Estimating late spring frost-induced growth anomalies in European beech forests in Italy

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Abstract
Weather extremes and extreme climate events, like late spring frosts, are expected to increase in frequency and duration during the next decades. Although spring phenology of European beech is well adapted to escape freeze damages on longer time scales, the effects of occasional late spring frosts (LSF) are among the main climatic damages to these forests to such an extent that they limit beech distribution and elevation range, especially at its southern margin. The aim of this work was to evaluate the short-term effects of two consecutive LSF events occurred in 2016 and 2017 in Italy on the beech forest vegetation activity. Remotely sensed land surface temperature (LST) data were used to detect the pixels where LSF occurred, while enhanced vegetation index (EVI) data were used to quantify LSF effects by computing a spring vegetation activity anomaly index (sAI). In 2016 and 2017, the LSF covered, respectively, about 29% and 32% of the total Italian beech-dominated area. The two LSF widely differed in their spatial patterns and their effects. In 2016, the pixels belonging to the sAI classes with the highest spring anomalies were also those where prolonged LSF occur, while, in 2017, the pixels belonging to the highest sAI classes were those that underwent the shorter (but probably more intense) LSF events. Under scenarios of increased frequency risk of repeated LSF, the proposed methodology may represent an automatic and low-cost tool both for monitoring and predicting European beech growth patterns.

Keywords Growth anomaly · Enhanced vegetation index · Extreme weather events · Spring frost · Southern Europe

Introduction
Changing climate represents the most important driver of change for temperate forests in the Mediterranean region, by affecting vitality and productivity. Increased intensity and frequency of temperature extremes represents the main driver affecting forest ecosystem structure and composition, with consequent changes in biomass distribution (Kramer et al. 2000; Lindner et al. 2014). The importance and rate of extreme weather events are increasing, causing alterations on species systems. Their role as major drivers of biodiversity and ecosystem changes is expected to increase in the future. The rate of occurrence of such extreme events will likely overcome the ability of many species to cope with them and/or adapt, augmenting the risk of cascading effects through ecosystem interactions. The long-term consequences of extreme events appear to be deleterious, especially to margin populations which are at risk of shifting their distribution and/or their phenology (Greco et al. 2018).

Climate-driven extreme events that have the potential to adversely impact on temperate forests include ice storms (Melanchon and Lechowicz 1987; Nagel et al. 2016; Weeks et al. 2009), summer droughts, and spring frosts. The latter is the most critical extreme-temperature event for temperate forests, given that below-zero temperatures occur right after bud burst (Zohner et al. 2018). Weather extremes and extreme climate events, like spring frost and summer drought, are expected to increase in frequency and duration during the next decades (Seneviratne et al. 2012), and winters are likely to become progressively milder, with an increased risk of exceptionally warm spells.
European beech (*Fagus sylvatica* L.) is the dominant native forest tree species in Central Europe (Leuschner et al. 2006) providing ecosystem services such as timber production, carbon sequestration, water quantity and quality, and preservation of biodiversity (Duncker et al. 2012). Spring vegetative phenology of beech is well adapted to escape freeze damages on longer timescales (Lenz et al. 2013; Vitasse et al. 2014), but occasional spring frosts may limit the edges of its distribution and its elevation range, especially at its southernmost margin where the species is potentially exposed to drought stress induced by increased evaporative demand (Maselli et al. 2014). Spring frosts events may reduce beech radial growth by more than 90% (Dittmar et al. 2006; Ningre and Colin 2007); furthermore, it has been recently shown that beech saplings may delay their bud set in autumn and mitigate growth losses induced by spring frost damage (Zohner et al. 2018), thus showing a mechanism of phenological compensation.

The coupling of extreme events such as winter or summer drought to repeated spring frosts may represent an unprecedented pressure on beech populations and lead to develop adaptive responses including phenotypic plasticity, local adaptation, migration, and extinction (Bussotti et al. 2015). Monitoring the spatial distribution of the damage to ecosystems caused by extreme events is fundamental to better assess their adaptive response to changing climate conditions.

