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Caso práctico

Simple models to estimate soybean and corn percent ground cover with vegetation indices from modis

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Abstract

Remote sensing images are a good source of crop and soil information, which can be used to derive agronomic information for field management and yield prediction. Soybean (*Glycine max* (L.) Merrill) and corn (*Zea mays* L.) are the most important crops in Argentina taking into account the economic yield obtained by farmers and the sown area. In this work, simple mathematical models (linear, second order polynomial and exponential), with different vegetation indices (VI) derived of Moderate-resolution Imaging Spectroradiometer (MODIS) images as inputs, were evaluated. The models were applied to estimate soybean and corn percent ground cover (fCover) over the growing season. The VI employed were the normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), a modified SAVI (MSAVI), simple ratio (SR) and perpendicular vegetation index (PVI). The performances of the models (linear, polynomial and exponential) were very good and their results were equivalent. Although all models could successfully estimate fCover, results showed that, excepted with SR input, a linear model can predict ground coverage with R^2 values greater than 0.86, when both crops are considered. When models are applied to soybean and corn separately, linear model with SAVI index has the best performance.

Key words: mathematical models, crops, remote sensing, vegetation index, MODIS.

Resumen

Las imágenes provenientes de sensores remotos constituyen una importante fuente de información sobre cultivos y suelos, la cual puede utilizarse para obtener parámetros agronómicos para el manejo del suelo y predicción de rendimientos. Los cultivos de soja (Glycine max (L.) Merrill) y maíz (Zea mays L.) son los más importantes en Argentina, teniendo en cuenta el área sembrada y los réditos económicos obtenidos por los productores. En este trabajo se evaluaron modelos matemáticos simples (lineales, polinomiales de segundo grado y exponenciales), a partir de diferentes índices de vegetación (VI) derivados del sensor Moderate-resolution Imaging Spectroradiometer (MODIS) tomados como datos de entrada. Los modelos se aplicaron para evaluar el porcentaje de cobertura (fCover) de soja y maíz durante toda la etapa de desarrollo de los cultivos. Los VI empleados fueron el índice de vegetación de diferencia normalizada (NDVI), el índice de vegetación ajustado por el suelo (SAVI), una modificación de éste (MSAVI), el cociente simple (SR) y el índice de vegetación perpendicular (PVI). El comportamiento de los modelos (lineales, polinomiales y exponenciales) fue muy bueno y sus resultados fueron equivalentes. Si bien todos los modelos estimaron adecuadamente fCover, los resultados mostraron que, excepto con SR, un modelo lineal puede predecir porcentaje de cobertura con valores de R^2 mayores que 0,86 cuando ambos cultivos son considerados. Cuando los modelos fueron aplicados en forma separada a soja y maíz, el modelo lineal con SAVI tuvo el mejor comportamiento.

Palabras clave: modelos matemáticos, cultivos, teledetección, índice de vegetación, MODIS.

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Introduction

Monitoring crop condition at different stages of crop growth is as important as knowing the exact production after harvest time. Identify crop condition as early as possible has great influence on the crop management, price, circulation and storage. Crop growth estimates based on field reports are often expensive and cannot provide real-time, spatially explicit estimates or forecasting of crop condition (Lobell *et al.*, 2003).

In particular, remote sensing applications for monitoring crop condition at regional scale have been studied extensively during the past several decades (Bocco *et al.*, 2007). Rajan and Maas (2009) showed that remote sensing images are effective in displaying the spatial variation in crop within agricultural fields. Satellite data provide a spatially and periodic, comprehensive view of actual crops state (Numata *et al.*, 2007; Bocco *et al.*, 2012).

With the launch and continuous availability of multi-spectral sensors (visible, near-infrared) onboard of satellites for earth observation, remote sensing data has become an important tool for surveying. The spatial resolution (250 m) and temporal (daily) coverage of Moderate-resolution Imaging Spectroradiometer (MODIS) data offers potential for retrieval of crop biophysical parameters and improved accuracy in crop yield assessment (Doraiswamy *et al.*, 2004).

Daily images in a continuous time series do not always precisely describe the condition of vegetation during the growing season, since contamination by clouds decreases the vegetation index quality. Consequently, the solution is to retain a high temporal resolution uncovering and removing cloudy pixels from daily images, thus creating composite images of 10 to 15 days only with data taken during the smallest cloud contamination days (Báez-González *et al.*, 2002).

