## Supplementary Materials for: Influence of Geographical Effects in Hedonic Pricing Models for Grass-Fed Cattle in Uruguay

### S.1 Hedonic Models

*Linear Regression*

To maintain consistency with previous studies, the theoretical model developed by Lanfranco et al. [2] was used as a reference; this model adopted the factor market method of Ladd and Martin [5] within a hedonic price framework. Hedonic price models can be estimated by an ordinary least squares (OLS) linear regression (LR). The response was the price in dollars per kilogram (US\$ kg$^{-1}$) of live weight recorded for each lot of cattle sold at auction. For the extended model of Lanfranco and Castaño [3], predictors included in matrix **x** represented overall market conditions at the time of the sale, marketing strategy at cattle auctions, cattle attributes included in the lots, and prevalent agro-ecological characteristics of the lot's police precinct of origin. The price function $y$ **(x)** allows the inclusion of nonlinear relationships; thus, quadratic terms for several of the predictors are included.

Following Lanfranco and Castaño [3], for lot $i = 1, \dots, N$ , and given a set of $K$ characteristics that describe it fully, the function $y$ **(x)** is expressed as follows:

$$y_i = \varphi + \sum_{k=1}^{K} \vartheta_k x_{ik} + \sum_{k=1}^{K} \rho_k x_{ik}^2 + \sum_{i=1}^{K} \sum_{k=1}^{K} \varsigma_{lk} x_{il} x_{ik} + \varepsilon_i, \qquad l \neq k \qquad (1)$$

where $y_i$ is the response (price) variable and predictors $x_{ik}$ and $x_{ik}^2$ represent linear and quadratic relationships of characteristic $k$, while the product $x_{il} x_{ik}$ is the potential interaction of the predictor

variable $k$ with the predictor variable $l$, for lot $N$. The model has $K$ linear relationships, $K$ quadratic

relationships, and $(K \times K) - K$ interactions. Model coefficients $\varphi$, $\vartheta_k$, $\rho_k$ and $\varsigma_{lk}$ are estimated by

OLS. Some interactions between predictors (e.g., breed × sex) were not considered, meaning that

some $\varsigma_{lk}$ coefficients were set to zero. For OLS, residual error $\varepsilon_i$ is assumed independent and

identically distributed, $\varepsilon_i \sim N(0, \sigma^2 I)$. Differentiating equation (1) with respect to $x_k$ gives the price

(or implicit marginal value) for a given characteristic $k$. Substituting the estimated coefficients for

parameters $\hat{\vartheta}_k$, $\hat{\rho}_k$ and $\hat{\varsigma}_{lk}$ and ignoring the lot subscript, provides the following expression that

includes quadratic relationships and factor interactions:

$$y_k = \hat{\vartheta}_k + 2\hat{\rho}_k x_k + \hat{\varsigma}_{lk} x_l, \qquad l \neq k \text{ and } k = 1, ..., K. \qquad (2)$$

The price or marginal values in equation (2) connect the reserve equilibrium prices, $\delta$ and $\theta$, with

characteristics that determine product quality, such that $\delta(\mathbf{x}) = y(\mathbf{x}) = \theta(\mathbf{x})$. This does not reveal

information concerning inherent supply and demand functions. Corrections were also applied to

mitigate against heteroscedasticity of the variance-covariance matrix [3] and were only applied for

LR. In summary, the following LR model was investigated:

$$PRICE = f(Beef\ and\ Market\ Cond. + Auction\ Strat. + Cattle\ Attri. + Agroeco\ Conditions) \qquad (3)$$