Remotely sensed vegetation indices, like EVI (Enhanced Vegetation Index), represent consistent tools for monitoring vegetation conditions at regional scale by quantifying intra-annual changes in vegetation activity timing and intensity (Bajocco et al. 2019), and relating these changes to environmental processes (Bajocco et al. 2017; Bascietto et al. 2018). Extreme events like droughts are well-known to be caught by satellite remote sensing, e.g., by using vegetation index data to explore their spatial extent and intensity (Rojas et al. 2011; Peña-Gallardo et al. 2018; Urban et al. 2018). Yet, only few studies so far have explored the effect of late spring frost events by satellite remote sensing (Kreyling et al. 2012; Nolè et al. 2018; Bascietto et al. 2018). In this framework, the aims of this study are to (i) detect the spatial distribution of two consecutive spring frost events occurred across Italian beech forests in 2016 and 2017 by means of remotely sensed land surface temperature data, (ii) quantify their impacts in terms of EVI time-series anomalies, and (iii) evaluate the association of the identified EVI-based anomalies with both spring frost duration and elevation belts.

### Materials and methods

**Study area**

Italy is located in southern Europe, extending for about 300,000 km²; it consists of the entirety of the Italian Peninsula and the two Mediterranean islands of Sicily and Sardinia, in addition to many smaller islands. The country is composed of about 35% mountainous regions (> 800 m a.s.l.) that are grouped into two major mountain ranges: the Alps (northern Italy) and the Apennines (central and southern Italy). Given the longitudinal extension of the peninsula and the mountainous internal conformation, climate of Italy is highly variable. In most of the inland northern and central regions, the climate ranges from humid subtropical to humid continental and oceanic, while the southern part of the country is generally characterized by Mediterranean climate. According to the Corine Land Cover (CLC) map of 2006 (ISPRA Ambiente 2010), the most widespread broadleaved forest category is *Fagus sylvatica* (European beech), covering about the 12% of the Italian territory, and mainly distributed along the major mountain ranges (Fig. 1).

The overlap between the Italian territory and the areas covered by beech-dominated forests, accordingly to the CLC 2006, defines the region of interest where all the analyses were performed.

### Late spring frost events identification

Moderate Resolution Imaging Spectroradiometer (MODIS) MOD11A2 product was used to localize the spring frost events. MOD11A2 provides an average, 8-day, daytime and nighttime land surface temperature (LST) at ~1 km spatial scale (Wan et al. 2015). Each pixel value in the MOD11A2 is a simple average of all the corresponding MOD11A1 LST pixels collected within an 8-day compositing period; twice this period is the exact ground track repeat period of the Terra and Aqua platforms (https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod11a2_v006). We used the nighttime LST threshold of below 0 °C in order to produce a mask and consider in the analysis only those pixel potentially exposed to frost. As spring frost events can occur until mid-May in Central and Southern Europe (Dittmar et al. 2006; Ningre and Colin 2007; Kreyling et al. 2012; Menzel et al. 2015; Bascietto et al. 2018), all the pixels that from 14th April to 17th May, for both 2016 and 2017, recorded nighttime LST values below 0 °C for at least one 8-day time period were labeled as LSF events. The persistence of freezing temperatures, i.e., the prolonged occurrence of an LSF event, is measured by counting the 8-day intervals with nighttime LST below 0 °C. Therefore, three categories of LSF duration were identified based on an 8-day time step: LSF1 (8 days), LSF2 (16 days), and LSF3 (≥ 24 days). MODIS LST image collections were processed on Google Earth Engine platform (Gorelick et al. 2017).
Spring growth anomaly estimation

MODIS Enhanced Vegetation Index (EVI) data were used to study the LSF impact on the beech forests. The EVI was developed to optimize the vegetation signal through a decoupling of the canopy background signal and also reducing the atmosphere effects (Huete et al. 2014; Broich et al. 2015; Wang et al. 2017). EVI is computed as follows:

\[
EVI = G \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + C_1 \times \rho_{\text{red}} - C_2 \times \rho_{\text{blue}} + L}
\]

where \( G \) is the gain factor, \( \rho \) is the surface reflectance (atmospherically corrected), \( C_1 \) and \( C_2 \) are the coefficients of the aerosol resistance term, and \( L \) is the canopy background adjustment. The coefficients adopted in the EVI algorithm are \( L = 1 \), \( C_1 = 6 \), \( C_2 = 7.5 \), and \( G = 2.5 \) (Huete et al. 2002).