Vegetation indices (VI) show the abundance and vigorousness of green plants and are among the oldest tools in remote sensing studies (Glenn *et al.*, 2008). Crop biophysical parameters are usually inferred from satellite image data through the calculation of VI, which are derived from several wavelength bands by using linear and nonlinear algorithms. These relationships between VI and crop parameters, as leaf area index (LAI), ground cover, chlorophyll content, above-ground green biomass and absorbed photosynthetically active radiation, are empirical (Liu *et al.*, 2006).

One of the earliest VI developed to identify the vegetation state in an image is the simple ratio vegetation index, created by dividing near infrared (NIR) by red (Red) reflectances. The basis of this relationship is the strong absorption (low reflectance) of red light by chlorophyll and low absorption (high reflectance and transmittance) in the NIR by green leaves. Dense green vegetation produces a high ratio while soil has a low value, thus yielding a contrast between the two surfaces (Shanahan *et al.*, 2001).

Gitelson *et al.* (2002) showed, for wheat (*Triticum aestivum* L.), that when percent cover increased from 0 to 50%, the reflectance in the red range decreased steeply, while the NIR increased. When ground cover exceeded 50%, the rate of change in both reflectances decreased, becoming invariant for cover values between 60% and 100%. These reports for wheat canopy are consistent with Kanemasu (1974) who reported a decrease of the NIR reflectances for soybean (*Glycine max* (L.) Merrill), wheat and sorghum (*Sorghum sp.*) in the midseason.

Actually, VI developed can be assigned into two broad categories; the ratio indices and orthogonal indices (Huete *et al.*, 1985). The near infrared to red ratio (SR), normalized difference vegetation index (NDVI), and the transformed difference vegetation index (TDVI) are the most common of the ratio transformations used for estimate vegetation status. The orthogonal transformation two-dimensional perpendicular vegetation index (PVI) was presented for Richardson and Wiegand (1977).

Mauget and Upchurch (2000), evaluated vegetation indices based on their ability to respond linearly to ground cover and LAI of cotton. Percent ground cover measurements were obtained from high resolution photographs through a maximum likelihood classifier algorithm that identified regions of shaded and un-shaded vegetation and bare soil. Cyr *et al.* (1995) studied the relation between

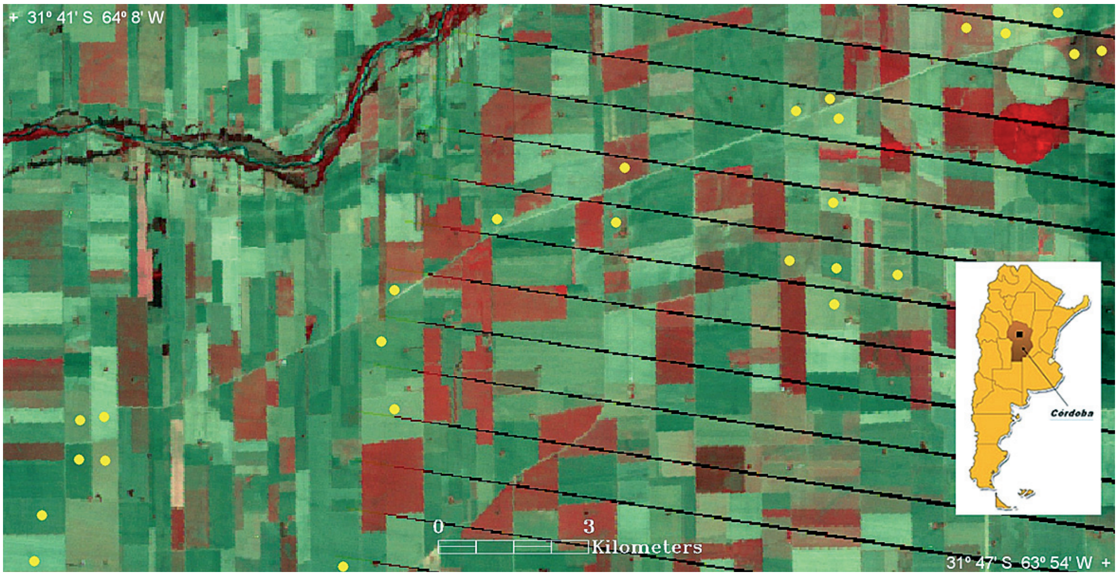

Figure 1: Study area in Córdoba, Argentina (LANDSAT Image). Dot marks indicate the studied plots. Figure adapted from Bocco *et al*. (2012)