2

### *Incorporating Spatial Effects through an Autocorrelated Error Term*

For spatial extensions, it is convenient to re-name the $K = 51$ coefficients $\varphi$, $\vartheta_k$, $\rho_k$, and $\varsigma_{lk}$, for the model in equation (3), to give a model with a $K$ x 1 vector of coefficients, named $\boldsymbol{\beta} = [\beta_0, \beta_1, \beta_2, \ldots, \beta_k]$. Thus, the regression in equation (1) can be re-written:

$$y_i = \beta_0 + \sum_{k=1}^{K} \beta_k x_{ik} + \varepsilon_i \tag{4}$$

where in matrix terms, the coefficients $\boldsymbol{\beta}$ are estimated via OLS using:

$$\widehat{\boldsymbol{\beta}}_{OLS} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}\mathbf{y} \tag{5}$$

where, $\mathbf{X}$ is a $(N \times (K + 1))$ predictor data matrix and $\mathbf{y}$ is a $(N \times 1)$ response data vector. Spatial autocorrelation in the error term can be accounted for, if present, by fitting a linear mixed model (LMM), where the coefficients are unbiasedly estimated using restricted maximum likelihood (REML) [59,31]:

$$\widehat{\boldsymbol{\beta}}_{REML} = (\mathbf{X}^T[\boldsymbol{\Sigma}_\Delta]^{-1}\mathbf{X})^{-1}\mathbf{X}^T[\boldsymbol{\Sigma}_\Delta]^{-1}\mathbf{y} \tag{6}$$

and where $[\boldsymbol{\Sigma}_\Delta]^{-1}$ represents unbiased variogram information of the (spatially-autocorrelated) residual process, $\mathbf{y} - \mathbf{X}\widehat{\boldsymbol{\beta}}_{REML}$. In this study, an exponential variogram model was chosen for this purpose, which can be defined as:

$$\gamma(h) = c_0 + c_1\left(1 - \exp\left(-\frac{h}{a}\right)\right) \tag{7}$$

where the parameters $c_0$ and $c_1$ represent the partial sills of the variogram and $a$ is the correlation range; $h$ is distance, assuming isotropy. Details for specifying variograms for an LMM can be found in Schabenberger and Gotway [16]. Failure to account for a spatially-autocorrelated error term in regression modelling are unreliable coefficient and uncertainty estimates from a naïve (OLS) LR fit. As with the LR model, an LMM was investigated following the same functional form given in equation (3). As this study is dealing with areal data, an alternative spatial regression could have been formulated using a simultaneous or conditional autoregressive model (i.e. a SAR or CAR model, respectively). This study's reporting of an $R^2$ value for the LMM, should be viewed cautiously, as the $R^2$ value (or coefficient of determination) is specifically designed for an OLS LR fit and therefore does not account for error variation due to residual spatial autocorrelation.

### *Incorporating Spatial Effects through Scale-dependent Relationships*

For the second spatial model, a geographically weighted regression (GWR) model was used [17]. GWR is a spatially varying coefficient (SVC) model that investigates how relationships between the response and predictors may vary across space. It is underpinned by the idea that global or whole map statistical models such as an LR/LMM may make unreasonable stationary assumptions amongst the regression's coefficients under investigation. GWR provides a measure of process spatial heterogeneity in data relationships, where local coefficients (i.e. the SVCs) and associated measures of uncertainty (e.g. $t$-values) can be mapped to explore this [36,44].

In its standard form, GWR calculates a series of local regressions at target locations, using nearby weighted data falling under a kernel at the center of each location. Only a single kernel bandwidth is used, which is limiting in that it unrealistically assumes the same level of spatial smoothness for each set of SVCs. Thus, when some relationships operate at a large-scale while others operate at a small-scale, standard GWR will not capture these differences and only find a 'best-on-average' scale of relationship nonstationarity (as using only a single kernel bandwidth). As a first step to mitigate against this limitation, mixed GWR can be implemented in which some relationships are taken as stationary (*globally-fixed*) whilst others are taken as nonstationary (*locally-varying)* [18]. However, a mixed GWR model does not fully address the limitation, as the subset of relationships that are locally-varying are all still taken to operate at the same spatial scale. Instead, multiscale GWR (MGWR) can be used [32,33,27,47,34,48], in which each relationship is characterized through its own bandwidth. Thus, the scale of relationship nonstationarity is allowed to vary for each response to predictor relationship.