Fifteen years (2003–2017) of EVI data were collected from MOD13Q1 Terra (Didan 2015a) and MYD13Q1 Aqua (Didan 2015b) 16-day maximum value composite products (250 m of pixel-size). The integration of these two MODIS products provides an annual time-series with a pace of 8 days (46 images per year). EVI pixels marked as cloudy by the pixel reliability band were filtered out. Any missing EVI value in each pixel time-series was imputed using a Kalman filter on a structural model fitted by maximum likelihood (Hyndman and Khandakar 2008; Moritz 2017). Then, to harmonize the slight discrepancy between the Terra and Aqua sensors, the 8-day EVI time-series of each pixel was smoothed using a 3-width moving window mean (Tuszynski 2014). The spatial resolution of MODIS LST and EVI products is different; it is to be noticed that this mismatch could have excluded smaller spots of frozen forests nested inside larger unfrozen forest areas due to the averaging of LST values on larger spatial scales than EVI. MODIS EVI image collections were processed on Google Earth Engine platform (Gorelick et al. 2017).

A recurrent neural network (RNN) (Abadi et al. 2015) was used to predict 2016 and 2017 EVI time-series. The RNN was trained on the 2003–2015 time-series. The RNNs were
composed of three long short-term memory (LSTM) layers and two densely connected layers run for 75 epochs on 23 samples per gradient update using the mean absolute error loss function and root mean squared propagation (RMSprop) as gradient descent optimization algorithm. Regularization was enforced by imposing dropout ratio values of 10%, 30%, and 30%; and recurrent dropouts of 20%, 50%, and 50% to the three LSTM layers. Model validation was performed by time-series cross-validation. In this procedure, there is a series of validation sets, each consisting of a modeled yearlong EVI profile. The corresponding training set consists of the multi-year EVI time-series that occurred prior to the validation set. The network prediction accuracy was computed by averaging over the validation sets.

EVI time-series were normalized to 0 mean and 1 standard deviation before submitting them to their network. Predicted EVI time-series were de-normalized according their original means and standard deviations. RNN was performed on R with keras package (Allaire et al. 2018; R Core Team 2018).

Each predicted EVI profile was matched to both the observed 2016 and 2017 EVI curves on a pixel by pixel basis. A spring vegetation activity anomaly index (sAI) was computed as the mean of negative difference between predicted and actual EVI values, in the time interval 21st April–31st May, thus encompassing the typical time range of potential late spring frost in beech forests. The sAI is a measure of the magnitude of the decrease (mean of negative differences) of the 2016 and 2017 EVI annual curve during springtime, with respect to the predicted year. The sAI classes have been identified using an equal interval classification and so deriving three classes of EVI-based anomaly categories: low anomaly (sAI1), moderate anomaly (sAI2), and high anomaly (sAI3).

To analyze the strength of association of the spring growth anomaly classes with the spring frost categories and the elevation belts, two separate permutational chi-square ($\chi^2$) tests were carried out, by comparing the observed values of $\chi^2$ to 9999 random values of $\chi^2$ under the null hypothesis of no association. The elevation data was extracted from the Digital Terrain Model provided by the Italian Ministry of Environment, with 75 m of pixel-size (http://www.pcn.minambiente.it). Given the altitudinal range of European beech forests in Italy (approximately 800–2000 m), the different elevation belts were obtained by subdividing the DTM data into three groups: < 1200 m (ELEV1), 1200–1600 m (ELEV2), and > 1600 m (ELEV3).

Finally, a change detection analysis was performed on sAI classes of the year 2016 (initial state) versus 2017 (final state) to reveal patterns of repeated frosts in Italian beech forests and find the pixels that have increased, remained stable, or decreased in terms of sAI class.

## Results

### Late spring frost events identification

Although freezing temperatures in spring were scattered all over Italy, they tended to concentrate mainly on three areas: the exterior valleys of eastern and western Alps, and the central Apennines (Fig. 2). The freezing temperatures interested 5235 pixels in 2016 and 5855 pixels in 2017 (Table 1), representing, respectively, the 29% and 32% of the total Italian forests dominated by beech area.