ground cover and different vegetation indices for soybean, corn (*Zea mays* L.), barley (*Hordeum vulgare*) and pastures, by photographic and radiometric measurements throughout the growing season.

Soybean is the most important crop in Argentina taking into account the economic yield obtained by farmers and the approximate sown area (18,886,600 ha in 2010-2011), followed by corn, with 4,559,800 ha. In particular, the province of Córdoba is the second producer of soybean and corn in Argentina with approximately 5,054,400 ha and 1,143,000 ha in 2010-2011, respectively (MAGyP, 2012).

The objective of this work was to prove that simple mathematical models, from different vegetation indices derived of MODIS images as inputs, allow estimating soybean and corn percent ground cover over the growing season. The application was carried out in Córdoba (Argentina).

Material and methods

Study site

The study area is located in the central plains of Córdoba province, Argentina (Figure 1), in the sub-region known as "Pampa Alta" (32° S; 64° W) which presents a slightly undulating relief of hills developed on loessic material, with silt loam texture with a slight slope to the east; soils in this area are classified as entic and typic Haplustol. The average annual rainfall is approximately 800 mm, concentrated in summer (INTA, 2006). The climate in the study area is classified as dry sub-humid (Mather, 1965).

In the agricultural area predominate two summer crops (soybean and corn) due to the annually rainfall distribution, which are concentrated around October-March, and, in smaller degree, winter cereals (principally wheat).

Ground data

Field data (179) were acquired continuously throughout the growing season in 33 cultivated plots, 7 of which were sown with corn and the remaining 26 with soybean. The number of each crop plots was selected taking account that, for this study area, the relation between cultivated area of corn and soybean was 26%. All plots should have an area larger than 50 ha to adjust to the resolution of the MODIS sensor.

In this region, agricultural production is mainly rainfed. Soybean is sown by direct seeding with maturity groups 3 and 4 of transgenic varieties resistant to glyphosate, with spacing between rows of 35 cm, without fertilizer application (Piatti and Ferreyra, 2009); on the other hand, corn, is sown late October to early November. This crop is also sown by direct seeding with a distance between rows of 53 cm with an average plant density of 76,000 per hectare (Piatti and Ferreyra, 2008).

In this study area, soybean and corn show a uniform distribution so, only three vertical digital photographs from 1.5 m high in each plot were used to estimate percentage of ground coverage (fCover). These digital photographs were classified into two classes: green vegetation and soil, using the maximum likelihood methodology.

Satellite data

Eleven images from AQUA satellite were used for the period, which corresponded to the time of field data acquisition; these came from the MODIS-MYD13Q1/Aqua 16-Day integrated L3 Global 250 m SIN Grid, Tile h12v12 and were obtained by the Land Processes Distributed Active Archive Center (LPDAAC)-US Geological Survey (USGS) for Earth Resources Observation and Science (EROS) Data Center.

In order to evaluate the information content in reflectance spectra and devise a technique for remote estimation of vegetation fraction, we used MODIS red reflectance (Red, 620-670 nm) and near infrared reflectance (NIR, 841-876 nm), for the central pixels in each one of the 33 plots as input.

Models

Three simple mathematical models were evaluated: linear, second order polynomial and exponential, which general formulas are as follows:

I. linear:
$\text{fCover}(VI) = a + bVI$
II. second order polynomial:
$\text{fCover}(VI) = a + bVI + cVI^2$
III. exponential:
$\text{fCover}(VI) = a + b\exp(cVI)$

where a, b and c are the coefficients of each model and the input variables used are the vegetation indices: NDVI, SR, SAVI, MSAVI and PVI.

From the combination of the three main simple model types with the five selected VI's, fifteen models are determined.