Following that given in Murakami et al. [48], a basic linear SVC model can be defined as:

$$y_i = \sum_{k=1}^{K} x_{ik}\beta_k(s_i) + \varepsilon_i, \qquad E[\varepsilon_i] = 0, \qquad Var[\varepsilon_i] = \sigma^2, \qquad (8)$$

where $\beta_k(s_i)$ denotes the $k$-th SVC for site $i$. This local approach estimates coefficients at the $i$-th site, $\{\beta_1(s_i),... \beta_k(s_i),... \beta_K(s_i)\}$, where in the case of standard GWR, a weighted least squares

estimation is applied to nearby sub-samples that are weighted through some distance-decay function at site *i*. Supposing $\boldsymbol{\beta}(s_i) = [\beta_1(s_i),... \beta_k(s_i),... \beta_K(s_i)]^{\mathrm{T}}$, the standard GWR estimator gives:

$$\widehat{\boldsymbol{\beta}}_{GWR}(s_i) = [\mathbf{X}^{\mathrm{T}}\mathbf{W}(s_i)\mathbf{X}]^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{W}(s_i)\mathbf{y} \tag{9}$$

where $\mathbf{W}(s_i)$ is an $N \times N$ diagonal matrix whose *j*-th element $g(s_i, s_j)$ represents the weight assigned to the *j*-th sample, and where, $g(s_i, s_j)$ is calculated by a kernel weighting function [56], such as a bi-square kernel:

$$g(s_i, s_j) = \begin{cases} 1 - \left( \dfrac{d(s_i, s_j)^2}{b^2} \right), & d(s_i, s_j) < b \\ 0, & otherwise \end{cases} \tag{10}$$

where *b* denotes the bandwidth parameter and $d(s_i, s_j)$ is the distance between locations $s_i$ and $s_j$. The SVCs from a standard GWR will tend to the constant coefficients of the OLS LR, if *b* is set sufficiently large enough; otherwise, the SVCs will be local. Bandwidths can be specified as a *fixed distance*, or an adaptive distance, where for the latter, bandwidths vary according to a *fixed local density* of sub-samples.

Standard GWR as described above, ignores differences of spatial scale across the SVCs, as the same (single) bandwidth is specified for all relationships. To counter this, each set of SVCs can be found using its own bandwidth, and thus extend GWR with multiple (or flexible) bandwidths, one for each relationship (i.e. MGWR). Here the bi-square kernel for MGWR is defined as:

$$g_k(s_i, s_j) = \begin{cases} 1 - \left( \dfrac{d(s_i, s_j)^2}{b_k{}^2} \right), & d(s_i, s_j) < b_k \\ 0, & otherwise \end{cases} \qquad (11)$$

where $b_k$ is the (*fixed distance*) bandwidth for the $k$-th coefficient. The estimated SVCs describe a global-scale process provided $b_k$ is set sufficiently large, and a local-scale process provided $b_k$ is set sufficiently small. Standard GWR is estimated in a two-stage procedure where first $b$ is optimally found through some measure of model fit (say, by maximizing the Akaike Information Criterion (AIC) [19]); and second, the SVCs are estimated by substituting the optimal value of $b$ into equation (9). The SVCs of MGWR are estimated in a similar manner except that a back-fitting approach is used in the first stage, which sequentially iterates the calibration of $b_k$ (or $b(s_i)_k{}^{ad}$) with the assumption that all bandwidth parameters are known. For this study, MGWR is calibrated using the bi-square function in equation (11) with fixed bandwidths optimally found via an AIC-based back-fitting approach.

As with the LR and the LMM, an MGWR was investigated following the same functional form given in equation (3). Here, the use of nonlinear quadratic terms in MGWR is unusual given nonstationary effects often mimic nonlinear effects but were retained for coherence and consistency between model forms. Standard or mixed GWR forms were not investigated. LR and LMM do not suffer from the problem of multiple hypothesis testing when determining coefficient significance (i.e. false discovery rates), whereas GWR models do. Thus, $p$-values from MGWR are adjusted for multiple comparisons as advocated in Fotheringham et al. [32]; Yu et al. [34].

