

Package: CompositionalSR (via r-universe)

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Type Package

Title Spatial Regression Models with Compositional Data

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Suggests Rfast2

Description Spatial and non-spatial regression models with
compositional responses (and compositional predictors) using
the alpha--transformation. Relevant papers include: Tsagris M.
and Pantazis Y. (2026), <[doi:10.48550/arXiv.2510.12663](https://doi.org/10.48550/arXiv.2510.12663)>,
Tsagris M. (2015),
<[https://soche.cl/chjs/volumes/06/02/Tsagris\(2015\).pdf](https://soche.cl/chjs/volumes/06/02/Tsagris(2015).pdf)>,
Tsagris M.T., Preston S. and Wood A.T.A. (2011),
<[doi:10.48550/arXiv.1106.1451](https://doi.org/10.48550/arXiv.1106.1451)>.

License GPL (>= 2)

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CompositionalSR-package

Spatial Regression Models with Compositional Data

Description

Spatial regression models with compositional responses using the α -transformation. The models included are the α -regression (not spatial), the α -regression (not spatial) with compositional predictors, the α -spatially lagged X (α -SLX) model, the geographically weighted α -regression (GW α R) model and the α -eigenvector spatial filtering (α -ESF) model.

Details

Package: CompositionalSR
Type: Package
Version: 1.4
Date: 2026-04-14
License: GPL-2

Maintainers

Michail Tsagris <mtsagris@uoc.gr>

Author(s)

Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

Tsagris M., Papadovasilakis Z., Lakiotaki K. and Tsamardinos I. (2022). The γ -OMP Algorithm for Feature Selection With Application to Gene Expression Data. IEEE/ACM Transactions on Computational Biology and Bioinformatics, 19(2), 1214–1224.

Compositional regression with compositional predictors using the
alpha-transformation

*Compositional regression with compositional predictors using the α -
transformation*

Description

Compositional regression with compositional predictors using the α -transformation.

Usage

```
alfa.pcreg(y, x, a, k, xnew = NULL, yb = NULL)
```

Arguments

y	A matrix with the compositional responses. Zero values are allowed.
x	A matrix with the compositional predictors. Zero values are allowed.
a	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0. If $\alpha = 0$ the isometric log-ratio transformation is applied and the solution exists in a closed form, since it the classical multivariate regression.
k	How many principal components to compute?
xnew	If you have new data use it, otherwise leave it NULL.
yb	If you have already transformed the data using the α -transformation with the same α as given in the argument "a", put it here. Otherwise leave it NULL.

Details

The α -transformation is applied to both the compositional responses and predictors. Then, principal component analysis is performed in the α -transformed predictors and the projected scores are used as predictors. The same value of α is used for both the responses and the predictors.

Value

A list including:

runtime	The time required by the regression.
be	The beta coefficients.
dev	The sum of the squared residuals, as produced by the function <code>minpack.lm::nls.lm()</code> .
est	The fitted values for xnew if xnew is not NULL.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

- Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>
- Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>
- Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>
- Mardia K.V., Kent J.T., and Bibby J.M. (1979). Multivariate analysis. Academic press.

See Also

[cv.alfapcreg](#), [areg](#)

Examples

```
data(fadn)
y <- fadn[, 3:7]
x <- fadn[, 8:11]
x <- x / rowSums(x)
mod <- alfa.pcreg(y, x, k = 3, 0.2)
```

Computation of the contiguity matrix W

Computation of the contiguity matrix W

Description

Computation of the contiguity matrix W .

Usage

```
contiguity(coords, k = 10)
```

Arguments

<code>coords</code>	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
<code>k</code>	The number of nearest neighbours to consider for the contiguity matrix.

Value

The contiguity matrix W . A square matrix with row standardised values (the elements of each row sum to 1).

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

See Also

[alfa.slx](#), [cv.alfaslx](#), [me.aslx](#)

Examples

```
data(fadn)
W <- contiguity(fadn[, 1:2])
```

fadn

FADN dataset

Description

A matrix with 11 columns. The first two are the locations (latitude and longitude), the next five contain the compositional data (percentages of cultivated area of five crops), Y1.1: cereals, Y2.1: cotton, Y3.1: tree crops, Y4.1: other annual crops and pasture and Y5.1: grapes and wine. The next four columns contain the covariates, G1: Human Influence Index, G2: soil pH, G3: topsoil organic carbon content and G7: erosion.

Usage

fadn

Format

A matrix with 168 rows and 11 columns.

Source

Clark and Dixon (2021), available at <https://github.com/nick3703/Chicago-Data>.

References

Clark, N. J. and P. M. Dixon (2021). A class of spatially correlated self-exciting statistical models. *Spatial Statistics*, 43, 1–18.

See Also

[alfa.slx](#), [gwar](#), [alfa.reg](#)

Examples

```
data(fadn)
y <- fadn[, 3:7]
x <- fadn[, 8:11]
mod <- alfa.reg(y, x, a = 0.1)
```

ICE plot for the alpha-ESF model
ICE plot for the α -ESF model

Description

ICE plot for the α -ESF model.

Usage

```
ice.aesf(be, gama, x, X.esf, ind = 1, frac = 0.25, pos = 0.5)
```

Arguments

be	A numerical matrix with the estimated β coefficients of the α -ESF model.
gama	A numerical matrix with the estimated γ coefficients of the α -ESF model.
x	A numerical matrix with the predictor variables.
X.esf	A matrix with the values of the eigenvectors computed.
ind	Which variable to select?.
frac	Fraction of observations to use. The default value is 0.25.
pos	This is a number between 0 and 1 and is used to place the legend in the appropriate place.

