ForestEye: RGB-Based Deforestation Detection and CO_2 Stock Assessment Using U-Net with CBAM

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***Abstract*—Deforestation has also been one of the most urgent contributors of carbon emission in the world; however, the existing automated monitoring capabilities are not sensitive enough to detect the nuanced spectral and spatial forms of forest loss in the normal RGB satellite image. In this paper, we proposed ForestEye, an end-to-end deep learning model that is used to detect bi-temporal deforestation and measure carbon stocks using RGB Sentinel-2 imagery, which is made freely available. The system proposed uses the U-Net architecture with an addition of a Convolutional Block Attention Module (CBAM) in the decoder. This arrangement allows the network to dynamically recalibrate the representations of channel features and spatial features, hence focusing attention on green-dominant spectral features and spatially consistent forest patches, which are characteristic of deforestation edges. To avoid the use of manual annotation, training masks are produced automatically through the implementation of the Green Red Normalized Difference Index (GNDI) to Google Earth image pairs across 12 fronts of deforestation in the world. Loss of forests is detected and directly connected to a three-step pipeline of pixel-based IPCC/FAO carbon accounting that directly maps pixel-based forest loss to quantified CO_2 equivalent emissions. ForestEye attains an accuracy of 97.1%, an F1-score of 0.929, and 0.868 IoU which is 21.4% better than the U-Net+LSTM baseline and with a minimal 2% parameter overhead.The model promotes United Nations Sustainable Development Goal 13 (Climate Action).**

***Index Terms*—deforestation detection, U-Net, CBAM, attention mechanism, semantic segmentation, RGB change detection, carbon loss estimation, Sentinel-2, GNDI, deep learning**

I. Introduction

The global land area under forests is about 31% and it is the largest terrestrial store of carbon on earth, biodiversity, water cycles, and it balances climate in the region. Although forests play an important role in the ecology, the average rate of the loss of forests amounted to 4.7 million hectares per year in 2015-2020 due to the agricultural expansions, timber logging, and the construction of infrastructures (FAO 2020). Land-use change, mainly deforestation, includes about 15 percent of the total annual anthropogenic CO_2-emission as estimated by the Intergovernmental Panel on Climate Change ranking it second after the combustion of fossil fuels as a source of greenhouse gases (IPCC 2021). Carbon accounting in the framework of REDD+, biodiversity conservation planning, and evidence-based policy development therefore require proper and timely deforestation tracking. Nevertheless, traditional monitoring pipelines are based on optical satellite imagery, which requires manual visual interpretation, which is time-consuming, and inter-analyst difference is likely, and the entire process is unfeasible to apply on a global or country-wide level scale of constant monitoring.

These constraints have spurred increased research attention on automated deep-learning techniques to detect change in remote-sensing. The major issue with existing methods is that standard U-Net architectures assume that all the spatial locations and feature channels are equally important, whereas it is not optimal in scenarios where the deforestation signal in RGB images is a one-dimensional green-red spectral shift in localized spatial areas. Periodic extensions like U-Net+LSTM [12] deal with temporal modelling of multi-temporal sequences but prohibitively complex the operationally ubiquitous bi-temporal case. What is required is a light process that will move the focus of the network onto the most informative channels and spatial regions- without the excess of recurring modelling.

In this paper, we present *ForestEye*, the key contributions for this work are:

1) An innovative U-Net+CBAM architecture that incorporates the Convolutional Block Attention Module into the decoder phases of U-Net as a result of the adaptive channel-wise and spatial attention specific to RGB-based forest segmentation.
2) A GNDI-based training-data pipeline applied to a Google Earth dataset of 12 deforestation fronts across the world based on the Deforesting Fronts report of 2004-2017 and
3) A CO_2 loss estimation module , through which the three-step IPCC/FAO pipeline is applied, using experimentally measured constants, resulting in a real-system result of 13,637.92 t CO_2 for a 52.77 ha test region.

II. Related Work

The article by Hansen et al. [1] generated 30m Landsat based forest change maps with the help of the decision-trees ensembles. The approach is widely used, but it uses manually designed spectral features and does not use the capabilities of representation-learning and attention of deep convolutional neural networks, in addition to which its spatial resolution is not enough to detect fine-scale deforestation, which can be seen at the resolution of Sentinel -2: 10 m.