## S.2 Supplementary Results

**Table S1.** Summaries (part 1) for the LR model.

| Description | Variable | Coefficient | Standard Error | *t*-statistic | *p*-value & significance | |
|---|---|---|---|---|---|---|
| Constant (intercept) | C | 0.65939 | 0.11990 | 5.49960 | 0.00000 | *** |
| Steer price (US $ / kg) | PSTEER | 0.67655 | 0.01488 | 45.47410 | 0.00000 | *** |
| Exch. rate (UY$/US$) | EXRT | -0.00810 | 0.00101 | -8.04384 | 0.00000 | *** |
| Order of entry (#) | ORDER | -0.00040 | 0.00007 | -5.92430 | 0.00000 | *** |
| ORDER quadratic (#) | ORDER2 | 0.00000 | 0.00000 | 7.05475 | 0.00000 | *** |
| Lot Size (#) | LOTSZ | 0.00054 | 0.00019 | 2.88571 | 0.00394 | ** |
| LOTSZ quadratic (#) | LOTSZ2 | 0.00000 | 0.00000 | -2.27386 | 0.02305 | * |
| Recommended lot (Y/N) | RECOM | 0.02954 | 0.00514 | 5.74496 | 0.00000 | *** |
| Males (Yes / No) | MALE | 0.16724 | 0.00466 | 35.89716 | 0.00000 | *** |
| Live weight (kg) | KLW | -0.00166 | 0.00016 | -10.71059 | 0.00000 | *** |
| KLW quadratic (kg$^2$) | KLW2 | 0.00000 | 0.00000 | 6.62661 | 0.00000 | *** |
| Class (scored 3 to 10) | CLASS | 0.01121 | 0.00132 | 8.51169 | 0.00000 | *** |
| Condition (scored 3 to 10) | COND | 0.00038 | 0.00440 | 0.08725 | 0.93048 | |
| Age uniformity (Y/N) | AGEU | 0.00610 | 0.00469 | 1.30013 | 0.19366 | |
| Shape uniformity (Y/N) | UNIF | -0.00062 | 0.00430 | -0.14393 | 0.88556 | |
| Improved nutrition (Y/N) | INUT | -0.00449 | 0.00503 | -0.89222 | 0.37235 | |
| Tick area (Y/N) | TKAR | -0.00082 | 0.00378 | -0.21789 | 0.82753 | |
| Mio-Mio (Y/N) | BCAR | 0.00395 | 0.00544 | 0.72557 | 0.46816 | |
| Aberdeen Angus (Y/N) | BD2 | 0.01645 | 0.00448 | 3.66980 | 0.00025 | *** |
| Other British (Y/N) | BD3 | -0.00078 | 0.00568 | -0.13782 | 0.89039 | |
| Continental breed (Y/N) | BD4 | 0.00304 | 0.00455 | 0.66879 | 0.50369 | |
| Dairy breed (Y/N) | BD5 | -0.01071 | 0.00461 | -2.32213 | 0.02030 | * |
| Zebu breed (Y/N) | BD6 | 0.00469 | 0.00637 | 0.73529 | 0.46223 | |
| Hereford × Angus (Y/N) | CZ1 | -0.02115 | 0.00505 | -4.18866 | 0.00003 | *** |
| Brit. × Continental (Y/N) | CZ2 | 0.00026 | 0.00913 | 0.02815 | 0.97754 | |
| Dairy × Zebu (Y/N) | CZ3 | 0.00059 | 0.00794 | 0.07459 | 0.94054 | |
| Lot size × Live weight (kg) | LXW | 0.00000 | 0.00000 | -0.84324 | 0.39917 | |
| Condition × Live weight (kg) | CXW | 0.00002 | 0.00002 | 1.09228 | 0.27481 | |

Significance level (α) of *Student's* $t_{12466}$ (two-tailed): *** 0.1%; ** 1%; * 5%, and ^ 10%, where the probability of committing a Type I error and statistical significance for four levels of α (0.1%, 1%, 5%, and 10%) are shown in the last two columns.