Vegetation indices

The NDVI is an indicator of vegetation cover density and plant growth condition; it has been widely employed to measure canopy attributes (D'Urso *et al.*, 2010):

$$NDVI = \frac{NIR - \text{Red}}{NIR + \text{Red}}$$

Several studies have found that NDVI saturates if the crop density or LAI is high (Srinivas *et al.*, 2004). Also, this index can be unstable, varying with soil, sun-view geometry, atmospheric conditions, and the presence of dead material, as well as with changes within the canopy itself. For this, many researchers tried correcting the index for soil and atmospheric sources of variance (Huete and Liu, 1994).

Other vegetation indices were developed to reduce or eliminate soil influence on solar reflectance values, such as Simple Ratio (SR) and Soil Adjusted Vegetation Index (SAVI), this last includes a constant to minimize the effect of soil background reflectance variation in the index (Zhang *et al.*, 2009):

$$SR = \frac{NIR}{\text{Red}}$$

$$SAVI = \frac{NIR - \text{Red}}{NIR + \text{Red} + \text{L}}(1 + L)$$

where L is a constant empirically determined (typically around 0.5, for intermediate vegetation cover ranges).

In particular, a modified SAVI, the MSAVI index, which uses an iterative, continuous function to optimize soil-adjustment and increases the dynamic range of the SAVI was introduced by Qi *et al.* (1994). This index is less sensitive to these external influences (Rondeaux *et al.*, 1996):

$$MSAVI = \frac{2\,NIR + 1 - \sqrt{(2\,NIR + 1)^2 - 8(NIR - \text{Red})}}{2}$$

Table 1: Coefficients for all models that estimate percent ground cover with different vegetation indices (VI) and their statistical R^2 values. (*) indicates that the coeffcient is not statistically significant ($p < 0.05$)

Model	VI	Coefficients *a*	*b*	*c*	R^2
Linear	NDVI	–33.348	131.439		0.88
Second order polynomial	NDVI	–12.692	36.921*	87.477	0.88
Exponential	NDVI	–70.6959	53.1947	1.2379	0.88
Linear	SR	5.908	5.225		0.68
Second order polynomial	SR	–15.674	13.854	–0.412	0.85
Exponential	SR	91.4525	–132.07	–0.2361	0.89
Linear	SAVI	–25.273	169.223		0.89
Second order polynomial	SAVI	–33.132	219.350	–61.516	0.89
Exponential	SAVI	297.632	–330.715	–0.669*	0.89
Linear	MSAVI	–16.731	146.620		0.88
Second order polynomial	MSAVI	–31.482	242.534	–110.83	0.89
Exponential	MSAVI	–1350.78*	1335.21*	0.10*	0.87
Linear	PVI	5.003	343.227		0.87
Second order polynomial	PVI	1.102*	520.264	–710.54	0.89
Exponential	PVI	138.365	–164.470	–3.909	0.90

To take into account the soil effect, Maas and Rajan (2008) used a 2D-scatterplot, produced by plotting the corresponding pixel values in the NIR and red spectral bands, to determinate a set of points along a straight line, called bare soil line, representing image pixels containing bare soil. The orthogonal distance from any point in the distribution to the bare soil line represents the perpendicular vegetation index (PVI):

$$PVI = \frac{NIR - a_1 \,\mathrm{Red} - a_0}{\sqrt{1 + a_1^2}}$$

where a_0 and a_1 are the intercept and slope, respectively, of the bare soil line.

The coefficient of determination (R^2) and the root mean squared error (RMSE) between observed and estimated values of percentage of ground coverage were used for the models evaluation and validation.

Results and discussion

For all plots and samples, fCover ranged between 0-98%. In Table 1, the coefficients of determination (R^2) values for linear, second order polynomial and exponential models, are shown. It can be observed that, in general, all models have a good performance for all VI used.

Analyzing the results presented in Table 1 we can state that, due to their simplicity and the significance level of its coefficients, linear models are more appropriate for NDVI, SAVI, MSAVI and PVI. For SR index, although the R^2 value equal to 0.68 is good, the exponential model is better ($R^2 = 0.89$).