Details

This function implements the Individual Conditional Expectation plots of Goldstein et al. (2015). See the references for more details.

Value

A graph with several curves, one for each component. The horizontal axis contains the selected variable, whereas the vertical axis contains the locally smoothed predicted compositional lines.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

<https://christophm.github.io/interpretable-ml-book/ice.html>

Goldstein, A., Kapelner, A., Bleich, J. and Pitkin, E. (2015). Peeking inside the black box: Visualizing statistical learning with plots of individual conditional expectation. *Journal of Computational and Graphical Statistics* 24(1): 44-65.

See Also

[areg](#), [cv.alfareg](#)

Examples

```
data(fadn)
coords <- fadn[, 1:2]
y <- fadn[, 3:7]
x <- fadn[, 8, drop = FALSE]
mod <- alfa.esf(y, x, a = 0.1, coords = coords)
```

ICE plot for the alpha-regression

ICE plot for the α -regression

Description

ICE plot for the α -regression.

Usage

```
ice.areg(be, x, ind = 1, frac = 0.25, pos = 0.5)
```

Arguments

be	A numerical matrix with the estimated α -regression coefficients.
x	A numerical matrix with the predictor variables.
ind	Which variable to select?.
frac	Fraction of observations to use. The default value is 0.25.
pos	This is a number between 0 and 1 and is used to place the legend in the appropriate place.

Details

This function implements the Individual Conditional Expectation plots of Goldstein et al. (2015). See the references for more details.

Value

A graph with several curves, one for each component. The horizontal axis contains the selected variable, whereas the vertical axis contains the locally smoothed predicted compositional lines.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

<https://christophm.github.io/interpretable-ml-book/ice.html>

Goldstein, A., Kapelner, A., Bleich, J. and Pitkin, E. (2015). Peeking inside the black box: Visualizing statistical learning with plots of individual conditional expectation. *Journal of Computational and Graphical Statistics* 24(1): 44-65.

See Also

[areg](#), [cv.alfareg](#)

Examples

```
data(fadn)
y <- fadn[, 3:7]
x <- fadn[, 8, drop = FALSE]
mod <- alfa.reg(y, x, 0.2)
ice <- ice.areg(mod$be, x, ind = 1)
```

K-fold cross-validation for the alpha-regression

K-fold cross-validation for the α -regression

Description

K-fold cross-validation for the α -regression.

Usage

```
cv.alfareg(y, x, a = seq(0.1, 1, by = 0.1), nfolds = 10,
folds = NULL, nc = 1, seed = NULL)
```

Arguments

y	A matrix with compositional data. zero values are allowed.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
a	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0. If $\alpha = 0$ the isometric log-ratio transformation is applied.
nfolds	The number of folds to split the data.
folds	If you have the list with the folds supply it here. You can also leave it NULL and it will create folds.

nc	The number of cores to use. IF you have a multicore computer it is advisable to use more than 1. It makes the procedure faster. It is advisable to use it if you have many observations and or many variables, otherwise it will slow down th process.
seed	You can specify your own seed number here or leave it NULL.

Details

Tuning the value of α in the α -regression takes place using K-fold cross-validation.

Value

A list including:

runtime	The runtime required by the cross-validation.
perf	A vector with the average Kullback-Leibler divergence, for every value of α .
opt	A vector with the minimum Kullback-Leibler divergence and the optimal value of α .

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[alfa.reg](#), [cv.alfaslx](#), [cv.gwar](#), [me.ar](#)

Examples

```
data(fadn)
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- cv.alfareg(y, x, a = c(0.5, 1))
```

K-fold cross-validation for the alpha-regression with compositional predictors

K-fold cross-validation the α -regression with compositional predictors

Description

K-fold cross-validation the α -regression with compositional predictors.

Usage

```
cv.alfapcreg(y, x, a = seq(0.1, 1, by = 0.1), k = dim(x)[2] - 2,
  nfolds = 10, folds = NULL, seed = NULL)
```

Arguments

y	A matrix with compositional response data. Zero values are allowed.
x	A matrix with the compositional predictor variables. Zero values are allowed.
a	A numerical vector with the values of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0. If $\alpha = 0$ the isometric log-ratio transformation is applied.
k	A number with the maximum number of principal components to consider. Use at most the default value, $\dim(x)[2] - 2$.
nfolds	The number of folds to split the data.
folds	If you have the list with the folds supply it here. You can also leave it NULL and it will create folds.
seed	You can specify your own seed number here or leave it NULL.

Details

Tuning the value of α and k, the number of principal components in the α -regression with compositional predictors takes place using the classical K-fold cross-validation.

Value

A list including:

runtime	The runtime required by the cross-validation.
perf	A matrix with the average Kullback-Leibler divergence, for every value of α and k.
kl	The minimum average value of the Kullback-Leibler divergence.
opt_a	The optimal value of α .
opt_k	The optimal value of k, the number of principal components.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[alfa.pcreg](#), [cv.alfareg](#)

Examples

```
data(fadn)
y <- fadn[, 3:7]
x <- fadn[, 8:11]
x <- x / rowSums(x)
mod <- cv.alfapcreg(y, x, a = c(0.5, 1))
```

Leave-one-out cross-validation for the GWalphaR model

Leave-one-out cross-validation for the GW α R model

Description

Leave-one-out cross-validation for the GW α R model

Usage

```
cv.gwar(y, x, a = c(0.1, 0.25, 0.5, 0.75, 1), coords, h,
n folds = 10, size = 1000, folds = NULL)
```

Arguments

y A matrix with compositional data. zero values are allowed.

x A matrix with the continuous predictor variables or a data frame including categorical predictor variables.

a	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0. If $\alpha = 0$ the isometric log-ratio transformation is applied.
coords	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
h	A vector with bandwidth values.
nfolds	The number of folds to split the data.
size	A numeric value of the specified range by which blocks are created and training/testing data are separated. This distance should be in metres. If you have big regions you should consider increasing this number. For more information see the package <i>blockCV</i> .
folds	If you have the list with the folds supply it here. You can also leave it NULL and it will create folds.