**Table S2.** Summaries (part 2) for the LR model.

| Description | Variable | Coefficient | Standard Error | *t*-statistic | *p*-value & significance | |
|---|---|---|---|---|---|---|
| Soil productivity (#) | CONEAT | 0.00018 | 0.00040 | 0.45099 | 0.65203 | |
| CONEAT quadratic (#) | CONEAT2 | 0.00000 | 0.00000 | 0.42903 | 0.66793 | |
| Water holding capacity (mm) | WHC | -0.00106 | 0.00037 | -2.86619 | 0.00419 | ** |
| WHC quadratic (mm$^2$) | WHC2 | 0.00000 | 0.00000 | 2.06729 | 0.03880 | * |
| Summer (Yes / No) | T1 | -0.01377 | 0.06787 | -0.20283 | 0.83929 | |
| Fall (Yes / No) | T2 | -0.12913 | 0.05592 | -2.30929 | 0.02100 | * |
| Winter (Yes / No) | T3 | 0.09679 | 0.07510 | 1.28878 | 0.19758 | |
| NDVI (#) | NDVI | -0.01071 | 0.00341 | -3.14370 | 0.00169 | ** |
| NDVI quadratic (#) | NDVI2 | 0.00010 | 0.00003 | 3.59105 | 0.00034 | *** |
| Surface water runoff (mm) | SWR | -0.00090 | 0.00041 | -2.19622 | 0.02816 | * |
| SWR quadratic (mm$^2$) | SWR2 | 0.00000 | 0.00000 | -5.76850 | 0.00000 | *** |
| Available water (%) | PAW | 0.00357 | 0.00120 | 2.96594 | 0.00304 | ** |
| PAW quadratic (%$^2$) | PAW2 | -0.00002 | 0.00001 | -2.20301 | 0.02768 | * |
| SWR × PAW | SXP | 0.00002 | 0.00000 | 3.68608 | 0.00023 | *** |
| NDVI × Summer | NXT1 | 0.00405 | 0.00099 | 4.08890 | 0.00004 | *** |
| NDVI × Fall | NXT2 | 0.00255 | 0.00089 | 2.87043 | 0.00413 | ** |
| NDVI × Winter | NXT3 | -0.00114 | 0.00102 | -1.10968 | 0.26723 | |
| SWR × Summer | SXT1 | -0.00010 | 0.00017 | -0.56159 | 0.57444 | |
| SWR × Fall | SXT2 | 0.00051 | 0.00015 | 3.34261 | 0.00084 | *** |
| SWR × Winter | SXT3 | -0.00013 | 0.00018 | -0.72649 | 0.46760 | |
| PAW × Summer | PXT1 | -0.00318 | 0.00057 | -5.55860 | 0.00000 | *** |
| PAW × Fall | PXT2 | -0.00043 | 0.00047 | -0.90305 | 0.36658 | |
| PAW × Winter | PXT3 | -0.00065 | 0.00049 | -1.32628 | 0.18486 | |

Significance level (α) of *Student's* t$_{12466}$ (two-tailed): *** 0.1%; ** 1%; * 5%, and ^ 10%, where the probability of committing a Type I error and statistical significance for four levels of α (0.1%, 1%, 5%, and 10%) are shown in the last two columns.

