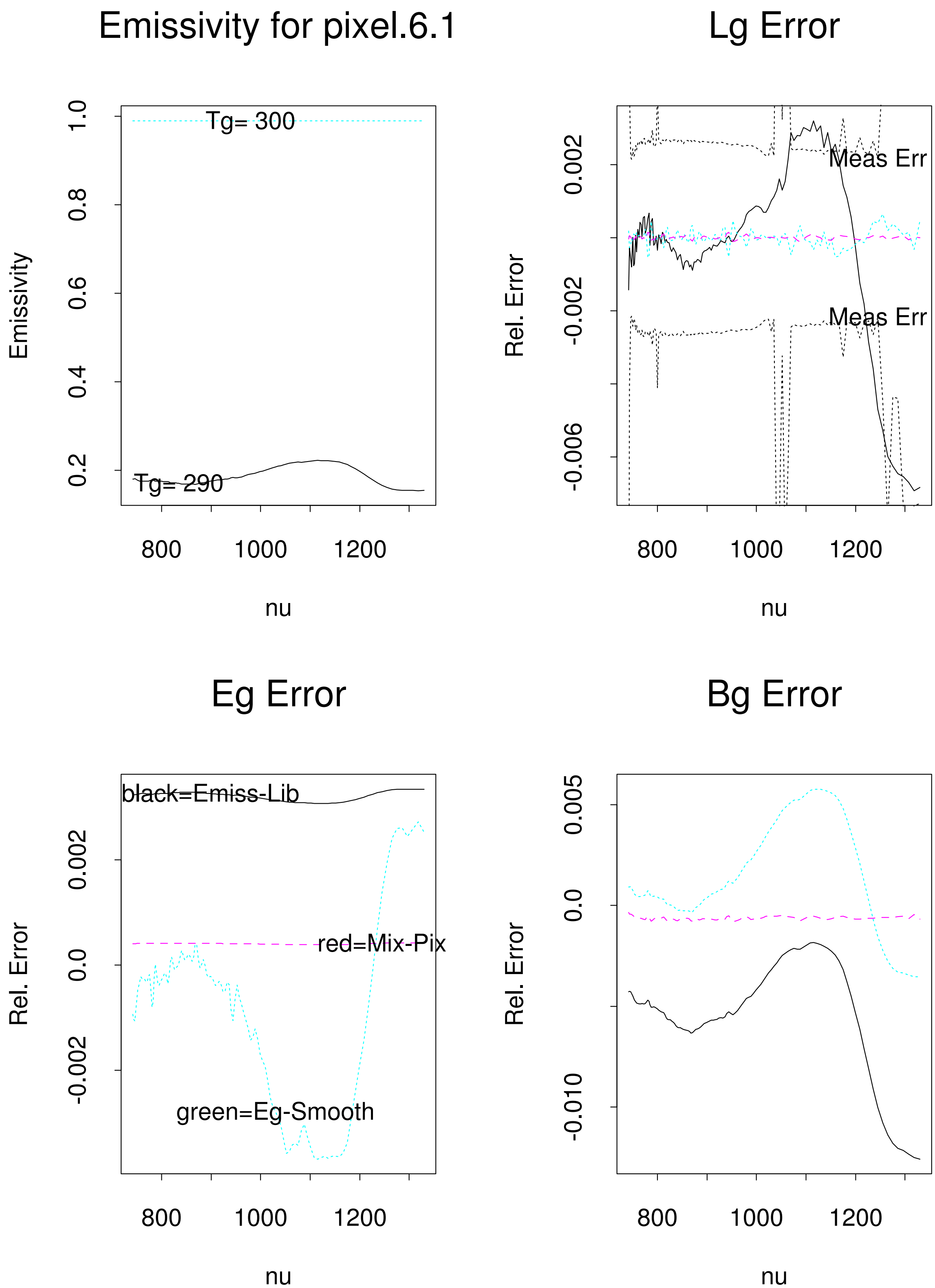


Figure A.9. Pixel 6.2: Hot Stack + Tin Roof, $sd(T) = 10C$

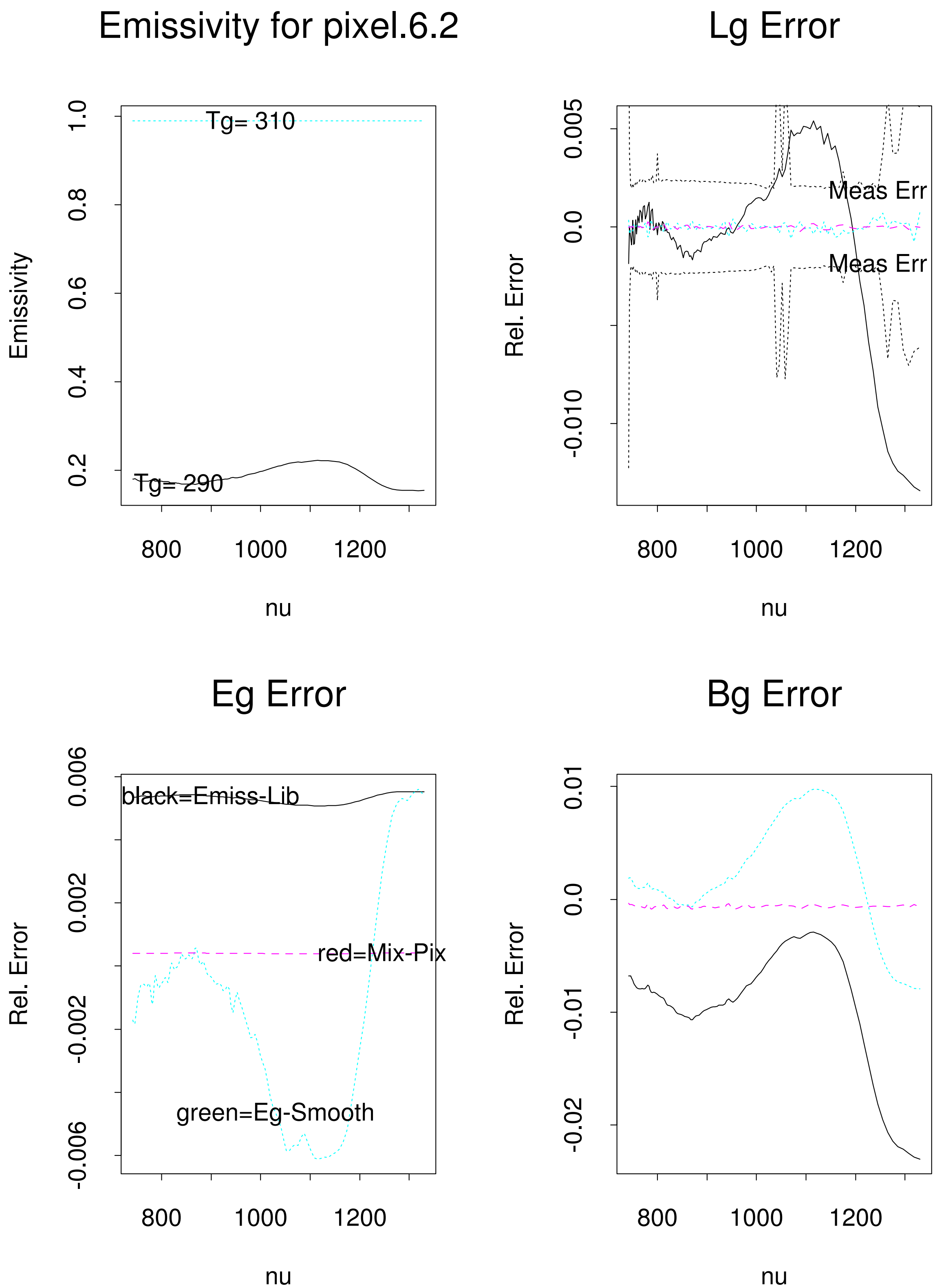