Details

The 10-fold spatial cross-validation protocol is applied to choose the optimal values of α and h.

Value

A list including:

runtime	The runtime required by the cross-validation.
perf	A vector with the average Kullback-Leibler divergence, for every value of α .
opt	A vector with the minimum Kullback-Leibler divergence, the optimal value of α and h.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. *Chilean Journal of Statistics*, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In *Proceedings of the 4th Compositional Data Analysis Workshop*, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[gwar](#), [me.gwar](#) [cv.alfaslx](#)

Examples

```
data(fadn)
coords <- fadn[, 1:2]
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- gwar(y, x, a = 1, coords, h = 0.001)
```

Marginal effects for the alpha-ESF model

Marginal effects for the α -ESF model

Description

Marginal effects for the α -ESF model.

Usage

```
me.aesf(be, gama, mu, x, X.esf)
```

Arguments

be	A matrix with the beta regression coefficients of the α -ESF model.
gama	A matrix with the beta regression coefficients of the α -ESF model.
mu	The fitted values of the α -ESF model.
x	A matrix with the continuous predictor variables or a data frame. Categorical predictor variables are not suited here.
X.esf	A matrix with the eigenvectors. Categorical predictor variables are not suited here.

Details

The marginal effects of the α -ESF model are computed.

Value

A list including:

me	An array with the marginal effects of each component for each predictor variable.
ame	The average marginal effects of each component for each predictor variable.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[me.aslx](#), [me.gwar](#), [alfa.reg](#)

Examples

```
data(fadn)
coords <- fadn[1:50, 1:2]
y <- fadn[, 3:7]
x <- fadn[, 8]
y <- fadn[1:50, 3:7]
x <- fadn[1:50, 8]
mod <- alfa.esf(y, x, a = 0.1, coords = coords, xnew = x, coordsnew = coords)
me <- me.aesf(mod$be, mod$gama, mod$est, x, mod$X.esf)
```

Marginal effects for the alpha-regression model

Marginal effects for the α -regression model

Description

Marginal effects for the α -regression model.

Usage

```
me.ar(be, mu, x, cov_be = NULL)
```

Arguments

be	A matrix with the beta regression coefficients of the α -regression model.
mu	The fitted values of the α -regression.
x	A matrix with the continuous predictor variables or a data frame. Categorical predictor variables are not suited here.
cov_be	The covariance matrix of the beta regression coefficients. If you pass this argument, then the standard error of the average marginal effects will be returned.

Details

The marginal effects of the α -regression model are computed.

Value

A list including:

me	An array with the marginal effects of each component for each predictor variable.
ame	The average marginal effects of each component for each predictor variable.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. *Chilean Journal of Statistics*, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In *Proceedings of the 4th Compositional Data Analysis Workshop*, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[me.aslx](#), [me.gwar](#), [alfa.reg](#)

Examples

```
data(fadn)
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- alfa.reg(y, x, 0.2, xnew = x)
me <- me.ar(mod$be, mod$est, x)
```

Marginal effects for the alpha-SAR model
Marginal effects for the α -SAR model

Description

Marginal effects for the α -SAR model.

Usage

```
me.asar(be, rho, mu, x, coords, k, cov_theta = NULL)
```

Arguments

be	A matrix with the beta coefficients of the α -SAR model.
rho	The spatial auto-regressive coefficient ρ of the α -SAR model.
mu	The fitted values of the α -SAR model.
x	A matrix with the continuous predictor variables or a data frame. Categorical predictor variables are not suited here.
coords	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
k	The number of nearest neighbours to consider for the contiguity matrix.
cov_theta	The covariance matrix of the beta and gamma regression coefficients. If you pass this argument, then the standard error of the average marginal effects will be returned.

Details

The marginal effects of the α -SAR model are computed.

Value

A list including:

me.dir	An array with the direct marginal effects of each component for each predictor variable.
me.indir	An array with the indirect marginal effects of each component for each predictor variable.
me.total	An array with the total marginal effects of each component for each predictor variable.
ame.dir	An array with the average direct marginal effects of each component for each predictor variable.
ame.indir	An array with the average indirect marginal effects of each component for each predictor variable.

<code>ame.total</code>	An array with the average total marginal effects of each component for each predictor variable.
<code>se.amedir</code>	An array with the standard errors of the average direct marginal effects of each component for each predictor variable. This is returned if you supply the covariance matrix <code>cov_theta</code> .
<code>se.ameindir</code>	An array with the standard errors of the average indirect marginal effects of each component for each predictor variable. This is returned if you supply the covariance matrix <code>cov_theta</code> .
<code>se.ametotal</code>	An array with the standard errors of the average total marginal effects of each component for each predictor variable. This is returned if you supply the covariance matrix <code>cov_theta</code> .

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[me.ar](#), [me.aslx](#), [me.gwar](#)

Examples

```
data(fadn)
coords <- fadn[, 1:2]
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- alfa.sar(y, x, a = 0.5, coords, k = 8)
me <- me.asar(mod$be, mod$rho, mod$est, x, coords, k = 6)
```

Marginal effects for the alpha-SLX model
Marginal effects for the α -SLX model

Description

Marginal effects for the α -SLX model.