**Table S3.** Summaries (part 1) for the LMM.

| Description | Variable | Coefficient | Standard Error | *t*-statistic | *p*-value & significance | |
|---|---|---|---|---|---|---|
| Constant (intercept) | C | 0.70575 | 0.12386 | 5.69778 | 0.00000 | *** |
| Steer price (US $ / kg) | PSTEER | 0.68200 | 0.01078 | 63.28919 | 0.00000 | *** |
| Exch. rate (UY$/US$) | EXRT | -0.00767 | 0.00102 | -7.48880 | 0.00000 | *** |
| Order of entry (#) | ORDER | -0.00040 | 0.00007 | -5.83070 | 0.00000 | *** |
| ORDER quadratic (#) | ORDER2 | 0.00000 | 0.00000 | 6.41632 | 0.00000 | *** |
| Lot Size (#) | LOTSZ | 0.00057 | 0.00017 | 3.26219 | 0.00112 | ** |
| LOTSZ quadratic (#) | LOTSZ2 | 0.00000 | 0.00000 | -2.10862 | 0.03507 | * |
| Recommended lot (Y/N) | RECOM | 0.02819 | 0.00513 | 5.49078 | 0.00000 | *** |
| Males (Yes / No) | MALE | 0.16732 | 0.00475 | 35.19650 | 0.00000 | *** |
| Live weight (kg) | KLW | -0.00165 | 0.00013 | -12.94867 | 0.00000 | *** |
| KLW quadratic (kg$^2$) | KLW2 | 0.00000 | 0.00000 | 7.90443 | 0.00000 | *** |
| Class (scored 3 to 10) | CLASS | 0.01066 | 0.00147 | 7.23449 | 0.00000 | *** |
| Condition (scored 3 to 10) | COND | -0.00090 | 0.00407 | -0.22048 | 0.82552 | |
| Age uniformity (Y/N) | AGEU | 0.00514 | 0.00419 | 1.22771 | 0.21966 | |
| Shape uniformity (Y/N) | UNIF | 0.00025 | 0.00432 | 0.05707 | 0.95449 | |
| Improved nutrition (Y/N) | INUT | -0.00179 | 0.00471 | -0.38006 | 0.70393 | |
| Tick area (Y/N) | TKAR | 0.00075 | 0.00449 | 0.16703 | 0.86736 | |
| Mio-Mio (Y/N) | BCAR | -0.00101 | 0.00598 | -0.16856 | 0.86616 | |
| Aberdeen Angus (Y/N) | BD2 | 0.01665 | 0.00434 | 3.83338 | 0.00013 | *** |
| Other British (Y/N) | BD3 | -0.00140 | 0.00607 | -0.22995 | 0.81815 | |
| Continental breed (Y/N) | BD4 | 0.00235 | 0.00466 | 0.50311 | 0.61493 | |
| Dairy breed (Y/N) | BD5 | -0.01086 | 0.00454 | -2.39410 | 0.01673 | * |
| Zebu breed (Y/N) | BD6 | 0.00410 | 0.00664 | 0.61813 | 0.53654 | |
| Hereford × Angus (Y/N) | CZ1 | -0.01845 | 0.00563 | -3.27863 | 0.00106 | ** |
| Brit. × Continental (Y/N) | CZ2 | 0.00007 | 0.00969 | 0.00718 | 0.99427 | |
| Dairy × Zebu (Y/N) | CZ3 | -0.00015 | 0.00865 | -0.01724 | 0.98625 | |
| Lot size × Live weight (kg) | LXW | 0.00000 | 0.00000 | -1.14491 | 0.25235 | |
| Condition × Live weight (kg) | CXW | 0.00002 | 0.00001 | 1.25120 | 0.21097 | |

Significance level (α) of *Student's* $t_{12466}$ (two-tailed): *** 0.1%; ** 1%; * 5%, and ^ 10%, where the probability of committing a Type I error and statistical significance for four levels of α (0.1%, 1%, 5%, and 10%) are shown in the last two columns.

**Table S4.** Summaries (part 2) for the LMM.

| Description | Variable | Coefficient | Standard Error | *t*-statistic | *p*-value & significance | |
|---|---|---|---|---|---|---|
| Soil productivity (#) | CONEAT | 0.00026 | 0.00053 | 0.49327 | 0.62186 | |
| CONEAT quadratic (#) | CONEAT2 | 0.00000 | 0.00000 | 0.24961 | 0.80291 | |
| Water holding capacity (mm) | WHC | -0.00128 | 0.00051 | -2.49462 | 0.01267 | * |
| WHC quadratic (mm$^2$) | WHC2 | 0.00000 | 0.00000 | 1.97112 | 0.04881 | * |
| Summer (Yes / No) | T1 | -0.01178 | 0.06479 | -0.18185 | 0.85571 | |
| Fall (Yes / No) | T2 | -0.13940 | 0.05625 | -2.47835 | 0.01326 | * |
| Winter (Yes / No) | T3 | 0.05952 | 0.06936 | 0.85818 | 0.39086 | |
| NDVI (#) | NDVI | -0.01181 | 0.00345 | -3.42363 | 0.00063 | *** |
| NDVI quadratic (#) | NDVI2 | 0.00011 | 0.00003 | 3.83767 | 0.00013 | *** |
| Surface water runoff (mm) | SWR | -0.00080 | 0.00047 | -1.70119 | 0.08902 | ^ |
| SWR quadratic (mm$^2$) | SWR2 | 0.00000 | 0.00000 | -5.24602 | 0.00000 | *** |
| Available water (%) | PAW | 0.00296 | 0.00128 | 2.30118 | 0.02145 | * |
| PAW quadratic (%$^2$) | PAW2 | -0.00001 | 0.00001 | -1.53039 | 0.12603 | |
| SWR × PAW | SXP | 0.00002 | 0.00001 | 3.08254 | 0.00207 | ** |
| NDVI × Summer | NXT1 | 0.00390 | 0.00088 | 4.44173 | 0.00001 | *** |
| NDVI × Fall | NXT2 | 0.00276 | 0.00080 | 3.42638 | 0.00062 | *** |
| NDVI × Winter | NXT3 | -0.00071 | 0.00090 | -0.79261 | 0.42807 | |
| SWR × Summer | SXT1 | -0.00013 | 0.00021 | -0.59719 | 0.55043 | |
| SWR × Fall | SXT2 | 0.00050 | 0.00015 | 3.24618 | 0.00118 | ** |
| SWR × Winter | SXT3 | -0.00016 | 0.00019 | -0.83109 | 0.40600 | |
| PAW × Summer | PXT1 | -0.00303 | 0.00065 | -4.67993 | 0.00000 | *** |
| PAW × Fall | PXT2 | -0.00045 | 0.00051 | -0.87510 | 0.38159 | |
| PAW × Winter | PXT3 | -0.00049 | 0.00050 | -0.97798 | 0.32817 | |