Figure A.10. Pixel 6.3: Hot Stack + Tin Roof, $sd(T) = 20C$

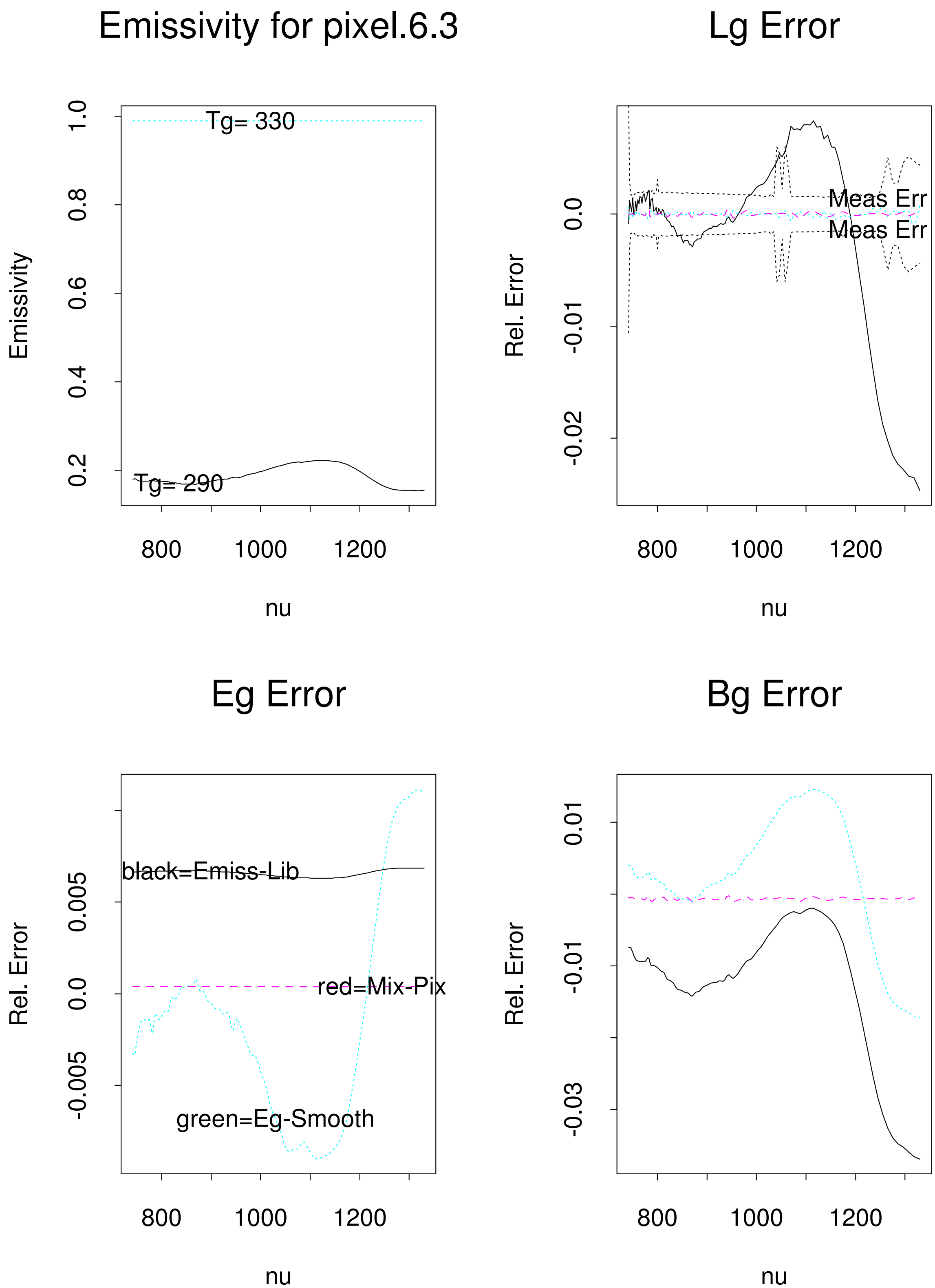