Usage

```
me.aslx(be, gama, mu, x, coords, k = 10, cov_theta = NULL)
```

Arguments

be	A matrix with the beta coefficients of the α -SLX model.
gama	A matrix with the gamma coefficients of the α -SLX model.
mu	The fitted values of the α -SLX model.
x	A matrix with the continuous predictor variables or a data frame. Categorical predictor variables are not suited here.
coords	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
k	The number of nearest neighbours to consider for the contiguity matrix.
cov_theta	The covariance matrix of the beta and gamma regression coefficients. If you pass this argument, then the standard error of the average marginal effects will be returned.

Details

The marginal effects of the α -SLX model are computed.

Value

A list including:

me.dir	An array with the direct marginal effects of each component for each predictor variable.
me.indir	An array with the indirect marginal effects of each component for each predictor variable.
me.total	An array with the total marginal effects of each component for each predictor variable.
ame.dir	An array with the average direct marginal effects of each component for each predictor variable.
ame.indir	An array with the average indirect marginal effects of each component for each predictor variable.

<code>ame.total</code>	An array with the average total marginal effects of each component for each predictor variable.
<code>se.amedir</code>	An array with the standard errors of the average direct marginal effects of each component for each predictor variable. This is returned if you supply the covariance matrix <code>cov_theta</code> .
<code>se.ameindir</code>	An array with the standard errors of the average indirect marginal effects of each component for each predictor variable. This is returned if you supply the covariance matrix <code>cov_theta</code> .
<code>se.ametotal</code>	An array with the standard errors of the average total marginal effects of each component for each predictor variable. This is returned if you supply the covariance matrix <code>cov_theta</code> .

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[me.gwar](#), [me.ar](#), [alfa.slx](#)

Examples

```
data(fadn)
coords <- fadn[, 1:2]
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- alfa.slx(y, x, a = 0.5, coords, k = 10, xnew = x, coordsnew = coords)
me <- me.aslx(mod$be, mod$gama, mod$est, x, coords, k = 10)
```

Marginal effects for the GWalphaR model
Marginal effects for the GW α R model

Description

Marginal effects for the GW α R model.

Usage

```
me.gwar(be, mu, x)
```

Arguments

be	A matrix with the beta regression coefficients of the α -regression model.
mu	The fitted values of the α -regression.
x	A matrix with the continuous predictor variables or a data frame. Categorical predictor variables are not suited here.

Details

The location-specific marginal effects for the GW α R model are computed.

Value

A list including:

me	An array with the location-specific marginal effects of each component for each predictor variable.
ame	The average location-specific marginal effects of each component for each predictor variable.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[gwar](#), [me.aslx](#), [me.ar](#)

Examples

```
data(fadn)
coords <- fadn[, 1:2]
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- gwar(y, x, a = 1, coords, h = 0.001)
me <- me.gwar(mod$be, mod$est, x)
```

Prediction with the GWalphaR model

Prediction with the GW α R model

Description

Prediction with GW α R model.

Usage

```
gwar.pred(y, x, a, coords, h, xnew, coordsnew)
```

Arguments

y	A matrix with the compositional data.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
a	A vector with values for the power transformation, it has to be between -1 and 1.
coords	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
h	A vector with bandwidth values.
xnew	The new data.
coordsnew	A matrix with the coordinates of the new locations. The first column is the latitude and the second is the longitude.

Details

The α -transformation is applied to the compositional data first and then the GW α R model is applied and predictions are given for each observation.

Value

A list including:

`runtime` The time required by the regression.
`est` A list with the fitted values, for each combination of α and h .

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[cv.gwar](#), [me.gwar](#), [alfa.slx](#), [alfa.reg](#)

Examples

```
data(fadn)
coords <- fadn[-c(1:10), 1:2]
y <- fadn[-c(1:10), 3:7]
x <- fadn[-c(1:10), 8]
xnew <- fadn[1:10, 8]
coordsnew <- fadn[1:10, 1:2]
mod <- gwar.pred(y, x, a = c(0.25, 0.5, 1), coords,
h = c(0.002, 0.006), xnew = xnew, coordsnew = coordsnew)
```

Regression with compositional data using the alpha-transformation

Regression with compositional data using the α -transformation

Description

Regression with compositional data using the α -transformation.

Usage

```

areg(y, x, a, covb = FALSE, xnew = NULL, yb = NULL)
alfa.reg(y, x, a, covb = FALSE, xnew = NULL, yb = NULL)
alfa.reg2(y, x, a, xnew = NULL, ncores = 1)
alfa.reg3(y, x, a = c(-1, 1), xnew = NULL)

```

Arguments

y	A matrix with the compositional data.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
a	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0. If $\alpha = 0$ the isometric log-ratio transformation is applied and the solution exists in a closed form, since it is the classical multivariate regression. For the <code>alfa.reg2()</code> this should be a vector of α values and the function call repeatedly the <code>alfa.reg()</code> function. For the <code>alfa.reg3()</code> function it should be a vector with two values, the endpoints of the interval of α . This function searches for the optimal value of α that minimizes the Kullback-Leibler between the observed and fitted compositions. Using the <code>optimize</code> function it searches for the optimal value of α . Instead of choosing the value of α using <code>cv.alfareg</code> (that uses cross-validation) one can select it this way. The function <code>areg()</code> is faster as it passes the Jacobian matrix to the <code>nls.lm()</code> function.
covb	Do you want the covariance matrix of the regression coefficients to be returned? If TRUE, this will slow down the process, as it is computed numerically.
xnew	If you have new data use it, otherwise leave it NULL.
ncores	The number of cores to use for parallel computations.
yb	If you have already transformed the data using the α -transformation with the same α as given in the argument "a", put it here. Otherwise leave it NULL. This is intended to be used in the function <code>cv.alfareg</code> in order to speed up the process. The time difference in that function is small for small samples. But, if you have a few thousands and or a few more components, there will be bigger differences.

