

**INTER-AMERICAN TROPICAL TUNA COMMISSION
SCIENTIFIC ADVISORY COMMITTEE**

FIFTH MEETING

La Jolla, California (USA)

12-16 May 2014

DOCUMENT SAC-05-08b

**UPDATED JAPANESE LONGLINE STANDARDIZED TRENDS FOR
BIGEYE TUNA IN THE EASTERN PACIFIC OCEAN FROM
OPERATIONAL-LEVEL DATA**

Cleridy E. Lennert-Cody, Hiroataka Ijima, Hiroaki Okamoto, Alexandre Aires-da-Silva and
Mark N. Maunder

SUMMARY

This document presents bigeye tuna standardized trends for the Japanese longline fishery from 1979-2012 in the four eastern Pacific Ocean stock assessment areas, based on the analysis of operational-level data. Results suggest that when differences in fishing efficiency among vessels are taken into consideration, the long-term trend in the index can be slightly more pessimistic, depending on the area. However, the operational-level standardized trends are generally similar to the indices currently used in the bigeye tuna stock assessment model, which are based on aggregated data. Development of more complex standardization models that could account for spatial variability in the number of hooks between floats was initiated but not completed due to computational challenges associated with analysis of large data sets.

1. BACKGROUND

Trends in longline catch-per-unit-effort (CPUE) are a very important driver in the bigeye and yellowfin tuna assessment of the eastern Pacific Ocean (EPO) (Aires-da-Silva and Maunder 2012, and references therein). In recent years concerns about possible trends in catchability due to improved vessel performance have been raised. Recent analyses of Japanese operational-level longline data from the eastern and western Pacific Ocean (Hoyle *et al.* 2010; Hoyle and Okamoto 2011; Lennert-Cody *et al.* 2013) have identified differences in fishing efficiency among vessels previously not accounted for in the generalized linear models (GLMs) used for estimation of indices of relative abundance. Given this, the previous analysis of EPO data (Lennert-Cody *et al.* 2013), which presented a standardized trend through 2011 for the Central area (Area 2) only, was updated through 2012, and standardized trends were also computed in the other three stock assessment areas (Figure 1). These and previous analyses were patterned after studies of data from the western Pacific Ocean (Hoyle *et al.* 2010; Hoyle and Okamoto 2011) to allow for comparability.

2. ANALYSIS OF TRENDS IN BIGEYE TUNA CPUE, WITH AND WITHOUT CALL SIGN EFFECT

By-set Japanese longline data for 1979-2012 were used in these analyses. The current time period for the EPO bigeye stock assessment (Aires-da-Silva and Maunder, 2012) is 1975-2012, however, vessel identifiers are not available prior to 1979. The methods of data processing are described in detail in Lennert-Cody *et al.* (2013). The operational-level data available for analysis included: vessel identifier (vessel call sign), date and location of fishing, number of hooks between floats (HBF), numbers of hooks in the set, and catch amounts by species. Analyses of the effect of differences in fishing efficiency among vessels on the estimates of bigeye relative abundance indices were conducted separately for each of the

four IATTC stock assessment areas (Figure 1). Given the shape of the overall frequency distribution of bigeye catches (Lennert-Cody *et al.* 2013), negative binomial (“NB”) models for bigeye counts were used in this analysis.

The following NB GLMs were fitted to the data by stock assessment area:

1. $\log(\mu) = \text{constant} + \beta \cdot \log(\text{number of hooks}) + \text{year-quarter effect} + 5^\circ \text{ area effect} + f(\text{HBF})$
2. $\log(\mu) = \text{constant} + \beta \cdot \log(\text{number of hooks}) + \text{year-quarter effect} + 5^\circ \text{ area effect} + f(\text{HBF}) + \text{call sign effect}$

where μ is the mean bigeye catch (number of fish), β the slope corresponding to the linear term $\log(\text{number of hooks})$, and f represents a natural spline smooth of degree 6. The form of the models above was selected to be consistent with analyses for the western Pacific Ocean (Hoyle *et al.* 2010). To provide more information on the relationship between hooks and catch, $\log(\text{number of hooks})$ was included in the model as a linear term, not as an “offset,” thereby obtaining an estimate of the slope coefficient (rather than assuming a value of 1.0). In Areas 1 and 3, the model run time for the NB GLM was extremely slow when estimating the scale parameter (θ) for the model with a call sign effect. Therefore, as was done previously (Lennert-Cody *et al.* 2013), the model was fitted with the estimated value of θ from the model without a call sign effect. All models were fitted using the *glm* and *glm.nb* functions of the MASS library (Venables and Ripley 2002) in R (R Development Core Team 2012).