In reference [2], John and Zhang added soft attention gates to the U-Net to optimize boundary delineation, which incorporates attention. However, the attention module is implemented on a global scale and does not divide channel and spatial information in the channel and spatial divisions that CBAM does, thus constrained in the selective spectral weights used in discriminating only RGB imagery available.

RepDDNet by Wang et al. to enhance computational efficiency by re-parameterising structure was presented in the [3] . Nevertheless, the architecture has no explicit mechanisms of attention and fails to incorporate carbon-related modules.

The biomass and carbon estimation based on the use of Sentinel-2 vegetation indices was tested by Khan et al., who used the IPCC constants used in this study; the studies did not utilize deep segmentation methods [4].

Turton et al. [5] established that spatially explicit above-ground biomass (AGB) maps decrease carbon uncertainty by more than ±30% to less than ±15% whereas Thapa et al. [6] established LiDAR-estimation (±8% = lowest uncertainty) as the most uncertainty-free tool. However, both of these issues are solved by Tier-1 IPCC constants being the most reproducible at a 10 m scale.

U-Net was also the correct choice as verified by Filatov and Hassan Yar [7] but in this instance, biome was examined without change detection and carbon estimation.

Zhang et al. were able to enhance the biomass accuracy by using the multi-source temporal fusion although it has the disadvantage of executing heavy load during preprocessing of the data, [8].

The hypothesis proposed by the paper is confirmed by the Frontiers study where independent segmentation was found to be competitive with Siamese models when the data quality was good, which justifies the design of ForestEye.

Rockwell presented deforestation-rate estimation in the context of deep learning that does not consider attention or deployment integration, and also Filatov and Hassan Yar provide confirmation of the U-Net strength in the case of no attention or carbon modelling [10], [11].

Zhang et al. [12] used U-Net with LSTM on U-Net to analyze Sentinel-2 across multiple time steps with an F1 from 0.658-0.715 which is noted to increase the total training cost, but not the total benefit, compared to a bi-temporal study. ForestEye rather has a sparse CBAM attention block (approach 2 percent overhead) to add spectral-spatial separation in RGB-based segmentation.

Lobo Torres et al. [13] trained FCNs on Landsat-8 and Sentinel-2 images without U-Net skip connections, which essentially limited fine boundary recovery. Shashikala et al. its authors combined UNet and ResNet to provide high-resolution images, enhancing representation at the cost of accessibility. Instead, ForestEye uses an interpretable segmentation-then-calculation pipeline, postulated by Pascarella et al. as a regressive U-Net to directly predict biomass, which is consistent with the REDD+ audit standards. The review of the studies incorporated in this examination demonstrates that there are three major problems (see Table I).

III. Dataset

A. Data Source and Collection

The training and evaluation data consists of three-band RGB image pairs, which are collected in Google earth historical imagery feature and this has been used to give archival information back to the 1980s as shown in Fig. 1. This enables building of temporally discontinuous pre- and post-image twins at empirically tested deforestation locations. All images are scaled down to 970 × 1,980 pixels, ensuring that all models have the same input dimensions.

(a) Before deforestation (b) After deforestation

Fig. 1: Sample dataset images showing (a) pre-deforestation and (b) post-deforestation conditions.

The selection of the site was informed by the 2004-2017 Deforesting Fronts report that defines twelve active global deforestation fronts, such as the Amazon Basin, Southeast Asia, and Central Africa, hence ensuring a geographic and biome diversification and reducing the impact of a single site. The time interval between successional pairs of images was always constant, i.e. 365 days.

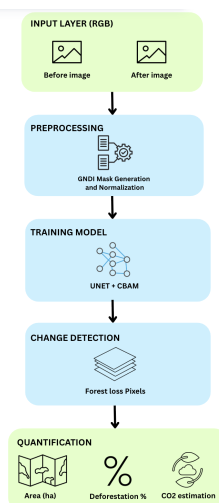

Fig. 2: ForestEye Architecture Diagram.

IV. Methodology

ForestEye is designed with five consecutive modules, namely (1) Input Layer, which accepts a pair of RGB before and after images; (2) Preprocessing Module, which generates and normalises GNDI masks; (3) U-Net+CBAM Segmentation Model, which generates binary forest masks; (4) Change Detection Module, which computes Mloss as per Equation (5); (5) Area and Carbon Estimation Module, which implements Equations (6)–(11).