Details

The α -transformation is applied to the compositional data first and then multivariate regression is applied. This involves numerical optimisation. The `alfa.reg2()` function accepts a vector with many values of α , while the `alfa.reg3()` function searches for the value of α that minimizes the Kullback-Leibler divergence between the observed and the fitted compositional values. The functions are highly optimized.

Value

For the `alfa.reg()` function a list including:

`runtime` The time required by the regression.

be	The beta coefficients.
covbe	The covariance matrix if covb was set to TRUE, otherwise NULL.
dev	The sum of the squared residuals, as produced by the function <code>minpack.lm::nls.lm()</code> .
est	The fitted values for xnew if xnew is not NULL.

For the `alfa.reg2()` function a list with the time required by all regressions and the regression coefficients and the fitted values for each value of α .

For the `alfa.reg3()` function a list with the previous elements plus an output "alfa", the optimal value of α .

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

Mardia K.V., Kent J.T., and Bibby J.M. (1979). Multivariate analysis. Academic press.

Aitchison J. (1986). The statistical analysis of compositional data. Chapman & Hall.

See Also

[cv.alfareg](#), [alfareg.nr](#), [alfa.slx](#)

Examples

```
data(fadn)
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- alfa.reg(y, x, 0.2)
```

Robust regression with compositional data using the alpha-transformation

Regression with compositional data using the α -transformation

Description

Regression with compositional data using the α -transformation.

Usage

```
rob.alfareg(y, x, a, loss = "welsh", xnew = NULL, yb = NULL)
```

Arguments

y	A matrix with the compositional data.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
a	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0. If $\alpha = 0$ the isometric log-ratio transformation is applied and the solution exists in a closed form, since it the classical multivariate regression.
loss	The loss function to use. One of these available options, "barron", "bisquare", "welsh", "optimal", "hampel", "ggw", or "lqq". For more information see the package <i>gshnls</i> .
xnew	If you have new data use it, otherwise leave it NULL.
yb	If you have already transformed the data using the α -transformation with the same α as given in the argument "a", put it here. Otherwise leave it NULL.

Details

The α -transformation is applied to the compositional data first and then robust multivariate regression is applied. This involves numerical optimisation.

Value

A list including:

runtime	The time required by the regression.
be	The beta coefficients.
est	The fitted values for xnew if xnew is not NULL.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

- Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>
- Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>
- Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>
- Mardia K.V., Kent J.T., and Bibby J.M. (1979). Multivariate analysis. Academic press.
- Aitchison J. (1986). The statistical analysis of compositional data. Chapman & Hall.

See Also

[alfa.reg](#), [alfareg.nr](#), [alfa.slx](#)

Examples

```
data(fadn)
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- rob.alfareg(y, x, 0.2)
```

Spatial K-fold cross-validation for the alpha-ESF model

Spatial K-fold cross-validation for the α -ESF model

Description

Spatial K-fold cross-validation for the α -ESF model

Usage

```
cv.alfaesf(y, x, a = seq(0.1, 1, by = 0.1), coords, model = "exp",
  nfold = 10, size = 1000, folds = NULL)
```

Arguments

- | | |
|---|--|
| y | A matrix with compositional data. zero values are allowed. |
| x | A matrix with the continuous predictor variables or a data frame including categorical predictor variables. |
| a | The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0. If $\alpha = 0$ the isometric log-ratio transformation is applied. |

coords	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
model	Type of kernel to model spatial dependence. The currently available options are "exp" for the exponential kernel, "gau" for the Gaussian kernel, and "sph" for the spherical kernel. For more information check the package "spmoran".
nfolds	The number of folds to split the data.
size	A numeric value of the specified range by which blocks are created and training/testing data are separated. This distance should be in metres. If you have big regions you should consider increasing this number. For more information see the package <i>blockCV</i> .
folds	If you have the list with the folds supply it here. You can also leave it NULL and it will create folds.

Details

The 10-fold spatial cross-validation protocol is applied to choose the optimal values of α and k .

Value

A list including:

runtime	The runtime required by the cross-validation.
perf	A vector with the average Kullback-Leibler divergence, for every value of α .
opt	A vector with the minimum Kullback-Leibler divergence, and the optimal value of α .

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, spatially-lagged, spatial autoregressive and geographically-weighted regression models. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. *Chilean Journal of Statistics*, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In *Proceedings of the 4th Compositional Data Analysis Workshop*, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

Tsagris M., Papadovasilakis Z., Lakiotaki K. and Tsamardinos I. (2022). The γ -OMP Algorithm for Feature Selection With Application to Gene Expression Data. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 19(2), 1214–1224.

See Also

[alfa.slx](#), [cv.gwar](#) [cv.alfareg](#)

Examples

```

data(fadn)
coords <- fadn[1:50, 1:2]
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- cv.alphaesf(y, x, a = c(0.1, 0.5), coords, nfolds = 5)

```

Spatial K-fold cross-validation for the alpha-SAR model

Spatial K-fold cross-validation for the α -SAR model

Description

Spatial K-fold cross-validation for the α -SAR model

Usage

```

cv.alfasar(y, x, a = seq(0.1, 1, by = 0.1), coords, k = 2:15,
nfolds = 10, size = 1000, folds = NULL)

```

Arguments

y	A matrix with compositional data. zero values are allowed.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
a	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0. If $\alpha = 0$ the isometric log-ratio transformation is applied.
coords	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
k	A vector with the nearest neighbours to consider for the contiguity matrix.
nfolds	The number of folds to split the data.
size	A numeric value of the specified range by which blocks are created and training/testing data are separated. This distance should be in metres. If you have big regions you should consider increasing this number. For more information see the package <i>blockCV</i> .
folds	If you have the list with the folds supply it here. You can also leave it NULL and it will create folds.