The LSF lasted for 8 days in the majority of pixels for both years (91% in 2016 and 77% in 2017), but while the year 2016 was characterized by a higher number of pixels belonging to LSF1, the year 2017 was characterized by a larger number of pixels belonging to more prolonged spring frost events.

### Spring growth anomalies estimation

The validation test results showed that, with the notable exception of the year 2007, the scores of the time-series cross-validation (mean absolute error) are centered on an average value of 0.35 for both spring frost years (Fig. 3), notwithstanding the length of the training sets.

According to Fig. 4, for each sAI classes, in the past decade, the annual EVI time-series profiles followed a similar pattern in shape and amplitude with the exception of LSF years. The sAI index can be considered as the integral of EVI values in the shaded area delimited by observed and RNN-predicted profiles during the period 21st April–31st May.

The year 2017 resulted as more affected by the LSF-induced growth anomaly than 2016 in terms of total number of pixels; to the contrary, the most anomalous classes (sAI2 and sAI3) were more abundant in 2016 than in 2017 (Table 2). The spatial distribution of the sAI classes for the 2016 and 2017 reveals that the beech forests growth anomalies were mainly concentrated in the Central Apennines (both years), North-eastern Alps (both years), and in the Northern Apennines (only year 2017) (Figs. 5, 6, and 7).

The permutational $\chi^2$ test between sAI classes and LSF categories gave an observed value of $\chi^2 = 350.317$ ($p = 0.0001$) for 2016, and of $\chi^2 = 405.959$ ($p = 0.0001$) for 2017. This result proves a high degree of association between growth anomaly levels and spring frost duration in Italy for both years. According to Table 3, in 2016, the sAI1 resulted positively associated with the LSF1 ($p = 0.05$) that expresses a frost duration no longer than 8 days. The sAI2 and sAI3, related to moderate and high anomaly, respectively, were both positively correlated with the LSF2 and LSF3 ($p = 0.05$) that indicate freezing events lasting 16 days or longer. In 2017, the correlation patterns are opposite to 2016: sAI1 resulted positively associated with the LSF2 and LSF3 ($p = 0.05$), while the
sAI2 and sAI3 were both positively correlated with the LSF1 ($p = 0.05$), expressing the shortest spring frost events.

The results of the association analysis between sAI classes and elevation belts gave an observed value of $\chi^2 = 2141.535$ ($p = 0.0001$) for 2016 and of $\chi^2 = 2458.005$ ($p = 0.0001$) for 2017. According to Table 4, both 2016 and 2017 showed the same correlation pattern: The lowest anomaly classes (sAI1) resulted positively associated with the ELEV1 ($p = 0.05$) that expresses the lowest altitudes, while sAI2 and sAI3 were both positively correlated with the ELEV2 and ELEV3 ($p = 0.05$), i.e. elevations higher than 1200 m.

Finally, results from the change detection analysis demonstrated that from 2016 to 2017, the level of LSF-induced growth anomaly considerably decreased (Table 5). In details, about one third of beech forest pixels that underwent a low (sAI1) or moderate (sAI2) growth anomaly in the year 2016 were subject to a repeated LSF effect in the year 2017 with the same intensity (32.24% and 36.61%, respectively). As for the pixels falling in sAI3 class in 2016, only the 26.82% did not suffer also the spring frost of 2017, while the remaining pixels were damaged again, becoming sAI1 (50.47%) and sAI2 (33.28%) classes.

**Discussion**

Despite a wide literature on the characterization of late spring frosts on beech forests and ecosystems, to the best of our knowledge, this is the first study reporting on a repeated spring frost in consecutive years in terms of patterns of LSF-induced growth anomaly. The repeated anomalies are coupled with evidences of a growth decline that are occurring on the southern margin of the beech distribution (Piovesan et al. 2008) from the 1970s, and on lower elevations (Jump et al. 2009) from the 2000s, probably due to climate constraints such as summer drought.

The occurrence of two consecutive spring frosts is a remarkable climate event, especially on central mountain ranges, also considering that no spring frost has been recorded during the previous 15 years (Bascietto et al. 2018). The spring frosts occurred in years 2016 and 2017 hit, respectively, 29% and 32% of the Italian beech forests and were spatially distributed mainly over the northern (Alps) and central (Apennines) mountain ranges of Italy.