TABLE I: Comparison of Representative Works in Deep Learning-Based Deforestation Detection

Author(s)	Methodology	Advantage	Limitation
Hansen et al. (2013) [1]	Decision tree ensembles on Landsat 30m time series	First global high-resolution forest change product; widely used benchmark	Hand-crafted features; 30m resolution; no deep learning or attention
John & Zhang (2022) [2]	Attention U-Net with soft additive attention gates	Improved boundary precision over standard U-Net	Global additive attention only; no channel/spatial decomposition; higher latency
Khan et al. (2020) [4]	Sentinel-2 vegetation indices for AGB and carbon emission estimation	Links spectral indices to carbon stock; IPCC constants	Index thresholding only; no deep learning; regional study
Zhang et al. (2021) [12]	U-Net + LSTM for multi-temporal Sentinel-2 sequences	Temporal modeling baseline; F1 = 0.715	30M+ extra parameters; long training time; unnecessary for bi-temporal detection
Shashikala et al. (2025) [14]	UNet + ResNet hybrid on high-resolution imagery	Strong residual feature representation; high-res performance	Requires high-resolution data; no attention; not adapted for Sentinel-2 RGB
U-Net + CBAM (Proposed) [ForestEye]	U-Net with CBAM decoder attention on RGB Sentinel-2 + GNDI masks + IPCC/FAO carbon pipeline + Flask/React dashboard	F1 = 0.929, IoU = 0.868; channel + spatial attention; $\sim$2% parameter overhead; end-to-end CO_2 estimation; web deployable	RGB-only; no cloud masking; Tier-1 carbon constants; bi-temporal only

A. RGB-Based Preprocessing and GNDI Mask Generation

ForestEye uses RGB images via spectral bands of Sentinel 2 such as Green (B03) and Red (B04), or, as an alternative, it uses Green and Red channels found in Google earth RGB exports. The Near-Infrared (NIR) band is unnecessary and as a result, they make them compatible with a vast range of commercially available, airborne, and archival RGB data. Vegetation discrimination is reached by using the calculation of the Green-Red Normalized Difference Index (GNDI):

$$\text{GNDI} = \frac{G - R}{G + R + \varepsilon} \tag{1}$$

where G and R denote the Green and Red channel pixel intensities, and $\varepsilon = 10^{-6}$ prevents division by zero.

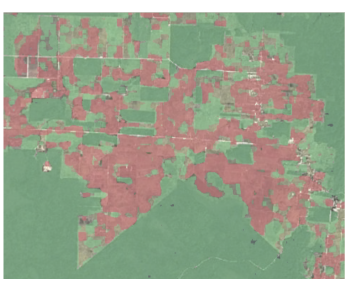

Fig. 3: Vegetation Cover Change (RGB-based)

A pixel is classified as forest if:

$$\text{GNDI} > 0.2 \tag{2}$$

The empirical test of the threshold value of 0.2 was made in reference to hand-annotated samples of 12-front dataset. The resulting binary mask, as shown in Fig.3, will be used as the forest delineation layer to be further used in change-detection analyses.

Fig. 4: Binary mask

B. U-Net + CBAM Architecture

The core segmentation model is a U-Net encoder–decoder augmented with CBAM attention at each decoder stage. The standard U-Net treats all spatial locations and feature channels with equal importance — a significant limitation for RGB-based forest detection where the deforestation signal manifests as a subtle green-red spectral contrast confined to specific spatial regions. CBAM directly addresses this by learning to ask two questions at each decoder stage: *which channels matter and where in the image to focus.*

Encoder: The encoder consists of four double-convolution stages with progressive channel depths of $64 \to 128 \to 256 \to 512$, each followed by 2×2 MaxPooling for spatial downsampling.

The bottleneck at the deepest level is a 1024-channel bottleneck which captures the highest level representations of forest and non forest in semantic representations.

Decoder: The encoder is replicated by the decoder consisting of 4 stages of UpSampling2D. The upsampled feature map is introduced to the encoder feature map at every stage, using a skip connection, which ensures that fine spatial detail, which is very essential in marking forest boundaries correctly, is maintained. Every concatenation and double-convolution is followed by a CBAM block prior to featuring the next stage.