Details

The 10-fold spatial cross-validation protocol is applied to choose the optimal values of α and k.

Value

A list including:

runtime	The runtime required by the cross-validation.
perf	A vector with the average Kullback-Leibler divergence, for every value of α .
opt	A vector with the minimum Kullback-Leibler divergence, the optimal value of α and k.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[alfa.slx](#), [cv.gwar](#) [cv.alfareg](#)

Examples

```
data(fadn)
coords <- fadn[1:50, 1:2]
y <- fadn[1:50, 3:7]
x <- fadn[1:50, 8]
```

Spatial K-fold cross-validation for the alpha-SLX model

Spatial K-fold cross-validation for the α -SLX model

Description

Spatial K-fold cross-validation for the α -SLX model

Usage

```
cv.alfaslx(y, x, a = seq(0.1, 1, by = 0.1), coords, k = 2:15,
nfolds = 10, size = 1000, folds = NULL)
```

Arguments

y	A matrix with compositional data. zero values are allowed.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
a	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0. If $\alpha = 0$ the isometric log-ratio transformation is applied.
coords	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
k	A vector with the nearest neighbours to consider for the contiguity matrix.
nfolds	The number of folds to split the data.
size	A numeric value of the specified range by which blocks are created and training/testing data are separated. This distance should be in metres. If you have big regions you should consider increasing this number. For more information see the package <i>blockCV</i> .
folds	If you have the list with the folds supply it here. You can also leave it NULL and it will create folds.

Details

The 10-fold spatial cross-validation protocol is applied to choose the optimal values of α and k.

Value

A list including:

runtime	The runtime required by the cross-validation.
perf	A vector with the average Kullback-Leibler divergence, for every value of α .
opt	A vector with the minimum Kullback-Leibler divergence, the optimal value of α and k.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

- Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>
- Tsagris M. (2015). Regression analysis with compositional data containing zero values. *Chilean Journal of Statistics*, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>
- Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In *Proceedings of the 4th Compositional Data Analysis Workshop*, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[alfa.slx](#), [cv.gwar](#) [cv.alfareg](#)

Examples

```
data(fadn)
coords <- fadn[1:60, 1:2]
y <- fadn[1:60, 3:7]
x <- fadn[1:60, 8]
mod <- cv.alfaslx(y, x, a = 0.5, coords, k = 2)
```

Spatial k-folds

Spatial k-folds

Description

Spatial k-folds.

Usage

```
spat.folds(coords, n folds = 10, size = 1000)
```

Arguments

<code>coords</code>	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
<code>n folds</code>	The number of spatial folds to create.
<code>size</code>	A numeric value of the specified range by which blocks are created and training/testing data are separated. This distance should be in metres. If you have big regions you should consider increasing this number. For more information see the package <i>blockCV</i> .

Details

Folds of data are created based on their coordinates. For more information see the package **blockCV**.

Value

A list with `n folds` elements. Each elements contains a list with two elements, the first is the indices of the training set and the second contains the indices of the test set.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

See Also

[cv.alfaslx](#), [me.aslx](#), [gwar](#), [alfa.reg](#)

Examples

```
data(fadn)
coords <- fadn[1:100, 1:2]
folds <- spat.folds(coords, nfold = 5)
```

The alpha-ESF model *The α -ESF model*

Description

The α -ESF model.

Usage

```
alfa.esf(y, x, a, coords, model = "exp", xnew = NULL, coordsnew, yb = NULL)
```

Arguments

<code>y</code>	A matrix with the compositional data.
<code>x</code>	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
<code>a</code>	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0. If $\alpha = 0$ the isometric log-ratio transformation is applied and the solution exists in a closed form, since it the classical multivariate regression.
<code>coords</code>	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
<code>model</code>	Type of kernel to model spatial dependence. The currently available options are "exp" for the exponential kernel, "gau" for the Gaussian kernel, and "sph" for the spherical kernel. For more information check the package "spmoran".
<code>xnew</code>	If you have new data use it, otherwise leave it NULL.
<code>coordsnew</code>	A matrix with the coordinates of the new locations. The first column is the latitude and the second is the longitude. If you do not have new data to make predictions leave this NULL.
<code>yb</code>	If you have already transformed the data using the α -transformation with the same α as given in the argument "a", put it here. Otherwise leave it NULL.

Details

The α -transformation is applied to the compositional data first. Then the eigenvectors of the kernelized distance matrix are computed and the appropriate number is selected to be included as predictors. The selection takes place using the γ -OMP algorithm (Tsagris et al., 2022).

Value

A list including:

<code>runtime</code>	The time required by the regression.
<code>be</code>	The beta coefficients.
<code>gama</code>	The gamma coefficients of the eigenvectors.
<code>ESF</code>	A vector with the indices of the eigenvectors used.
<code>X.esf</code>	A matrix with the values of the eigenvectors used.
<code>dev</code>	The sum of the squared residuals, as produced by the function <code>minpack.lm::nls.lm()</code> .
<code>est</code>	The fitted values for <code>xnew</code> if <code>xnew</code> and <code>coordsnew</code> are not <code>NULL</code> .