Standardized trends for bigeye from the NB GLM models, with and without a call sign effect, were computed for Areas 1-4 for 1979-2012 (Figure 2). The standardized trends from the model with a call sign effect suggests a slightly more pessimistic trend in Areas 2 and 4, as compared to that from the model without a call sign effect. In Area 3, currently the main area of the fishery, the two trends were nearly identical. Both trends in Area 1 are highly variable. These standardized trends are generally similar to the indices currently used in the stock assessment model (Figure 3), with exception that in recent years the operational-level relative indices are slightly more optimistic in Areas 2-3. These differences may be due to differences in the model formulation and in the method of standardization. In contrast to the NB GLM models above, the current assessment indices are based on a delta-lognormal model of CPUE in which the explanatory variables are quarter, latitude, longitude, and hooks per basket (Hoyle and Maunder 2006).

3. DISCUSSION

As part of the work to update the operational-level trends, an effort was made to improve the models by addressing some of the aspects of spatial misfit noted previously (Lennert-Cody *et al.* 2013). As a first step, models that accounted for spatial variability in the HBF were explored using NB and lognormal generalized additive models (GAMs; Wood 2006). The base model replaced the 5° area effect of equations (1)-(2) with a 2-dimensional smooth surface in latitude and longitude (both at 1° resolution) using thin plate regression splines. Spatial structure in HBF was modelled by replacing the 2-D smooth spatial surface and the smooth term for HBF of equations (1)-(2) with a 3-dimensional smooth surface on latitude, longitude and HBF using tensor product smoothers. The GAMs were fitted in R using the *mgcv* library (Wood 2006). However, fitting such models proved to be problematic because of computational problems due to the large amount of data available, and because of model instability for the NB models. In Area 2, where the lognormal assumption is most tenable, there was little difference between standardized trends from models fitted with and without the complex spatial structure in number of HBF (Figure 4), as compared to differences in the trend due to addition of a vessel effect. A comparison of the NB GLM and lognormal GAM trends, both with vessel effects, is shown in Figure 4; normalized NB GLM and lognormal GAM indices were more similar and are not shown.

In the future, further analyses of model misfit could be conducted, for example, incorporating environmental covariates and exploring other stochastic component options, but first computational difficulties associated with large data sets and model instability will need to be addressed. An analysis of

targeting might be useful to develop guidelines for selecting a subset of the vessels represented in the current trends analysis, which could help to reduce the size of the data set. Other studies (*e.g.*, Hoyle *et al.* 2011) have randomly subsetted the full data set to reduce the amount of data used for trend estimation. Neither of these approaches has yet been explored with the longline data for the EPO.

ACKNOWLEDGMENTS

Special thanks to the NRIFS for granting access to the operational-level data.

REFERENCES

- Aires-da-Silva, A. and Maunder, M.N. 2012. Status of bigeye tuna in the eastern Pacific Ocean in 2011 and outlook for the future. In: IATTC Stock Assessment Report 13. <http://www.iattc.org/PDFFiles2/StockAssessmentReports/SAR-13-BETENG.pdf>
- Hoyle, S.D. and M.N. Maunder. 2006 Standardization of yellowfin and bigeye CPUE data from Japanese longliners, 1975-2004. IATTC Working Group on Stock Assessments, 7th Meeting, SAR-7-07. (<http://www.iattc.org/PDFFiles2/SAR-7-07-LL-CPUE-standardization.pdf>)
- Hoyle, S. D., Shono, H., Okamoto, H. and Langley, A.D. 2010. Analysis of Japanese longline operational catch and effort for bigeye tuna in the WCPO. Document WCPFC-SC6-2010/SA-WP-02.
- Hoyle, S.D. and Okamoto, H. 2011. Analyses of Japanese longline operational catch and effort for bigeye and yellowfin tuna in the WCPO. Document WCPFC-SC7-2011/SA IP-01.
- Lennert-Cody, C.E., Okamoto, H., Maunder, M.N. 2013. Analyses of Japanese longline operational-level catch and effort data for bigeye tuna in the eastern Pacific Ocean. Document SAC-04-05B, Scientific Advisory Committee Meeting, 29 April -3 May, 2013. <http://www.iattc.org/Meetings/Meetings2013/MaySAC/Pdfs/SAC-04-05b-Analyses-of-JPN-LL-BET-CPUE.pdf>
- Maunder, M.N., Hinton, M.G., Bigelow, K.A. and Langley, A.D. 2006. Developing indices of abundance using habitat data in a statistical framework. *Bulletin of Marine Science* 79:545-559.
- R Development Core Team 2012. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL <http://www.R-project.org/>
- Venables, W. N. and Ripley, B. D. 2002. *Modern Applied Statistics with S*. Fourth Edition. Springer, New York. ISBN 0-387-95457-0
- Wood, S.N. 2006. *Generalized Additive Models: An Introduction with R*. Chapman and Hall/CRC.