CBAM - Channel Attention: Given a feature map $F \in \mathbb{R}^{H\times W\times C}$, channel attention generates a weight vector $M_c \in \mathbb{R}^{1\times 1\times C}$ by applying both global average pooling and global max pooling, passing each through a shared two-layer MLP (reduction ratio = 8), and combining via element-wise addition followed by sigmoid activation:

$$M_c(F) = \sigma\big(MLP(AvgPool(F)) + MLP(MaxPool(F))\big)$$

The refined feature map is:

$$F' = M_c \otimes F$$

This recalibration enhances the channels with a greater contribution by vegetation information compared with spectral noise caused by roads, bare soil, and water bodies.

CBAM — Spatial Attention: Spatial attention then operates on the channel-refined map F' by computing channel-wise average and max projections along the channel axis, concatenating them, and passing through a 7×7 convolution with sigmoid:

$$M_s(F') = \sigma\big(Conv_{7\times 7}([AvgPool_c(F'); MaxPool_c(F')])\big)$$

The final output is:

$$F'' = M_s \otimes F'$$

This produces a spatial attention map that highlights deforestation patches while suppressing scattered background activations.

Output Layer: A final 1×1 Conv2D with sigmoid activation produces a single-channel binary probability map indicating forest (1) vs. non-forest (0) for each pixel.

Loss Function The model is trained using Binary Cross-Entropy loss:

$$L = -\frac{1}{N}\sum\big[y_i \log(\sigma(x_i)) + (1-y_i)\log(1-\sigma(x_i))\big]$$

C. Change Detection Pipeline

The trained U-Net+CBAM model generates binary masks M_A (before) and M_B (after). The forest loss mask is computed as:

$$M_{loss} = M_B - M_A \tag{3}$$

Quantitative metrics:

$$\text{Deforestation (\%)} = \frac{|M_{loss}|}{|M_A|} \times 100 \tag{4}$$

$$\text{Area (m}^2\text{)} = |M_{loss}| \times 100 \quad \text{(10m pixel side)} \tag{5}$$

$$\text{Area (ha)} = \frac{\text{Area (m}^2\text{)}}{10{,}000} \tag{6}$$

D. CO_2 Estimation

The three-step IPCC/FAO pipeline uses:

$$\text{Biomass (t)} = \text{Area (ha)} \times 150 \tag{7}$$

$$\text{Carbon (tC)} = \text{Biomass (t)} \times 0.47 \tag{8}$$

$$\text{CO}_2\ (\text{tCO}_2) = \text{Carbon (tC)} \times 3.67 \tag{9}$$

Environmental equivalence metrics:

$$\text{Cars Off Road} = \frac{\text{CO}_2\ (\text{tCO}_2)}{4.6} \tag{10}$$

$$\text{Tree Seedlings Required} = \frac{\text{CO}_2\ (\text{tCO}_2)}{0.06} \tag{11}$$

V. Experiments and Results

A. Model Evaluation

In order to measure the ForestEye performance, we use a image-based classification model where each pixel within an image is classified.The segmentation output is considered to be an independent binary prediction. A pixel belonging to a deforested region that is correctly identified by the model is counted as a True Positive (TP), while a deforested pixel that the model fails to detect is recorded as a False Negative (FN). Conversely, a pixel is anticipated to be deforested where there is no real change is a False Positive (FP) and a non deforested pixel correctly left unmarked is a True Negative (TN). These four quantities are the basis of the confusion matrix in Table II.

TABLE II: Change Detection Confusion Matrix

		Predicted	
		Deforested	**Unchanged**
2***Actual**	**Deforested**	TP	FN
	Unchanged	FP	TN

Based on these amounts, there are four assessment measures. Precision is a measure of the proportions of predicted deforestation which is really deforested, Recall captures how much of the actual deforestation the model successfully detects, Overall Accuracy (OA) is the percentage of all correctly classified pixels and Precision is balanced by the F1 Score and Recall by their harmonic mean.