Glenn *et al.* (2008), using NDVI data obtained with a Dycam digital camera that records Red, Blue and NIR reflectances, found a linear regression with vegetation fraction for tree species ($R^2 = 0.82$). Liu *et al.* (2008) correlated various vegetation indices (including NDVI, SAVI, and MSAVI calculated with hyperspectral Compact Airborne Spectrographic Imager (CASI) data) with measured crop fractions of corn, soybean, and wheat. They found that all these indices were highly correlated ($R^2 = 0.90$) with the field data. The coefficients of determination obtained in our study are similar to those reported by Glenn *et al.* (2008) and Liu *et al.* (2008) although the latter were obtained from higher spatial resolution sensors.

Radari *et al.* (2010) compared different VI using Landsat Multispectral Scanner (MSS), Landsat Thematic Mapper (TM) and Enhan-

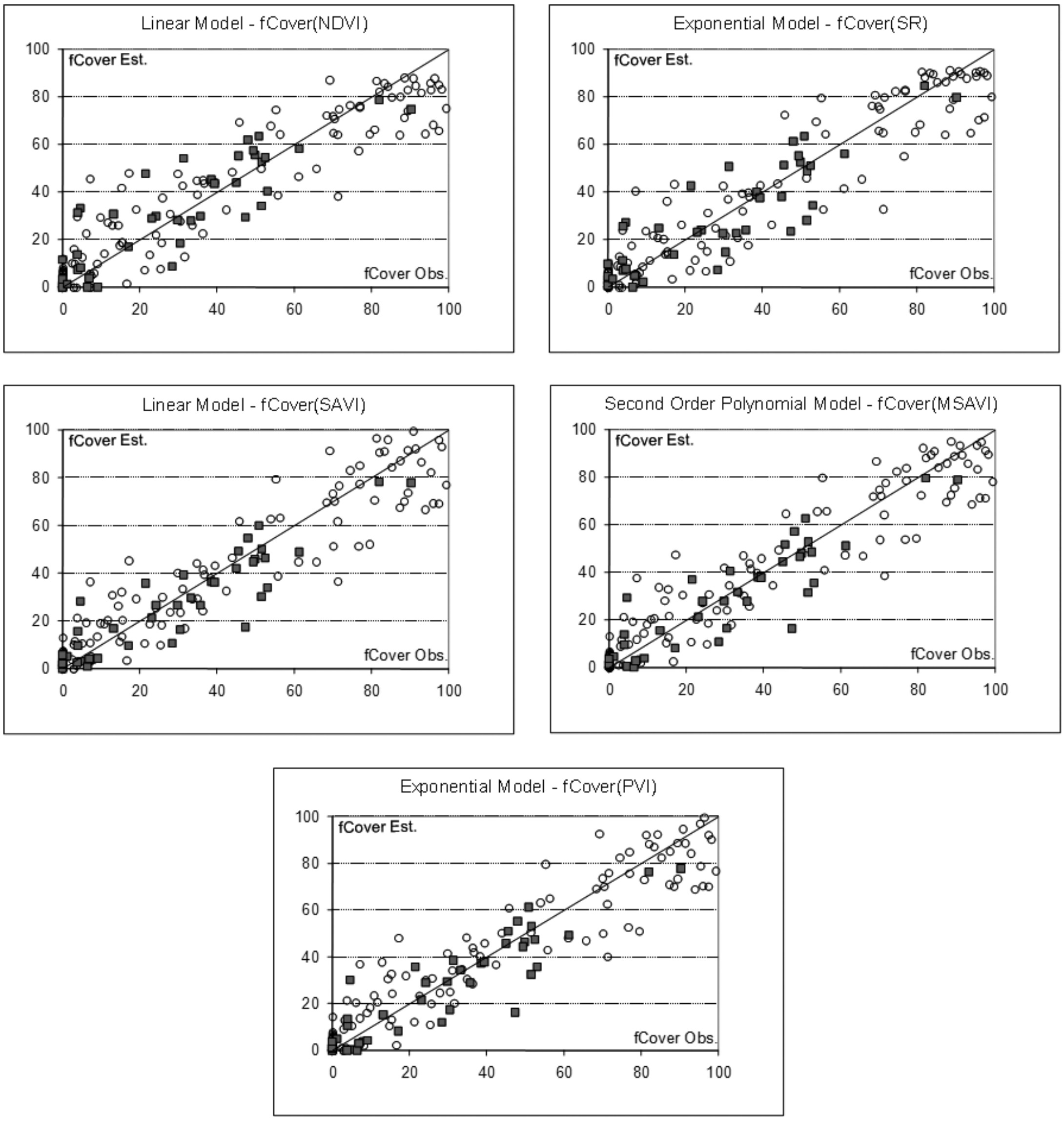

Figure 2: Percent ground cover estimated (fCover Est.) versus observed (fCover Obs.) for the best models of each vegetation index (NDVI-SR-SAVI-MSAVI-PVI) for soybean (○) and corn (■) crops.