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. *Chilean Journal of Statistics*, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In *Proceedings of the 4th Compositional Data Analysis Workshop*, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

Tsagris M., Papadovasilakis Z., Lakiotaki K. and Tsamardinos I. (2022). The γ -OMP Algorithm for Feature Selection With Application to Gene Expression Data. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 19(2), 1214–1224.

See Also

[cv.alphaesf](#), [alfa.sar](#), [alfa.slx](#), [alfa.reg](#)

Examples

```
data(fadn)
coords <- fadn[1:50, 1:2]
y <- fadn[1:50, 3:7]
x <- fadn[1:50, 8]
mod <- alfa.esf(y, x, a = 0.1, coords = coords)
```

The alpha-regression using Newton-Raphson
The alpha-regression using Newton-Raphson

Description

The *alpha*-regression using Newton-Raphson.

Usage

```
alfareg.nr(y, x, alpha = 1, beta_init = NULL, max_iter = 100,
tol = 1e-6, line_search = TRUE, hess.eps = 1e-5)
```

Arguments

y	A matrix with the compositional data.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
alpha	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0.
beta_init	A vector of initial parameters (optional). This is then transformed into a matrix.
max_iter	The maximum number of iterations for the Newton-Raphson algorithm.
tol	The tolerance value to terminate the Newton-Raphson algorithm.
line_search	Do you want to perform line search? The default value is TRUE.
hess.eps	This is the infinitesimal change to compute the Hessian matrix numerically.

Details

The α -transformation is applied to the compositional data first and then multivariate regression is applied. This involves numerical optimisation.

Value

A list including:

runtime	The time required by the regression.
iters	The iterations of the Newton-Raphson algorithm
be	The beta coefficients.
objective	The sum of the squared residuals.
est	The predicted values if xnew is not NULL.
covb	The covariance matrix of the beta coefficients, or NULL if it is singular.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

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See Also

[alfa.reg](#), [cv.alfareg](#), [alfa.slx](#)

Examples

```
data(fadn)
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- alfareg.nr(y, x, a = 0.2)
mod2 <- alfa.reg(y, x, 0.2)
```

The alpha-SAR model *The α -SAR model*

Description

The α -SAR model.

Usage

```
alfa.sar(y, x, a, coords, k = 10, covb = FALSE, xnew = NULL, coordsnew, yb = NULL)
```

Arguments

y	A matrix with the compositional data.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
a	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0. If $\alpha = 0$ the isometric log-ratio transformation is applied and the solution exists in a closed form, since it the classical multivariate regression.
coords	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
k	The number of nearest neighbours to consider for the contiguity matrix.
covb	Do you want the covariance matrix of the spatial autoregressive parameter and the regression coefficients to be returned? If TRUE, this will slow down the process, as it is computed numerically.
xnew	If you have new data use it, otherwise leave it NULL.
coordsnew	A matrix with the coordinates of the new locations. The first column is the latitude and the second is the longitude. If you do not have new data to make predictions leave this NULL.
yb	If you have already transformed the data using the α -transformation with the same α as given in the argument "a", put it here. Otherwise leave it NULL.

Details

The α -transformation is applied to the compositional data first and the spatial autocorrelation (SAR) model is applied. The function performs a grid search searching for the range of good values of ρ and then uses that as starting value.

Value

A list including:

runtime	The time required by the regression.
be	The beta coefficients.
covbe	The covariance matrix if covb was set to TRUE, otherwise NULL.
dev	The sum of the squared residuals, as produced by the function <code>minpack.lm::nls.lm()</code> .
est	The fitted values for xnew if xnew and coordsnew are not NULL.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

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See Also

[cv.alfaslx](#), [me.aslx](#), [gwar](#), [alfa.reg](#)

Examples

```
data(fadn)
coords <- fadn[1:50, 1:2]
y <- fadn[1:50, 3:7]
x <- fadn[1:50, 8]
```

The alpha-SLX model *The α -SLX model*

Description

The α -SLX model.

Usage

```
alfa.slx(y, x, a, coords, k = 10, covb = FALSE, xnew = NULL, coordsnew, yb = NULL)
alfa.slx2(y, x, a, coords, k = 2:15, xnew = NULL, coordsnew, yb = NULL)
```

Arguments

y	A matrix with the compositional data.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
a	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0. If $\alpha = 0$ the isometric log-ratio transformation is applied and the solution exists in a closed form, since it the classical multivariate regression.
coords	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
k	The number of nearest neighbours to consider for the contiguity matrix. For the <code>alfa.slx2()</code> this should be a vector.

covb	Do you want the covariance matrix of the regression coefficients to be returned? If TRUE, this will slow down the process, as it is computed numerically.
xnew	If you have new data use it, otherwise leave it NULL.
coordsnew	A matrix with the coordinates of the new locations. The first column is the latitude and the second is the longitude. If you do not have new data to make predictions leave this NULL.
yb	If you have already transformed the data using the α -transformation with the same α as given in the argument "a", put it here. Otherwise leave it NULL. This is intended to be used in the function <code>cv.alfareg</code> in order to speed up the process. The time difference in that function is small for small samples. But, if you have a few thousands and or a few more components, there will be bigger differences.

Details

The α -transformation is applied to the compositional data first and then the spatially lagged X (SLX) model is applied.

Value

For the `alfa.slx()` a list including:

runtime	The time required by the regression.
be	The beta coefficients.
gama	The gamma coefficients.
covbe	The covariance matrix if covb was set to TRUE, otherwise NULL.
dev	The sum of the squared residuals, as produced by the function <code>minpack.lm::nls.lm()</code> .
est	The fitted values for xnew if xnew and coordsnew are not NULL.