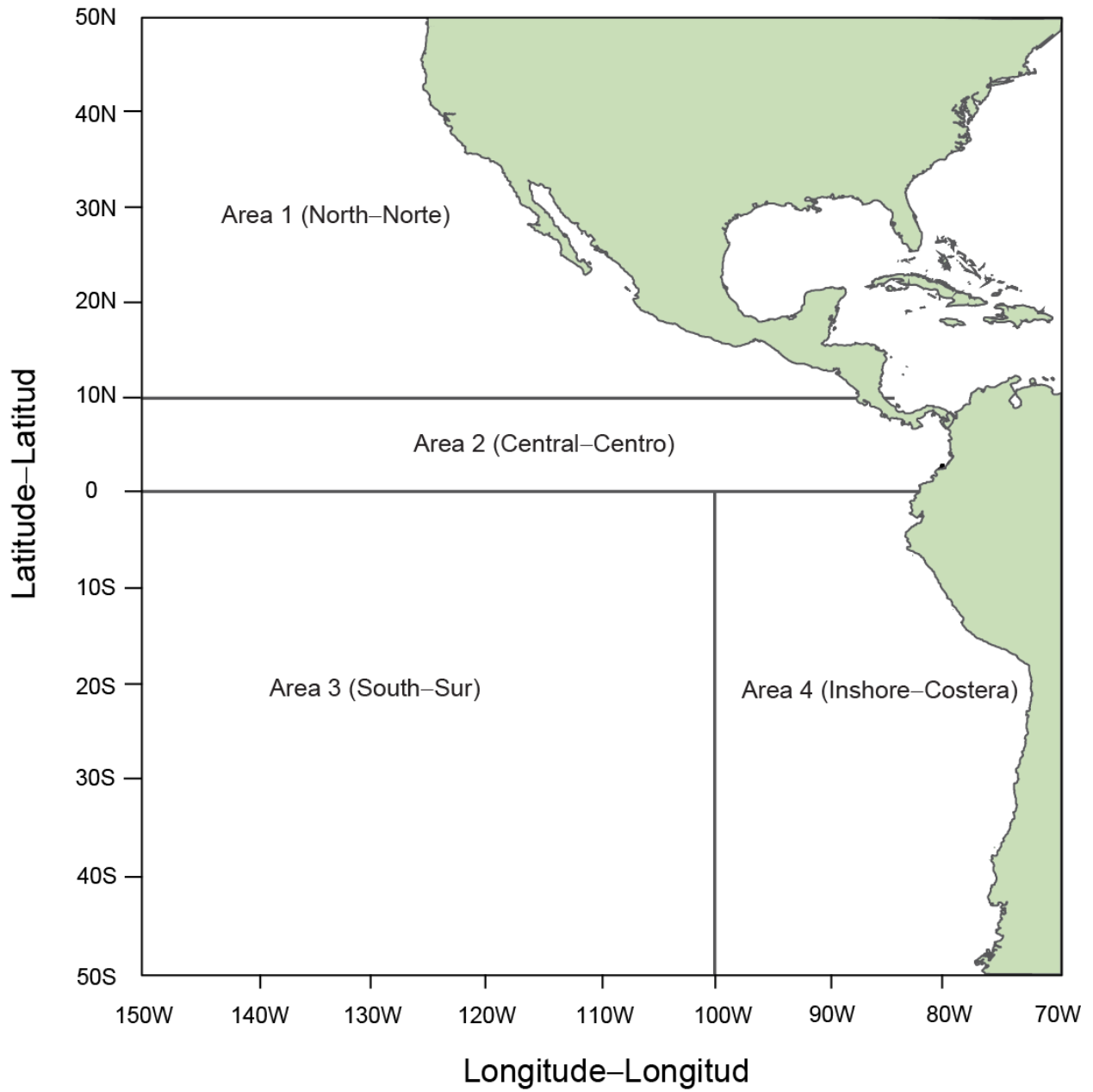


FIGURE 1. Map of the most recent IATTC stock assessment areas for bigeye tuna.