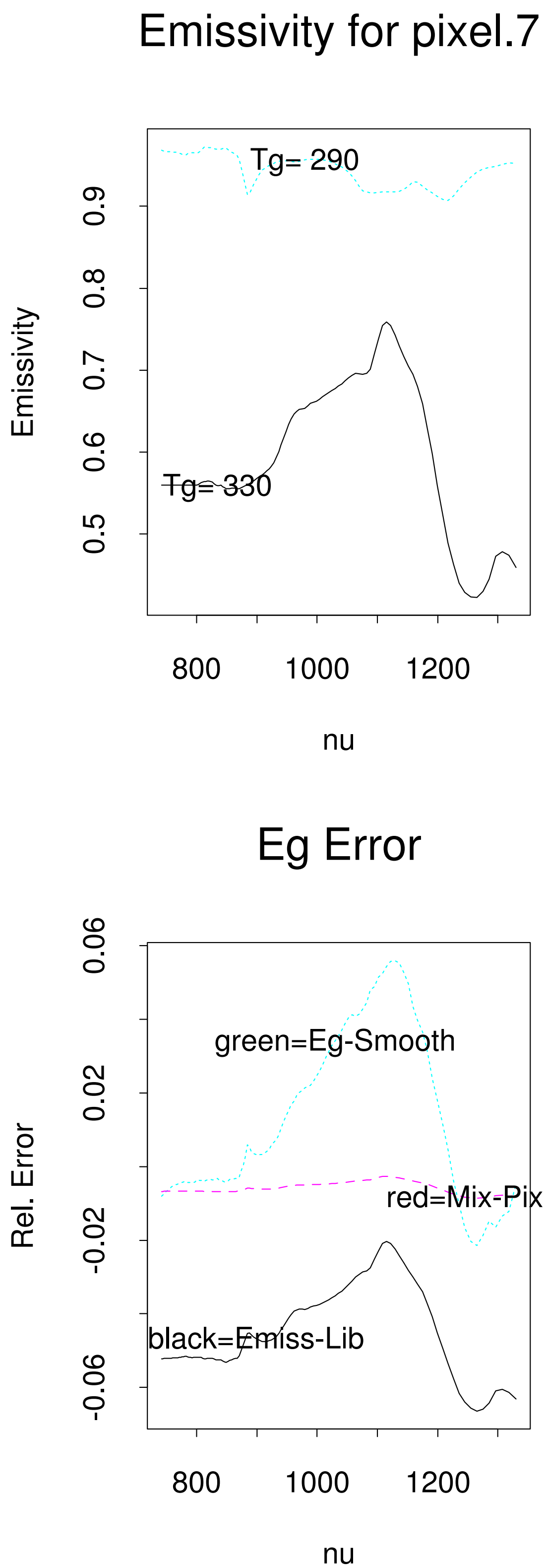


Figure A.11. Pixel 7: Worst Case Pixel, $sd(T) = 20C$



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