For the `alfa.slx2()` a list including:

runtime	The time required by the regression.
be	A list with the beta coefficients for each value of k.
gama	A list with the gamma coefficients.
dev	A vector with the sum of the squared residuals, as produced by the function <code>minpack.lm::nls.lm()</code> . The positions of the vector are the ones defined by the argument k that is a vector.
est	A list with the fitted values for the xnew and coordsnew, for each value of k.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[cv.alfaslx](#), [me.aslx](#), [gwar](#), [alfa.reg](#)

Examples

```
data(fadn)
coords <- fadn[, 1:2]
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- alfa.slx(y, x, a = 0.5, coords, k = 10)
```

The gradient vector of the alpha-regression model at each observation

The gradient vector of the α -regression model at each observation

Description

The gradient vector of the α -regression model at each observation.

Usage

```
ar.grads(y, x, a, be)
```

Arguments

y	A matrix with the compositional data.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
a	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0.
be	The regression coefficients of the α -SAR model.

Details

The gradient vector of the α -regression model is computed at each observation.

Value

A matrix with the gradient vector computed at each observation.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

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See Also

[alfa.sar](#), [cv.alfasar](#), [alfa.reg](#)

Examples

```
data(fadn)
coords <- fadn[, 1:2]
y <- fadn[, 3:7]
x <- fadn[, 8:10]
mod <- alfa.reg(y, x, 0.5)
grads <- ar.grads(y, x, a = 0.5, mod$be)
colSums(grads)
```

The gradient vector of the alpha-SAR model at each observation

The gradient vector of the α -SAR model at each observation

Description

The gradient vector of the α -SAR model at each observation.

Usage

```
asar.grads(y, x, a, rho, be, coords, k)
```

Arguments

y	A matrix with the compositional data.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
a	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0.
rho	The spatial autocorrelation parameter ρ .
be	The regression coefficients of the α -SAR model.
coords	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
k	The number of nearest neighbours to consider for the contiguity matrix.

Details

The gradient vector of the α -SAR model is computed at each observation.

Value

A matrix with the gradient vector computed at each observation.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[alfa.sar](#), [cv.alfasar](#), [alfa.reg](#)

Examples

```
data(fadn)
coords <- fadn[, 1:2]
y <- fadn[, 3:7]
x <- fadn[, 8:10]
```

```
be <- matrix( c( 12.72191991, 0.04300266, -1.78301001, -3.02074120, -23.54785921,
0.06771573, 2.71969599, 1.89312564, 5.38640736, 0.05179626, -1.21336879, 0.40175088,
-1.98258721, 0.06815682, -0.64458883, 0.95470802 ), ncol = 4 )
```

The gradient vector of the alpha-SLX model at each observation

The gradient vector of the α -SLX model at each observation

Description

The gradient vector of the α -SLX model at each observation.

Usage

```
aslx.grads(y, x, a, be, gama, coords, k = 10)
```

Arguments

y	A matrix with the compositional data.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
a	The value of the power transformation, it has to be between -1 and 1. If zero values are present it has to be greater than 0.
be	The regression coefficients of the α -SLX model.
gama	The gamma coefficients of the α -SLX model.
coords	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
k	The number of nearest neighbours to consider for the contiguity matrix.

Details

The gradient vector of the α -SLX model is computed at each observation.

Value

A matrix with the gradient vector computed at each observation.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

Tsagris M. (2015). Regression analysis with compositional data containing zero values. Chilean Journal of Statistics, 6(2): 47-57. <https://arxiv.org/pdf/1508.01913v1.pdf>

Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[alfa.sar](#), [cv.alfasar](#), [alfa.reg](#)

Examples

```
data(fadn)
coords <- fadn[, 1:2]
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- alfa.slx(y, x, a = 0.5, coords, k = 10)
grads <- aslx.grads(y, x, a = 0.5, mod$be, mod$gama, coords, k = 10)
colSums(grads)
```

The GWaR model

The GW α R model

Description

The GW α R model.

Usage

```
gwar(y, x, a, coords, h, yb = NULL, nc = 1)
```

Arguments

y	A matrix with the compositional data.
x	A matrix with the continuous predictor variables or a data frame including categorical predictor variables.
a	The value of the power transformation, it has to be between -1 and 1.
coords	A matrix with the coordinates of the locations. The first column is the latitude and the second is the longitude.
h	The bandwidth value.
yb	If you have already transformed the data using the α -transformation with the same α as given in the argument "a", put it here. Otherwise leave it NULL.

`nc` The number of cores to use. IF you have a multicore computer it is advisable to use more than 1. It makes the procedure faster. It is advisable to use it if you have many observations and or many variables, otherwise it will slow down th process.

Details

The α -transformation is applied to the compositional data first and then the GW α R model is applied.

Value

A list including:

`runtime` The time required by the regression.
`be` The beta coefficients.
`est` The fitted values.

Author(s)

Michail Tsagris.

R implementation and documentation: Michail Tsagris <mtsagris@uoc.gr>.

References

Tsagris M. and Pantazis Y. (2026). The α -regression for compositional data: a unified framework for standard, temporal and spatial regression models including compositional predictors. <https://arxiv.org/pdf/2510.12663>

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Tsagris M.T., Preston S. and Wood A.T.A. (2011). A data-based power transformation for compositional data. In Proceedings of the 4th Compositional Data Analysis Workshop, Girona, Spain. <https://arxiv.org/pdf/1106.1451.pdf>

See Also

[cv.gwar](#), [me.gwar](#), [alfa.slx](#), [alfa.reg](#)

Examples

```
data(fadn)
coords <- fadn[, 1:2]
y <- fadn[, 3:7]
x <- fadn[, 8]
mod <- gwar(y, x, a = 1, coords, h = 0.001)
```

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