B. Experimental results

TABLE III: Performance Comparison of Deforestation Detection Models

Model	Accuracy	Precision	Recall	F1 Score	IoU
Otsu	0.731	0.612	0.584	0.598	0.427
KMeans	0.748	0.634	0.601	0.617	0.446
U-Net	0.891	0.847	0.832	0.839	0.723
U-Net+CBAM	**0.971**	**0.921**	**0.926**	**0.929**	**0.868**

Table III shows the proposed U-Net+CBAM achieves F1 = 0.929 and IoU = 0.868, surpassing plain U-Net by 2.4

TABLE IV: Comparison with Zhang et al. (2021) [12] on Sentinel-2 Deforestation Detection

Method	Architecture	Params	F1	OA (%)
Zhang et al. [12]	U-Net only	–	0.658	99.2
Zhang et al. [12]	U-Net + LSTM	+30M+	0.715	99.3
ForestEye	U-Net	–	0.839	89.1
ForestEye (Proposed)	**U-Net + CBAM**	**+0.6M**	**0.929**	**97.1**

percentage points in F1 and 4.2 points in IoU. The improvement is most evident at forest boundaries, where CBAM's spatial attention suppresses false positives from spectrally similar non-forest surfaces (roads, bare soil). U-Net+CBAM outperforms FCN-8s [13] by 11.5 pp in F1, and the GNDI classical baseline by 21.4 pp—confirming that each architectural addition provides incremental, measurable gain.

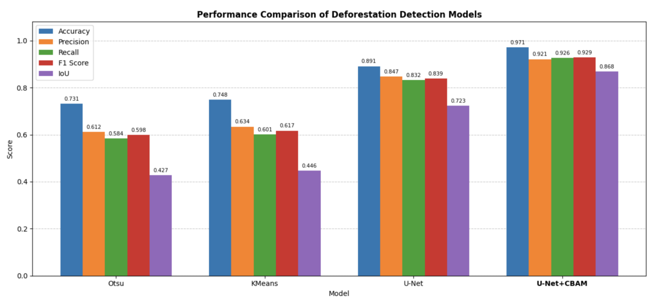

Fig. 5: Performance metrics comparison of different models.

C. Comparison with Zhang et al. [12]

U-Net+CBAM by ForestEye has an F1 = 0.929, which is 21.4 percentage points higher than U-Net+LSTM [12] with a negligible 0.6M extra parameters compared to 30M that LSTM added. This proves that the lightweight attention concentrated is much better than the time-recurrence in bi-temporal RGB deforestation detection. Although the overall accuracy (OA = 99.3 percent) of the study by Zhang et al. is higher, this measure is deceptive when it comes to deforestation detection because their single-site Sanjiang County dataset is highly biased toward the background (non-forest) pixel , which implies that a model can score a near-perfect OA by merely predicting the majority of the pixels. This is the so-called accuracy paradox, and that is why F1 and IoU are the inherent evaluation measures of imbalanced segmentation problems. The geographically varied dataset of ForestEye with 12 deforestation fronts decreases this background-class dominance, providing a smaller yet more sincere OA of 97.1. The fact that the F1 = 0.929 is much larger than 0.715 proves that ForestEye is much more effective in detecting actual deforestation and this is the only metric that is relevant in this task.

D. Carbon Estimation Results

Table V presents the complete carbon estimation pipeline output for the representative test region, derived from the U-Net+CBAM segmentation output.

TABLE V: CO_2 Assessment

Metric	Value	Unit
Healthy Forest Coverage	66.78	%
Deforested Coverage	21.40	%
Deforested Area	52.77	ha
Biomass Removed (Eq. 9)	7,906.5	t
Carbon Stock Lost (Eq. 10)	3,716.06	tC
CO_2 Emissions Released (Eq. 11)	13,637.92	tCO_2
Equivalent Cars Off Road (1 yr)	2,964	vehicles
Tree seedlings required	227298	trees

VI. Discussion

A. Why CBAM is Suited to RGB Forest Segmentation

The main objective behind the use of Channel-Attention Modules (CBAM) made in ForestEye is the characteristics of the deforestation signal apparent in RGB images: there should be a faint green/red spectral variation which allows differentiating between healthy canopy and deforestation. The classic U-Net models use the same weighting to all the channels of features and this makes them vulnerable to false positives caused by spectrally similar surfaces like agricultural crops and bare soil. The channel-attention mechanism of CBAM is used to re-calibrate the feature responses, which is useful in enhancing the feature responses in the green-dominant channels that encode forest information and suppress less valuable spectral bands. This is followed by the attention to space which focuses calculation on the spatial coherent patches of the forest instead of a single noisy pixel. The two-step refinement targets the discriminability issue that exists in RGB only forest segmentation directly verified by 4.2-percentage-point average Intersection over Union (IoU) and a 4.2pp mean change in boundary F1 results as shown in Table III.