Significance level (α) of *Student's* $t_{12466}$ (two-tailed): *** 0.1%; ** 1%; * 5%, and ^ 10%, where the probability of committing a Type I error and statistical significance for four levels of α (0.1%, 1%, 5%, and 10%) are shown in the last two columns.

**Table S5.** Estimated stationary coefficients for MGWR (medians from MGWR outputs).

| Variable | Coefficient | Variable | Coefficient | Variable | Coefficient |
|---|---|---|---|---|---|
| C | - | BCAR | -0.00812 | T3 | - |
| PSTEER | - | BD2 | - | NDVI | - |
| EXRT* | -0.00817 | BD3 | -0.00200 | NDVI2* | 0.00010 |
| ORDER* | -0.00040 | BD4 | - | SWR | -0.00083 |
| ORDER2* | 0.00000 | BD5* | -0.00951 | SWR2* | 0.00000 |
| LOTSZ* | 0.00045 | BD6 | - | PAW* | 0.00311 |
| LOTSZ2 | -0.00000 | CZ1* | -0.01270 | PAW2 | -0.00001 |
| RECOM* | 0.02548 | CZ2 | - | SXP* | 0.00002 |
| MALE | - | CZ3 | -0.00270 | NXT1* | 0.00271 |
| KLW | - | LXW | -0.00000 | NXT2* | 0.00181 |
| KLW2* | 0.00000 | CXW | -0.00002 | NXT3 | -0.00115 |
| CLASS* | 0.00889 | CONEAT | 0.00014 | SXT1 | -0.00011 |
| COND | -0.00310 | CONEAT2 | 0.00000 | SXT2 | - |
| AGEU | 0.00177 | WHC* | -0.00078 | SXT3 | - |
| UNIF | - | WHC2 | 0.00000 | PXT1* | -0.00298 |
| INUT | - | T1 | - | PXT2 | -0.00042 |
| TKAR | 0.00022 | T2 | -0.07877 | PXT3 | -0.00003 |

Entries highlighted in blue are nonstationary (see main text). * Significant at the 5% level or lower.

## S.3 Data Preparation

In section 2.3 of the main text, a preferential sampling issue was resolved by taking a stratified random sample from the full database used in previous studies [2,3], to yield a study dataset of $N$ = 2,845 observations. Here, a more sophisticated weighted approach via spatial kernel density estimation could have been adopted similar to that proposed in Diggle et al. [35]. This study's pragmatic approach to preferential sampling is still subject to bias, but not as great as that would be found using the full dataset. Further, a sensitivity analysis on the effects of sampling variation could have been achieved via a parametric bootstrap but would have been computationally expensive. It would also have been possible to assess the *out-of-sample* prediction of accuracy of the study models using the larger set-aside dataset (the LMM then becomes a regression kriging model). As previous studies used the full database, then some differences would be expected between previous LR results and this study's LR results, as reported above.