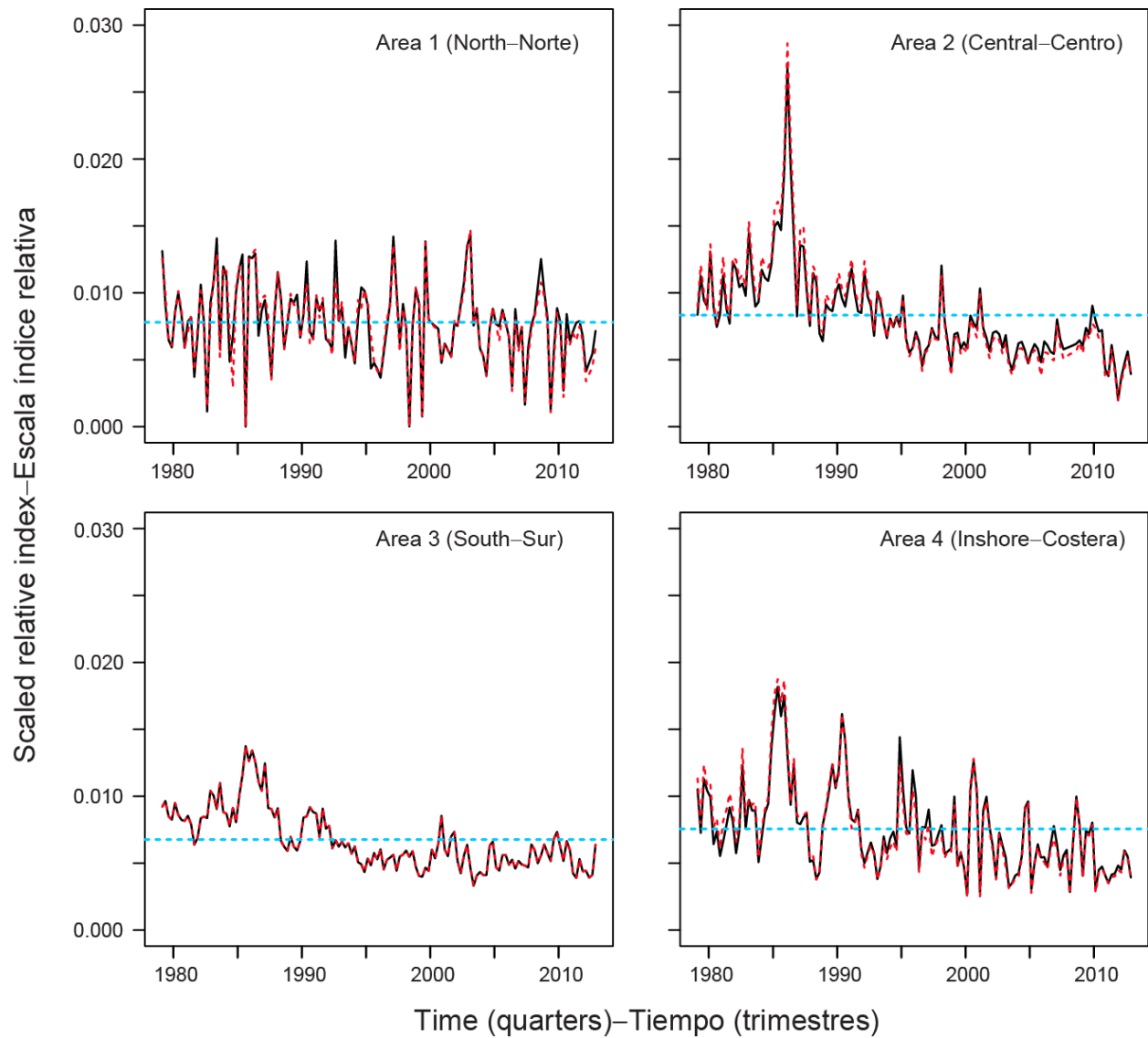


FIGURE 2. Standardized trends based on models with (red dashed lines) and without (black solid lines) vessel effects, by stock assessment area. Turquoise dashed line shows the average index value.