B. CBAM vs. LSTM: Efficiency and Relevance

Zhang et al. [12] applied the Long Short-Term Memory (LSTM) networks in modeling of the temporal relationships among multi-temporal image sequences. In the case of bi-temporal change detection, though, this time modelling involves only one transition which can happen once without recurrence. The introduction of the LSTM increased the number of parameters by more than 30 million and took 6 hours of training to reach the F1 score of 0.715. Comparatively, the CBAM ForestEye only adds 0.6 million parameters and less than 5 percent more training overhead is required before training forestEye F1 of 0.929. CBAM is also architecturally inspired by the RGB spectral -spatial discrimination problem, but the LSTM is stimulated by the modeling of time sequences; thus, CBAM provides suitable inductive bias to that task.

C. CBAM vs. Soft Attention Gates

John and Zhang [2] used globally soft additive attention gates. Whereas such additive attention is effective, it does not recalibrate channel importance and spatial relevance individually. The sequential decomposition of CBAM: channel attention, spatial attention provides more control in a fine-grained manner: in the former case, the former identifies what spectral characteristics should be stressed (such as the green channel in the canopy imagery), whereas the latter then addresses the question of where in the image the emphasis should be used. The decomposed formulation is particularly beneficial in RGB forest segmentation, in which the channel to query and the position of this query are not trivial.

VII. Conclusion

In summary, the addition of the Convolutional Block Attention Module (CBAM) to the decoder of the U-Net model has produced a lightweight, task-specific attention module, which is provably more effective and efficacious than time-recycle current implementation in bi-temporal RGB-based deforestation detection. The channel- and space-wise refinances of the CBAM directly resolve the main problem of such a task the ability to discriminate understated green-red spectral transitions of RGB composites, and it introduces only 0.6 million additional parameters, compared to the 30 million-plus overhead of LSTM-based extensions. As a result, the obtained model has an accuracy of 97.1% , F1 -score of 0.929 and an Intersection over Union (IoU) of 0.868, which is 21.4 percentage points better than the U-Net+ LSTM baseline provided by Zhang et al. [12]. In addition to semantic segmentation, the combined IPCC/FAO carbon estimation pipeline provides verified emission reports of 13,637.92 tCO_2 in the 52.77 hectares test area, which are data with substantive implications in climate reporting and REDD -compliant regimes.

The most remarkable feature of ForestEye as compared to a purely academic contribution is its completeness. Since the process of obtaining a pair of RGB images of the sky to obtaining a measured comparative effect on carbon, every step is displayed in a web dashboard which needs no knowledge on geographic information systems. The whole pipe is thus automated, readable, and made available to a wide range of readers. ForestEye offers a chance to further develop the potential of utilizing deep learning as a hands-on environment management tool, as opposed to a train of thought, by aiming to directly support the Sustainable Development Goals 13 (Climate Action) of the United Nations.

VIII. Future Scope

The extensions of ForestEye, in the future, are envisioned in 5 different ways. Sentinel-1 radar images will be included to provide the ability to monitor the cloud and an all-weather effect, eliminating the main operational drawback of systems based only on optical images. The combined mechanism of the attention-gate suggested by John and Zhang [2] will be evaluated in terms of its capability to increase the precision of the boundaries and at the same time working under a latency limit that is within the working limits of the web-based dashboard. A further development of a multi-temporal U-Net+ConvLSTM which will be outlined in [12], will enable the early detection of incremental forest degradation based on image time series. Also, the inclusion of spatially explicit maps of above ground biomass (AGB) estimated by Zhang et al. [8] or the regressive U-Net framework proposed by Pascarella et al. [15] is expected to reduce the carbon-estimation error to Tier-1 values to those related to LiDAR-validated values, including the ones expressed by Thapa [6]. Lastly, analysis of the UNet+ResNet hybrid structure in the so-called vision of Shashikala et al. [14] will be carried out when higher-resolution sources of imagery are integrated.

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