**Table 1** Count of MOD11A2 pixels for each LSF class in 2016 and 2017

<table>
<thead>
<tr>
<th>LSF duration</th>
<th>2016</th>
<th>2017</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSF1</td>
<td>8 days</td>
<td>4752</td>
</tr>
<tr>
<td>LSF2</td>
<td>16 days</td>
<td>353</td>
</tr>
<tr>
<td>LSF3 $\geq$ 24 days</td>
<td>130</td>
<td>452</td>
</tr>
<tr>
<td>Total</td>
<td>5235</td>
<td>5855</td>
</tr>
</tbody>
</table>
Evidences from this study revealed that the two spring frost events analyzed were widely different in their spatial patterns and their effects. The LSF during 2017 were more widespread with respect to 2016, with events lasting more days; however, the pixels subject to high vegetation activity anomalies in 2016 were more abundant than in 2017. In 2016, the pixels characterized by the highest spring vegetation activity anomalies were subject to more prolonged freezing temperatures, while, the following year, they were subject to less prolonged spring frost events. This insight hints to the fact that the severity of the vegetation anomaly depends on the exact timing of the frost rather than its duration.

Contrary to the spring frost duration, the elevation profile of the anomaly among frost-affected beech forests did not vary among the 2 years. In these frost-affected forests, the pixels that underwent the highest anomalies were always those located at the highest elevations.

Fig. 3  Validation scores (mean absolute error) of the RNN runs for 2016 (red line) and for 2017 (cyan line). The training sets correspond to the years on x-axis; the validation set corresponds to the year on the label.

Fig. 4  Mean MODIS EVI time-series profiles across sAI classes from year 2009 onwards. Observed EVI profiles in red color predicted EVI profiles in cyan color (years 2016 and 2017). The shaded areas mark the 21st April–31st May time-period.
A large portion of frost-affected beech forests underwent a repeated vegetation activity anomaly of the same or lower intensity from 2016 to 2017, indicating that spring frost in the year 2017 has impacted on mostly the same beech forests that were impacted by the earlier one, although with different patterns of intensity. The effect of the late spring frost events recorded in 2016 and 2017 is clearly recorded in their EVI profiles: In such years, with respect to the previous ones, the steep EVI green-up increase in springtime is replaced by a delayed and slower ascent that tops much later in summer (end of July), thus reducing summer EVI productivity. Notable deviations of the observed EVI profiles from the predicted profiles in 2016 and 2017 also include lower peak vegetation activity. The delay of the end of season timing, apparently shown by sAI2 and sAI3 classes (respectively, moderate and high anomaly), may hint to a prolonged duration of the senescence period.

Such evidences prove that, at regional scale, the spring frost effects mainly depend solely on the exceptional climatic conditions of that year, notwithstanding their geographical and altitudinal location. The exact timing of the freezing temperatures occurrence may directly affect the severity of the damages (i.e., the level of vegetation activity anomaly), by taking place during the delicate phenological phase of bud-burst and leaf flushing. Once the forest canopy has been exposed to late spring frost damage, the persistence of the freezing temperatures does not necessarily affect the intensity of the growth decrease. Other factors, including the complex pattern of micro-habitats characterizing these beech forests, may better explain the severity of spring frost anomaly. In this perspective, remotely sensed data at finer scale may open the possibility to explore uncharted issues, like the spatial variability of LSF events, allowing insights into compensatory mechanisms and their drivers.

From a methodological point of view, the time-series cross-validation of the neural net model has shown a constant performance in predicting each successive year in terms of EVI time-series, even when the training sets were as short as 3 years. The absence of a clear trend in validation scores may be the result of very homogeneous and recurrent annual EVI time-series, hinting at the possibility of using shorter time-series for future anomaly analyses on beech forests. This result mitigates the danger of learning misleading or