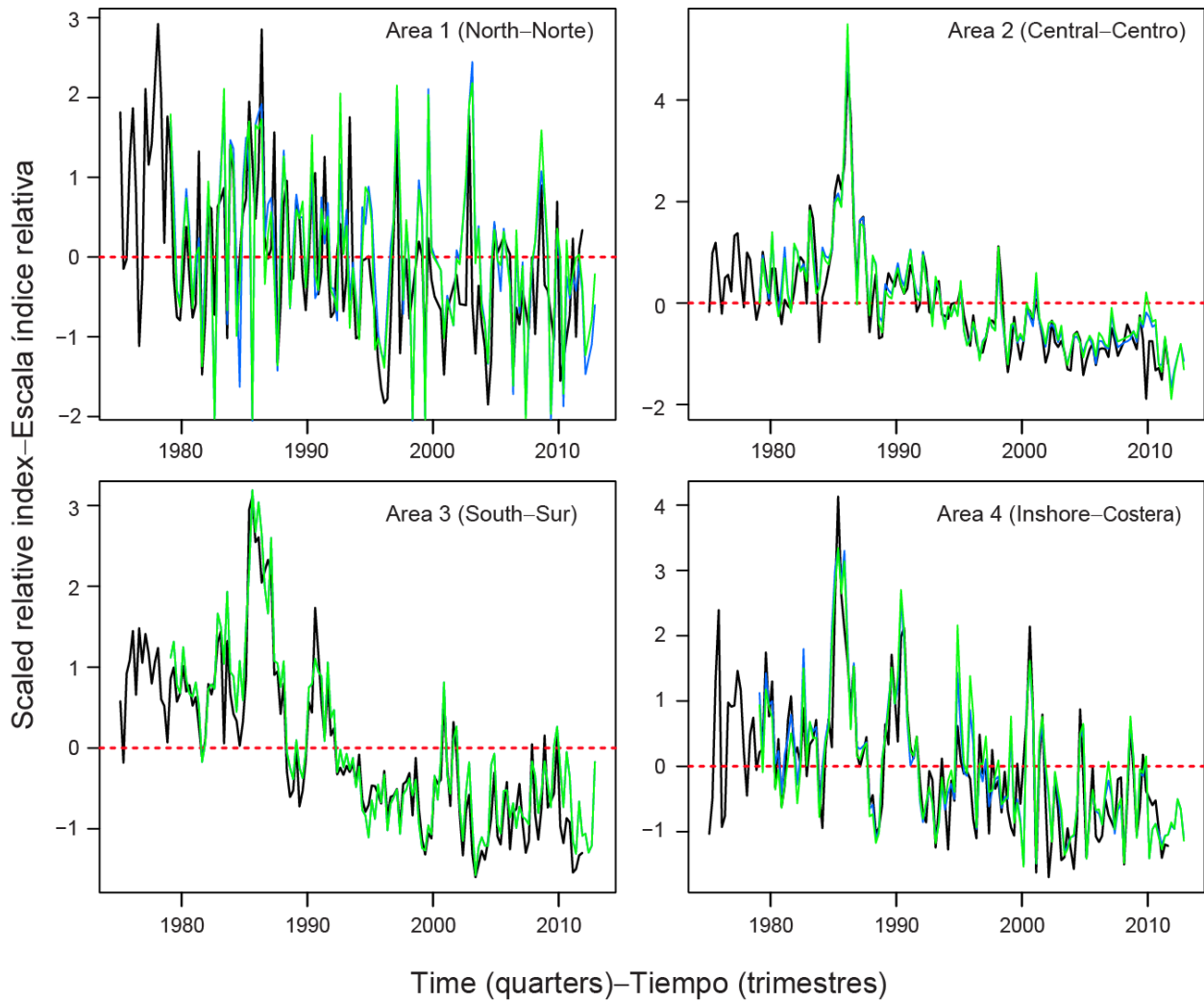


FIGURE 3. Normalized trends with (blue lines) and without (green lines) vessel effects (Figure 2) and the SAC4 stock assessment indices (black lines). Each index was normalized by subtracting the mean index value and dividing by the standard deviation of index values.