ced Thematic Mapper Plus (ETM+) images to estimate cover of crown trees from linear regressions. Among different vegetation indices considered, SAVI had the highest value of determination coefficient ($R^2 = 0.78$). González-Dugo and Mateos (2008) also found a linear relationship between ground cover and SAVI obtained from satellite data for commercial fields of cotton and sugar beet crops. They stated that the determination of the relationship between fCover and the VI, when the crop has grown, is more sensitive to errors when NDVI is used than when SAVI is the input. In this work, SAVI had the best performance for all models considered ($R^2 = 0.89$).

On the other hand, Vaesen *et al.* (2001) found, for fCover, a linear correlation with PVI and a nonlinear regression using NDVI ($R^2 = 0.63$ and $R^2 = 0.68$, respectively), for paddy rice with reflectance data acquired with a hand-held multi-spectral Cropscan radiometer.

Figure 2 shows the relationship between estimated and observed fCover for the best model of each vegetation index (NDVI-SR-SAVI-MSAVI-PVI) for soybean and corn.

Table 2: Models for estimating percent cover (fCover) in soybean and corn: R^2 values. Numbers between parentheses indicate the amount of samples considered.

Model	Linear	Polynomial (2^{nd} Order)	Linear	Exponential	Exponential
Vegetation Indices (input)	NDVI	MSAVI	SAVI	PVI	SR
Soybean (138)	0.89	0.91	0.90	0.90	0.90
Corn (41)	0.76	0.83	0.83	0.83	0.77

The errors between estimated and observed fCover were quantified using RMSE. For the linear model, RMSE values of 11.7% and 10.7% were found, when the input variables were NDVI and SAVI, respectively. The quadratic model, using MSAVI, presented a RMSE value equal to 10.3%; for the exponential model, considering PVI and SR as inputs, RMSE values of 10.6% and 11.0%, respectively, were obtained.

Zhang *et al.* (2011), when estimated fCover from digital photographs of various grassland components, in Canada, using a linear relationship with NDVI calculated from LANDSAT 5 TM, obtained R^2 of 0.55, with RMSE equal to 5.71%. Although the linear model using NDVI (with MODIS data) in our work presented a higher RMSE value, the coefficient of determination value in our model was also higher ($R^2 = 0.88$), despite the lower spatial satellite resolution used in our paper.

Jiménez-Muñoz *et al.* (2009) over different crops in an agricultural area in Spain obtained RMSE values between 13% and 19% when estimated fCover by means of a linear relationship with NDVI calculated from CHRIS/Proba.

Models were also applied in soybean and corn separately, the coefficients of determination obtained for the best models are shown in Table 2.

In soybean, the coefficient of determination remained similar to those obtained using both crops, perhaps due to the data from this crop represents 77% of total; however in corn, when we applied the linear model (with NDVI index), this had a lower value, suggesting that VI which consider the soil background estimate fCover more adequately for this specie. The SR index with an exponential model showed more difference in R^2 values between soybean and corn.

Conclusions

With simple mathematical models based on vegetation indices, obtained from red and NIR reflectances of MODIS sensor, the percent ground cover for soybean and corn could be described adequately.

The estimations obtained using linear models with NDVI, MSAVI, SAVI and PVI presented the practical advantage of simplicity and good accuracy; while for SR the best fit was found with an exponential model for both crops. SAVI index with linear model showed the highest determination coefficient value for soybean and corn separately.

For corn, models which include VI considering the soil background, estimated fCover more adequately than NDVI based models. So, in order to improve the models performance, errors to estimate fCover associated with effect of soil (row orientation, water content, etc) must be reduced.

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