<table>
<thead>
<tr>
<th></th>
<th>2016</th>
<th>2017</th>
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</thead>
<tbody>
<tr>
<td>sAI1</td>
<td>15,016</td>
<td>21,413</td>
</tr>
<tr>
<td>sAI2</td>
<td>21,398</td>
<td>20,833</td>
</tr>
<tr>
<td>sAI3</td>
<td>3335</td>
<td>1119</td>
</tr>
<tr>
<td>Total</td>
<td>39,749</td>
<td>43,365</td>
</tr>
</tbody>
</table>

Table 2  Distribution of MOD11A2 pixels across the three sAI classes in years 2016 and 2017

Fig. 5 Spatial distribution of sAI classes in central Apennines in 2016 (left) and 2017 (right)
Fig. 6  Spatial distribution of sAI classes in eastern Alps in 2016 (left) and 2017 (right)

Fig. 7  Spatial distribution of sAI classes in western Alps in 2016 (left) and 2017 (right)
irrelevant patterns that may be present in the training time-series sets (probably thanks to the aggressive regularization deployed in the model). Short time-series training sets may effectively be used to predict future vegetation index trends in broadleaf forest ecosystems (provided no extreme unusual events occurred), with the aim to undercover the presence of possible local niches where beech stands escaped spring frost damages and to better comprehend the potential trend in the adaptive response of beech.

In the complex scenario where (i) frequency of spring frosts may increase, (ii) beech is slightly decreasing its spring phenology sensitivity to climate warming (Fu et al. 2015; Zhang et al. 2015), and (iii) beech is reducing its growth due to extreme drought events specifically at its southern margin, the occurrence of repeated spring frosts may augment beech forest current growth decline (Lindner et al. 2014) and may further trigger (or accelerate) mechanisms of adaptive response (Bussotti et al. 2015; Jump et al. 2009), mostly in Mediterranean regions like Italy. Such mechanisms rely on the extent of the genetic diversity between and within the population, the phenotypic plasticity, or the migration capacity, although the adaptive strategies are not mutually exclusive (Nicotha et al. 2010). Beech has shown a high within-population variability that can be evolutionarily advantageous in the presence of environmental changes (Bresson et al. 2011; Buiteveld et al. 2007; Müller 2017). On this variability, the climate may act to drive the phenotypic plasticity leading to a better acclimatization (Vitasse et al. 2013).

Adaptive responses play a pivotal role at the edge of the distribution, where the selective pressure is higher (Kramer et al. 2017). It has been recently shown that beech saplings may delay their bud set in autumn and mitigate growth losses induced by spring frost damage (Zohner et al. 2018) thus showing a mechanism of phenological compensation. Further insight is needed as to whether this adaptive response is shared by mature trees at regional scale.

Table 3  Contingency table showing the number of pixels shared between the sAI classes and the LSF categories. Italicized cells indicate a positive association between the level of growth anomaly and the corresponding spring frost duration, whereas normal characters denote a negative association. All values are significant at the $p = 0.05$ level, except those with NS

<table>
<thead>
<tr>
<th></th>
<th>2016</th>
<th>2017</th>
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<tbody>
<tr>
<td></td>
<td>sAI1</td>
<td>sAI2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LSF1</td>
<td>14,771</td>
<td>20438</td>
</tr>
<tr>
<td>LSF2</td>
<td>196</td>
<td>818</td>
</tr>
<tr>
<td>LSF3</td>
<td>49</td>
<td>142</td>
</tr>
</tbody>
</table>

Table 4  Contingency table showing the number of pixels shared between the sAI classes and the ELEV categories. Italicized values are percentages of pixels subject to a less intense effect. All values are percentage of pixels subject to the same class of growth anomaly in both years. Italic values are percentages of pixels subject to a less intense spring growth anomaly in 2017 than in 2016

<table>
<thead>
<tr>
<th></th>
<th>2016 (%)</th>
<th>2017 (%)</th>
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<tbody>
<tr>
<td></td>
<td>sAI1</td>
<td>sAI2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>sAI1</td>
<td>50.47</td>
<td>33.28</td>
</tr>
<tr>
<td>sAI2</td>
<td>32.24</td>
<td>28.39</td>
</tr>
<tr>
<td>sAI3</td>
<td>17.11</td>
<td>36.61</td>
</tr>
<tr>
<td>No sAI</td>
<td>0.19</td>
<td>1.72</td>
</tr>
</tbody>
</table>

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