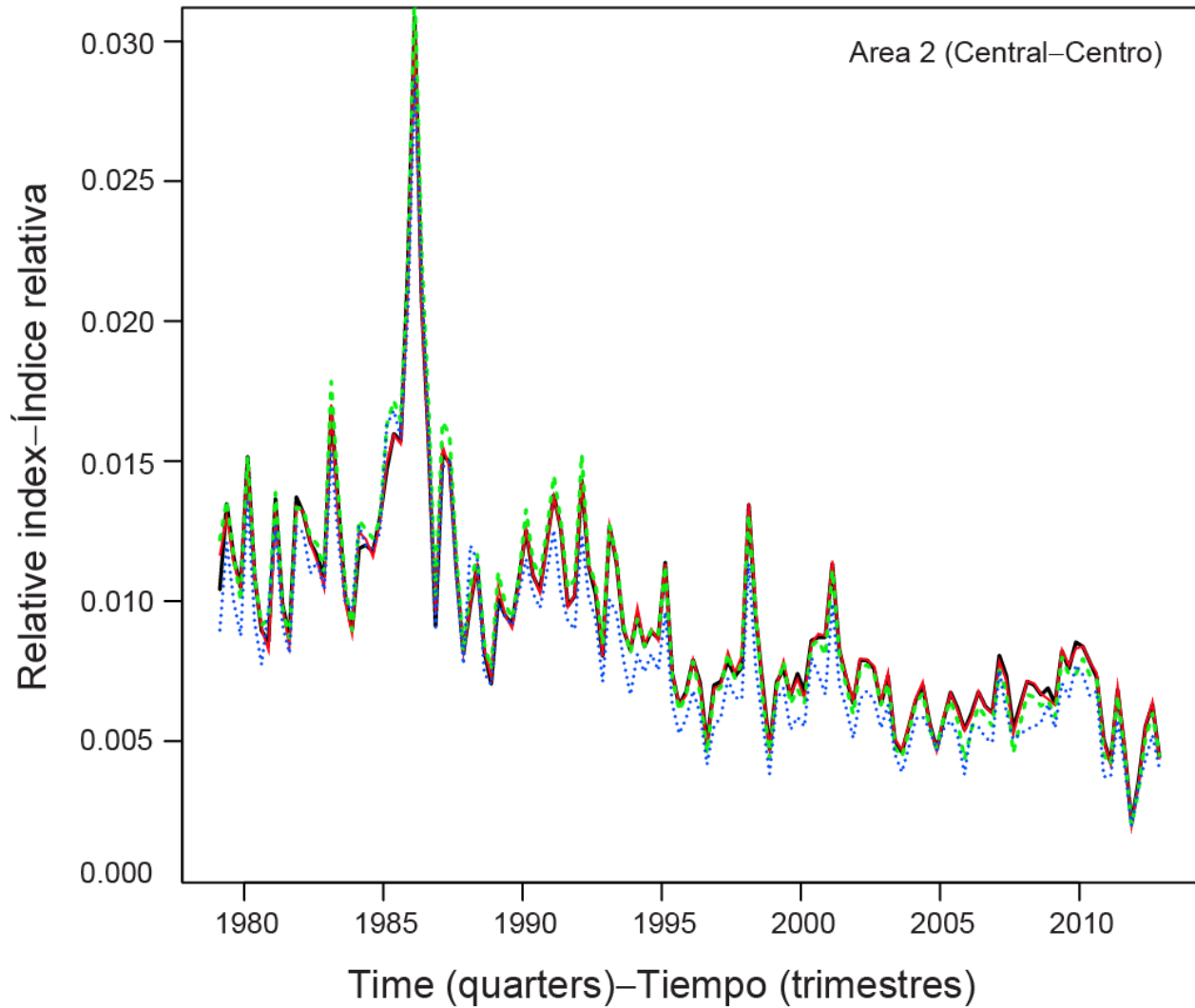


FIGURE 4. Standardized trends based on lognormal GAMs and NB GLM fitted to the data of Area 2 (Figure 1). Black solid line: no vessel effect or HBF-spatial interaction (GAM); red dashed line: HBF-spatial interaction but no vessel effect (GAM); green dashed line: HBF-spatial interaction and vessel effect (GAM); blue dotted line: NB GLM index with vessel effects (from Figure 2).